15th Triennial World Congress, Barcelona, Spain

# MODEL-BASED ESTIMATION OF MOLTEN METAL ANALYSIS IN THE LD CONVERTER: EXPERIMENTAL RESULTS

**Alexander Medvedev** [*,**] **Andreas Johansson** [*] **Wolfgang Birk** [*]
**Daniel Widlund** [****] **Robert Johansson** [***]

[*] *Luleå University of Technology, SE-971 87, Luleå, SWEDEN*
[**] *Uppsala University, Box 337, SE-751 05, Uppsala, SWEDEN*
[***] *SSAB Tunnplåt AB, SE-971 88, Luleå, SWEDEN*
[****] *SSAB Oxelösund, SE-613 80, Oxelösund, SWEDEN*

Abstract: Experiences from field tests of a nonlinear observer-based molten metal analysis estimation system are reported. The system performance is tested for a wide range of process conditions both on bulk data and in a supervised experimental campaign. Estimation of process model parameters and the observer design are discussed and exemplified on logged data. Observer performance is shown to be high with a mean absolute final carbon content estimation error for admissible heats equal to $0.0012\%$.

Keywords: Process control, Metals, Nonlinear systems, Observers

## 1. PROBLEM DEFINITION

The aim of the top blown basic oxygen process is to reduce the contents of carbon, silicon and other contaminating components in the hot metal from the blast furnace by oxidation.

The converter is controlled by an operator, who judges the state of the process based upon a number of measurements, *e. g.* a sound level measurement obtained by a sonicmeter and analysis of the waste gas, (Widlund *et al.*, 1998). The blowing is completed when the content of carbon in the metal is considered to be right. The quality of the final product is therefore highly dependent on the experience and judgment of the individual operator.

The main quality measure of the final product is the carbon content since no silicon is normally left by the end of a heat. However, direct measurement of the carbon content during the heat is not possible due to the high temperature and hostile environment in the converter.

If the predefined carbon content is not achieved, the process needs to be repeated with a significant loss of energy and other resources as a result. When the final carbon content is too low, compared to the ordered quality, then some superfluous oxygen has been spent and the process has not been run efficiently.

## 2. SOLUTION

An observer comprised of a nonlinear simplified mathematical model of the LD-converter (Widlund *et al.*, 1998) and a nonlinear feedback is employed in order to obtain real-time estimates of the molten metal analysis. Measurements of the oxygen flow through the lance as well as the analysis and the flow of waste gas are used for updating the process model, Fig. 1. The observer design method is based on evaluating the sensitivity functions of the process output signals, *i. e.* the off-gas analysis, with respect to the process states, *i. e.* the carbon and silicon content, (Johansson *et al.*, 2000). A detailed stability analysis of the design is carried out in (Johansson and Medvedev, 2001).

In the sequel, the observer structure and design are evaluated on experimental data for a wide range of process conditions, providing insights into the accuracy and robustness of the final carbon content estimate.

## 3. PROCESS MODEL

A process model has been developed at the Division of Metallurgy of the Royal Institute of Technology in Stockholm, Sweden and can be simplified to

$$\begin{aligned} \dot{p} &= Ap + Bu + Ey \\ y &= h(p, u) \end{aligned} \tag{1}$$

The state vector $p = [p_{\mathrm{Si}}\ p_{\mathrm{C}}]^T$ represents the total contents of $C$ and $Si$ in the metal, given in moles. The linear part of (1) is asymptotically stable since $A = \mathrm{diag}(-a_1, -a_2)$ where the coefficients $a_1$ and $a_2$ are both positive, although $a_2$ is very close to zero.

The derived model of the LD-converter is based on mathematical description of the physical and chemical processes taking place in the process during a heat. Therefore, the process model is independent of the actual converter individual it works with. Of course, this is achieved at cost of quite coarse description of the physical and chemical phenomena and should be compensated for via a robust design of the observer feedback.

### 3.1 *Input signals*

The first element $u_1$ of the input vector $u = [u_1\ v^T]^T$ represents the inflow of oxygen.

