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ANALYSIS OF THE EAF OPERATION BY PROCESS MODELLING

ANALIZA PRACY ELEKTRYCZNEGO PIECA ŁUKOWEGO PRZEZ MODELOWANIE

Process modelling is often used for the observation and control of the EAF process. Online process models allow the calculation of values incapable of measurement like the actual liquid and solid steel mass in the furnace or the permanent monitoring of the actual mean temperature of the liquid steel.

An additional benefit comes from offline process simulations allowing an affordable scientific investigation of the EAF operation. The process model can be regarded as a software replacement of the real furnace. Since a specific process model may predict not all relevant information and not all model parameters are known with a sufficient accuracy, the process models need to be validated. For studying the fundamental behaviour of the process and its optimization options, the model has to be as simple as possible – but not simpler.

By using a multi-zone meltdown model [1], the EAF operation is analysed on a theoretical basis. An exemplary model analysis is provided. The process modelling tools are used to demonstrate how to determine optimum DRI feeding or scrap charging procedures. The model predictive control (MPC) approach for continuous DRI feeding is found to be as efficient as global process optimizations (in theory).

Keywords: modelling, electric steel making, melting, electric arc furnace (EAF), process model, model predictive control, optimization, automation, charging

Modelowanie procesu jest często wykorzystywane do obserwacji i sterowania piecem łukowym (EAF). Modele procesu on-line pozwalają na obliczenie wartości niemożliwych do zmierzenia, jak aktualna masa stali w postaci ciekłej i stałej w piecu lub stały monitoring bieżącej temperatury ciekłej stali. Dodatkową korzyścią pochodzącą z symulacji off-line procesu jest możliwość badań naukowych, dotyczących sterowania EAF. Model procesu może być traktowany jak komputerowe zastąpienie rzeczywistego pieca. Ponieważ określony model procesu nie może przewidywać wszystkich istotnych informacji i nie wszystkie parametry modelu są znane z dostateczną dokładnością, modele procesu muszą być weryfikowane. Aby zbadać właściwe zachowanie procesu i parametry jego optymalizacji, model musi być jak prostszy.

Używając kilkustrefowego modelu topienia, praca pieca łukowego jest analizowana w oparciu o teorię. W artykule przeprowadzono przykładową analizę modelu. Narzędzia procesu modelowania są wykorzystane do przedstawienia możliwości uzyskania optimum dozowania DRI lub ładowania złomu. Ujęcie sterowania modelem przewidywania (MPC) dla ciągłego dozowania DRI jest tak skuteczne, jak całościowa optymalizacja procesu (teoretycznie).

1. Introduction

The scientific investigation of the Electric Arc Furnace (EAF) is limited by experimental constraints and the tremendous costs of experiments in production or pilot plants. Process modelling can offer an alternative route to gain a theoretical understanding and ideas for the optimization of the operating procedures at comparable low costs [10, 11]. As sketched in Fig. 1, the process model requires input data x_i which can be deduced from the information on the real process (e.g. effective electric arc power, scrap charging data, etc.). The model parameters p_k have to be determined from fundamental science or inverse modelling (see below). The model finally delivers output variables y_j which represent measurements on the virtual process. The end user can treat process models as a black box and use them as a virtual EAF to perform process simulations. In this paper, an exemplary model analysis and theoretical process optimization procedure using a simple model of the meltdown process (see next section and [1]) is provided. Similar investigations can also be undertaken using other process models

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(e.g. [2–5]) – even if they are more complex, as long as they are detailed enough to be sensitive to the parameters and variables under investigation.

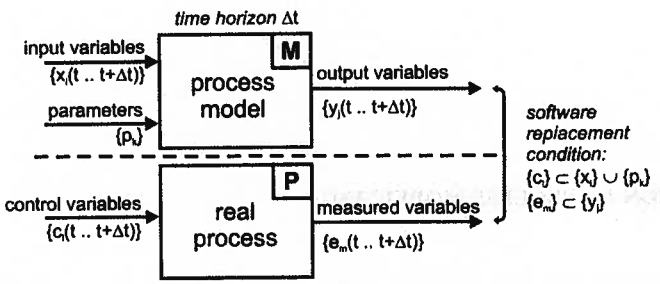

Fig. 1. Process model as a software replacement of the real process

This paper focuses on the model analysis and validation, not on the details inside the computational model, which are briefly summarized in the next section. The term *model validation* is used, because it is common for the confirmation or corroboration of a model.

