Deliverable 5.3

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

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Event-triggered through process optimisation methods for the control of a chain of batch processes

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Dissemination level

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RE	restricted to a group specified by the consortium (incl. the Commission Services)	☐
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CONTENT

1 Introduction

This deliverable summarizes the results of the optimization studies performed with different models developed over a chain of batch processes, exemplified for the liquid steelmaking use case. Providing the same high quality of liquid steel while decreasing energy and resource inputs and thus production costs is necessary due to the competitive global market. Finding suitable metallurgical procedures and according optimal plant operations over several batch processes is a complex task.
Model based event triggered optimisation returns optimal operating procedures over a chain of batch processes, which may include many constraints such as energy and resource use, quality or safety. Within the RECOBA project, different types of models are used. The suggested control methodology can be applied for each model type and can thus be used also in other considered process industries (for instance, silicon … etc.)

2 Event triggered optimization of batch process chains by through process control techniques for the steel refining processes

In this section, the application of through process control techniques for the batch process chain of liquid steel refining is presented, followed by the process control results using model based controller.

2.1 Event triggered ILC-MPC structure

In the application for the liquid steelmaking process a MPC-ILC (ILC = Iterative Learning Control) approach is used for batch process chains. The demands for these algorithms have been defined in deliverables 2.2 and 2.4. The control structure is shown in Figure 1. It consists of an inner MPC control loop and an outer Learning Control (ILC) loop.

For the event triggered MPC the Lasso MPC approach, as presented in deliverable 5.2 is applied, [1]. It controls the final melt temperature by adjusting the amount of cooling scrap and aluminium for chemical heating added to the melt. The parameters of the model used in the MPC are switched from batch to batch of the process chain, and within the batch process by external signals, e.g. by events as adding alloys.
The ILC controller adjusts the set point of the BOF tapping temperature heat by heat in such a way that the amount of added aluminium and cooling scrap is reduced if possible.

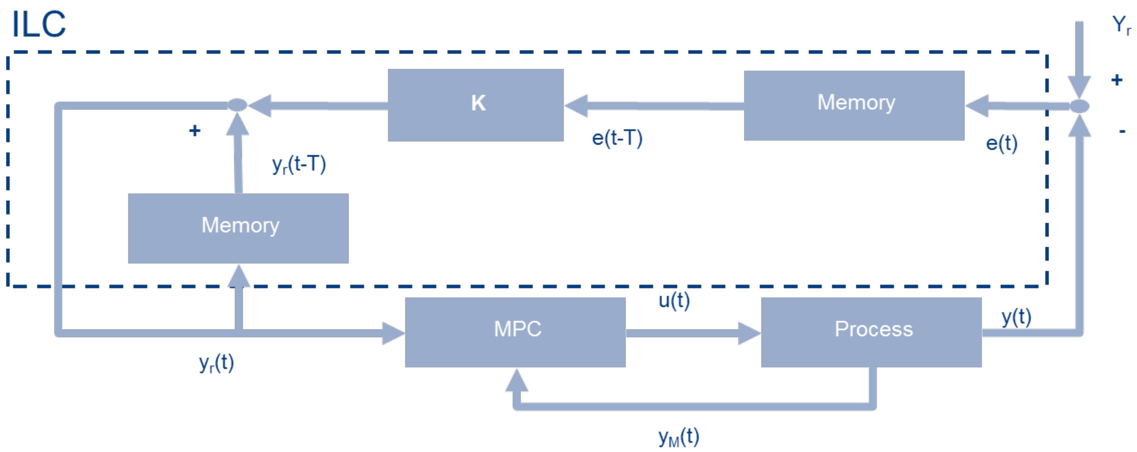

Figure 1: ILC-MPC control structure for event triggered optimization of liquid steelmaking process

2.2 Result of the controller

In this section first some results of the event trigger of a process chain are presented, followed by the results of the ILC to reduce the correction actions (e.g. aluminium addition for chemical heating) used during liquid steelmaking.

