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Smart consideration of actual ladle status monitored by novel sensors for secondary metallurgy process parameters and ladle maintenance strategies

SmartLadle

Public

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Deliverable 6.1 – Evaluation of final industrial tests and of achieved as well as possible improvements in ladle treatment and maintenance

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Lead beneficiary: SWERIM

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Project summary

What is the effect of the actual ladle status -new to worn- on steel bath properties? How do e.g. temperature or fluid flow vary with ladle conditions? When is the optimal moment for relining?

SmartLadle will provide a solution for online monitoring and dynamic incorporation of actual ladle status for process control. A soft sensor for ladle status shall be developed, supported by a smart sensor for detecting refractory wear and thermal status. Measurement data, models and advisory tools shall provide information for decision making to operators to adapt ladle metallurgy process parameters to actual ladle status and decide about maintenance actions.

Definition of terms used in the project

Soft sensor: Mathematical calculation of value of a process parameter that is difficult or so far impossible to measure directly and online, based on other process values, measurements, models and smart sensor data.

Smart sensor: Combination of a pure sensor for the acquisition of a measured value, e.g. refractory temperature, and a small computing unit with implemented simplified models, e.g. for refractory wear.

ML model: Data-driven model that analysis data and detects relationships (linear or non-linear) among variables based on real-world data using Machine Learning (ML) Techniques.

1. Introduction

The deliverable D6.1 describes the work of work package 6 and provides information about

- test of smart and soft sensors, optimisation of ML tools and verification/optimisation of soft sensor and Advisory Tool, and
- evaluation of improvements regarding ladle life, temperature distribution within refractory, economic and environmental aspects.

BFI and SWG focused on the test of the smart sensor as well as soft sensors for refractory and wear lining thickness prediction developed in previous work packages.

Uddeholm AB and Swerim collaborated in building the soft sensor algorithm which was followed by series of tests to validate and optimise the soft sensor and advisory tool. The tools provide additional information for decision making to decrease wear and thus increase ladle life.

For Sidenor, this deliverable describes the final updates and connections of the models to conform the advisory tool and how they connect to the final trials in the tundish smart sensor measuring refractory temperature.

Finally, all partners contributed to an evaluation of the results and transferability assessment. Details are described in the following chapters.

2. Test of smart and soft sensors

2.1 BFI and SWG use case

The smart sensor from WP2 as well as the soft sensors for wear and temperature prediction from WP4 and WP5 were applied and tested within the final WP6. For better understanding, at first the results of the soft sensor for temperature prediction are described, followed by the results of the smart sensor and soft sensor for wear prediction.

The process data that was used for the software tasks included data for one selected ladle journey, where also partly temperature measurements by thermocouples and smart sensor were available. This ladle journey comprises 23 heats with VD treatment, divided into two parts due to a production stop in between:

- Part 1: Preheating and 15 heats
- Part 2: Preheating and 8 heats

The second preheating started one month after the first preheating started, and between the 15th heat and the 2nd preheating the ladle was not heated and thus cooled down completely.

Soft sensor to calculate the refractory temperature of the SWG ladle

As described in Deliverable D4.1, a Long Short-Term Memory (LSTM) neural network for performing regression tasks was developed and trained as well as a XGBoost model. Due to the slightly better performance, the LSTM model was chosen for the work in WP6.

The input data for the soft sensor included for the chosen ladle journey:

- Preheating temperature over time
- Liquid steel temperature (one average value from tapping to casting)
- Air temperature in heating periods (one value)
- Time with steel in ladle for different cases (VD treatment, VOD treatment, long VD and VOD treatments)
- Time without steel in ladle for different cases (heating and short heating of empty ladle between casting and next tapping)

In the diagrams showing the results over time, always the time since the beginning of the first preheating is plotted on the x-axis.

The results for part 1 are presented in **Figure 1**, whereas the ones for part 2 are presented in **Figure 2**. Soft sensor predictions are displayed in red. To assess the performance of the soft sensor, also FEM calculations were performed using the FEM model that was used for training, but now calculating the refractory temperature distribution based on the actual boundary conditions. Thus, not standard times and temperatures for the heats were used (as originally for training calculations), but the ones that were also used as input values for the soft sensor for this chosen ladle journey. FEM results are plotted in blue for the position that was selected for the soft sensor (at the cold face of the wear lining in steel part of the ladle, see also D4.1). Additionally, as far as available also temperature measurements at the position selected for the soft sensor calculation are plotted in green. They were made during 1st preheating using a datalogger and after three heats in part 2 manually. Unfortunately, due to the tight schedule in part 1, there were no manual measurements possible. The datalogger could not remain at the ladle during the heat treatments because the temperature in the protection box was expected to be too high. Finally, the temperature used as boundary condition (preheating temperature, liquid steel temperature for heats and air temperature in heating periods between heats) is plotted in grey.

