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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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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. State of the art

Modelling of temperature and stress in refractory material as well as of liquid steel temperature and of fluid flow in steelmaking ladle

The refractory lining in steelmaking ladles have the function to ensure a safe transport and treatment of liquid steel. Severe surrounding conditions as high steel temperatures, thermal shock, temperature gradients within the refractory layer, pressure from liquid steel weight, fluid flow of liquid steel and chemical attack from liquid slag cause wear of refractory. The wear of ladle refractory has been in the focus of several studies [P3] [1]-[8]. This includes studies about material properties and its optimisation regarding performance [1], as different raw material (e.g. alumina, magnesia, with and without carbon) are used for different requirements. The properties of ladle refractory were investigated to ensure the selection of the best fitting material [2], [3], or to adjust influencing variables such as slag composition [4]. Also in previous RFCS projects [P2, P3 and P4], laboratory studies and numerical models such as Finite Element Method (FEM) were used to investigate the properties of refractory materials i.e. the temperature and stress distribution in refractory material, and to improve the lifetime of these materials. Thermal stress simulation is used to enhance understanding of thermomechanical failure, e.g. the influence of preheating as thermal shock impact on different lining configurations, and whether or not thermal expansion is restricted externally, as done in [5]. Calculation of temperature distribution is used for reproducing the effect of different lining materials and thicknesses regarding temperature profile in the ladle wall and bottom as well as for evaluation of thermal losses [6]. These simulations are also used for adjusting process conditions such as ladle preheating [7] and RH process [8].

As laboratory work and simulations can only be performed offline, also simplified models have been developed to be used online [P2], [9], [10]. Here the focus is on stable performance and short computation time. In [P5] and [9] a temperature prediction model for the whole chain of liquid steelmaking to control casting superheat temperatures were developed and solved by finite difference methods and nonlinear regression model. Another semi-analytical model approach based on ordinary differential equations and statistical relations is described in [10] and further developed in [P6], where the model parameters are considered unknown and obtained from an automatic calibration procedure using process data. Additionally, models and measurements were combined to develop improved online models. Within [P2] the idea was followed to combine an online model with an inline measurement of refractory temperature. It was possible to use the information from thermal camera about refractory (hot) surface temperature, but the attempt to use information from internal refractory temperature measurement by a wireless temperature sensor could not be realised online. Nevertheless, the basic idea was proved successful, so a further development is desirable. In the projects P3 and P4 the attempt was made to evaluate the performance of the refractories and to provide a prediction for their wear.

There have also been numerous approaches to model the ladle process using computational fluid dynamics (CFD) concepts throughout the years [11]-[19]. Mainly two different approaches for modelling gas stirred ladle process can be named: continuum and discrete models. The continuum models following the Euler-Euler approach consider the bubbles as a continuum phase [11]-[14], [16], [17], [19], while in the discrete models which are also known as Euler-Lagrange approach the injected gas phase is modelled as individual bubbles [15], [18], which allows to take into account the dynamic and stochastic behaviour of the bubbles. However, this approach is computationally expensive since the software must keep track of discrete particles (bubbles). In comparison, the Euler-Euler approach is computationally suitable but loses the resolution of the injected gas phase. In the framework of RFCS projects, often CFD models based on the Eulerian approach were used [P8-P11] for an “ideal ladle”, which is defined as freshly relined ladle. In the prior two works [P10, P11], the models were two-dimensional, and [P11] only considers liquid steel. Furthermore, [P10] tried to integrate thermodynamic equilibrium calculations into the CFD model to predict the changes in the nitrogen, hydrogen and sulphur contents, which was successful for nitrogen removal but did not return reliable data regarding the other elements. In [P9] a three-dimensional model was developed where the liquid phase consisted of steel and slag. With this model a parametric study of the viscosity of slag alongside the porous plug position and their effects on open-eye was conducted. Furthermore, the study investigated the slag entrapment phenomenon utilising the dimensionless “Weber number” with a fixed value for the steel-slag surface tension. Later on, a three-dimensional

model was also developed for induction stirring [P8]. The model also included the heating in ladle furnace and inclusion modelling since the objective of the project was on steel cleanness and control of inclusion chemistry. [P7] focused on policies for heat-individual dynamic stirring for improvement of inclusion removal.
The free surface has been ignored in modelling of the ladle process in many cases [11]-[18]. By ignoring the liquid-gas interface, the resolution of upper surface behaviour, e.g., surface deformation, has not been as detailed as in physical models. In recent years, there have been models where the free-surface has been taken into account [19].