Each element $v_i$ in the vector $v$ represents the flow of additive $i$ released into the liquid metal due to melting and is thus not an actual control signal. Melting is assumed to start when the additive is heated to its melting point and after that proceed at a constant rate. Defining $T_i$ and $\tau_i$ as the heating time and the melting time, respectively, $v_i$ can therefore be expressed as

$$v_i(t) = \frac{1}{\tau_i}\left(w_i(t - T_i) - w_i(t - T_i - \tau_i)\right)$$

where $w_i(t)$ is the accumulated inflow of additive $i$, which can be regarded as a control signal or a measurable disturbance.

The matrix $B$ consists of two rows of elements specifying the percentage of $Si$ and $C$ in each additive. The elements of $B$ and the parameters $\tau_i$ and $T_i$ account for the main source of uncertainty in the model.

### 3.2 *Output signals*

The output $y$ denotes the decarburization rate and is a nonlinear function of the state $p$ and the input $u_1$. Since it represents the rate at which carbon is oxidized, it affects the derivative of the carbon content through the coefficient $-1$, which motivates the vector $E = [0\ -1]^T$.

The decarburization rate is modeled as

$$h(p, u) = \frac{1}{1/s_1(p_{\mathrm{C}}) + 1/s_2(p_{\mathrm{Si}}, u_1)} \tag{2}$$

where

$$\begin{aligned} s_1(p_{\mathrm{C}}) &\triangleq k_{\mathrm{C}}(p_{\mathrm{C}} - p_{\mathrm{C}}^0) \\ s_2(p_{\mathrm{Si}}, u_1) &\triangleq 2(u_1 - k_{\mathrm{Si}} p_{\mathrm{Si}}) \end{aligned}$$

For convenience, the arguments of $s_1$ and $s_2$ are dropped in the sequel when there is no risk of ambiguity.

In fact, the actual measurement signal from the converter is not the decarburization rate $y$. Instead, the waste gas flow and the content of $CO$, $CO_2$, and $O_2$ in it are measured. Since the three components in the waste gas analysis depend only on the decarburization rate, they can be regarded as redundant measurements of the latter. An estimate of the decarburization rate is thus calculated by the control system of the plant and this estimate is used as a measured output.

### 3.3 *Model parameters*

Process model (1) includes a number of parameters that have somehow to be evaluated. On the one hand, estimates of those can be obtained by considering the physical and chemical phenomena occurring during the heat. On the other hand, the parameters can be seen as degrees of freedom of the model and be estimated from experimental data to achieve best observer performance. In practice, it is reasonable to combine those two by first obtaining a coarse estimate of the quantity in question from the first principles model and then to update it by optimizing the model performance in the estimation algorithm.

In the present application, model optimization is complicated by the lack of dynamic metal analysis data. Only final values of carbon content are available. Thus physical estimates of the model parameters are of importance.

In (2), the constant $k_C$ can be for instance estimated from a logged decarburization rate signal. For this end, some simplifications of (1) have to be done.

By the end of a heat, there is no silicon left in the metal which justifies the reduction of one of the process state, *i. e.* $p_{\mathrm{Si}} \equiv 0$. Since only the final part of the decarburization signal will be used for parameter estimation, the inflow of oxygen can assumed to be constant $\dot{u}_1 \equiv 0$, $u_1(t) \equiv U_1$. Furthermore, it is assumed that $a_2 = 0$ and there are no additives, *i. e.* $v \equiv 0$.

Then, process model (1) reduces to a first order differential equation

$$\dot{p}_{\mathrm{C}} = -y$$

where

$$y = \frac{1}{\frac{1}{k_{\mathrm{C}}(p_{\mathrm{C}} - p_{\mathrm{C}}^{0})} + \frac{1}{2U_1}}$$

Expressed in $y$, the process model is, after some rearrangement

$$\dot{y} = -\frac{k_{\mathrm{C}} y (y - 2U_1)^2}{4U_1^2}$$

Define $x = y/(2U_1)$ and

$$z = \frac{x e^{\frac{1}{1-x}}}{1 - x}$$

In the new variable $z$, the process model is

$$\dot{z} = -k_{\mathrm{C}} z \tag{3}$$

By identifying the parameter in the model above, estimates of $k_C$ can be obtained.

