Deliverable 7.5

EC's Framework Programme for Research and Innovation Horizon 2020 (2014-2020)
Grant agreement no. 636820

Cross-sectorial real-time sensing, advanced control and optimisation of batch processes saving energy and raw materials (RECOBA)

Start of the project:	Jan 1st, 2015
Duration:	36 month

Report about results of the comparison between conventional practice and new methods

Due date:	December 31, 2017
Actual submission date:	January 15, 2018
Lead contractor for this deliverable:	BFI

Author:

Company	Name
BASF	
TKSE	S. Will, M. Skorianz
ELKEM	
UCAM	
RWTH	
VSCHT	
PMAT	
BFI	B. Kleimt , A. Wolff, T. Kordel
CYB	
MINKON	M. Potter, T. Lamp

Dissemination level

PU	public	☒
PP	restricted to other programme participants (incl. the Commission Services)	☐
RE	restricted to a group specified by the consortium (incl. the Commission Services)	☐
CO	Confidential, only for members of the consortium (incl. the Commission Services)	☐

CONTENT

1 Introduction

In this deliverable the enhanced real-time control concept of the batch process chain for liquid steelmaking with focus on the steel melt temperature is described. For process optimization and control, the novel DynTemp in-line temperature measurement system and dynamic, predictive through process models are combined with innovative control tools as Model Predictive Control and Iterative Learning techniques, to ensure an energy and resource efficient achievement of the narrow target temperature window at the end of the batch process chain.

These newly developed closed loop control methods are first described in detail, and optimum measurement, modelling and control practices are recommended. Finally the new real-time control approach will be compared with the conventional control practice in a steelmaking plant.

2 Structure of the newly developed real-time control approach

The structure of the newly developed real-time control approach for the liquid steelmaking batch process route of a conventional oxygen steelmaking plant is illustrated in **Figure 1**.

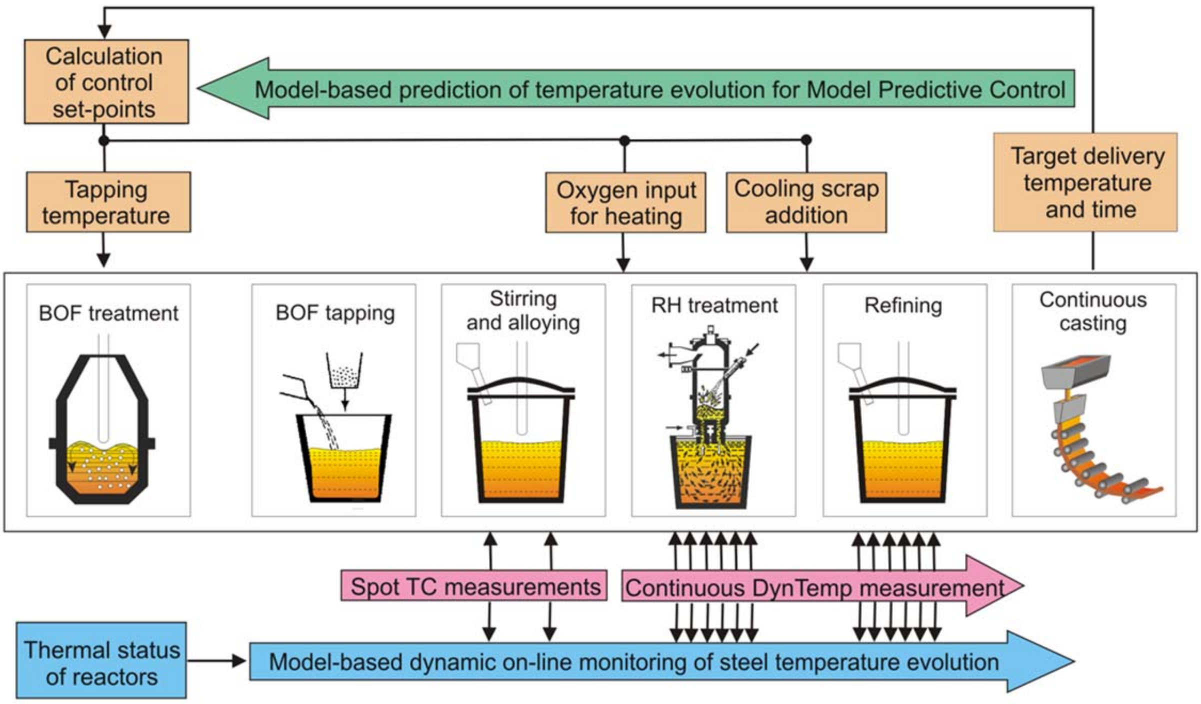

Fig. 1: Structure of real-time control for the liquid steelmaking batch process route

Detailed process models, which also consider the thermal status of the reactors, enable an accurate on-line monitoring and prediction of steel temperature evolution along the entire batch process chain of liquid steelmaking, from tapping of the BOF converter up to the delivery of the melt to the continuous casting plant.