(Online) Sensors for ladle monitoring

In addition to modelling, several measurement systems and sensors were developed for monitoring steelmaking ladles. Temperature measurement using thermocouples are conducted during campaigns where thermocouples are inserted in the refractory at positions with different distances to the ladle shell [P2], [20] or in the refractory of stirring plugs [P4]. A permanent installation of several thermocouples in the refractory lining has been proved to be inefficient and costly and raised numerous problems. In contrast, common noncontact temperature measurement techniques (pyrometric, thermographic) [21], [22] tended to overcome some of the difficulties concerning installation and continuous operation. The laser contouring system is a commercially available measurement technique which is nowadays widely used for refractory wear measurement dedicatedly for safety purposes [23]. Camera systems are more and more used for monitoring purposes, not only giving information about refractory surface temperature or ladle shell temperature for hot spot detection [24], [25], but also used for monitoring stirring processes [P7], [26], [27] and for identification of ladles [28]. Identification can also be done using wireless sensors based on RFID or SAW[29]-[32]. Additionally, vibration sensors can be used for monitoring plug status in terms of stirring efficiency as part of the ladle status [P9],[29], [30]. Laser Induced Breakdown Spectroscopy (LIBS) systems have been used to analyse, besides many others, refractory material [33], hot metal [34] and slags [35]. The analysis method is in general a technology that can be adapted to demanding environments as in steel plants [33].
Besides the information from these sensors, additionally process data is available that can be used to describe the process and ladle/plug condition, e.g. stirring gas flow rate and pressure or steel temperature loss throughout the heat. Although attempts have been made to couple some of the measurement data and models, e.g. [P2], [25], [36], [37], a successful approach to combine all information about one ladle and then use these information for adaption of process parameters to actual ladle status is not known to the authors. The possible realisation of a similar sensor system has been shown by Stuhlsatz et al. [38] who applied a smart measuring system at a BOF converter oxygen blowing lance and in downstream processes.

Basing process control decisions on smart sensors requires robustness which is hard to obtain in the harsh environment of steel ladles. Robustness can be obtained by the use of soft sensors that rely on many data sources to statistically estimate the smart sensor signals or outputs in the case of sensor failure. Soft sensors for the steel industry for various purposes have been developed and tested [39]-[42]. Tian et. al. have developed neural network soft sensor for liquid steel temperature in a ladle furnace [39]. Ping et.al have shown the use of soft sensors for indirect estimation of end-point of the EAF operation [40]. Moreover, Kadlec et. al. have written an in-depth report on the use of soft sensors in the process industry [41], and Sandberg et.al. have developed soft sensors for estimation of meltdown degree and steel temperature in the EAF [42]. These reports deal with not only different processes e.g., continuous and batch processes, but also describe the various development methodologies and use of soft sensors in process industry. In [P3], a preliminary soft sensor was developed for ladles, but it was limited by the lower amount of data and measurement capabilities. Besides this, no publication related to the use of soft sensor in ladle status estimation has been found. Thus, the project will continue the work of [P3] and will develop for the first time a soft sensor for ladle status.

Data analytics and Industry 4.0

Most of the extensive researches on ladle refractory wear focused on concrete aspects as the different behaviour of the refractory, the effect of thermal stress or slag chemical interaction. All these aspects are important for the ladle life, but the complexity of the industrial phenomena

makes it difficult to use any of them as the main factor to interpret industrial results. The complexity comes from at least two sources: ladle life is complex and each part of the ladle refractory does not suffer the same effects. Considering all those difficulties [P3] project offered a first approximation of applying a ML model to quantify the effect of different factors over refractory wear rate and consequently ladle life. [P3] divided the ladle in two zones and collected a series of production data for them guided by thermochemical and thermomechanical model outputs. Finally it used a multiple linear regression model to explain refractory wear rate.
At the same time ML models have been revealed as a valuable tool to understand and predict complex systems in the past few years by "learning from data". The availability of increased number and type of data combined with the enormous increase of computing power accessibility has offered many good examples of successful ML model applications. A data science competition web page [43] illustrates many impressive examples from use cases in health, science, real state, banking and industry. Concretely neural networks have become ubiquitous in image processing and NLP (Natural Language Processing) as well as time series analysis and algorithms like Random Forests and Boosting have become a powerful tool for complex data problems.
Although there have been examples of those algorithms used in steel industry, no one has been found related to ladles.

ML and data analytics are one of the main components in the digitalisation, that has become of large interest since around 2011. The term "Industrie 4.0" was born in Germany to describe that a new generation of industrial production is coming up if a consequent digitalisation will be realised. Over the years, this idea was adapted to be used to describe more detailed production parts, e.g. as “Refractories 4.0” [44] and “Combustion chamber 4.0” [45]. All these terms are originated by the manufacturing industry in which it is much easier to follow the product along the production chain, which is a precondition to realise Cyber Physical Systems (CPS). The term CPS refers to the tight conjoining of and coordination between computational and physical resources. [46], [47]. In [48] and [49] the perspective for steel industry regarding the topic of digitalisation is discussed and here the point of "product tracking" has been mentioned as one of the most important points to realise a "smart factory" in steel industry.
The project I2MSteel [P12] developed a completely new paradigm for steel specific automation and information techniques, replacing the common centralised by a decentralised planning and optimisation. This new paradigm would benefit from a suitable monitoring of ladle status in the steel shop, thus the objectives of the project would be an excellent addition/complement to I2MSteel. Within project P14 the approach of merging different models, simulations and communication tools for process optimisation and optimised predictive maintenance is already followed, but in the downstream area of long production facilities. In the same area, P15 offers concepts and methods for the fusion of various data sources to be evaluated by means of data mining techniques. Although designed to predict the occurrence of defects, the approaches and methods used in P15 are of interest for SmartLadle. The still ongoing project P13 aims at the realisation of automated ladle tracking throughout the liquid steelmaking process chain and an optimisation of the ladle logistics. Regarding the latter, first works are available, e.g. [50], and discuss the potentials of logistic optimisation.