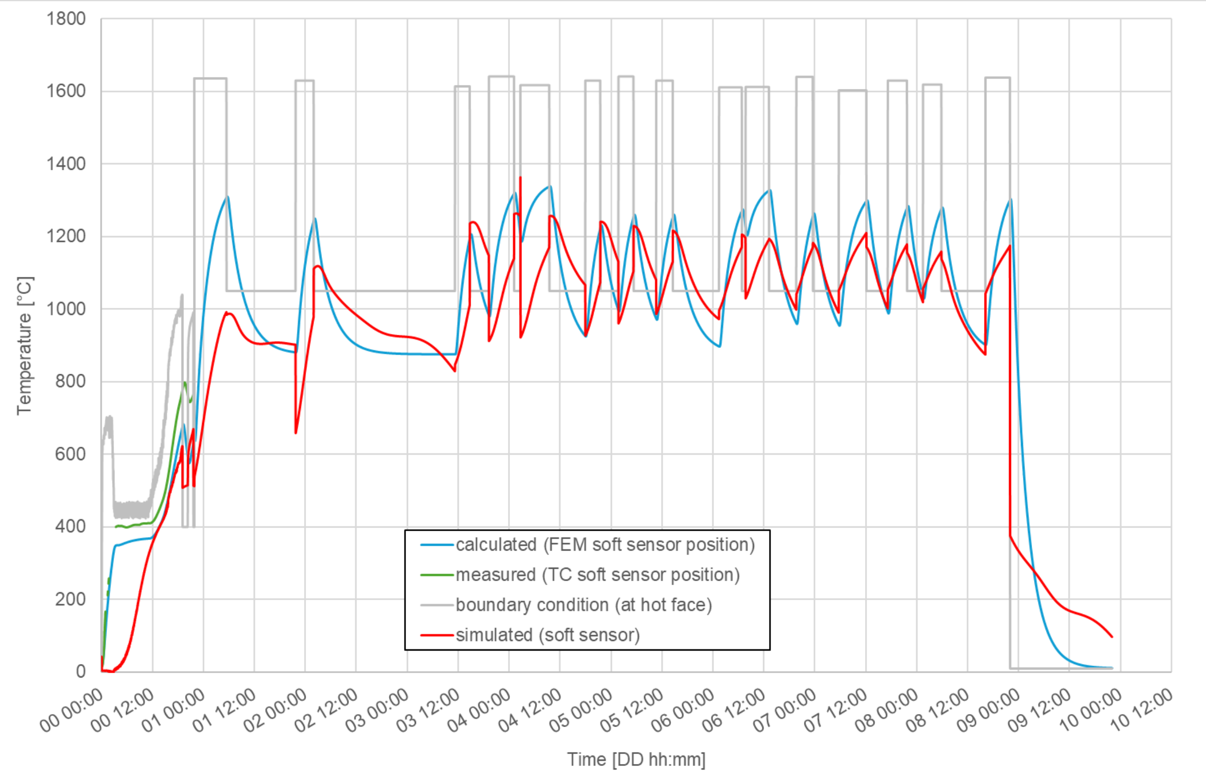

Figure 1: Soft sensor in industrial trial, part 1

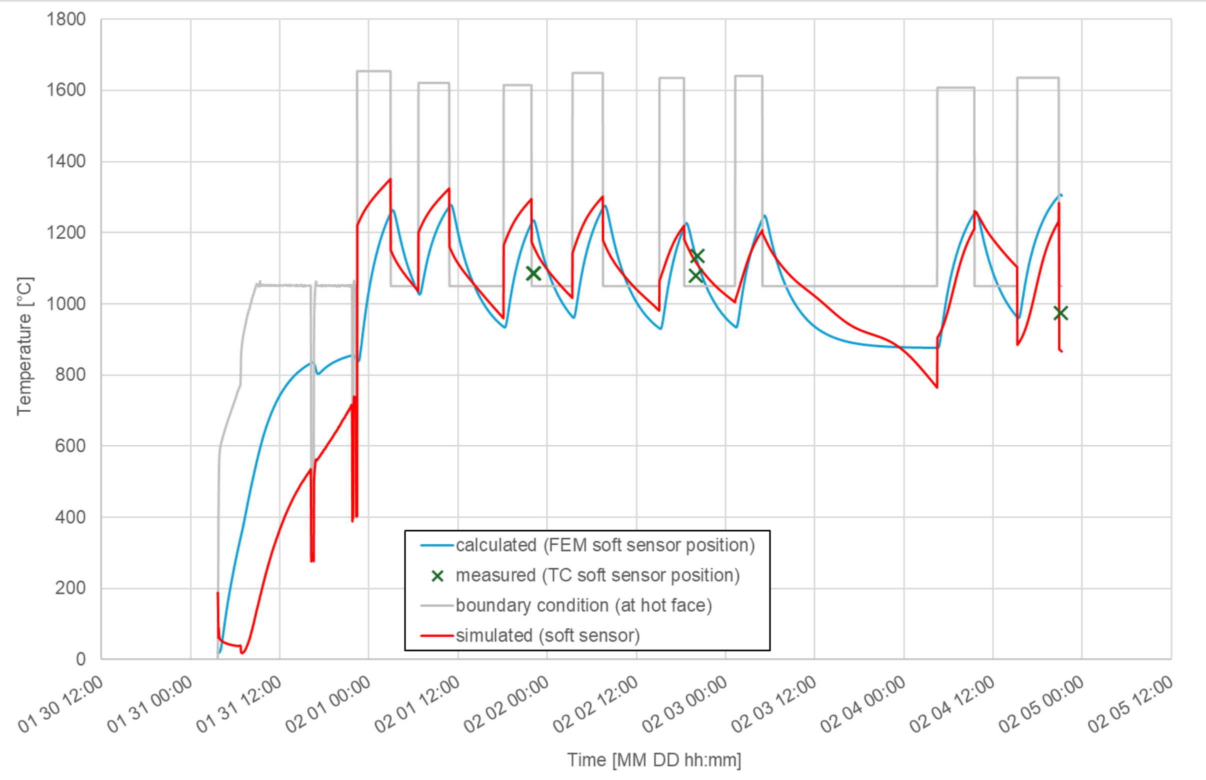

Figure 2: Soft sensor in industrial trial, part 2

Considering the low number of 21 training sets (described in Deliverable D4.1) – being a basic calculation, 2x7 variations of the production cycle for two different steel temperatures (being the same for all 10 heats), 3 variations where one or two heats have a different steel temperature than the other heats, and 3 variations of preheating – the soft sensor shows quite accurate results using actual process data as input values:
With the FEM results at the soft sensor position for assessment of the model accuracy, the R^2 is 0.829 for part 1 and 0.503 for part 2.

A clear deviation can be seen in the preheating curves (being the first 24 hours in each figure), but this can be further improved when using more datasets for training. Although never trained, the cooling periods during preheating (when the ladle is e.g. moved for installation of slide gates and stirring plug or to other ladle preheating stations) were reproduced, but overdone.

Despite this, the performance especially for prediction of temperature during the heats is good, which can also be seen when comparing the soft sensor predictions to the measurements (**Table 1**).

Table 1: Comparison of temperature at selected times for soft sensor, thermocouple (TC) measurement and FEM calculation

	Soft sensor [°C]	TC measurement [°C]	FEM [°C]
End of 1st preheating	514	765	632
After 18th heat	1160*	1085*	1234*
After 20th heat	1114*	1107*	1125*
After 23rd heat	868	974	1307

* mean value between two subsequent measurements

Smart sensor for measurement of temperature in refractory and assessment of wear at SWG ladle

In a second step, the smart sensor temperature measurement was evaluated together with the soft sensor for temperature prediction. The smart sensor (**Figure 3**) was placed at the ladle bottom protected against thermal and mechanical impact, and the receiver was placed in the steel plant connected to a portable PC. Due to the problems with the temperature protection, application of the smart sensor was not possible when the ladle was in production cycles. Thus, it was not connected to the process control system of SWG. The assessment of wear was also done offline.

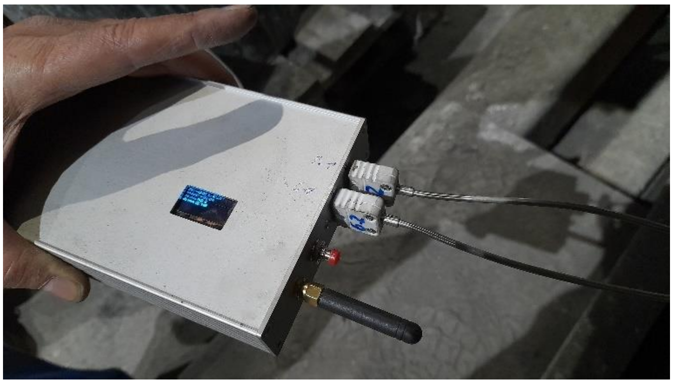

Figure 3: Smart sensor before installation at the ladle bottom

Results of the smart sensor temperature measurement are plotted together with the results of the soft sensor in **Figure 4** and **Figure 5**. The smart sensor measurement position is not the same as the position where the soft sensor is predicting the temperature. The soft sensor was trained before the industrial trials took place, and thus a position at the cold face of the wear lining in steel part was chosen. Later it was decided to place the smart sensor a bit higher, closer to the region of the steel/slag interface, as this area is mainly affected by wear. Thus, the soft sensor temperature prediction (in red) is the same as in Figure 1, but in contrary the smart sensor measurement (in purple), the thermocouple measurement (in green) and the FEM results (in blue) are now for the smart sensor position.

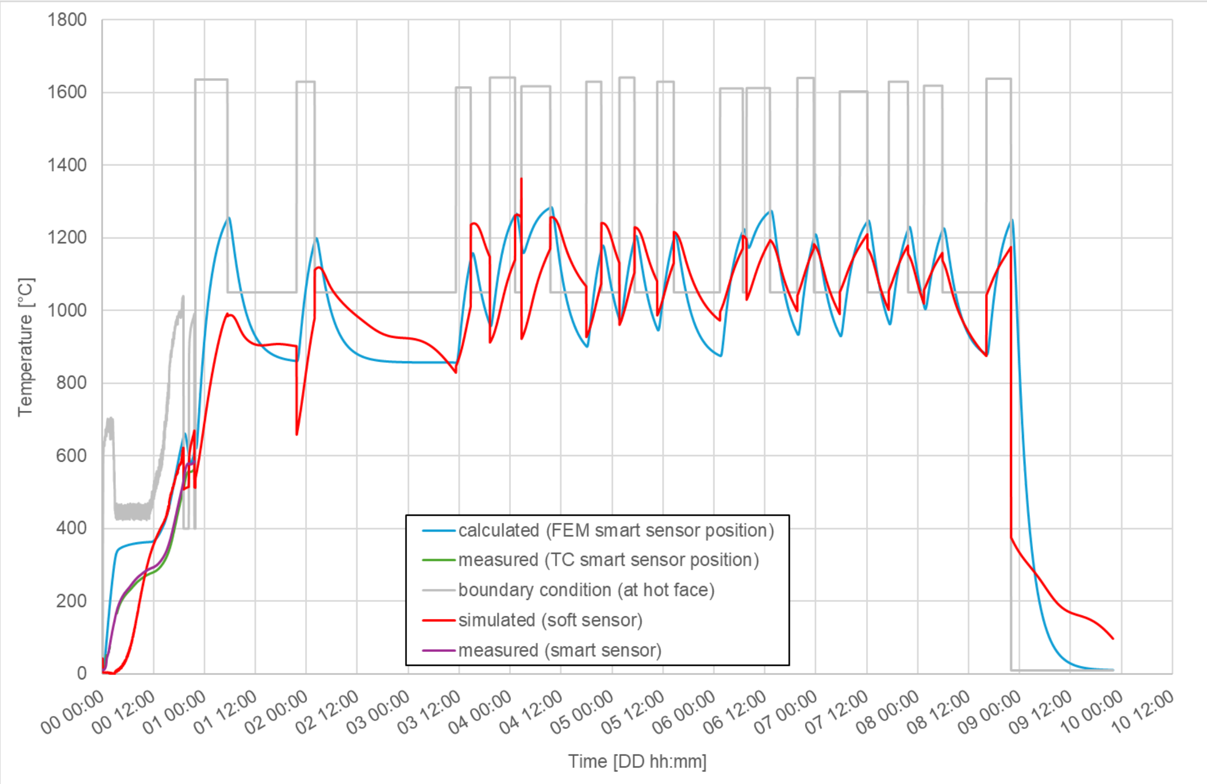

Figure 4: Smart sensor in industrial trial

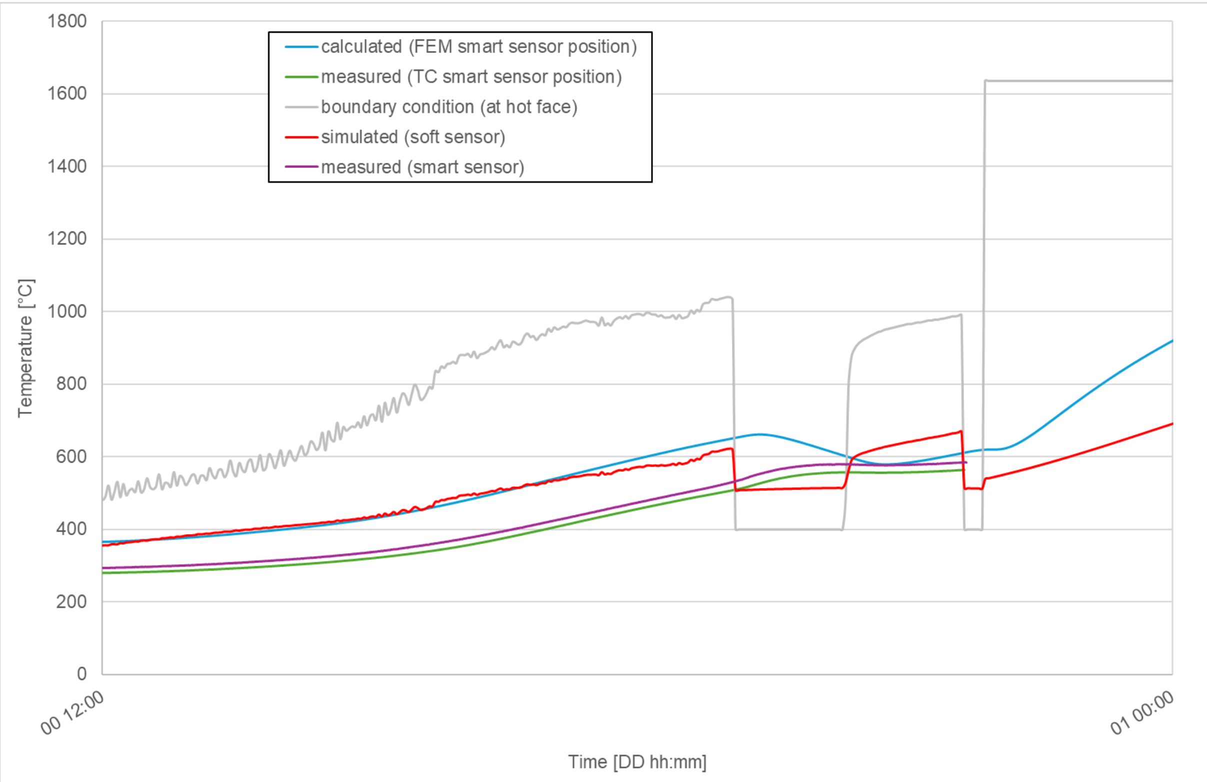

Figure 5: Smart sensor in industrial trial – Zoom to end of preheating process

The temperatures at end of 1st preheating were:

Measured by smart sensor:	585 °C
Measured by thermocouple at smart sensor position:	564 °C
Calculated by FEM at smart sensor position:	612 °C
Soft sensor prediction (not at smart sensor position):	514 °C

It can be seen that there are deviations between the prediction of the soft sensor, that shall mimic the smart sensor, and the measurement of the smart sensor. Reasons for this are most likely the low number of training sets for the soft sensor development (as explained above) and the different positions of smart and soft sensor. The first could be overcome by further training of the soft sensor, also with measurement data of the smart sensor. During this training, also the adapted position of the smart sensor can be considered. Due to the timeline of the project, this was not possible within SmartLadle project but would be an interesting work to perform within a subsequent project.

For wear assessment the XGBoost model developed within WP5 was used, which showed a better performance than the random forest model.

The input data for the soft sensor included for the chosen ladle journey:

- Steel grade
- Ladle no.
- Ladle journey
- No. of heat in journey
- Time with steel in ladle

For evaluation of the results of the soft sensor, also the remaining wear lining thickness assessed by SWG were used.

The results of the soft sensor's wear prediction for the selected ladle journey are illustrated (in orange) in **Figure 6** together with the assessed remaining wear lining thickness (in blue). The first point at sample index 0 shows the original wear lining thickness (of a new brick), which was only partly included in the training data. Following this, the remaining wear lining thickness (= output value) after each subsequent heat (= sample index) is plotted, and it can be seen how the wear lining thickness decreases over one ladle journey.

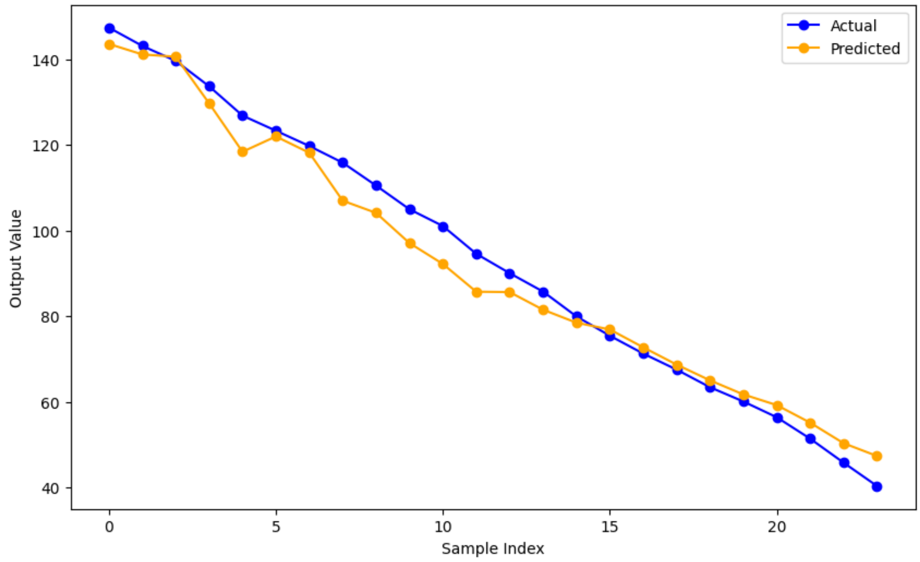

Figure 6: Soft sensor prediction of remaining wear lining thickness in industrial trial (predicted) and assessed wall thickness (actual)

The prediction of the wear lining thickness is fitting well the assessed values of SWG. This can also be seen when looking at the accuracy of the model (**Figure 7**) and the R^2 being 0,976.

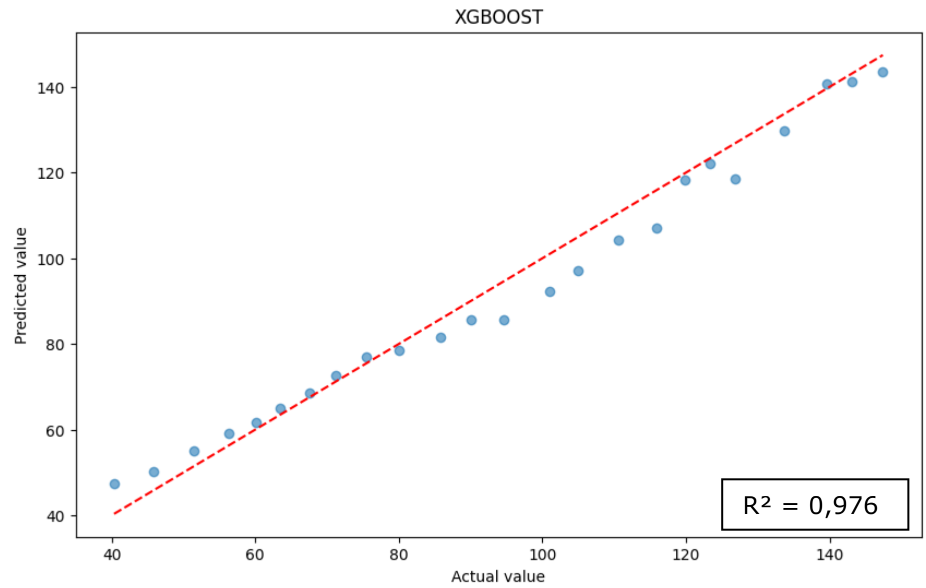

Figure 7: Accuracy of soft sensor wear lining thickness prediction

2.2 SID use case

In WP2 and WP4 different trials with thermocouples in the billet tundish helped to characterize the thermal profile inside the refractory during preheating and working conditions. In this final period of the project, it was tried a step beyond: Thermocouples were placed in a tundish and protected in their positions, looking for a more stable measurement allowing a wireless data transmission. The experience gained in previous trials was important to get them well placed.

Those thermocouples were placed in July 2024 and were still working in January 2025. Initially, standard dataloggers were used to take measurements from them and after some other additional trials they were measured using wireless dataloggers inside a protective box (**Figure 8**). Those dataloggers can collect the data and send the value to the antenna in the casting machine cabin without problems, and they are also capable of storing data from some time, in case the antenna is not connected. The protective box and a configuration in which the contact with the tundish is minimum, the datalogger can last for a long time unattended, thanks to the protecting box and long lasting battery; and will offer the data once it is within the range of the antenna.

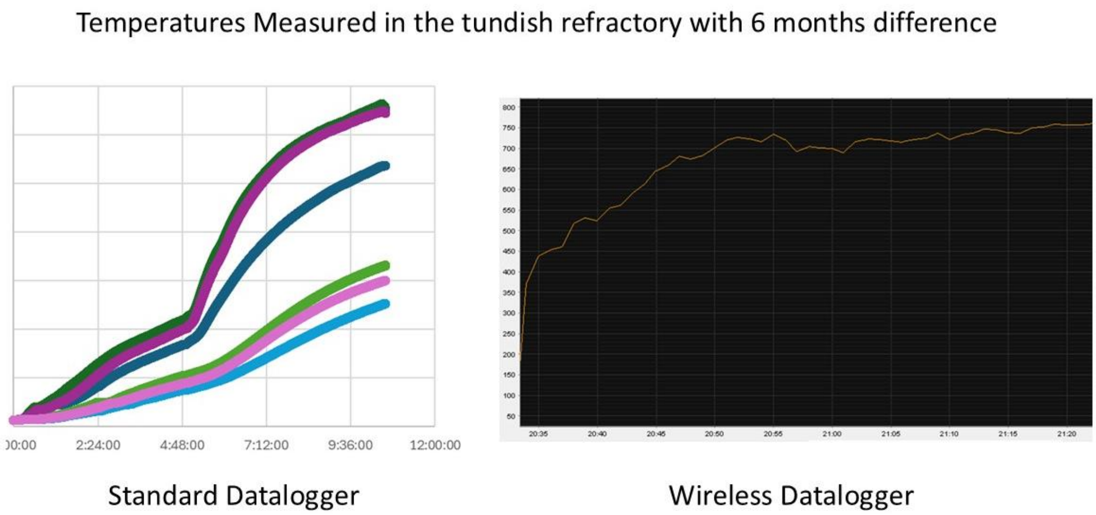

Figure 8: Temperatures measured in the tundish with 6 months of difference and using two different systems for data logging.