In the first steps of the process chain, i.e. during stirring and alloying for homogenisation after tapping of the melt into the ladle, the melt temperature is measured by conventional spot thermocouple measurements. In the final phases of liquid steel refining, i.e. during RH vacuum degassing and argon stirring, the melt temperature is measured continuously by the DynTemp measurement system. This allows a more accurate assessment of the actual melt temperature evolution.

A simplified version of the dynamic process model is used in a Model Predictive Controller, to determine optimal control set-points, either for oxygen input to

chemically heat up the melt during RH vacuum treatment, or for cooling scrap addition to cool down the melt.
An Iterative Learning Control loop optimizes the BOF tapping temperature on a heat-by-heat basis, to minimize the need for the control actions of heating and cooling on a long term.

In the following, the different components of the real-time control approach are described in more detail.

2.1 Through process dynamic model for melt temperature evolution

The dynamic process model for the evolution of the steel melt temperature covers the complete process chain from tapping of the BOF converter up to the delivery of the melt to the continuous casting plant. Its structure, the main equations and its validation with the help of thermocouple temperature measurements and further industrial data, acquired at the steel plant of tkSE, have been described in detail in the deliverable D4.6. Furthermore, the dynamic temperature model has been validated and improved by evaluation of the DynTemp trials with continuous temperature measurement at the RH vacuum degassing and the Argon stirring station. This was described in detail in Deliverable D7.4. The finally achieved model accuracy along the batch process chain has fully reached the level which was initially defined as target in Deliverable D2.2.

Thus the dynamic model is suitable for on-line monitoring of the melt temperature evolution along the entire batch process chain of liquid steelmaking.

2.2 Continuous temperature measurement with DynTemp system

The fibre optical temperature sensor DynTemp allows a continuous in-line measurement of the liquid steel temperature. The validation of the measurement results by comparison to thermocouple spot measurements and dynamic model calculations has been described in detail in Deliverable D7.4.

Measurement campaigns with the DynTemp system were performed at the RH vacuum degassing and the Argon stirring plant. The results have been described in detail in the Deliverables D7.2 and D7.3. For evaluation of these measurement trials the dynamic model calculations were applied for the corresponding trial heats.

The continuous temperature measurement allows

- to assess variable temperature effects like the thermal state of refractories and the impact of material additions (like chemical heating by Aluminum addition)

- to optimize the procedures in terms of purging gas flow rate and process time depending on the amount of material and energy input

- a more detailed estimation of model parameters of the dynamic process model,

and thus to adjust the melt temperature to the target value for continuous casting more accurately.

2.3 Model predictive and iterative learning control

The dynamic process model applied within real-time control tools has to be simple enough to allow iterative calculations, but has to provide a sufficiently accurate description of the different phenomena occurring in the process.

For the purpose of process optimization and control, the temperature model for the chain of batch processes of liquid steelmaking has been simplified with respect to:

- Reduced number of state variables, i.e. three temperatures (melt, ladle, vacuum vessel), but no steel melt composition
- Straight-forward, piece-wise linear calculations for thermodynamic relations

Information on the evolution of the current process state is provided by self-triggered switching Kalman filters, which estimate the unmeasured states using the process model output and the available measurement information. The self-triggered Kalman filter always triggers a measurement when the accuracy of the estimated temperature is not sufficient. This allows a better estimation of the states with the same number of measurements by using less accurate models, compared to the current procedure.

Dedicated parameter estimation methods are applied to identify the model parameters from the limited number of spot temperature measurements.

For process control a combined approach of event-triggered Model Predictive Control (MPC) and Iterative Learning Control (ILC) was chosen, which is sketched in Figure 2.

