Abstract: One factor influencing the current efficiency in an aluminium electrolysis cell is the concentration of dissolved alumina in the electrolyte. Unfortunately, no direct measurement of alumina concentration is usually available and present control strategies for alumina feed control rely heavily on the change in cell pseudo-resistance. This paper describes work done to investigate the possibility of using additional measurements of anode current distribution in an extended Kalman filter for the purpose of detecting malfunctioning alumina feeders.

Keywords: Extended Kalman Filter, parameter estimation, fault detection.

1. INTRODUCTION

The energy efficiency in an aluminium electrolysis cell depends on several factors, one being the concentration of dissolved alumina in the electrolyte. Both too high and too low concentration of alumina may lead to serious operational problems. One such problem is the so-called anode effect which occurs at low alumina concentrations. However, the control of alumina concentration is not very accurate because of the limited process information that is available online. Frequent measurements of key control variables like temperature and concentration of alumina in the electrolyte are in general not available. Present control strategies are based mainly on measurements that can be obtained from the outside of the cell, in practice change in cell pseudo-resistance which is calculated from the measured line amperage and total cell voltage drop. No cost efficient sensors for measuring alumina concentration for industrial use have yet been developed. According to Bearne (1999) it is probable that the change in pseudo-resistance with alumina concentration will continue to be used for control for many years. On these premises, any additional measurements that can give insight into how alumina is distributed in the cell may help improve alumina feed control and reduce spatial variation within the cell.

Motivated by the observations made by Rye et al. (1998) this paper investigates the possibility of using measurements of anode current distribution to help detect and if possibly identify the cause of abnormal alumina addition and distribution in the cell. At low alumina concentration, Rye et al. (1998) found that anodes located in areas where the alumina concentration was low took less current than anodes in areas where the alumina concentration was higher. A previous paper (Jakobsen et al., 2001) describes work done to estimate alumina concentration profiles based on measured cell voltage drop and anode current distribution. Here the focus is on detecting faulty feed rate using data from anode current distribution and total cell voltage drop.
2. PROCESS DESCRIPTION

Aluminium is produced by electrochemical reduction of aluminium oxide ($Al_2O_3$, also called alumina) dissolved in a liquid electrolyte at temperatures close to 1000°C. A sketch of a modern electrolysis cell is given in Fig. 1. The cells studied in this work have 18 prebaked anodes arranged in two rows and connected in parallel to the horizontal bus bars. The anodes are partly submerged in the liquid electrolyte which consists mainly of molten cryolite ($Na_3AlF_6$), excess aluminium fluoride ($AlF_3$) and alumina. The DC electrolysis current enters the cell through the bus bars and is distributed among the individual anodes. As the high amperage current passes through the electrolyte and into the cathode, liquid aluminium is formed at the metal/bath interface acting as the cathode while carbon-oxide gases are produced at the anodes. The main cell reaction is given as

$$Al_2O_3(diss) + \frac{3}{2}C(s) \rightarrow 2Al(l) + \frac{3}{2}CO_2(g)$$ (1)

The anode carbon is consumed in the reaction so the individual anodes have to be replaced at regular intervals, about once a month.

The alumina is fed to the electrolyte through two point feeders, one in each end of the cell. Because the electrolyte is covered by a layer of frozen electrolyte and alumina powder, each feeding operation implies making a hole in the top crust with a bar and allowing a controlled amount of alumina powder to be dropped into and dissolved in the electrolyte. If the concentration of dissolved alumina in the electrolyte drops below a critical level, an anode effect may arise. During anode effect, depletion of alumina underneath the anodes causes the resistance (and cell voltage) to increase dramatically without any corresponding increase in metal production. In addition to giving low energy efficiency and disturbing the cell energy balance, anode effect causes production of significant amounts of CFC gases, which are harmful to the environment and have a very strong "greenhouse effect". At the same time, addition of too much alumina may lead to sludge formation as undissolved alumina is deposited at the cathode surface. Faulty equipment, for example a leak in one of the feeders or a malfunctioning bar, could mean that the amount of alumina that is actually dissolved in the electrolyte is considerably different from what is assumed by the process control system. If this situation goes on unnoticed over time, it may eventually lead to an unwanted anode effect or sludge problems.

The voltage drop between the anode-bus bar contact point and the cathode is the same for all anodes in a cell. According to Ohm’s law, more

Fig. 1. An illustration of a prebake aluminium electrolysis cell, as seen from the shorter side. The current will go where there is less resistance, and the way the current distributes between the individual anodes depend upon the resistance in the anodes and in the inter-electrode gap. Because anode resistance is fairly constant over time, and resistance in the electrolyte strongly depends on alumina concentration, the anode current distribution should give information about alumina distribution and concentration in the cell.

3. PROCESS MODELING

In (Jakobsen et al., 2001) a model for estimation of alumina concentration profile in an aluminium electrolysis cell was presented. The cell was divided into 18 control volumes, one for each anode, and a nonlinear state space model for estimation of alumina concentration in each control volume was developed from mass balances and known physical and empirical relations. Here, the objective is to detect abnormal changes in alumina concentration between different parts of the cell and hence the detailed distribution of alumina in the cell is not so important.