On the other hand, the thermal images of the tundish did not work as expected as the outer surface of the tundish is well isolated from the refractory and the temperature there is not so high and gets heated with a long delay compared to the process and the working refractory.

The soft sensor is centred in the application of the two liquid steel thermal models, with some components related to ladles thermal state and wear state. The models’ final version (within the project) is explained in the chapter 3.2 of this deliverable report, and it is considered successful enough with error margins in the area of 10 ºC merging the two liquid steel models. This is within the accepted gap in the casting temperature.

3. Optimisation of ML tools and verification/optimisation of soft sensor and Advisory Tool

3.1 SWERIM and Uddeholm use case

3.1.1 Uddeholm model test campaign

Uddeholm AB ran campaigns after the soft sensor model was developed. The first test campaign was carried out as shown in **Figure 9**. Ladle no. 20 was chosen for the campaign. The plan was to carry out ladle treatment as normal, the data were used for validation of the ML model. The wall thickness measurement mentioned in deliverable D4.1 was also carried out to processing the laser scanning data for improving the ML and CFD models. Accelerometers were placed in the ladle exterior for additional data during the process, the data were also used for ML model. The data from the ML and CFD model were used in the advisory guideline.

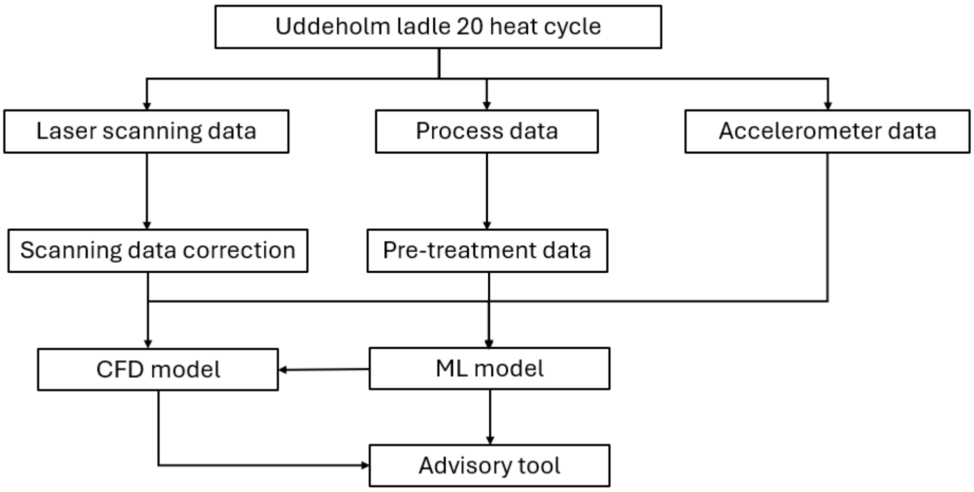

Figure 9: 1st test campaign in Uddeholm after ML model development

3.1.1.1 ML model and optimization

SWERIM and Uddeholm tested the soft sensor model i.e., the prediction model at the end of the 1st campaign. The objective of the first trial was to retrain the model with the laser scanning data corrected for wall thickness measurement. The **Figure 10** shows the prediction model that was developed before the campaign (in WP4) and the optimization model that was added to the ML model (in WP5). The model was retrained with the laser scanning data after the correction based on the wall thickness measurement. The prediction model provides information on the wall thickness at different height and angle at the end of the heat cycle. The optimization model provides information on process parameters that can be changed to reduce the wall thickness as advice for the operators.

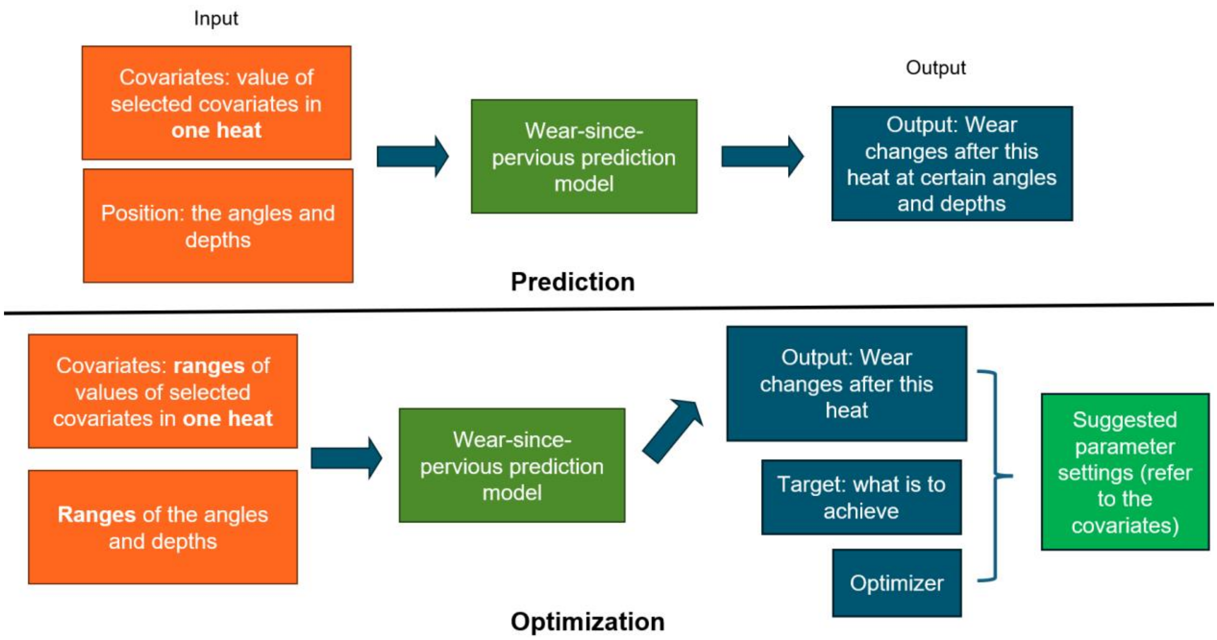

Figure 10: ML model showing prediction and optimizer model

The **Table 2** below shows the limit for parameter settings in 1 heat based on the optimization model where the maximum and minimum time for the key process parameters which has major contribution to the wall wear is proposed. The optimization parameters need to have constrained for different steel grades, and upstream information for individualised suggestions. This constrains needs to be defined for entire steel grades produced, considering the refining process for each grade.

Table 2: Proposed limits for parameter settings for a heat

Total time with Ar flow - low	Total EMS time low A in DH	Total EMS time mid A in DH	Steel temp min	Total time with Ar flow - high	
0	11.95	0	1477.5	0	Minimum
85.68	44.61	46.62	1558.0	10.27	Maximum

3.1.2 Validation campaign

In 2nd trials, ladle no. 23 was tracked, and the process data was recorded. The objective of the trial was for testing and validation of the ML model along with improving the model confidence. The wall thickness measurement as shown in **Figure 11**, was carried out at the end of the cycle to compare with the ML model results. The wall measurement in the slag line was around 90mm ± 5 mm, while deep inside the ladle, the wall thickness was around 100mm. The ML model showed wall thickness ranging between 80-90mm at different location which is thinner than the measurement, but since the overprediction of model result is better than underpredicting the thickness.

Figure 11: Wall thickness measurement during 2nd campaign

The statistical data of electromagnetics stirring operation during the ladle cycle was plotted as shown in **Figure 12**. The operation time of EMS at Max, Mid, and Low Ampere i.e., power is shown over the number of each heat in the ladle cycle. The operation time of the EMS running at Max power averaged shows a natural decline in the EMS run time. The EMS strategy is determined by the steel grade, the production plan could be used where steel grade with longer EMS run time are cast earlier in ladle life cycle and its impact on the wall wear, but more analysis and trials need to be carried out for such suggestion.