## 4. MOLTEN METAL ANALYSIS OBSERVER

Since it is technically complicated and costly to implement a real-time chemical analysis of the molten metal in the converter during the heat, different estimation techniques based on mathematical modeling of the process and on-line sensory data are often used.

However, nonlinear observers have never before been used in an industrial scale molten metal analysis estimation system. All previously developed solutions rely on static process models and/or neural networks as the implementation engine. The use of physical models in the estimation system allows for its further development into a closed-loop control system for the converter process. It also enables a thorough mathematical analysis of the stability and convergence properties of the estimation algorithm.

### 4.1 *Observer structure*

Designing a feedback from all three components of the off-gas analysis $\psi$ to an estimate $\hat{p}$ of the state vector $p$ is a complicated task, which is the reason for feeding back the estimated decarburization rate $y$ instead. This signal is scalar and likely to contain the major part of the relevant information in the off-gas analysis.

The suggested observer structure is

$$\begin{aligned} \dot{\hat{p}} &= A\hat{p} + Bu + Ey + Kh'(\hat{p}, u)(y - \hat{y}) \\ \hat{y} &= h(\hat{p}, u) \end{aligned} \tag{4}$$

where $h'(p, u) \triangleq \partial h\,(p, u)^T / \partial p$ and the gain matrix $K$ is a positive definite solution to the Lyapunov equation $-D = A^T K^{-1} + K^{-1} A$ where the design matrix $D$ is positive semidefinite.

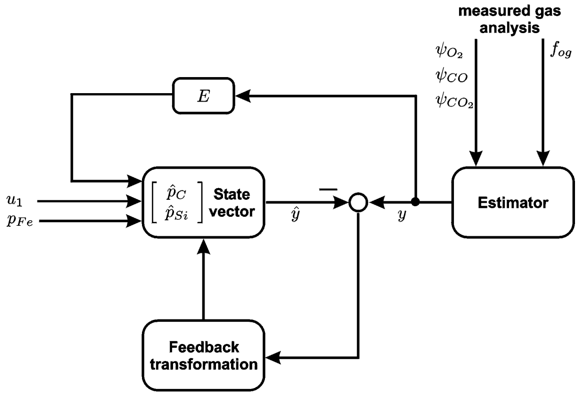


Fig. 1. Nonlinear molten metal analysis observer

The factor $h'(\hat{p}, u)$ in the feedback term weighs the measurement by its relevance. If the sensitivity to the state is low then the measurement contains little information about the state. In this case the feedback weight is weak in order not to affect the state estimate with irrelevant information. If the sensitivity is high then there is relevant information about the state in the measurement and the weight is consequently strong. Ideally, the weight should be $h'(p, u)$ but since this quantity is not available, it is assumed that $\hat{p} \approx p$ and the sensitivity calculated at the estimated state, $h'(\hat{p}, u)$, can be used instead.

### 4.2 *Observer analysis and design*

A painstaking study of stability and convergence properties of observer (4) has been carried out in (Johansson and Medvedev, 2001). It has been shown that the observer can be seen as a special case of the Extended Kalman Filter and is suitable for a broad class of dynamic systems with a nonlinear output transformation. It is also proved that the estimation error dynamics are asymptotically stable and a region of attraction is derived. From analytical results, the obtained estimate of the latter appears though to be quite conservative.

Some idea of the real region of attraction can be obtained by simulating the observer over finite time for some combinations of errors in the initial value of the state vector and taking the difference between the final value of the estimate and the final value of the open loop estimate. If this difference is large, it is likely that the observer estimate would have diverged as $t \to \infty$ and if it is small the estimate would have converged.