2.2.1 Simulation study of the Event triggered MPC for a batch process chain

Two simulations are shown in this study. First an optimal scenario is presented where all the predictions are working perfectly. Second a scenario is shown where the prediction of the melt temperature during RH-treatment doesn't work perfectly.

2.2.1.1 First scenario: No model error

In Figure 2 and Figure 3 the results of the optimal scenario are shown. The melt temperature is first measured during tapping. The MPC is triggered to calculate the aluminium addition the first time. The simulation is carried out to analyse if the target temperature is still met. If this is not the case a recalculation of the aluminium addition is made. The second measurement is taken during stirring and alloying. Then the above mentioned sequence is repeated. At the beginning of the RH treatment also measurements are taken and the aluminium addition is recalculated again. The aluminium addition is performed at this stage of the process chain. Thereafter, the melt temperature is measured and a prediction is made considering model uncertainty to verify if the target temperature would properly be met at the end of the refining process. If necessary, the above sequence is repeated.

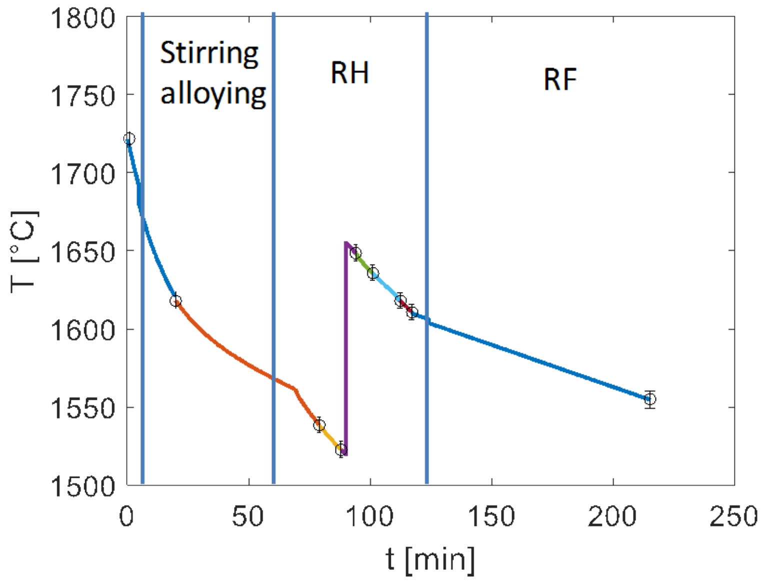

Figure 2: MPC strategy of the melt temperature for chain of batch processes in liquid steel production. No significant model error. Course of the melt temperature. Four batch processes are shown: tapping, Stirring and alloying, **RH** treatment and Refining (**RF)** treatment.