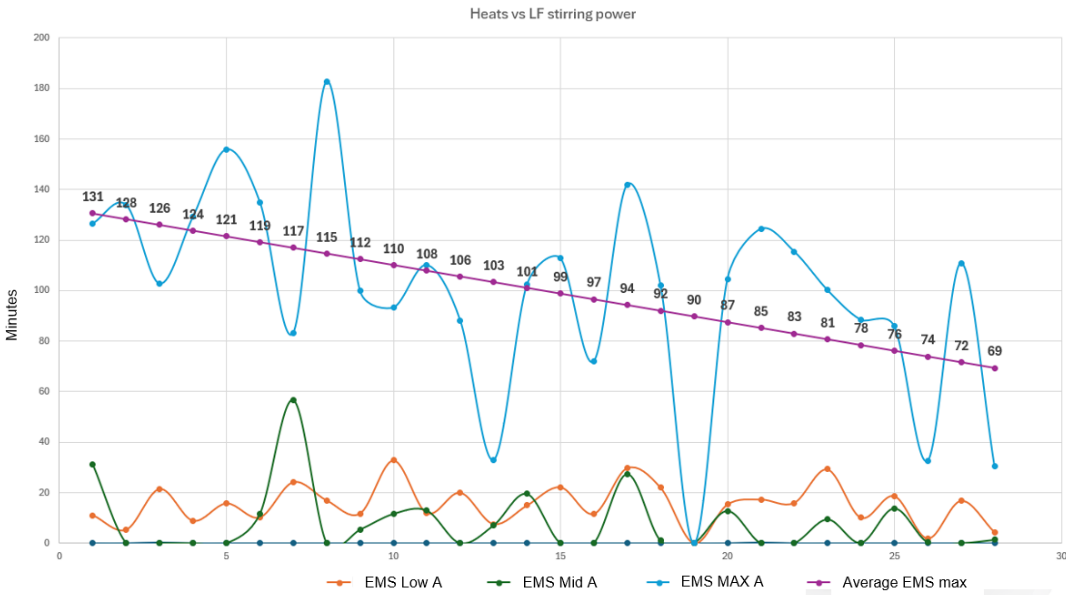

Figure 12: EMS operational time during ladle heat cycle

3.1.2.1 Advisory tool campaign

The advisory tool includes the ML prediction, optimisation code, and the CFD result look up table. Two strategies for the advisory tool were discussed. The first option was to reduce the EMS operation time without changing the EMS power, and the second option was to reduce the EMS power without changing the run time. The campaign was planned for 26 heats, the process parameters data was compiled at the end of the week by Uddeholm and send to Swerim. The wall thickness status and the strategy for EMS stirring was to be proposed. During the campaign preparation, the impact of EMS operational time on refining was questioned. Further internal discussion led to running the campaign where the wall thickness prediction was provided for Uddeholm at the end of each week, but the advisory tool guidelines were not tested.

```
In [90]: %runcell -n 'apply for trial' C:/Users/han.yu/.spyder-py3/SmartLadle/thickness_prediction_result_without_temp_max_min_ori.py
top 10% avg of wear: 172.31263040150586
top 10% avg of wear above: 287.8618456542935
top 10% avg of wear below: 66.16546844126549
Cylinder 1 (above) radius: 1.2885 m, height: 1.05 m, volume: 5.4768 m³
Cylinder 2 (below) radius: 1.2650 m, height: 1.65 m, volume: 8.2945 m³
total simulated volume of ladle after heats: 13.7713 m³
difference from the original volume: 1.1742 m³
average wear above: 85.5242 mm
average wear below: 36.4645 mm
```

Figure 13: Interface for wall thickness and wear

3.1.3 Deviations

The CFD models were rerun with new CAD geometry after the laser scanning data corrections. The result from CFD models shows the homogenisation time for the first and last heat ladle shape, but the refining of the different elements is not included in the modelling. The refining of elements requires a mix of EMS, Gas stirring, and Vacuum treatment as seen in **Table 3**.

Table 3: Elements and refining strategy

Element	**stirring strategy**
Sulfur (S)	EMS + Gas Stirring
Hydrogen (H)	Gas Stirring + Vacuum
Oxygen (O)	EMS + Gas Stirring
Phosphorus (P)	Gas Stirring
Nitrogen (N)	Gas Stirring + Vacuum
Inclusions (Al2O3, MgO, TiN)	EMS + Gas Stirring

The homogenization time for steel chemistry and temperature could be modelled for a variety of ladle statuses using the soft sensor for brick thickness and the CFD model for ladle stirring. The proposed new stirring strategy by the advisory tool, with regards to homogenization time, will in many cases result in reduced stirring time and reduced stirring power.
Operation with such low stirring time and low power is not well represented in historical process data and therefore calibration of a soft sensor for steel quality will not be reliable. Additionally, the influence of reduced EMS operational time and power on the slag-metal interaction and refining of steel was not extensively studied. With these uncertainties, we didn’t implement the new stirring strategy for the ladle life cycle at UAB. Future works were recommended to test the new stirring strategy on individual heats (with respect to effects on steel quality) before rolling out the strategy for entire ladle cycle.

3.2 SID use case

In Deliverable 3.3 was shown a set of models connected to offer a complete description of the ladle/refractory/stirring/liquid steel system (**Figure 14**). It was an aspirational overview to in-spire not only the work in this project but also future improvements and developments.

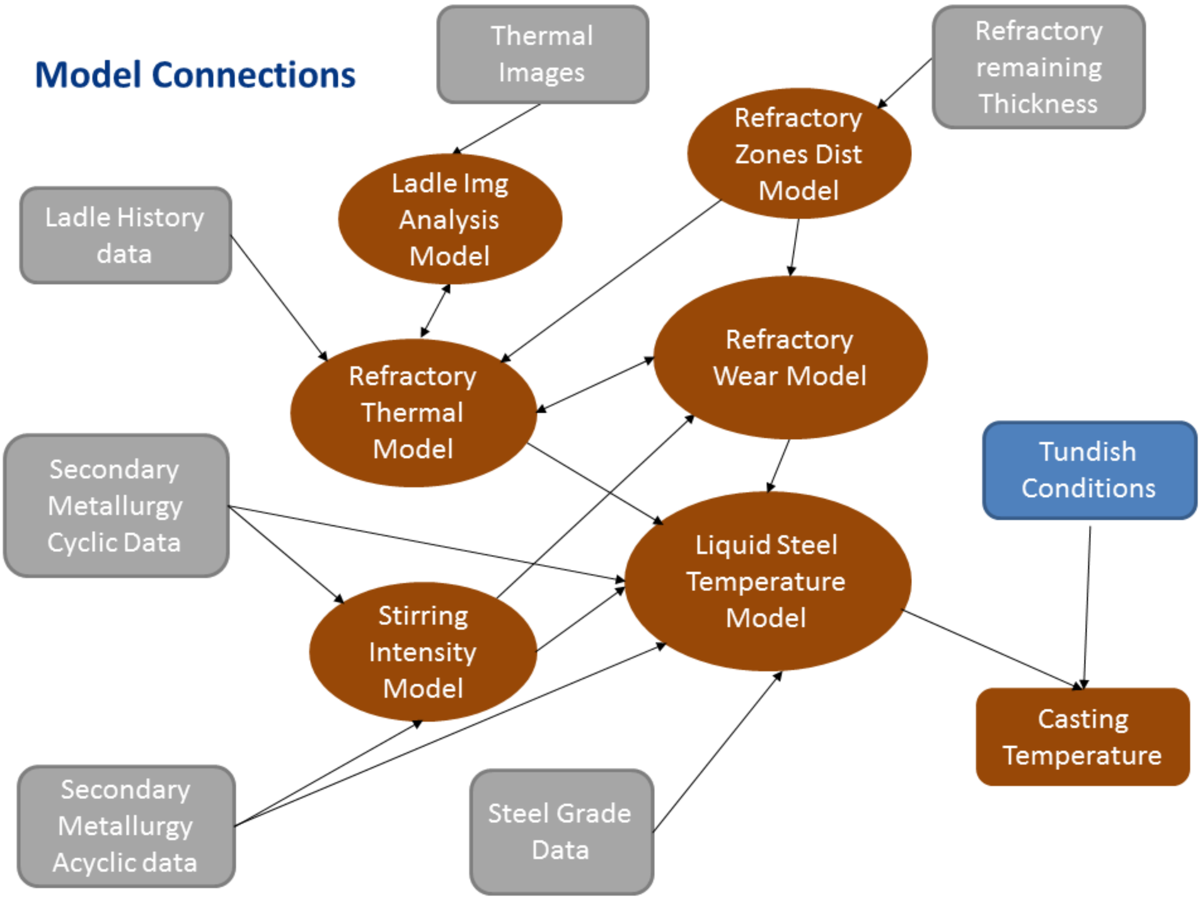

Figure 14: Schema of model connections from WP3.

From those sets, in WP4 and WP5 a narrower selection was done to focus mainly on the models used in the advisory tool (WP5), that were updated with more recent data. This is the final work done in them in WP6, model by model:

Liquid Steel Temperature model (ladle):
This data-based model is, together with the tundish version of it, the cornerstone of the project work. The initial version from WP3 was updated with new data from 2023 and 2024, using the same input variables conceptually, so the main update was to collect and calculate them again. Those data are summarized in:

- Temperature measurements (the model calculated the difference between them as main output) and they mark the time periods for the rest of variables.
- Additions between temperatures.
- Vacuum treatment between temperatures.
- Ladle thermal state (thermal state model)
- Stirring power.
- Ladle ID and car ID, in case there are differences between them.

In this version of the model more than 30000 rows of data were collected, and a complete version and a simplified version of input data were elaborated to be able to use it in advisory tool conditions.

From the algorithms tried in WP3 only two have been used in the WP6 version:

- Random Forest offered a good precision with a RMSE of 6.7 ºC in validation data and a R^2 of 0.92 (**Figure 15**)
- Linear Model was worse (RMSE of 10.0 ºC and a R^2 of 0.79), but it is considered useful for some aspects of implementation as explained in WP5