Power supply
Thermoelectric (TE) materials are semiconductors using the Seebeck effect to generate electrical power when opposite ends of a piece of the material are subjected to hot and cold temperatures, respectively. Well known applications of TEG are in the aero and space industry, power supply in remote areas and waste heat recovery. Most research projects aim to develop TE materials or techniques with increased efficiency e.g. [51]. Another important research field is system integration e.g. for waste heat recovery in industrial applications such as steelmaking [52] which would lead to reduced costs of TEG. The possibilities of thermoelectric (TE) power generation using industrial gaseous waste heat are determined in project P16.

To summarise, it can be stated that a lot of work on refractory and ladles has already been performed, and numerous technological advancements in monitoring and control of the ladle steelmaking processes have been achieved. Nevertheless, as the road map for secondary steelmaking set up in the dissemination project P1 revealed, there is still further high interest of the steelmakers on the topics of ladle refractory materials regarding inline monitoring of refractory state/erosion for predictive maintenance and fundamental investigations on refractories effect on steel quality, as well as on inline measurement of ladle status and of actual stirring behaviour, which are considered in the SmartLadle project.

The approach of this project is to build the foundations for a smart ladle by developing a soft sensor supported by a new smart sensor and a data-based solution to collect relevant data about the ladle. The lade will be the central unit for the soft sensor that will be developed, but process data from all process steps in liquid steelmaking will be considered and measurement data of other installations will be used as well, e.g. by a smart sensor at the tundish. Their conditions affect the liquid steelmaking ladle treatment processes. The relevant data could be for example refractory temperature for assessing wear status and thermal status of the ladle, vibration signals for stirring evaluation, data from cameras for hot spot warning and laser contouring of the inner state of the ladle and other process data. This information shall be used to give advice to the steel plant operator and ladle management personal to **adapt process parameters considering the actual ladle status and decide about maintenance actions**. It shall be realised by combining models with measurement data within an Advisory Tool. Previous works within the framework of ECSC/RFCS research did not fully explore the possibilities of combining available technologies with the extensive data collected by industrial plants to create such a coherent monitoring system and an Advisory Tool.
The system shall be used to give advice, e.g. by providing possibilities to adapt process parameters for upcoming events based on historical operational data, to make suggestions for the most optimum ladle treatment and decisions regarding maintenance actions. The objective of the proposed research shall be realised by modelling in combination with measurement data and monitoring of ladles throughout their lifetime.

2. Problem description

Steelmaking ladles evolved from being a transportation vessel to being a liquid steel processing unit. The ladle has a strong influence on the success of secondary metallurgical treatment during liquid steel production. The thermal state of the ladle influences temperature evolution of the melt, and the history and ladle lining influence the steel quality. The cost of ladle refractory is quite high in secondary metallurgy, and a sufficient refractory thickness that decreases over ladle lifetime must be guaranteed for safety reasons. Additionally, the status of the stirring plug (wear, blockage) and the stirring strategy have significant influence on the stirring efficiency and consequently on reaching the metallurgical aims.
Throughout the ladle life, alterations such as changes in refractory material properties and ladle/plug geometry due to wear will occur. These effects have different impacts on different parts of the ladle. Although their foot-prints can be significant, the influence and impacts of such phenomena on the actual status of the ladle and stirring plug are mostly unknown and are thus not yet considered in operation of the secondary metallurgy treatment stations. As an example: Due to erosion of the refractory at the wall and vicinity of the porous plug(s), the flow of steel bath changes over ladle lifetime, hence, the optimum stirring intensity should depend on the ladle age and state. Only first rough attempts were made in production process, e.g. by adjusting the tapping temperature of liquid steel for the first few heats after new lining. However, the ladle status is not considered in dynamic adjustment of process parameters, such as stirring gas flow rate and pressure, or for optimum maintenance (relining) – both are performed according to defined static practices and schedules.

3. Proposed approach

The overall objective of this project is the online monitoring of the ladle status using a soft sensor supported by a new smart sensor and a data-based solution for the dynamic consideration of the actual ladle status in process control.