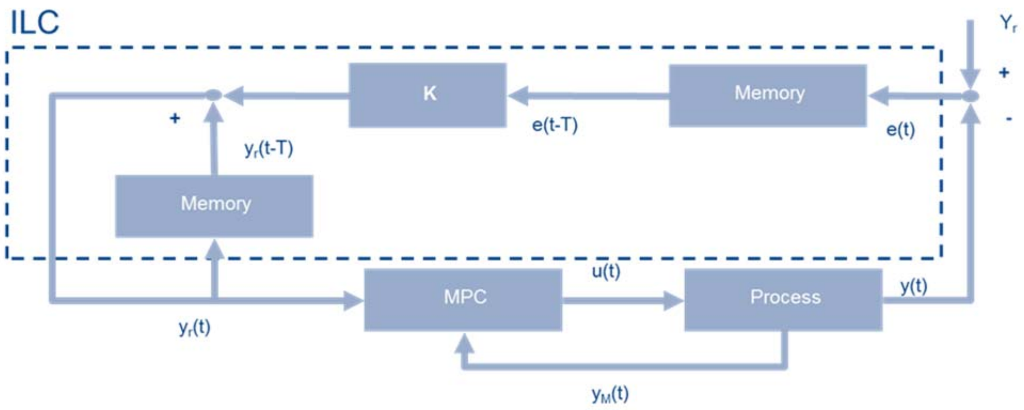

Fig. 2: Structure of combined Model Predictive / Iterative Learning Control

The MPC part controls the final melt temperature by adjusting the amounts of aluminum and oxygen input for chemical heating as well as cooling scrap additions. Parameters of the model used in MPC are switched for the different ladle treatment batch processes. MPC is triggered by external events like material additions or temperature measurements. Figure 3 shows the result of the MPC regarding prediction of the melt temperature evolution and the calculated amount of Aluminum addition for an example heat.

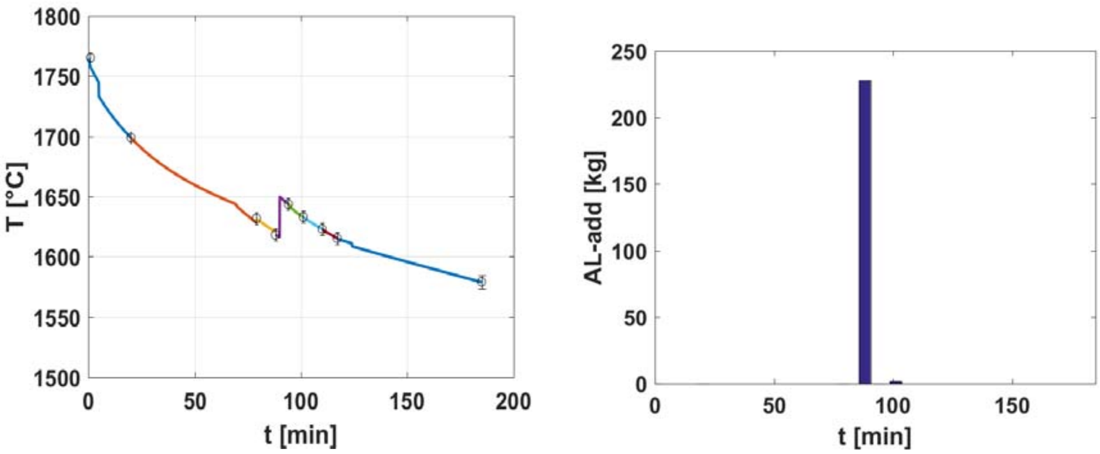

Fig. 3: Results of MPC for an example heat

The ILC is used to adjust the set-point for the BOF tapping temperature on a heat by heat basis, so that the added amounts of aluminum are minimised. The aim is to reduce the average amount of aluminum addition per heat to around 300 kg while keeping the BOF tapping temperature in a predefined interval of [1680 - 1780°C]. Figure 4 shows a simulation result of the ILC for adapting the BOF tapping temperature, to minimise the amount of aluminum for chemical heating on a heat by heat basis.