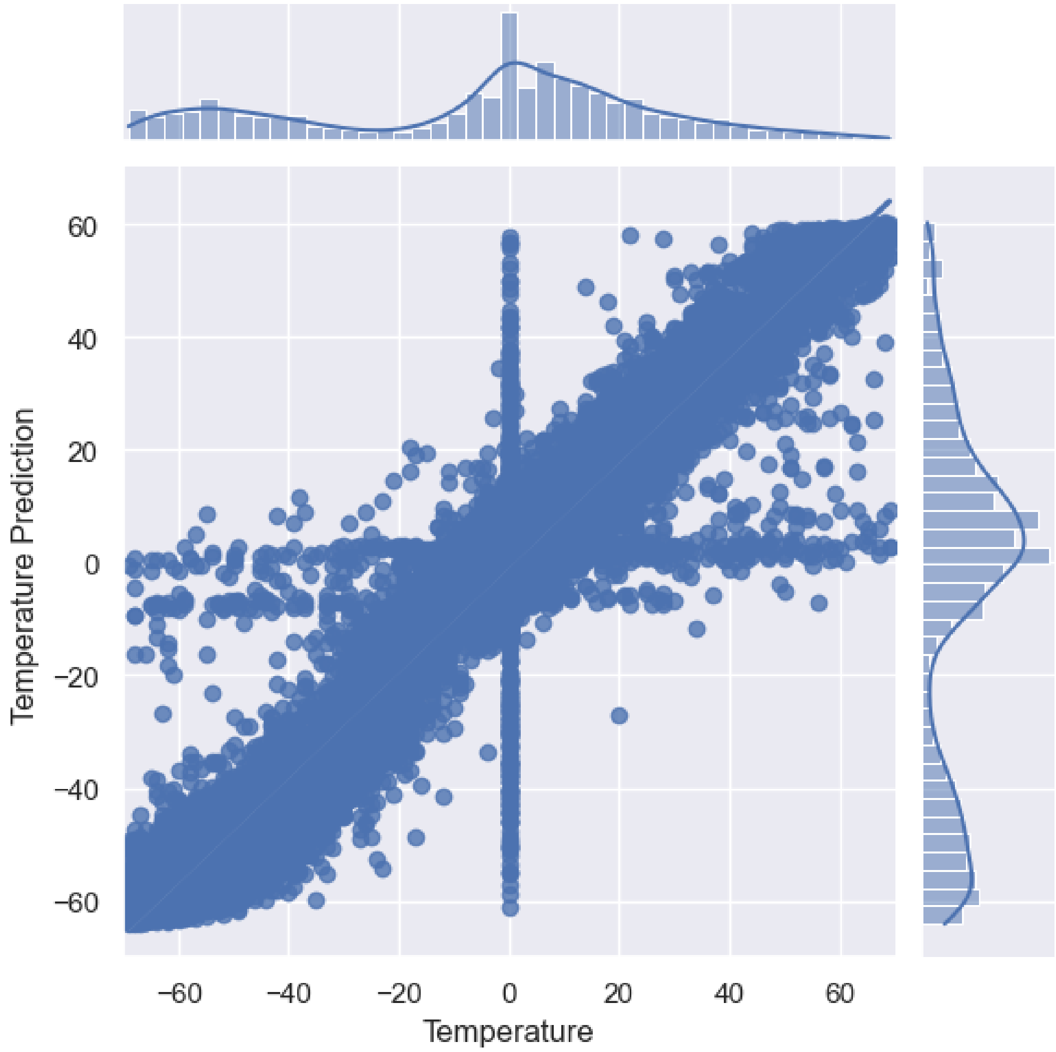

Figure 15: Predicted vs measured Temperature differences in the liquid steel temperature model in ladle calculated with Random Forest.

The simplified version of the Random Forest worsens the RMSE to 7.4 ºC. Both the Random Forest and the Linear model are used in the secondary metallurgy pages as the main calculating models.

Liquid Steel Temperature model (tundish):

This model was only outlined in WP3 and later elaborated in WP4, WP5 and WP6 using the knowledge from temperature measurements and soft sensor results in the tundish and the analytical model in WP5 for the tundish refractory.

The output variable is the liquid steel temperature change rate in the tundish. This approach is based on the linear behaviour of the temperature data and the small changes in the temperature at the same time. The process time is not so different from heat to heat but available temperatures can be different and this way the data are equalized. Most important input variables are the sequence number, previous tundish temperature, temperature from ladle liquid steel.

It is important to note that the thermal state of the tundish is strongly correlated to the number of heats in the sequence. The explanation surged from the thermocouple data and can be interpreted as follows: all tundishes have similar preheating curves, so start the first heat in the sequence in a similar thermal state, and, in the data collected in Sidenor they follow a thermal curve that is quite linear in the internal data from the second heat; they do not reach to thermal soaking (**Figure 8**).

The linear model is not too accurate, but a Random Forest offers enough precision with a R2 = 0.63 and a RMSE 0.09ºC/min.

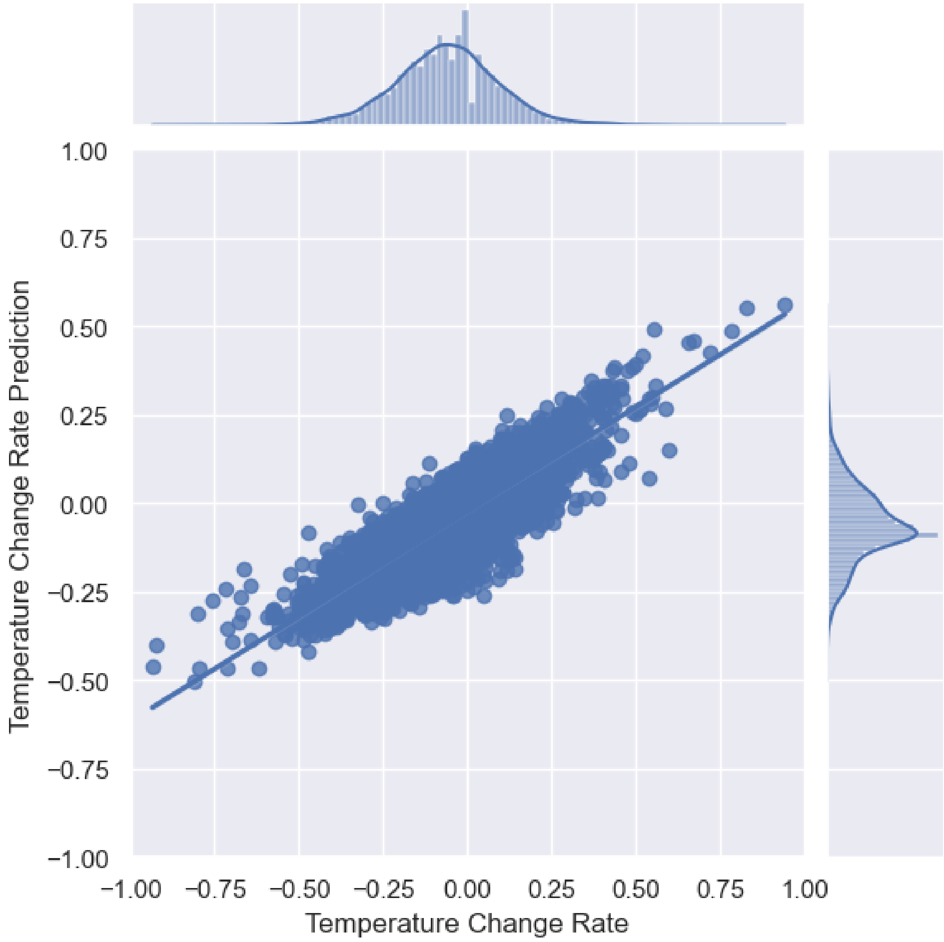

Figure 16: Predicted vs measured Temperature change rate (in K/min) in the liquid steel temperature model in tundish calculated with Random Forest.

This model is the main element in the tundish part of the user interface via web page. It is included in the general simulation, and it is somehow used in the LF1 and LF2 pages.

Refractory Thermal Model:

The model is based in a 1D FEM approach using the refractory layers in the ladle and their thermal properties. The ladle history is a key factor for the thermal model as it feeds the story of each ladle with the input data about preheating, time with liquid steel, stops,… It runs every hour for the working ladles and stores the thermal state data in a database. It takes into account the wear state of the ladle. Those data were summarized in a value about thermal state which was used in the liquid steel thermal model in the ladle.

The model was developed before the project, but it was updated and the way of connecting it to the other models was rethought.

One option initially considered was to set it up as a data model, using the analytical model to train the data model. This option could offer a better performance in terms of precision/time of calculation and could ease to use it in a more sophisticated way. But this approach was not fulfilled in the project, and it is considered an option for the future.

Finally, the precision of this model is difficult to measure, interesting but requires specific work that was not done. Nevertheless, and indirect measurement is the importance in the liquid steel temperature model in ladle: the thermal state variable was among the top 5 most influential in the model.

Refractory Wear Model:

The refractory wear model was initially thought as a supervised data model for each of the refractory zones defined in the refractory zones distribution model. And this approach is considered still valid and useful, if enough data can be obtained. The traditional way of obtaining postmortem wear data in the ladle (used for the refractory zones distribution model) has two inconveniences: the effect that many variables are averaged over the ladle life, and the number of data per month is low. In consequence, it is necessary to have stable conditions to accumulate enough data for the model to be able to make reasonable predictions. However, during the years of the project, the stability of refractory conditions has been considered insufficient: there have been changes in the production rate due to several crisis, changes in refractory materials to adapt to those changing conditions, and changes in the production mix.

The consequence is that a simpler approach has been followed, absorbing the values of the industrial trials in WP4 and some others: A general wear rate is calculated by zone and penalizations are included for the worse case scenarios/factors. The wear rate is calculated to the three zones determined in the refractory zones distribution model and this was used for the ladle building optimization tool. But for the calculations of the refractory thermal model only one zone, the steel part, is considered, as it is the most influential in the thermal model and this offers a useful simplification.

On the other hand, a measurement system as the laser contour measurement tried by other partners in this project has the potential to make a difference by multiplying the data collection, if heat by heat data are obtained reliably.

Refractory Zones Distribution Model

The model used in the WP3 analysis was checked and the results remain valid. The output was to define 3 wear zones in the ladle based on the post-mortem remaining thickness of the bricks row by row. They were grouped by a clustering algorithm and the three clusters solution was the most successful one.

Stirring Intensity Model

Stirring intensity has been the focus of many projects and measuring techniques. The approach in this project was to get a reasonable way to assess its effect over thermal evolution; it would be also a factor in the refractory wear rate but this aspect has not been considered.

For that purpose, the flow rate and counterpressure data measured in the ladles were used. Previous to the project an index of effective stirring power was developed based on the ratio between those variables, but those data had an important amount of “noise”. Effectively, in more than 50 million rows of data per year (one per second in each ladle car) there are many non-valuable data. Some of them are obvious, but other as transitory states in flow rate changes are more difficult to filter.