Two main objectives will be pursued:

1) The **soft sensor for ladle status** shall **collect** all available process data, including the information from the new smart sensor, during the liquid steelmaking process, in order to enable a robust and reliable estimation of the ladle status. The data of other metallurgical vessels and the tundish conditions are also considered in the solution as important boundary conditions for the liquid steelmaking ladle treatment processes. The information from the smart sensor, upon its availability, will provide additional input and thus improve the accuracy of the soft sensor. Nevertheless, the soft sensor will be able to describe the ladle status solely based on available process data, for the case that the smart sensor is not in operation.
2) The **liquid steel production process** shall be **improved** by adjusting the process parameters (e.g. stirring strategy, ladle reheating time between two heats) to the actual ladle status (e.g. ladle wear and thermal status, ladle history). This will be achieved by developing an **Advisory Tool**.

To reach the objectives of the project, the proposed approach is to realise a soft sensor supported by developing a smart sensor and a data-base driven tool to collect relevant data about the ladle, e.g. refractory temperature for assessing wear and thermal status of ladle, and related relevant process data. The additional information will be used to give advice to the steel plant operator and ladle management personal to adapt process parameters to the actual ladle status and decide about maintenance actions. This will be realised by modelling work in combination with measurement data within monitoring and an Advisory Tool (**Figure 1**).

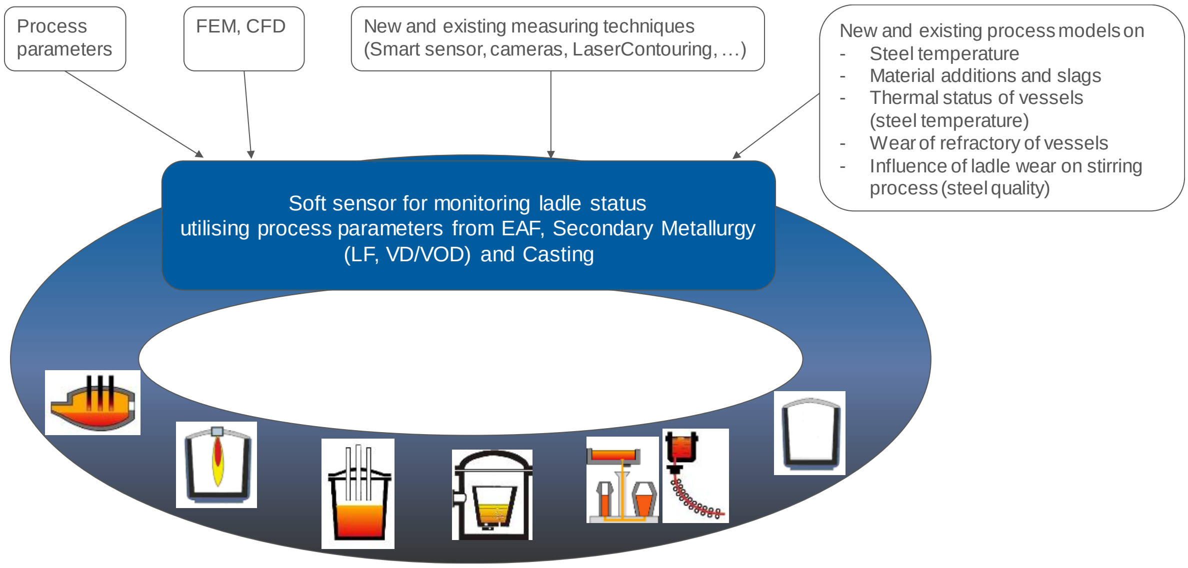

Figure 1: Schema of SmartLadle approach

Soft sensor that will be developed
A **soft sensor** (sometimes called virtual sensor or state observer) is a mathematical algorithm that calculates the value of a parameter, which is not measured directly, by using the measured values of other parameters. The use of soft sensors has been increased in the past two decades as a valuable alternative to the traditional means of the acquisition of critical process variables, process monitoring and other tasks which are related to process control. This is mostly due to the lack of continuous direct measurements of key parameters. The soft sensor that will be developed in this project will estimate the change in the ladle status, i.e. thermal and refractory condition, during different events e.g. preheating, EAF tapping, LF processing, ladle empty time.
In the steel industry soft sensors have even larger significance since it is generally difficult to conduct direct measurements. A direct measurement, when possible, can be excessively costly, unreliable or dangerous, and may therefore not be available at the desirable frequency. Therefore, there is a need for continuous estimation of values in between direct measurements. Of course, dynamic process models have been used widely based on these grounds, therefore it is important to distinguish differences between a soft sensor and a dynamic process model. A dynamic process model is usually based on first principle models and possibly empirical factors, while soft sensors are based on statistical correlations between measured signals and the output signals. Therefore, the calibration of a soft sensor is based on fitting a regression

model of the parameter. This regression model may be of any type, e.g. linear (MLR, PLS, OPLS, PCR, etc.) or nonlinear (Neural networks, exponential, quadratic, logarithmic, etc.). Hence, a soft sensor can receive signals from "real sensors" (direct measurements), calculated data from dynamic process models and signals from other "soft sensors". However, soft sensors are not predictive instruments because they only calculate the current value of the target parameter based on current and historical signal values.