2. Model of the EAF

The internal details of a process model are often confidential and not available to the end users. The process models can have their own user interface, they can be integrated into a level-2 automation environment (online model, see e.g. [3]) or they can be accessed through common interfaces [6]. In this work, a fast and simple EAF process model is used (for more details see [1]). For judging the dynamic modelling results, the model is summarized briefly.

Following the *as simple as possible but not simpler* approach and currently restricting its application area to the meltdown process, it uses as much fundamental physics as possible and only a minimum of process dependent coefficients. The model solves differential equations of physical conservation laws for mass, momentum, energy and species. For a conserved quantity ψ_i in the zone i, the differential equation for the time evolution of ψ_i is

$$\frac{d}{dt}\psi_i = \sum_j F_{\psi,i,j} + S_{\psi,i}, \qquad (1)$$

here $S_{\psi,i}$ is the sum over all source terms of the balanced quantity ψ in the zone i and $F_{\psi,i,j}$ are the fluxes of ψ between the zones i and j. As an example, for the simple case of heat transport without mass or species transport between two zones, the interaction term for the total enthalpy H (in J) exchanged between zone i and j can be modelled by

$$F_{H,i,j} = A_{i,j}\,\alpha_{i,j}(T_{i,j}^{boundary} - T_i). \qquad (2)$$

The interaction area $A_{i,j}$ and the heat transfer coefficient $\alpha_{i,j}$ must be provided, while the actual boundary temperature $T_{i,j}^{boundary}$ has to be calculated, e.g. from symmetry relations. As the zones are modelled by accumulated contents like H, the heat conduction inside the zones has to be included into $\alpha_{i,j}$, which is also used to take boundary layer effects into account. For interactions like melting or chemical reactions, where combined heat, mass and species transport takes place, the interrelations of the $F_{\psi,i,j}$ have to be taken into account, i.e. by solving the resulting (nonlinear) equation system to determine all $F_{\psi,i,j}$ self consistently. The source terms $S_{\psi,i}$ are used to include external parameters like electric arc heating, alloying, charging etc.

In Table 1, the different zones and balanced quantities are summarized. The enthalpy H is balanced for all zones, while the mass can change only in the zones 2–5 and the carbon mass M_C is balanced only between liquid and solid.

TABLE 1
Zones and balances quantities of the EAF process model

No./balances quantity		0	1	2
1	upper shell	H [J]	–	–
2	liquid metal	H [J]	M [kg]	M_C [kg]
3	solid metal	H [J]	M [kg]	M_C [kg]
4	slag	H [J]	M [kg]	–
5	gas	H [J]	M [kg]	–
6	roof	H [J]	–	–
7	lower shell	H [J]	–	–

An example of the dynamical modelling results is shown in Fig. 2 and 3. The calculation was done for a model furnace (without using chemical energy inputs) and the parameters were obtained by optimization as follows. The optimization target was the energy efficiency. The parameters varied were the weight distribution between the two baskets and in Fig. 3 also the overheating before setting basket 2, while in Fig. 2 basket 2 is set after the melting of 90% of basket 1. Electric power was fixed to 80 MW, tapping weight to 80 t and tapping temperature to 2073 K. Under these circumstances, higher energy efficiency and smaller tap-to-tap times are predicted for the second parameter setting (Fig. 3), where the second basket is dropped into an overheated melt minimizing the freezing of the liquid steel onto the scrap of the second basket, as shown in Fig. 2. Such an optimization procedure cannot deliver results of universal applicability. It has to be performed after obtaining the parameters and constraints for a specific furnace. The model is also able to run online using real plant data and the optimization procedure is fast enough to be in-

tegrated into the level-2 system, i.e. as an "optimized meltdown recipe proposal system".