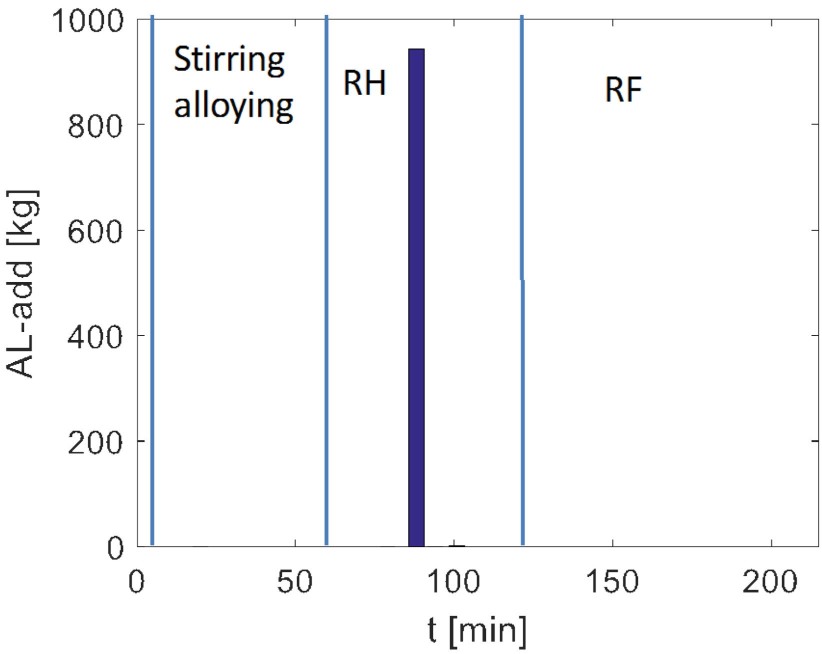

Figure 3: MPC strategy of the melt temperature control for chain of batch processes in liquid steel production. No significant model error. Sequence of the AL addition. Four batches are shown: tapping, Stirring and alloying, **RH**-treatment and **RF** treatment

2.2.1.2 Second scenario: significant model error during RH-treatment

This subsection summarizes the analysis of process batches scenario, which do not meet the process requirements and are corrected in order to keep the product in specifications. Assume that a simulation of the process shows high temperature of the liquid steel melt. This could be, for example due to error in model of RH process. In order to the keep the process in spec, temperature correction in refining treatment batch process is carried out as shown in Figure 4 and Figure 5. A mismatch due to a model error occurs at the end of the RH process hence resulting in wrong model predictions, thus showing a mismatch between the predicted and the target temperature at the end of the refining process.

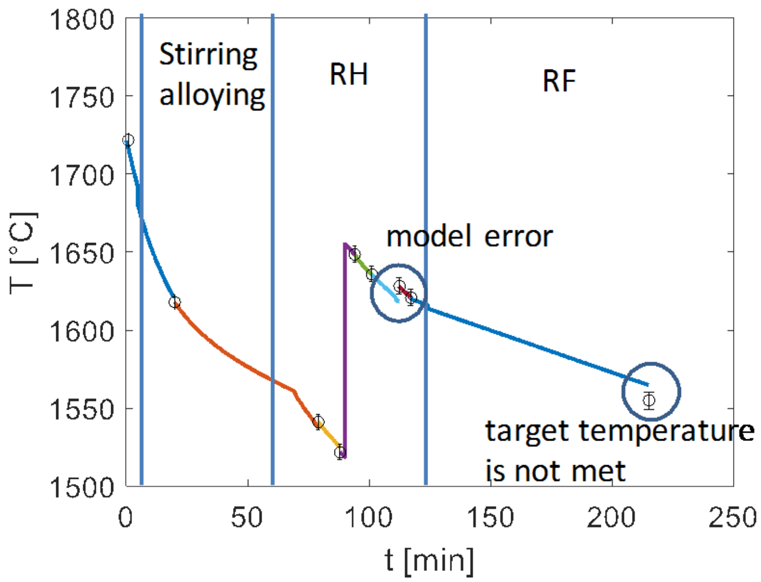

Figure 4: MPC strategy of the melt temperature control for chain of batch processes in liquid steel production. Course of the melt temperature. Significant model error causes a too high liquid steel temperature during RH treatment, so that the target temperature is not met at the end of the refining treatment. Four batches are shown: tapping, Stirring and alloying, **RH**-treatment and **RF** treatment.

Therefore during the refining process (following batch process), two additional temperature measurements would be triggered, to verify the temperature deviations. This is shown in Figure 6. If the deviation still exits, the amount of required cooling scrap is calculated and added to the melt, as seen in Figure 6 and Figure 7. The melt temperature is measured again, and target temperature at end of the refining process is predicted.

The procedure could be repeated if necessary, but should be avoided, if possible.