Measurement systems that will be developed and used

The **smart sensor** (see **Figure 2**) will consist of a computing unit, e.g. a mini PC, and will be connected to periphery, e.g. a temperature signal transmitter, that is necessary for transfer of measurement data such as refractory temperature from thermocouple (analogue signal) to the computing unit (named "sensor" in Figure).

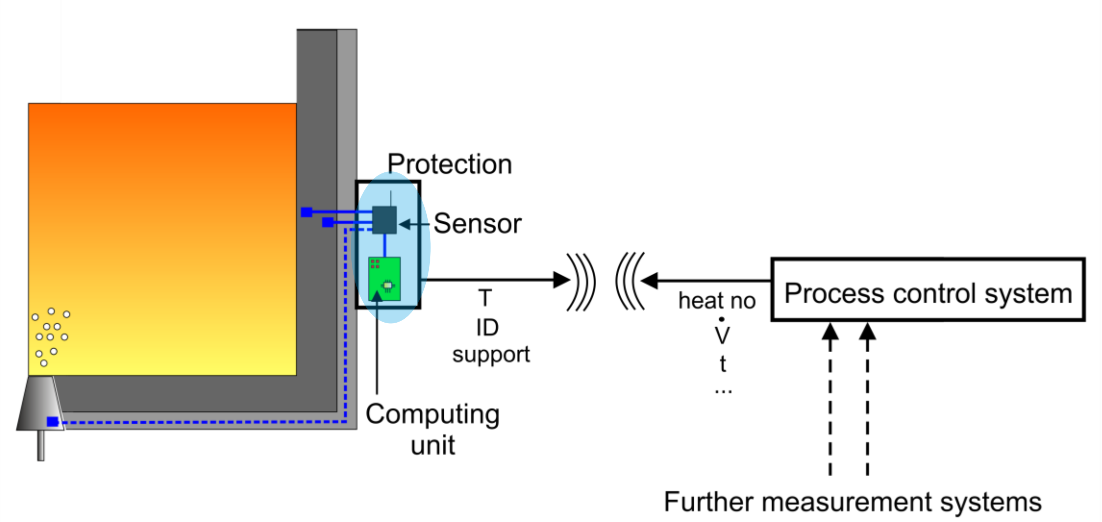

Figure 2: Schematic idea of smart sensor (blue oval)

The computing unit will save the measurement data in a database (SDB: Smart sensor Data-Base) and will use simple models, e.g. for assessing refractory wear status or thermal status of ladle.

Wireless transfer of data will be foreseen to exchange data with the process control system in both directions.

Two topics need severe investigation in order to make the approach feasible: At first, sufficient protection must be provided, as otherwise technical devices cannot withstand the high temperatures at the wall of the steel ladle. Previous experience from the partners has proven successful on developing protection systems withstanding temperatures at ladle shell up to 350 °C for several weeks covering 86 heats [P2 and P4] and up to about 500 °C for at least 45 minutes [P4]. In addition, FEM calculations of optimal layout that will be performed, and the use of new isolation materials (e.g. based on aerogel or ionic liquids) will ensure sufficient protection of the smart sensor. The second topic concerns the wireless transfer of data, where the fast development of different techniques (WLAN, Bluetooth, LoRa…), as already realised e.g. for crane control, provides a good basis, even for low power applications.

To minimise the risk of failure, the smart sensor will at first be developed for an application at the stationary vessel of the EAF with less challenging conditions (vessel is not moving, temperature at the EAF bottom is lower than at ladle shell, especially during and after vacuum treatment, access is much easier). The experiences gained from this first application will be used to develop the smart sensor for the application at a ladle. To further increase the robustness of the ladle status monitoring, the soft sensor for ladle status based on measured process data will be utilised to complement the smart sensor signal in case of failure.

One additional topic for study is the power supply for the smart sensor, especially for application at a ladle. Therefore, a survey on using thermoelectric generator (TEG) at steelmaking ladle is foreseen besides consideration of energy consumption of components and suitable energy supply via (recharcheable) batteries during layout of the sensor.

The reasons for the smart sensor travelling with the ladle and not being a centralised tool are:

- On the one hand, the temperature data are used from inside the ladle refractory and the ladle is mobile, contrary to e.g. an electric arc furnace or blast furnace, where measurement equipment can be installed by fixed cabling, and
- On the other hand, this project is the first step towards a ladle as a Cyber Physical System (CPS) that can be part of a network of agents (ladle2CPS).

Another version of the smart sensor will be used to measure the thermal condition of the tundish. The tundish is a vessel that has been less studied than the ladle as its working conditions are less demanding. It always works a lower number of heats than the ladle, and the refractory wear is not such a critical factor. It is changed in function of the change of sequence in production. Nevertheless, it plays an important role in the thermal evolution of the heat just prior to casting, and it has a strong impact on costs and safety. These reasons, together with the fact that its status has been less studied than that of the ladle, make it interesting to monitor the tundish and use the results in the ladle soft sensor taking into account that the ultimate objective of liquid steel thermal control is to adjust to a proper casting temperature.