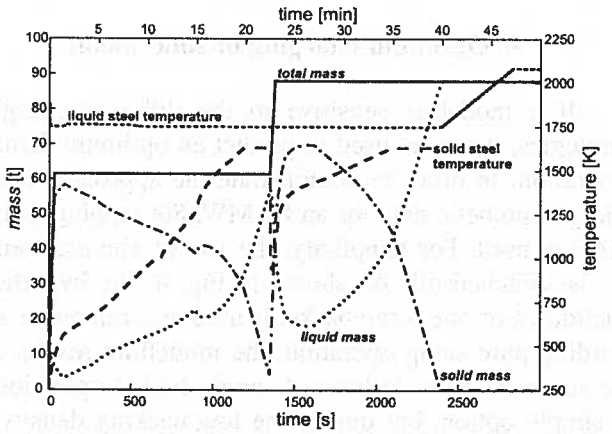

Fig. 2. Results of the dynamic EAF process model (80 MW, no chemical energy) without overheating phase before charging the second scrap basket

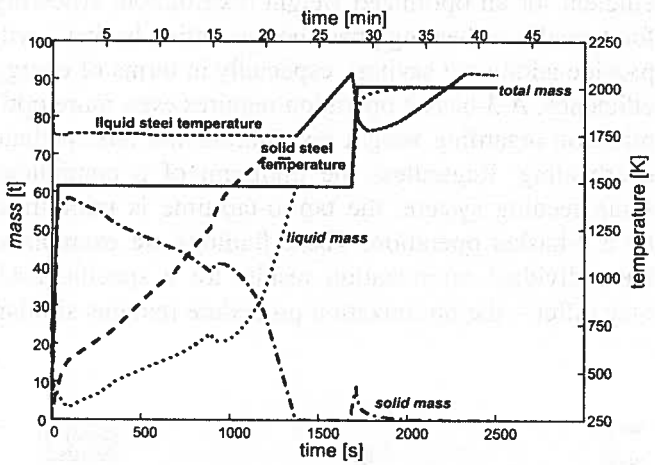

Fig. 3. Results of the dynamic EAF process model (80 MW, no chemical energy) with an overheating phase before charging the second scrap basket

3. Process model analysis

Using the simple model described above as an example, the general procedure of a systematic analysis of an EAF process model is now described. For simplicity, chemical energy inputs are neglected and the target parameters are selected to be energy efficiency (kWh/t) and tap-to-tap time (TTT).

The first model analysis task is the **sensitivity analysis**. This procedure allows the determination of the sensitivity of a specific output value y_j of the process (or the model) to changes in a specific input value x_i or parameter p_k. The local sensitivity of the result y_j for the parameter p_k and the input vector x with respect to the variable x_i is obtained by calculating

$$S_{x_i}^{p_k}(y_j) = \left.\frac{\partial y_j}{\partial x_i}\right|_{x_i,p_k} \approx \frac{y_j(x_i + \Delta x_i) - y_j(x_i - \Delta x_i)}{2\Delta x_i} \quad (3)$$

As an example, a scrap weighting error of 1% yields an uncertainty of 0.2% in the energy efficiency (kWh/t) and 1% in the tap-to-tap-time. The sensitivity analysis is used to quantify the local importance of variables (x_i or p_k). As an example, the relative sensitivity of the calculated energy efficiency related to the heat transfer coefficient α_{sl} from the solid to the liquid is 0.3, i.e. a 10% uncertainty in α_{sl} yields a 3% uncertainty in the energy efficiency.

The sensitivity analysis is of special importance for the judgement of modelling accuracies. As an example, a scrap weighting error of 1% implies a 15 K uncertainty in the liquid steel temperature prediction around the tapping point. Deviations between model predictions and measured values have to be weighted against the principal inaccuracies of the parameters and input values. In the EAF, the most inaccurate factors seem to be the weighting and property determination of the charging materials, the deslagging amounts and the off-gas flow (false air).