Fig. 2 shows the result of such a simulation with different errors in the initial values. The error in the estimate $\tilde{p} = p - \hat{p}$ is assumed to have converged if the final value $|\tilde{p}|$ is less than 500 moles, which is an acceptable error window for the estimate. This yields the band-shaped region on the left side of Fig. 2. If only the error in the carbon content $\tilde{p}_C = p_C - \hat{p}_C$, which is the important quality measure of the

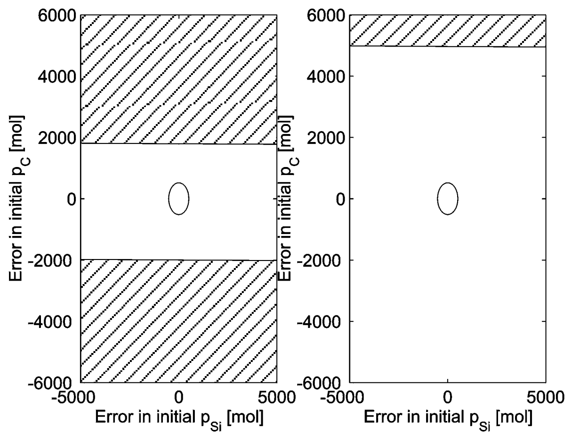


Fig. 2. Estimated region of attraction for $|\tilde{p}|$ (left) and $|\tilde{p}_C|$ (right). The circle represents the theoretically calculated region of attraction.

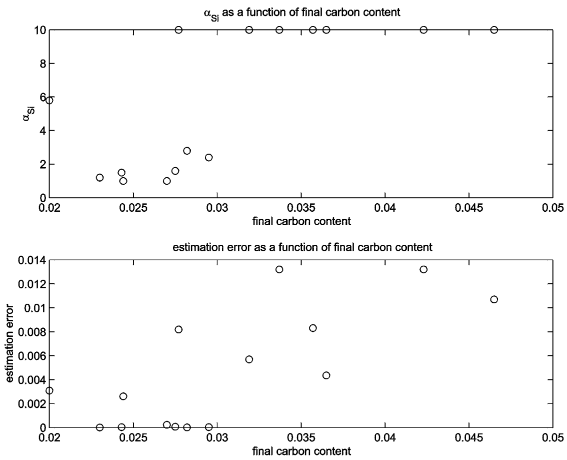


Fig. 3. Best value of the factor in the equation for $s_2$ in (2)

observer, is considered, then the region of convergence becomes considerably larger (Fig. 2, right).

### 4.3 *Observer model validation*

To validate the process model adopted for observer design, optimization of a known parameter in the equation for $s_2$ in (2) has been used. There, the factor 2 is very certain and appears due to the fact that there are two atoms of oxygen in a molecule of $O_2$. Allowing variation of this factor, the value of it providing best estimate of the measured final carbon content for a number of heats is sought. The results are presented in Fig. 3. Since the computations are performed for the model in closed loop, *i. e.* used in an observer, the results reflect not only the model quality but as well the observer performance.

Obviously, for the heats with low final carbon content estimation errors, the value of the estimated parameter is very near to 2. The heats with relatively high estimation errors correspond to high, physically unplausible, values of the coefficient. Thus, one can conclude that the quality of the model is satisfactory when it applies. The deviating heats will be further addressed in the sequel.

### 4.4 *Observer implementation*

In order to investigate the performance of the observer-based estimation technique on different LD-converters and for a broad range of process conditions, long-term real-time tests of the algorithm have been launched at SSAB Tunnplåt in Luleå and SSAB Oxelösund.

The observer is implemented on a process control computer monitoring regular steel production in steel converters, with OpenVMS as the operating system. The molten metal analysis observer is run as an asynchronous system process with a fixed cycle time of one second.

During a heat, the estimation algorithm acquires external data from the LD converter process, generates internal data, *i. e.* process state information, and generates output data, *i. e.* molten metal analysis in real time. These data and additional information on the heat are written to files in Matlab format. Each heat is assigned to a separate file. The data are subject to thorough examination and analysis if a significant discrepancy between the predicted and actual final carbon content is observed. Extra measurements with the sublance and controlled introduction of additives are a part of the experimental program.