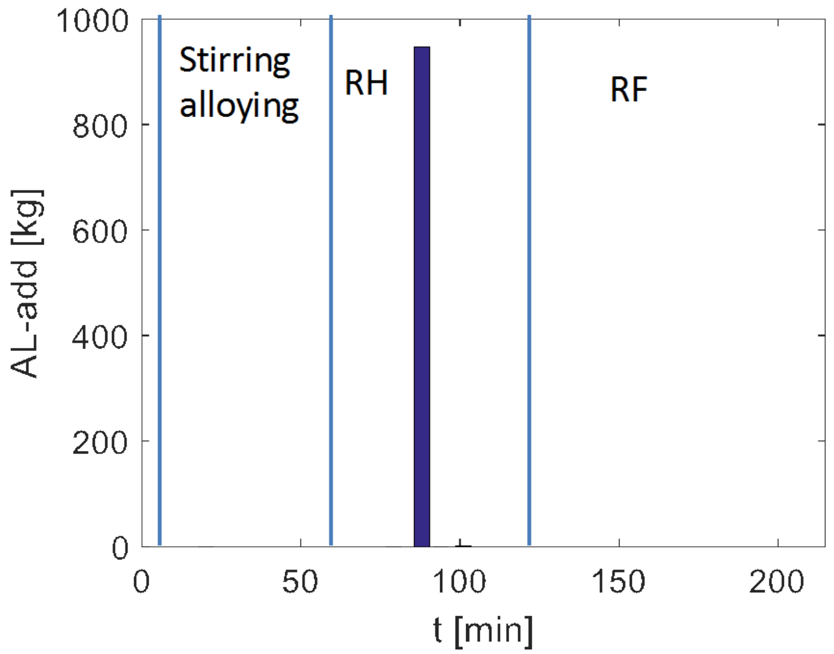

Figure 5: MPC strategy of the melt temperature control for chain of batch processes in liquid steel production. Course of the aluminium addition. Significant model error causes a too high liquid steel temperature during RH treatment, so that the target temperature is not met at the end of the refining treatment. Four batches are shown: tapping, Stirring and alloying, **RH**-treatment and **RF** treatment.

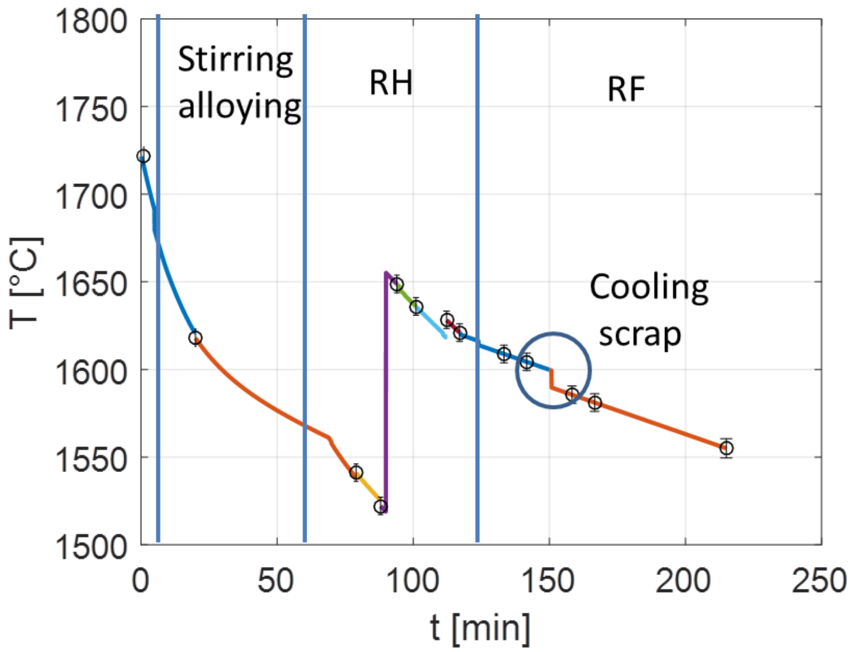

Figure 6: MPC strategy of the melt temperature control for chain of batch processes in liquid steel production. Course of the melt temperature. Significant model error causes a too high liquid steel temperature during RH treatment. This is corrected by adding cooling scrap during the refining batch process. Now the target temperature is met at the end of the refining treatment. Four batches are shown: tapping, Stirring and alloying, **RH**-treatment and **RF** treatment.