The **second task** is the **determination of** the model **parameters** p_k. If possible, one should use independent experiments or calculations. All process models have parameters to be set by the end user. It is the task of the model developers to reduce the number of the required parameters to a minimum. Accurate modelling of physical processes (e.g. heat conduction in the lining) can replace parameters difficult to get from experiment. Laboratory experiments (e.g. [7]) and fundamental modelling can give independent parameter setting information, e.g. for the α_{sl}parameter mentioned above. Finally, a (limited) number of parameters have to be determined from plant operation data. By varying these parameters and calculation of the mean (quadratic) deviation between measured values (e.g. liquid steel temperature in the overheating phase) and predicted values can be minimized. This procedure is similar to regression methods and often called **inverse modelling**. Only deviations above those resulting from the inaccuracies of the input values should be counted. Additionally, a significant sensitivity of the parameter to be determined against the measurements used must exist. As an example, melt temperatures can be used for parameter determination only if they where measured in an overheating phase without any skull material left in the melt – since its amount cannot be measured.

The **third task** is the determination of the models **prediction horizon**. This term can have different meanings. As an example, there is a temporal prediction horizon for the melt temperature. As long as the exact mass and all energy sources and losses are known as a function

of time, the melt temperature can be predicted forever. If there is an uncertainty in the mass or the energy balances, the temporal prediction horizon can be calculated analogous to the sensitivity mentioned above.

Another method is the comparison between predicted and measured values as mentioned above in order to calculate some measure for the prediction horizon of a specific parameter set in terms of correctly predicted heats. This gives important information on the interpolation and extrapolation capabilities of the model as discussed in the following paragraph.

A complex question is the prediction horizon regarding the optimization of the process with respect to a specific target function (e.g. energy efficiency). The results of the optimization may lie in parameter ranges where no experimental data was available during the parameter determination step. As long as this is not the case, numerical process optimizations should be reliable (interpolation mode). If not, the **extrapolation capabilities** of the process model need to be determined. This can be done without new plant experiments by partitioning the available data with respect to the parameters of interest. If only one part of the data is used for the parameter determination, the other part can be used for testing the extrapolation capability of the model. The resulting information should be used to limit the stepping in parameter space outside the area covered by available plant data. This will allow for a secure process optimization maximizing the yield in terms of data and sustainable results at the lowest level of risk.

Similar methods can be used for model simplification or falsification efforts. These methods support research prioritization and sustain the confidence into the models by quantifying their strengths and weaknesses. The methods can be used for benchmarking and heuristic model verification.

An illustrative example will demonstrate the risks taken by not performing the steps above. Any process model can "predict" the tapping temperature as long as the furnace operation procedures and the inputs during the parameter determination and model validation phase are left unchanged. Alternatively, a process model can be adapted at any time to a measured liquid steel temperature value leading to a good "temperature prediction performance" for some amount of time after feeding the measurements into the model. Such insufficiently validated models or parameter sets can be identified by trying to make predictive calculations for unusual charging modes or any other case where the models extrapolation capability is tested and the model does not get any information on the anticipated results in advance.

The next section will try to demonstrate – on a theoretical basis – the opportunities of a virtual EAF process optimization by process modelling.

4. Optimum charging of solid metal

If a model is sensitive to the different charging strategies, it can be used to predict an optimum furnace operation. In order to demonstrate the approach, exemplary hypothetic data for an 80 MW, 80t tapping weight EAF is used. For simplicity, the use of chemical energy is switched off. As shown in Fig. 4, the hypothetic meltdown of one scrap basket is used as a reference. Regarding pure scrap operation, the modelling results can be summarized as follows: A single basket operation is a simple option, but due to the low packing density of the scrap often not possible in practice. Two baskets are worse if the weight distribution is 50:50 and the 2^{nd} basket is set after melting of the 1^{st}. It becomes more efficient for an optimized weight distribution. Allowing for a small overheating phase before setting basket 2 will provide additional savings, especially in terms of energy efficiency. A 3-basket operation requires even more optimization regarding weight distribution and intermediate overheating. Regardless the optimum of a continuous scrap feeding system, the tap-to-tap-time is minimized by a 2-basket operation. These findings are exemplary, the individual optimization results for a specific EAF may differ – the optimization procedure remains similar.