Beside this, several further proven measurement techniques will be used within this project to investigate the status of ladle and plugs. A direct integration of these techniques in the smart sensor is not foreseen within this project but could be realised in the future. Therefore, standard protocols and interfaces will be used and the database set-up will be extendible to ensure easy implementation of other applications. A close collaboration of the partners using the different techniques will support this action. The applications of these tools have been realised before, so the risk of failure is low.

The **Laser Contouring System (LCS)** is a successful commercial system which is used nowadays in the steel plants for predicting the break-through in the refining vessels, mainly in BOF but also in some cases in ladles. Currently, the steel plants use the system after a specific number of heats and scan the inner surface of the vessel dedicatedly for safety purposes. The output data are then transferred and saved in a CAD format and the thickness of the refractory will be returned as a grid with specific numbers (thickness) assigned to grid points.
The life span of a ladle is hugely dependent on the material to process (steel and slag compositions) and the methodology used for refining. For example, in some cases during the ladle process addition of flux to change the characteristics of the slag to become more liquid, will contribute to larger wear of the refractory at the slag level. This will play an important role in the life span of a ladle since the larger wear means more frequent relining and larger stop-time.

With **Laser Induced Breakdown Spectroscopy (LIBS)** it is possible to determine the atomic and, with limitations, also the molecular composition of a sample. The high temperature induced by a laser pulse causes the formation of a light-emitting plasma whose emission is characteristic for the material that is analysed. The radiation emitted by the plasma is conducted via an optical fibre to a spectrometer and analysed using special software. Within a campaign in this project, a fast slag analysis will be tested and assessed whether it can be used to provide in real time a further process parameter relevant for the ladle status. The analysis will be carried out directly on site without extensive sample preparation or sample transport to a factory laboratory. Thus, the analysis times can be reduced from at least 7 minutes total cycle time by conventional analysis to less than one minute. This is made possible by homogenisation of measured values instead of sample material. In trials, the measurement system will be calibrated and tested, as well as evaluated regarding positive effect by direct slag conditioning on refractory wear, improved quality and reduced alloy material consumption.

The **vibration** of the ladle will be used as an input data to the refractory wear model and the definition of the stirring intensity. One possible measurement option is to use accelerometers mounted on the ladle stand in combination with one installed on the platform to cancel the noise from the environment. A contactless laser-based accelerometer, commercially available, can also monitor the vibration of the exterior of the ladle with a frequency band of zero to 25 kHz. This frequency band is equal to normal human audibility. The vibration data will be used as input to predict the refining process. The collected data can be used to identify the intensity of the stirring and will be compared afterwards with the refractory wear.

Melt Surface Monitoring by an installed camera will be used to collect pictures of the surface of the bath in the ladle. Furthermore, these frames will be used for imaging processes in order to estimate the open-eye and droplet characteristics. This information, later on, will be used to correlate the gas stirring intensity with the open-eye and droplet characteristics.

Modelling tools that will be used and developed
For using the measured temperature values to give an assessment about ladle wear and thermal status, a systematic investigation of temperature evolution is needed. Therefore, numerical modelling work using Finite Element Method (**FEM**) is applied. The existing model will be enhanced to consider wear influences by e.g. implementing changing boundary conditions for reproducing the decrease of working lining thickness. FEM models have been effectively used in the past to investigate different scenarios [P2, P3], and influences of process parameters on e.g. thermal profile can be estimated. To ensure a best fitting numerical model, temperature inside the ladle refractory at different positions will be used to adapt the model. Such ladle instrumentation has been successfully realised by the partners involved in previous projects [P2, P4].

The Computational Fluid Dynamics (**CFD**) models developed in the framework of RFCS projects, as mentioned, have two major shortcomings. Firstly, there has been no free-surface, hence the surface deformation and the open-eye profile could not be predicted by the models. Secondly, the geometry has been based on the ideal ladle state, i.e. no wear condition, although erosion can play significant role in flow profile.
The CFD model to be applied in the SmartLadle project aims to continue previous modelling works by adding the free-surface so that the open-eye can be predicted more accurately. Furthermore, the CFD model is not going to focus on the ideal ladle geometry as in previous models, but use the information collected by the LCS.
Swerim has developed an internal competence to use open source GNU applications in the field of CFD modelling. Therefore, the project will focus on the utilisation of this type of applications omitting licensing cost for industrial purposes and also providing transferability to the industry. Moreover, the commercial CFD application PHOENICS will also be tried to model the ladle stirring process to compare results between the opensource GNU application and commercial one to increase the confidence in the GNU application.