In those data, a better filtering (including elimination of flow rate transition) has been developed, and the result is considered successful: in one month period data (2 million rows) the correlation between flow rate and counter pressure has improved from 0.86 to 0.93.

A vibration sensor has also been checked, and it is considered useful and meaningful, in fact it is correlated with flow rate with a correlation factor of 0.72 (unfiltered) or 0.82 (filtered). This also confirms that the filtering is working. However, vibration values are in general shakier, they are valuable when the stirring rate is low and open eye is not present, so for the purpose of this project the value obtained from counterpressure after filtering was used for the data model as input.

Ladle Thermal Images Analysis Model

Ladle thermal images were taken at the beginning of the project in the ladle cleaning station, and in that position, it was very helpful to be able to identify the ladle by the number in the ladle shell, because different ladles could be together in that position. And this was the intention of this model, but the camera taking those images was removed and alternative cameras positioned in the ladle introduction position in the secondary metallurgy. For this reason, the identification by the image is no longer needed and the model for it is not useful in this moment.

The concept presented in Task 3.3 in **Figure 14** was the basis of the rest of the work; it helped to get a broad perspective and focus the efforts on the rest of the project. Many of the models have not reached a complete maturity as it has been explained, but they have been useful in the advisory tool. And, thus, there are still open threads that can help in the future fine tuning. Many of the activities of the rest of the partners have been inspirational too for future advances.

4. Evaluation of improvements regarding ladle life, temperature distribution within refractory, economic and environmental aspects

4.1 Performance of tools

The smart sensor at SWG performed well over the whole trial durations considering the low temperatures at the smart sensor position during “cold” preparation of the ladle, providing measurement data reliably and constantly. Only the sensor internal temperature was not always available, but this problem can be solved by new thermocouple or plug. Power supply was stable for more than two days in a row. Here, testing the use of TEGs, as suggested in the study, will make one step forward to less maintenance effort during permanent application.

Smart sensor performance at SID was satisfactory as a tool to understand the thermal performance of the tundish. After initial data acquisition with standard dataloggers, enough experience was gained to use a wireless logger and transmitter that worked robustly for more than a month without requiring installation and deinstallation.

The FEM models were further advanced to calculate temperature distribution and mechanical stresses in the ladle refractory and worked well. They were used to not only calculate different possible scenarios for ladle optimisation, but also training sets for soft sensor development.

The CFD model provided information for flow behaviour, and homogenization in the ladle at different ladle wear geometry, and EMS power.

The BFI soft sensor model performances were very good, providing suitable results for the very low number of training sets in the case of the temperature prediction. This can be further improved by continuing training with further data sets. The soft sensor for wear lining thickness assessment provided well suiting results compared to the assessment of SWG. A next step, which is very time consuming and thus would require a new project, could be to evaluate real wear data by measurement of remaining brick thickness or by measurement of Laser Contouring System (LCS) as done at UAB and use this as input data for the soft sensor developed by BFI.

The SWERIM soft sensor performed well, providing the wall thickness and wear rate after each heat of the ladle process. The sensor overpredicts the wall wear which is better than underpredicting as there is a safety buffer. The optimisation model provides the maximum and minimum time for each of the highly influential process parameters.

The results obtained by the SID models were quite successful in terms of prediction accuracy and an advisory tool has been developed with a practical objective: To offer advice in the different installations regarding heating and to offer information about the ladles to decide with model data about ladle life ending or repair decisions. Those products are expected to be positive not only in a direct sense, but also in more indirect one of helping to adapt to changing production circumstances and challenges.

The Laser Countouring System (LCS) is a system commercially available, performed well considering the environment in a melt shop and was user-friendly for the operators. The LCS improved confidence in running extra number of heats thereby increasing the ladle life cycle by 28 % (in terms of number of heats). Although the LCS at UAB initially thought to be performing remarkably, after evaluation of the raw data from the LCS, the slag glazing anomaly mentioned earlier resulted in questioning the performance and output of the system.

Finally, the connection of the different aspects/problems/models is important in the Smart Ladle concept, especially for SID. Every part of the whole does not have to be perfect, but it needs a minimum performance.

4.2 Quantified improvements

To quantify improvements possible by implementing the tools of the SmartLadle project, the two main drivers of industrial benefit regarding the steelmaking production were investigated: The temperatures at casting and the ladle life. Additionally, the improvement by application of LIBS at SWG and non-quantified advances are discussed below.

Liquid Steel Temperature:
The temperature at casting has some degree of freedom from metallurgical point of view: The target temperature is based on the liquidus temperature of that steel grade plus some overheating fixed for the steel grade too. Although there is a margin, to achieve a lower temperature increases the risk of clogging and highly the risk of breakout, and a higher temperature will have the problem of more energy waste in LF; this is the aspect we can use to estimate the benefit:

The formula to calculate the amount of electrical energy saving (and associated costs and CO2 emissions) during one year of production would be:

$\boldsymbol{KWh_{year}[KWh] = Temperature[ºC] * KWh_{1C} * Heats_{Year}}$ **(Equation 1)**

$Costs_{year}[€] = KWh_{year}[KWh] * Cost_{KWh}\ [€]$ **(Equation 2)**

$CO_{2_{year}}[Tons\ CO_2eq] = KWh_{year}[KWh] * EmissionFactor_{KWh}\ [Tons\ CO_2eq/KWh]$ **(Equation 3)**

The variables short explanation:
- KWh_{year} = The estimated saving in electrical energy per year
- Temperature = The average difference in casting temperature gap (average gap between target and measured value) between the two semesters in 2024
- KWh_{1C} = Electrical energy needed to heat 1ºC the liquid steel in the ladle (obtained by the linear model in liquid steel in ladle.
- $Heats_{year}$ = Number of heats in a standard one year production.
- $Costs_{KWh}$ = Cost of electrical energy, standard Spanish 2024.[1]
- $Costs_{year}$ = Cost savings over a year associated with the reduction of Temperature.
- $EmissionFactor_{KWh}$ = Official emission factor from the Spanish regulator.[2]
- CO_{2year} = The amount of CO_{2eq} kg saved in one year from the electricity saving.

The details of the numbers are in the RP2 report, but the final values for SID calculated with the aforementioned formulas are:
- Temperature = 1.8 ºC
- $Costs_{year}$ = 55329 €
- CO_{2year} = 216.000 kg CO_{2eq}

Additionally, due to lower heating input improvements can be expected in refractory consumption (apart from the refractory analysis) and some small productivity potential.

[1] Official Wholesale Electricity market in Spain (OMIE). https://www.omie.es/es/market-results/interannual/continuous-intradaily-market/intradaily-prices?scope=interannual&system=1
[2] From the REE web page for 2024. https://www.ree.es/es

At SWG, the Advisory Tool was not installed, thus a direct quantification of improvements was not possible. Nevertheless, an estimation was done, based on the procedure of SID. For the calculation, a possible improvement was assumed for a 1 K temperature reduction of the difference in casting temperature gap (average gap between target and measured value).

Again, the details of the numbers are in the RP2 report, but the final values for SWG calculated with the aforementioned formulas are:

- Temperature = 1 ºC
- $Costs_{year}$ = 11333 €
- CO_{2year} = 18.000 kg CO_{2eq}

Ladle Life:
The second main parameter that may get benefit from the project work is the ladle life. This aspect has been less protagonist in the Sidenor work but the wear estimation approach, some industrial trials, and the **Tool for helping in ladle building decisions** (Task 5.1) are focused in helping to improve ladle life and understanding the causes behind.

The tool for helping in ladle building decisions itself has been used for the estimation of benefits. The calculation uses following formulas:

$$\boldsymbol{NumberLadles0} = \frac{\boldsymbol{Heats_{Year}}}{\boldsymbol{HeatsPerLadle0}} \quad \textbf{(Equation 4)}$$

$$\boldsymbol{NumberLadles1} = \frac{\boldsymbol{Heats_{Year}}}{\boldsymbol{HeatsPerLadle0+ImprovementHeatsPerLadle}} \quad \textbf{(Equation 5)}$$

$$Costs_{year}[€] = (NumberLadles0 - NumberLadles1) * Cost_{Ladle}\ [€] \quad \textbf{(Equation 6)}$$

$$CO_{2_{year}}[Kgrs\ CO_2eq] = (NumberLadles0 - NumberLadles1) * Weight_{Ladle}[Kgrs] * EmissionFactor_{Ref}\ [Kgrs\ CO_2eq/Kgrs] \quad \textbf{(Equation 7)}$$

The variables short explanation:

- NumberLadles0 = The estimated total number of ladles per year in base conditions
- NumberLadles1 = The estimated total number of ladles per year in improved conditions
- HeatsPerLadle0 = Ladle Life in base conditions.
- ImprovementHeatsPerLadle: Improvement in ladle life (number of heats per ladle life)
- $Heats_{year}$ = Number of heats in a standard one year production.
- $Weight_{Ladle}$ = Total weight of ladle working refractory, including partial repair.
- $Costs_{Ladle}$ = Cost of working refractory for one ladle.
- $Costs_{year}$ = Cost savings over a year associated with the increase of ladle life.
- $EmissionFactor_{Ref}$ = Emissions of MgO-C refractory per weight.
- CO_{2year} = The amount of CO_{2eq} kg saved in one year from the improvement of ladle use.