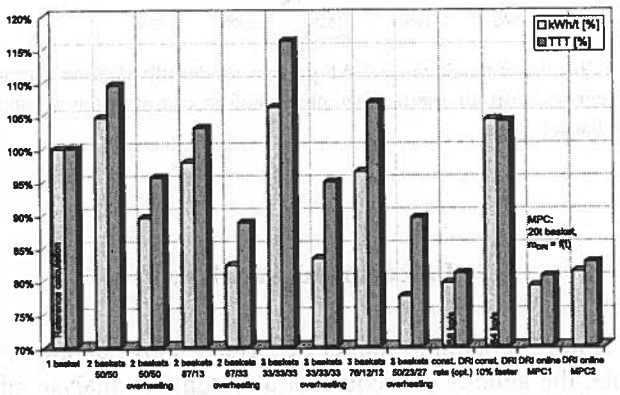

Fig. 4. Comparison of TTT and energy requirements for different charging strategies

Continuous charging operation is very efficient in terms of productivity and energy utilization, but the knowledge of the optimum feeding rate is required. Using a constant DRI feeding rate, the optimum rate can be predicted by several process simulations carried out in advance (4^{th} bars from the right). As shown in Fig. 5, the optimized meltdown process is obtained by feeding the DRI into a slightly overheated melt, while the amount

of solid in the EAF is relatively small (non equilibrium melting). When increasing the DRI feeding rate by 10%, as shown in Fig. 6, this quasi-stationary state is disturbed and the DRI forms an iceberg. As a result, the energy efficiency is significantly lower and the tap-to-tap-time larger. The optimum DRI feeding rate is thus the maximum feeding rate possible without significantly influencing the amount of solid or the melt temperature. Process simulations (inverse modelling) allow determining this global optimum rate. Such an optimization is more complex than the calculation of a current optimum feeding rate from the present EAF state information, as described next.

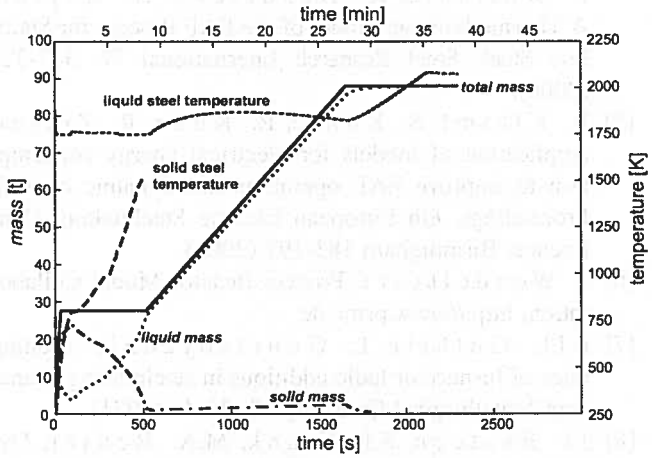

Fig. 5. Results of the dynamic EAF process model (80MW, no chemical energy) for a constant DRI feeding rate of 58 kg/s (other parameters optimized)