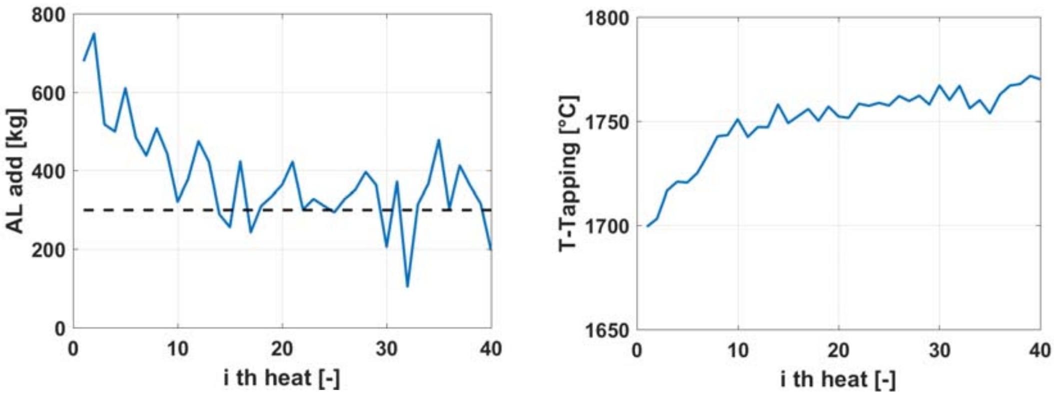

Fig. 4: Results of ILC regarding Al addition (left) and BOF tapping temperature (right) for a number of consecutive heats

3 Comparison between conventional practice and new control approach

The dynamic process model is suitable for on-line monitoring and prediction of the melt temperature evolution along the entire batch process chain of liquid steelmaking, from tapping of the melt into the ladle up to the delivery to the continuous casting plant. It fully covers the interaction and interdependency between the different batch processes of the liquid steelmaking process chain. Also the effect of the thermal states of ladle and vacuum vessel is taken into account by integrating the temperatures of these refractory-lined reactors as separate state variables.

Compared to the conventional practice to perform several thermocouple spot measurements of the melt temperature, the continuous in-line melt temperature measurement allows to assess different process phenomena in more detail and thus to optimise the conventional control practice:

- Quantification of the specific melt temperature reduction after different alloy material and slag former additions
- Optimization of the procedures in terms of purging gas flow rate and process time depending on the amount of material and energy input
- Determination of time constants for mixing, homogenization and thermal phenomena like melting and dissolution of different alloy materials additions and slag formers, as well as for heating of refractory material of the ladles and RH vacuum vessels

This additional information can be used to optimize the timing of thermocouple based spot temperature measurements and to identify the parameters of the dynamic model for the melt temperature evolution.

The in-line melt temperature measurement can also be applied for a more accurate control of the melt temperature evolution on a heat-by-heat basis:

- Continuous in-line temperature measurements not only give an absolute value for the melt temperature, but also a temperature change in time as well as a standard deviation of the individual measurement values can be calculated.
- The homogenisation level can be analysed (based on the scattering of the measurement values and the deviation between measurements and modelling values), to estimate the difference between the local measurement value of thermocouple spot measurements and the average melt temperature and to quantify the error of the thermocouple measurement.
- The efficiency of correction actions of temperature control like aluminothermal heating can be specifically monitored for each heat, which is an important but varying input value for dynamic process control to adjust the target temperature of the continuous casting process.

The combination of a self-triggering Kalman filter and inline temperature measurement results in a more accurate estimation of ladle and vacuum vessel temperature with a limited number of measurements. In addition, the modeling accuracy does not have to be so high to achieve the same prediction accuracy.

4 Conclusions

The real-time control of the batch process chain for liquid steelmaking was enhanced with focus on the steel melt temperature by application of novel sensor techniques, predictive process models as well as innovative process control and optimization tools. The DynTemp fibre optical temperature sensor allows a continuous in-line measurement of the liquid steel temperature. Continuous in-line measurements of the melt temperature gives a direct feedback of the melt temperature to the control loop and corrective actions to adjust the melt temperature to the target value for continuous casting more accurately.

Detailed process models enable an accurate real-time monitoring and prediction of steel temperature evolution along the whole batch process chain of liquid steelmaking.

For process optimization and control the DynTemp in-line temperature measurement and the process models are combined with innovative control tools as Model Predictive Control and Iterative Learning Control techniques, to ensure an energy and resource efficient achievement of the narrow target temperature window at the end of the batch process chain.

The integration of a self-triggering Kalman filter and inline temperature measurement results in a more accurate estimation of ladle and vacuum vessel temperature with a limited number of measurements.