## 5. EXPERIMENTAL RESULTS

The above described molten metal analysis observer has lately been intensively tested on three different converters at two steel mills belonging to the SSAB Group. Hundreds of heats have been examined and the results are reported in (Birk *et al.*, 2002). A conference version of this paper can be found in (Birk *et al.*, 2001). Generally, one can conclude that the accuracy and robustness of the estimation algorithm have great potential. However, based on the bulk information, it is difficult to point out exactly in what way the process model and observer design ought to be improved to provide higher accuracy for a broader class of process conditions. It has also become clear that a significant portion of collected data is unreliable due to different kinds of process and measurement irregularities.

### 5.1 *Supervised experimental campaign*

In this section, the data and results of a supervised experimental campaign are presented. All process data are carefully checked and the process conditions such as target carbon content and lance program, are selected to cover the ordinary production envelope. Introduction of additives late in the heat has been prohibited. The goal of the campaign is to fairly evaluate the achievable estimation accuracy in final carbon

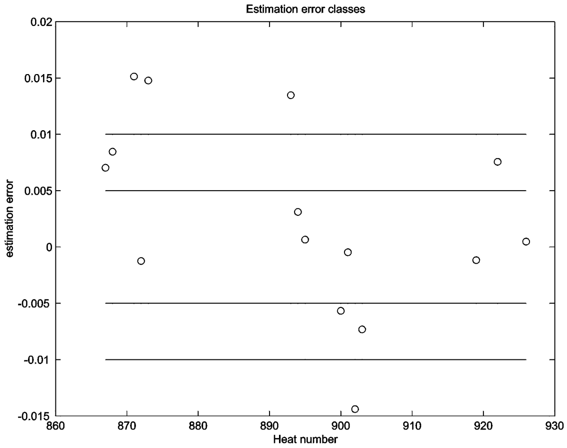


Fig. 4. Final carbon content estimation error for each heat

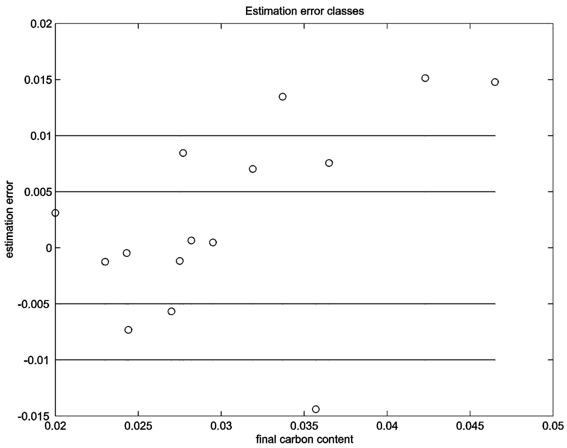


Fig. 5. Final carbon content estimate error vs final carbon content

content and isolate individual process factors that lead to significant estimate deviations. The test data set includes $15$ heats. The outcome of final carbon content estimation is depicted in Fig. 4.

Clearly, both underestimation and overestimation of final carbon content occur. Furthermore, neither high nor low values of the estimation error are bound to a particular time interval. The predominantly positive values of the estimation error corresponding to underestimation of the actual final carbon content can be explained by the observer design. Since the feedback signal of the observer is weighted by the sensitivity function of the decarburization rate with respect to the carbon and silicon content, it is more likely that the estimate does not converge for relatively high values of carbon content where the sensitivity function is low. It is also confirmed by Fig. 5 where the estimation error is plotted as a function of final carbon content.

Since the process model includes a number of parameters, it is interesting to know whether adjustments of those lead to significant improvements in estimation accuracy. Fig. 6 shows the best achievable accuracy in final carbon content for the constant $k_C$ being adjusted for each heat. As it has been shown before