In the recent years the amount of data generated in industry has been increased substantially. Ladles are not an exception, including cyclic process data, acyclic process data, data of ladle preheating burners or thermographs. And in this project even more data are going to be generated. Combining all those information sources, different among each other and coming in different formats and frequencies, is a challenging task. And getting meaningful answers to the critical questions in ladle management is even more challenging. Questions like: What is the main factor affecting our ladle life? What kind of improvement can be obtained by changing reheating process or a critical process in secondary metallurgy?
ML models offer new capabilities of seeking non-linear relationships between variables and complex pattern matching. ML models need rich data, and one of the driving forces of the project is to collect high quality data from different sources as explained in the previous paragraph. A good part of the project work will consist of treating those raw data to get meaningful variables for the ML models as described in Technical Annex, Task 3.3.

Around 70-80% of the work for any data science problem consists in data treatment and preparation, and this project will be an example of that. Even more, ML models will be assembled to get a better result, combining each one's strengths. The important help from the data science field is that ML models are built in a way that their performance is evaluated and optimised. The data are divided in training and testing datasets. One is used for model parameter definition and the second to test the prediction accuracy. This procedure allows not only model optimisation but also model selection or combination and model result evaluation. Thus, it is expected to get improved insights and numerical prediction capability regarding ladle refractory.

Advisory Tool that will be developed
Steel plant process computers collect large amounts of data, not just during the ladle treatment but also during other production processes, e.g. melting in EAF or casting via tundish. These data usually are treated independently or with weak links to other data collected during the production. One innovative feature of the proposed **Advisory Tool** is the soft sensor with the two main features:

- The fusion of data collected at the involved processes (from EAF to casting), in-situ measurements and data calculated by FEM and CDF modelling and LCS
- The evaluation of these data by means of machine learning methods like neural nets or Random Forests. The soft sensor will supply information about the ladle wear state, used in addition or as fall-back system of the smart sensor.

The Advisory Tool itself will process the soft sensor results to provide the steel plant operators with:

- information on refractory temperature for wear and thermal status assessment,
- information and advice regarding actual/optimal stirring parameters (gas flow rate, stirring times, ...),
- advice for maintenance strategy (ladle management and relevant process parameter), and
- suggestion for which ladle to use for the next refining process and thus provide support in the production planning.

For the decision-making process of the Advisory Tool different approaches will be evaluated like fuzzy rule-based system, Random Forest classification or neural net methods.

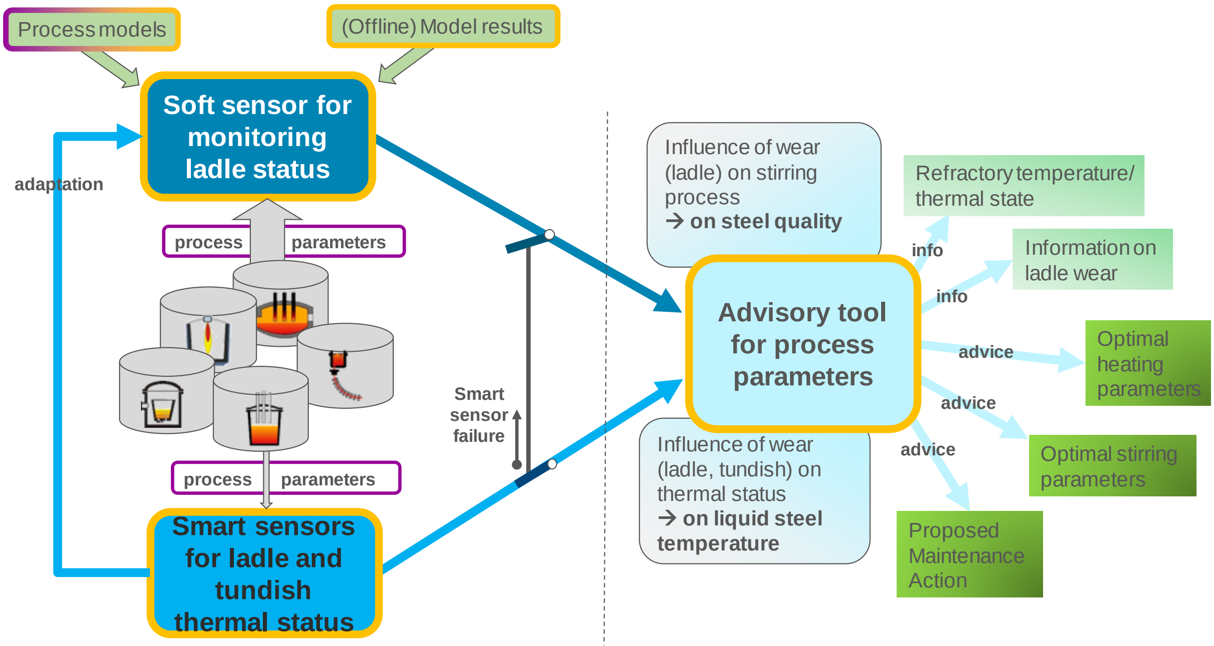

Figure 3: Structure of monitoring and Advisory Tool

The structure of the complete monitoring and the novel Advisory Tool for the actual ladle status is shown together with input and output variables in **Figure 3**, where the framing colour *purple* indicates already existing variables and *yellow* the tools/variables to be developed within SmartLadle.