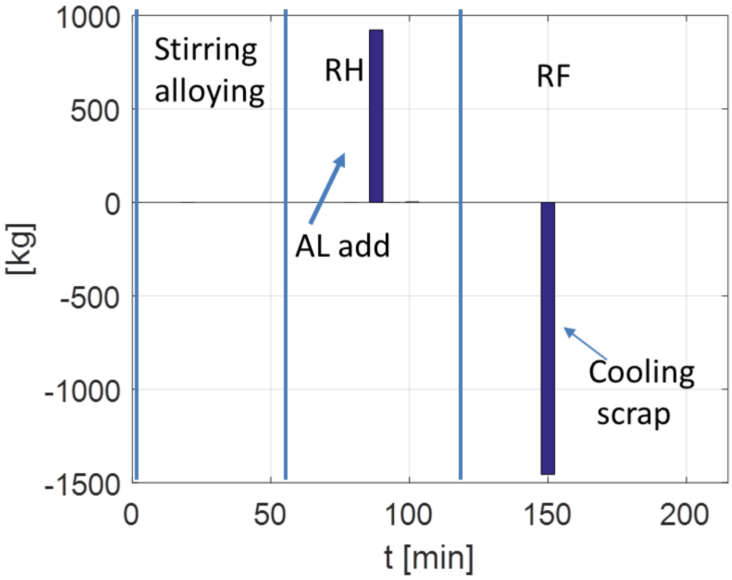

Figure 7: MPC strategy of the melt temperature control for chain of batch processes in liquid steel production. Course of the aluminium and cooling scrap addition (shown as negative value). Significant model error causes a too high liquid steel temperature during RH treatment. This is corrected by adding some cooling scrap during the refining batch process. Now the target temperature is met at the end of the refining treatment. Four batches are shown: tapping, Stirring and alloying, RH-treatment and RF treatment

2.2.2 Simulation of the ILC for adapting the amount of aluminum for heating

One of the aim of RECOBA is to develop novel methods to reduce the use of energy and resources for liquid steel production. This deliverable shows the simulation based study, using ILC to reduce the average amount of cooling scrap addition, [2]. The ILC approach does this iteratively heat by heat cycle. To represent reality, the simulation uses model. whose parameters and disturbances have standard variance of 5 %.

It is aimed in this simulation to keep the average value of aluminium addition per heat by around 600 kg if possible. The BOF tapping temperature is a process constraint and it should be in specified temperature bound [1680°C 1780°C]. It is important to ensure process stability e.g. the melt is cold before reaching the RH-treatment or high temperature will increase the wear of BOF converter and ladle in refractory lining. The simulation results are shown in Figure 8 and Figure 9. Starting from an initial BOF tapping temperature of 1680°C, the temperature is slowly increased heat by heat, as seen in Figure 8. The average amount of aluminium used for heating up the melt during RH-treatment is reduced and stabilised around 600kg, as seen in Figure 9.