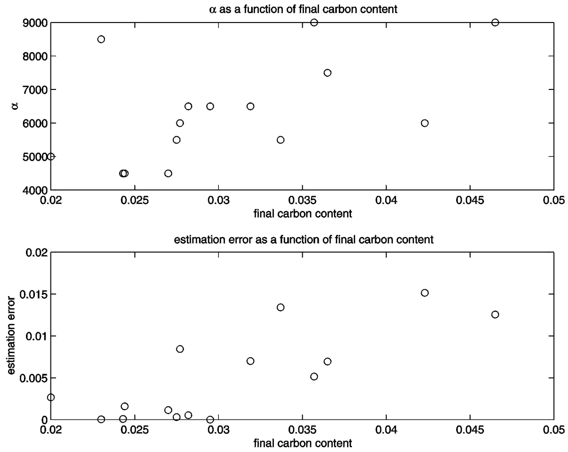


Fig. 6. Absolute value of best achieved final carbon content estimate error with $k_C = \text{var.}$ $\alpha$ is proportional to $k_C$.

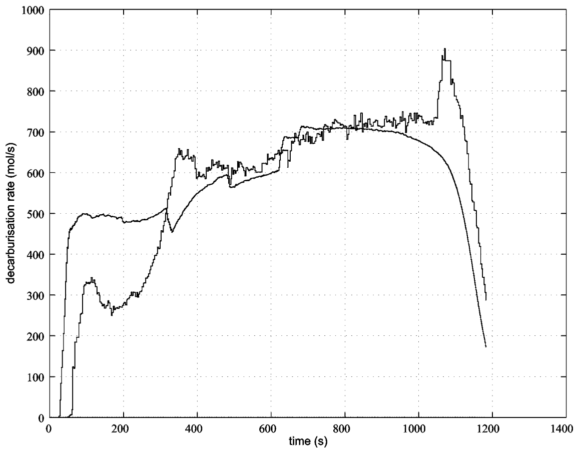


Fig. 7. Measured and estimated decarburization rate for heat number 902. Notice a drastic disturbance in the measured decarburization rate in the beginning of the downward slope.

(see (3)), the value of $k_C$ is of crucial importance for the decarburization process. Apparently, despite the significant variations in the value of the constant, no visible progress is achieved for the worst estimates.

This insignificant effect of parameter optimization on the poor estimates is quite typical and also applies to variation of other process and design parameters. Thus, the observed relatively large deviations from the measured metal analysis have little to do with the observer but are caused by process disturbances.

In Fig. 7, the measured decarburization rate for heat number $902$ is plotted. From Fig. 4, it can be seen that a significant overestimation of the final carbon content has occurred for this heat. The observer could not track the unmodeled drastic increase in the measured decarburization rate just before the downward slope. In fact, this disturbance is caused by a corresponding drastic increase in the waste gas flow, a phenomenon that cannot be explained from the logged signals.

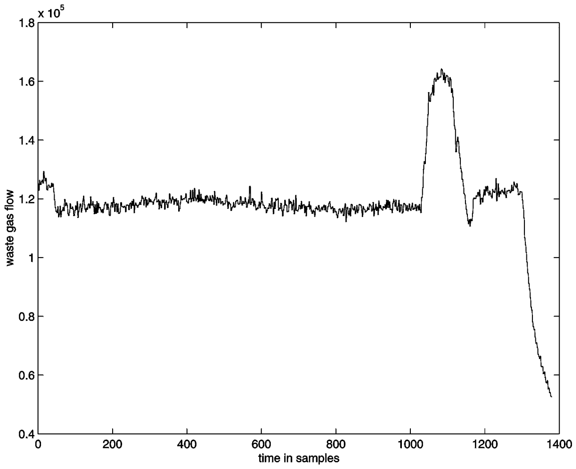


Fig. 8. Waste gas flow for heat number 902.

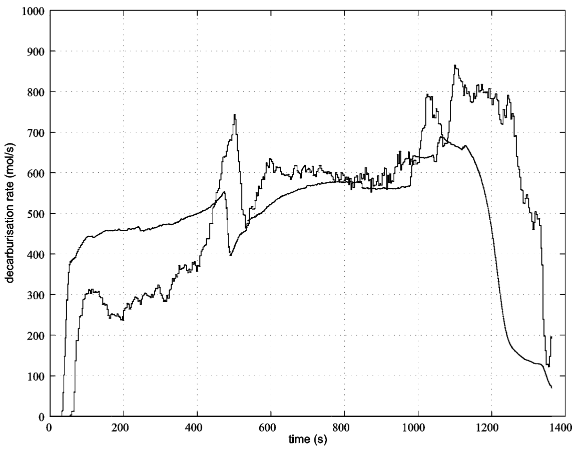


Fig. 9. Measured and estimated decarburization rate for heat number 871. Notice a peak the measured decarburization rate in the end of the downward slope.