The details of the numbers are in the RP2 report, but the final values for SID calculated with the aforementioned formulas are:

- ImprovementHeatsPerLadle = 2
- $Costs_{year}$ = 137473 €
- CO_{2year} = 423.500 kg CO_{2eq}

Again, for an estimation of improvements for SWG performed based on the one for SID, Equations 4 to 7 were used. For the calculation, a possible improvement was assumed for a 1 heat per ladle life increase.

Once more, the details of the numbers are in the RP2 report, but the final values for SWG calculated with the aforementioned formulas are:

- ImprovementHeatsPerLadle = 1
- $Costs_{year}$ = 45470 €
- CO_{2year} = 230.057 kg CO_{2eq}

Effects of LIBS equipment at SWG:
During the project, fast analysis of pre-material such as ferro alloys based on LIBS was installed at SWG. The main advantage is that all lots supplied can be checked due to the fast measurement, and thus the use of poor-quality alloying materials (and resulting failures) is avoided. This reduces quality losses and related costs.
Additionally, approximately 0.83 hours of working time are saved per measurement because a measurement with the LIBS device is significantly faster than a RFA measurement. The personnel cost savings are approx. 10083 € per year.

Stirring strategy and quality of steel at UAB:
The proposed new stirring strategy by the advisory tool, with regards to homogenization time, will in many cases result in reduced stirring time and reduced stirring power. Operation with such low stirring time and low power is not well represented in historical process data and therefore calibration of a soft sensor for steel quality will not be reliable. With this uncertainty, the new stirring strategy for the ladle life cycle was not implemented at UAB. Future works were proposed to implement the stirring strategy to test in individual heats before rolling out the strategy for entire ladle cycle.

Conclusions about the results
The main numbers calculated in the previous paragraphs are considering the improvements that hold for one year; so, although being positive they are not high for a steelmaking factory standard.

However, there are many other outcomes not so easy to quantify but valuable as well. Some of them are:

- The closer observation of the actual ladle status in terms of wear results in a reduced probability of break-throughs; the benefit is hard to quantify, but invaluable for improved operator safety. Also, the plant equipment is less at risk, which means downtime and repair costs can be avoided.
- The set of tools offers more **adaptability**; in a very variable production context, having tools to prepare for changes helps to change faster and in a more convenient way.
- The **connection** among them helps understand the implication of changes and possible decisions.
- If the models deviate, for example in temperature or ladle wear, it is in fact an **alarm system** showing changes in significant aspects of the process.
- The classification of open aspects helps to prioritize future developments.
- The quantitative understanding of many of the effects opens options of CO_2 emission calculations and simulations related to them.

4.3 Transferability of the project work

It can be divided in two parts: the techniques and the models/advisory systems. The developments within the projects are widely transferable for the European steel industry because ladles are present in all the factories, tundishes in most of them, and temperature control is useful in all too. With a well thought-out design, both thermocouple instrumentation and the use of a smart sensor can be realised also for ladles used in BOF plants, although a higher number of thermocouples could be considered to scale-up the system to larger ladles. Especially the thermocouple instrumentation has already been done before by one partner at a BOF plant with no significant differences. For the models it makes no difference if a ladle is used in an electric steelmaking plant (as in the project), or in a BOF plant. They have to be adapted/trained anyway (see also below), always considering the relevant input data.

Regarding the techniques:

- Thermocouple data acquisition in ladle: Ladles in different steel plants have different layouts, thus the positions of the thermocouples need to be adapted accordingly. Despite a higher installation effort, it is recommended to place several thermocouples in different positions to gain a complete first view in terms of thermal behaviour. Afterwards a selection of a few positions (see also smart sensor application below) is sufficient to monitor the ladle thermal status. The thermocouples need to be installed with care to avoid air holes that falsify results. The main challenge is the sufficient protection of the datalogger against the high temperature during steel production, and especially VOD treatments, and mechanical impact. It is strongly recommended to place the protection box at the ladle wall if a steel plant uses tanks for degassing and to measure the temperature inside the protection box with a dummy before use of the logger.
- Thermocouple data acquisition in tundish: it is less challenging than in ladles, but it is important to find the way to get the thermocouples out of tundish shell and to protect them. For long term data acquisition, it is critical to find a position for the logger and thermocouple head well protected mechanically in the tundish demolition process and thermally in the preheating and working conditions.
- Smart sensor application in a ladle: it requires less installation effort due to a limited number of measurement positions (in BFI/SWG case 2 in the ladle refractory). Nevertheless, the thermal protection of the smart sensor must be even better than for a (high temperature resistant) datalogger due to the electronics used.
- Ladle measuring with laser system: The laser scanning system used at UAB improved confidence in running higher number of heats. The system is easy to implement and measure, also in other plants and for ladles of different sizes. A key factor to consider is the slag glazing left on the wall and its impact on the wall thickness measurement, which could lead to false confidence during operation. The slag composition and its affinity to glazing needs to be examined. Additionally, ways to reduce slag glazing need to be examined before implementation.
- Fast slag and ferroalloy analysis: a transfer of the LIBS measurement system to other steel plants is possible, but before use an extensive calibration with the slags or ferroalloys of that steel plant is needed. The calibration of the fast slag analysis system for SWG slags was challenging and, in the end, not precisely enough for multi-component slag systems to be used as an online tool to obtain a new process parameter for adaption of slag conditioning. Nevertheless, the fast LIBS-based analysis has been used to analyse feedstock material such as ferro alloys in the steel plant and this analysis has been established at SWG.

Regarding the models:

The exact data and models depend on the concrete installations but most of the approaches of this project can be transferred to other plants. The procedure to transfer them can be summarized as:

Data Gathering: This is in fact the most critical part for most models. The models cannot be better than the data with which they are fed or done, and if the data do not contain the relevant information it will have to be estimated with indirect data or estimations. The following data are needed for a period considered sufficient to obtain enough data for the models (will depend on production rate):

- Liquid Steel temperature model
  - Ladle furnace heating values and times.
  - Alloys additions and times.
  - Slag formers additions and times.
  - Stirring connected values per time.
  - Vacuum pressure and time.
  - Estimation of ladle thermal state (from thermal model)

- Ladle thermal model/Refractory temperature model:
  - Data related to time with liquid steel
  - Time in (pre-)heating by burners
  - Ladle refractory configuration
  - (Trials with thermocouples in refractory recommended)
  - (Ladle wear estimation is advised)

- Ladle wear model/Remaining ladle wear lining thickness model:
  - Ladle history in terms of heats and ladle journeys
  - Final wear data in form of residual length of the bricks
  - Time in (pre-)heating by burners
  - Ladle refractory configuration
  - (Ladle contour laser measurement can be of great use)

- Tundish liquid steel temperature model:
  - Liquid steel temperatures in tundish
  - Time in tundish
  - Temperature of the steel coming from ladle
  - Previous heat temperature
  - Sequence numbers.
  - (Refractory temperature measurements recommended)

Modelling: It will depend on the concrete case and amount of data, the explanations in section 3.2 can help. Data models are a great tool but not the only one, in each case it is convenient to think about the type of problem, type of data and desired output. In some of the cases even if linear models were not the best they offer interesting insights about variable effects and their quantification.
In this project Random Forest models worked well for the two liquid steel temperature cases at Sidenor, and the thermal model is FEM based (simplified). Wear model can also be done with machine learning approach, but enough data are required.
At BFI, for refractory temperature prediction a LSTM model is preferred, and for wear prediction a XGBoost model.
The machine learning (ML) model developed by Swerim and UAB consists of both prediction and optimization models. While the prediction model can be directly implemented in the plant for monitoring wear trends, the optimization model requires defining process parameter limits, which vary for each steel grade. Therefore, a comprehensive evaluation of refining parameters and their relationship to process conditions is necessary before deploying the optimization strategy full scale. When applying in other steel plants, the ML model should be adapted by first analysing ladle wear patterns specific to each facility's operational conditions using LCS, and historic process data. Initial implementation should prioritize the prediction model to establish baseline wear trends, followed by the gradual integration of the optimization model once the refining parameters for different steel grades are well understood.
Additionally, the models should be retrained accordingly, and validation trials conducted to ensure accuracy and reliability.

Supporting modelling: The CFD models developed in this project provide insights into the homogenization rate in both new and worn-out ladles at UAB. Additionally, the models simulated two different EMS power regimes currently used by UAB. For application in other steel plants, these CFD models can be used straight away by running the simulations by replacing the geometry with plant-specific ladle LCS data. By integrating plant-specific operational data, such as EMS power settings, stirring patterns, and refining chemistry, the models can provide customized insights into homogenization efficiency and process optimization for that ladle.
The FEM models further developed in this project provide information about the thermal and thermo-mechanical conditions of SWG ladle and were used to calculate different scenarios as well as training sets for ML models. They can be used to also calculate temperature and thermo-mechanical stresses for ladles of other steel plants. As all FEM models, they need to be adapted to the different ladle geometry, different material properties and different boundary conditions.

User Interface: This aspect has become easier during the last years. For example, within the project the Streamlit library has been used by Sidenor; it helps to use ML models and connect them to production data with a straightforward approach. It is important to think about possible users and number of simultaneous users, which are not so many in steel making factories.
The user interface of the Swerim ML model is designed to be intuitive and user-friendly, allowing process engineers and operators to efficiently analyse ladle wear. The interface enables users to import process parameter data from the UAB in-house system in Excel format, which then provides key outputs such as maximum and average wall wear, as well as wall thickness measurements. Additionally, when the optimization model is activated, the interface offers recommendations on the maximum and minimum operational times for each key process parameter, assisting in process refinement and efficiency improvements. For usage in other steel plants, the interface and ML model can be adapted to integrate plant-specific data management systems, ensuring compatibility with various data formats.