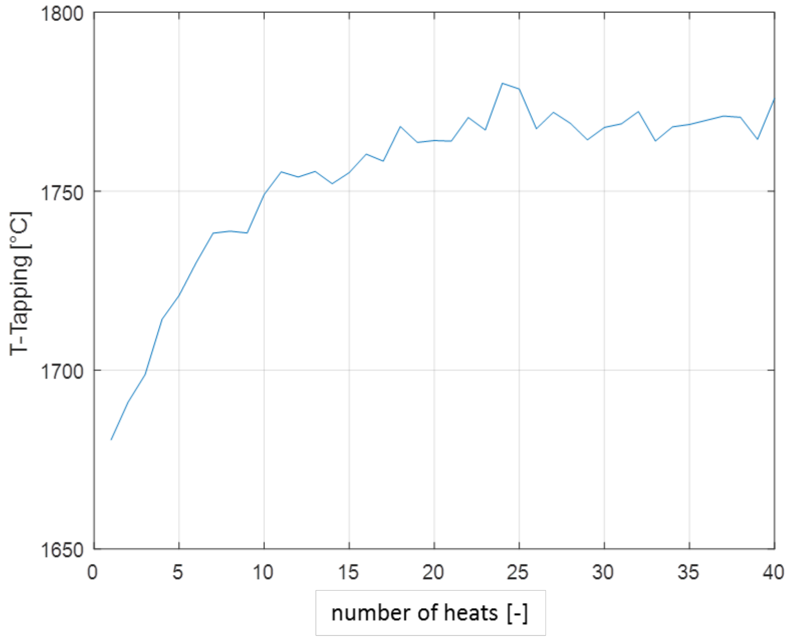

Figure 8: Results of the ILC over a sequence of heats to reduce the average amount of AL addition during liquid steelmaking, course of the tapping temperature

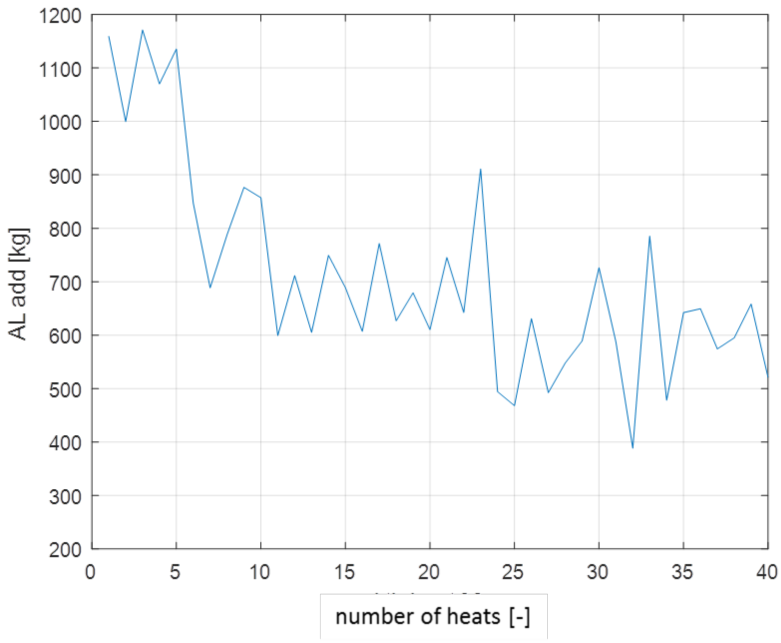

Figure 9: Results of the ILC over a sequence of heats to reduce the average amount of AL addition during liquid steelmaking, course of AL addition

3 Summary and conclusion

This deliverable shows the benefit of a MPC-ILC (ILC = Iterative Learning Control) approach for a chain of batch processes. It is shown that use of model predictive methods improves the insight into the process as well as allows to timely control the process using degrees of freedom to restrict the effect of process disturbances, thus ensuring optimum process operation in all conditions, with distinctive focus on production of in-spec product quality. This is shown in two particular scenarios: a) An ideal scenario where plant-model mismatch is negligible, resulting in prefect predictions and, b)a realistic (non-ideal) scenario with plant-model mismatch..

The deliverable also shows that use of novel model based methods can help to optimize (reduce) the use of energy and feedstock resources for energy intensive steel making processes, which is in line with RECOBA project goals In considered simulation scenario, model based ILC technique reduces the average amount of aluminium addition to achieve desired temperature set-point.

4 Bibliography

[1] M. Gallieri and J. M. Maciejowski, “Stabilisierung Terminal Cost and Terminal Controller for Lasso -MPC: Enhanced Optimality and Region of Attration,” *2013 European Control Conference (ECC),* pp. 524-529 , 17-19 July 2013.

[2] H. S. Ahn, K. Moore and C. Yang Qwuan, Iterative Learning Control, London: Springer, 2007.