Another type of process disturbance causing abnormal deviations in the observer estimate can be seen in heat number 871, where the final carbon content is underestimated. In Fig. 9, a disturbance peak is obvious on the downward slope of the measured decarburization rate curve. This time, the disturbance can be clearly attributed to an imperfection in the waste gas analysis operation, as Fig. 10 indicates.

Similar explanations can be found in the logged data for all the heats where the absolute value of the final carbon content estimation error exceeds $0.005\%$. This is well in line with the initial experiments with the molten metal analysis observer reported in (Johansson *et al.*, 2000).

## 6. CONCLUSIONS

A nonlinear observer is shown to correctly estimate final carbon content of molten metal in the Lintz and Donawitz (LD) converter process. The mean absolute finite carbon content estimation error for the heats where the process model is validated has been found to be $0.0012\%$. The overall mean absolute estimation

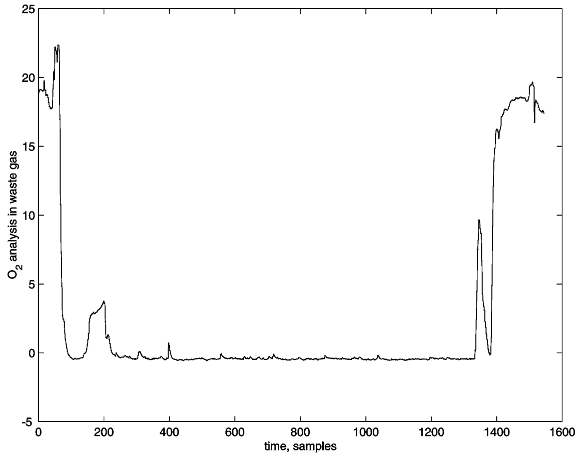


Fig. 10. Measured content of $O_2$ in the waste gas for heat heat number 871. Notice the sharp peak just before the end of the process.

error for the whole supervised experimental campaign, including the heats subject to severe unmodeled process disturbances, is $0.0067\%$. Apparently, to achieve high estimation accuracy, the process itself and the measurement equipment should be in a flawless condition.

## 7. REFERENCES


Birk, Wolfgang, Andreas Johansson, Alexander Medvedev and Robert Johansson (2001). Model-based estimation of molten metal analysis in the LD-converter: Experiments at SSAB Tunnplåt AB in Luleå. In: *Proceedings of IAS2001 Annual Meeting*. Chicago, Illinois. pp. (available on CD–ROM), recommended for publication in IEEE Trans. on IA.

Birk, Wolfgang, Andreas Johansson, Alexander Medvedev and Robert Johansson (2002). Model-based estimation of molten metal analysis in the LD-converter: Experiments at SSAB Tunnplåt AB in luleå. *IEEE Transactions on Industry Applications* **38**, (to appear).

Johansson, Andreas, Alexander Medvedev and Daniel Widlund (2000). Model-based estimation of metal analysis in steel converters. In: *39th IEEE Conference on Decision and Control*. Sydney, Australia. pp. 2017–2022.

Johansson, Andreas and Alexander Medvedev (2001). Non-linear observer for estimation of metal analysis in steel converters. In: *Proceedings of the 5th IFAC Symposium "Nonlinear Control Systems"*. St. Petersburg, Russia. pp. 1402–1407.

Widlund, D., A. Medvedev and R. Gyllenram (1998). Towards model-based closed-loop control of the basic oxygen steelmaking process. In: *9th IFAC Symposium on Automation in Mining, Mineral and Metal Processing*. Cologne, Germany. pp. 69–74.