The Advisory Tool will use the soft sensor if any or all other physical sensor are unavailable. A strategy to reduce the complexity during the development is to focus on only a limited number of output parameters at a time by temporarily leaving out some paths of advice decision making. By dividing the development work into smaller, manageable parts, the risk of not getting usable information from the Advisory Tool is reduced during the project. One example of this strategy is that the Advisory Tool will be laid out likewise, but the primary focus differs for the steel plants as a starting point, e.g. UAB focuses on optimal stirring parameters (during VD), SWG and SID on proposed maintenance actions.

4. Outcome

The industrial, economic and environmental benefits, which are expected from the dynamic consideration of ladle status in process control by online monitoring of ladle status using the soft sensor supported by smart sensor as well as a data-based solution, are:

- More reliable ladle management (improved reproducibility and predictability) and better prediction of wear rate with the reduction of ladle lining cost will lead to a better adaptation capability to production stops by a smart-decision-making application, and will thus increase **plant productivity** and save costs:
  - By implementing the smart sensor as basis for the new Cyber Physical System, for knowledge about actual process and for improved accuracy of already existing individual models, an increased productivity can be expected with savings of about 5 €/ton → 500.000 € per year e.g. for an annual production of 100.000 tons of ingot steel.
  - Further cost reduction can be achieved by the optimisation of ladles in use and reduction of ladle reheating burner energy. Considering that a reference value of natural gas costs of 1 €/ton of steel an improvement of 5 % with an annual production of 800.000 tons would lead to savings of 40.000 € per year in this aspect.
- Refractory materials amount for about 10% of the total transformation cost in SBQ steels grades production. In consequence, an improvement in their use will have a direct impact on the increase of refractory life time and in **refractory cost reductions.** Ladle refractory costs vary depending on steel grades, process conditions, ladle geometry, e.g. for SBQ steel is in the range of 4-9 € per ton of steel. Important cost savings are possible and are one of the aims, even more when considering that the scarcity of fused MgO in the global market has increased the bricks prizes 30-40% the last year.
- Benefits are expected regarding the **improvement of the steelmaking process** due to knowledge of actual ladle status and to dynamic adaption of operational process parameters, e.g. regarding stirring:
  - Optimisation of stirring rates with a subsequent reduction of duration of the metallurgical operation (increased stirring efficiency) will reduce energy and material consumption and thereby costs.
  - The desired cleanness can be achieved with higher reliability and reproducibility, leading to more stable steelmaking processes and an improved steel quality. Cleanness improvements can be translated to less internal rejection in steelmaking production.
- The better knowledge of wear of each ladle will help to **prevent ladle break-through** - a serious risk for workers safety.
- The **environmental benefit** can also be important considering two aspects:
  - The optimisation of ladles would reduce the use of refractory material and thus the carbon footprint associated with refractory production.
  - Ladles preheating and heating from heat to heat requires the main natural gas use in most liquid steelmaking facilities.

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Projects of general nature

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[P3] **Enhanced steel ladle life by improving the resistance of lining to thermal, thermomechanical and thermochemical alteration, LADLIFE** RFSR-CT-2009-00003 (2009 – 2012)

[P4] **Stirring plug monitoring system for improvement of plug availability and stirring performance, PLUGWATCH** RFSR-CT-2012-00005 (2012-2015)

[P5] **Multi-criteria through-process optimisation of liquid steelmaking, TOTOPTLIS** RFSR-CT-2010-00003 (2010-2013)

[P6] **Continuous performance monitoring and calibration of model and control functions for liquid steelmaking processes, PERMONLIST** RFCS no. 709620 (2016) (2016-2019)

[P7] **Dynamic stirring for improvement of energy efficiency in secondary steelmaking, DYNSTIR** RFSR-CT-2015-00004 (2015-2018)

[P8] **Improved control of inclusion chemistry and steel cleanness in the ladle furnace** ECSC- STEEL C 7210-PR/331 (2002-2005)

[P9] **Development of advanced methods for the control of ladle stirring process** ECSC-STEEL C 7210-PR/330 (2002-2005)

[P10] **Production of EAF steels with low content of N2 and S through vacuum treatment** ECSC- STEEL C 7210-PR/135 (1999-2002)

[P11] **Control of inclusion, slag foaming and temperature in vacuum degassing** ECSC-STEEL C 7210-PR/079 (1998-2001)

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[P12] **Development of a new automation and information paradigm for integrated intelligent manu-facturing in steel industry based on holonic agent technology, I2MSTEEL** RFSR-CT-2012-00038 (2012-2015)

[P13] **Consistent ladle tracking for optimisation of steel plant logistics and product quality, TrackOpt** RFCS no. 753592 (2017) (2018-2021)

[P14] **Virtual design of cyber-physical production optimization systems for long production factories, CYBER-POS** RFCS no. 709669 (2016) (2016-2019)

[P15] **Predictive sensor data mining for product quality improvement, PRESED** RFSR-CT-2014-00031 (2014-2017)

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