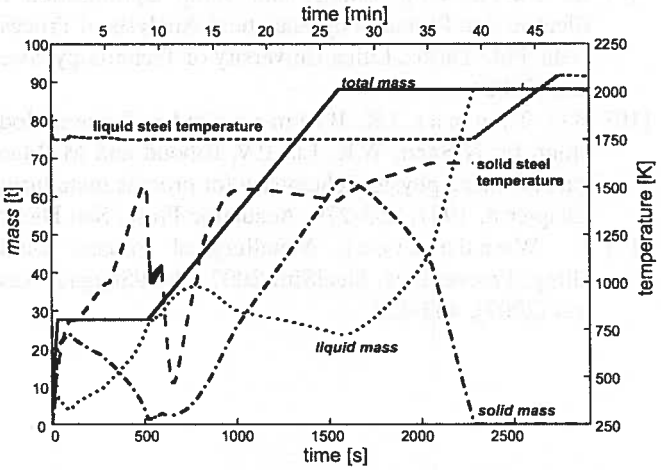

Fig. 6. Results of the dynamic EAF process model for the same parameters as in figure 5 but a DRI feeding rate of 64 kg/s (+10%)

Running the process model online (integrated into the level-2 system), it can be extended by a some type of PID-software-controller for the DRI feeding rate (MPC1, 2nd bars from the right) or the model can calculate an optimum feeding rate from its internal knowledge of the current process state (MPC2). This model predictive control (MPC) approach can be as efficient as the more complex global optimization. Additionally, MPC online models can react on operating disturbances without the requirement to redo the optimization calculations.

An important remark on the percentages provided in Fig. 4 has to be placed. These figures may differ for a specific real furnace, as chemical energy was neglected here and the calculations have to be repeated for a specific EAF after obtaining the plant specific parameters by inverse modelling. Finally, the optimizer may deliver results in a parameter range beyond the extrapolation capability of the model. It may point to an operation not covered by the plant data used for the calculation of the model parameters. The practical EAF operation optimization may require some experimental steps and may deliver less than expected. At least, process simulations can offer ideas for the best optimization directions.

5. Plant data analysis and real furnace operations optimization

While the offline optimization procedures did not suffer from imperfections in the input values, real plant data show a significant amount of uncertainty and scatter. The detailed scrap properties are often highly fluctuating. As long as the sensitivities to such details are sufficiently small, the modelling results make predictions possible. The most straightforward way of getting plant operation data for offline modelling and model parameter determination is the installation of the same model into the level-2 environment (online). By logging the inputs to the model and the measurements, all necessary data for offline modelling can be collected.

After collecting the data, its integrity can be checked and optimized by a data reconciliation step (see e.g. [8]). Now the real world data sets are available as offline model inputs and the results can be compared with the measurements. The data can be used for the parameter determination step, as described in section 3. If the interpolation capabilities of the model are checked and a single consistent parameter set describing all heats is determined, the model can be assumed to describe the real process of a specific EAF. In this case, the model allows a scatter free analysis of the plant operation procedures and their optimization opportunities. This procedure is advantageous against the trial and error approach since promising optimization directions are not hidden in the scatter of the real data.

Additionally a statistical analysis of the process data (see e.g. [9]) can be helpful to predict variables not described by the model (e.g. impurities) or to detect quality changes in the charging information (scrap quality). Sometimes a combination of statistical analysis and pro-

cess simulation can deliver data of practical importance (e.g. the hot heel mass).

6. Summary and conclusions

The analysis of the EAF operation by process modelling was demonstrated using a meltdown process model as a black box for simulating the meltdown of solid material and the temperature development in the furnace. After a brief introduction of the model, the basic steps of model analysis where demonstrated exemplarily. For the simple case of zero chemical energy inputs, the charging of solid material was optimized for 1-3 scrap baskets and continuous DRI feeding. The results agree with practical experience and the concept of model predictive control (MPC) was demonstrated for the calculation of the optimum DRI feeding rate by the model itself. The MPC results are as good as the more resource intensive offline optimization. Even such a simple model may be used to obtain directions for process optimization.

While the quantitative results will be different in real plant observations, the model analysis, parameter determination and optimization procedures can be repeated using real EAF plant data. The general procedure of a systematic analysis of a specific EAF process will provide a virtual EAF for simulations and the calculation of optimisation directions.

The iterative repetition of these steps after changes in the process model is required and the procedures can be automated. By strengthening in each case the weakest link (the charging materials quality, the furnace instrumentation, the model) production optimization means to direct both efforts – practical and computational – into the most demanding directions.

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