Based on the model presented in (Jakobsen et al., 2001), a simplified model is developed where the number of control volumes is reduced to three, all assumed to contain the same volume of electrolyte. Undissolved alumina is fed to the cell, and the rate of dissolution of alumina is assumed to be proportional to both the concentration of undissolved alumina and the degree of under-saturation of dissolved alumina in the electrolyte. The rate of metal production (and alumina consumption) is given by Faraday’s law and the cell current efficiency factor. Mass transport of both undis-
solved and dissolved alumina between adjacent control volumes are described by dispersion. Neglecting all temperature variations, the resulting state space model derived from the mass balance of undissolved and dissolved alumina and change in anode-cathode distance can be written as

\[
\dot{x} = f(x, u, \theta) \quad (2)
\]
\[
y = g(x, u)
\]

Here both \( f \) and \( g \) are nonlinear functions. For each control volume, the state vector \( x = [\psi, c, \delta]^T \) where \( \psi \) and \( c \) are the concentration of undissolved and dissolved alumina respectively, and \( \delta \) is the anode-cathode distance. The parameter vector \( \theta = [k_{1 \to 2}, k_{2 \to 3}, k_{\text{mtf}}, M_e] \) where \( k_{1 \to 2} \) and \( k_{2 \to 3} \) are dispersion parameters, \( k_{\text{mtf}} \) is the mass transfer coefficient for dissolution of alumina and \( M_e \) is the mass of electrolyte in each control volume. The model inputs \( u = [F_1, F_2, ACD, I_1, I_2, I_3] \) are the feed rate alumina for the two point feeders, the change in anode-cathode distance and the anode currents through the three sections in the cell.

Fig. 2 shows the layout of the cells studied. The two dispersion coefficients, \( k_{1 \to 2} \) and \( k_{2 \to 3} \), the mass transfer coefficient \( k_{\text{mtf}} \) and the mass of electrolyte in a control volume \( M_e \) are unknown and must be estimated from experimental data.

The measurement vector, \( y \), consists of the calculated total cell voltage drop and the estimated alumina concentration for each control volume. The total cell voltage drop consists of several terms, some of which depend on the alumina concentration. The equations for calculation of \( y \) are found from literature data (Solheim, 1998; Haupin, 1998).

4. EXPERIMENTAL

The model is validated against three experimental data sets collected from industrial working electrolysis cells at Elkem Aluminium ANS’ plant in Mosjøen, Norway. Normal cells with no indications of abnormal process conditions were chosen for the experiments. Thus, the measurements are assumed to be corrupted with the normal amount of process and measurement noise. The experiments involved introducing rather large changes in normal feed rate at the same time as anode current distribution and cell voltage were logged. During the time of feed disturbance, also the concentration of alumina in the electrolyte and electrolyte temperature were measured at regular intervals at six positions in the cell (see Fig. 2).

The experiments considered here are:

- **Experimental run 1**: Feeder in position F1 was closed down at the end of an underfeeding period. The total cell feed rate was kept at 50% of normal feed rate until anode effect arose.
- **Experimental run 2**: Both feeders in the cell were closed down at the end of an overfeeding period. The feeding was stopped until anode effect arose.
- **Experimental run 3**: Normal feed cycle. A period of overfeeding (more than theoretical consumption rate) followed by a period of underfeeding (less than theoretical consumption rate). The cell was kept at underfeeding until anode effect arose.

5. ESTIMATION

5.1 Parameters and initial conditions

The parameter vector \( \theta \) and the initial conditions \( x_0 \) were estimated using the program SENIT ModelFit. This program which was developed at the Norwegian research institution SINTEF, utilizes an algorithm based on a modified extended Kalman filter (Schei, 1997) to estimate states and parameters in nonlinear state space models. An outer SQP-type optimization loop optimizes the initial values for the parameters and states by minimizing the difference between the measured output, here measured alumina concentration and
total cell voltage drop, and the corresponding simulated model output.

The dispersion parameters $k_{1-2}$ and $k_{2-3}$, the mass transfer coefficient $k_{naf}$, the mass of electrolyte in a control volume $M_e$ and the initial conditions for anode-cathode distance, $d_0$ were estimated simultaneously by fitting the model response to the measured data from experimental run 1. Reasonable estimates of initial undissolved and dissolved alumina concentration were found by manual comparison with the measured alumina concentration. The optimal model response for experimental run 1 is shown in Fig. 3.

![Fig. 3. Estimation of parameters and initial states.](image)

Measured alumina concentration compared to model output (no Kalman filter update) for experimental run 1 using the optimal parameter values and initial states.

The parameters describe physical properties of the process and the values are expected to vary somewhat over time and from cell to cell. The optimal parameter values estimated using data from experimental run 1 proved to yield acceptable model response also when applied to input data from the other two experiments. Minor adjustments of the mass of electrolyte $M_e$, and the dispersion parameters further improved the model response. This was expected since the mass of electrolyte are known to vary and the magnitude of the dispersion parameters depends on the actual convection flow pattern in the cell at the time.

The initial conditions for anode-cathode distance had to be optimized for each experimental run in order to get acceptable results. This was done by fitting the cell voltage drop estimated by the model to the first few cell voltage measurements in the relevant experiment. Fig. 7 illustrates how the initial values for anode cathode distance affect the estimate of alumina concentration through the Kalman filter. Bad initial values are usually indicated by a difference between calculated model voltage drop and measured cell voltage drop, and this results in a large prediction error.

### 5.2 State estimation and fault detection

In normal operation alumina concentration is measured only about once a day and only in one position in the cell. A good model should therefore be able to give reliable estimates also when no concentration measurements are available. After a set of acceptable parameter values and initial conditions are identified using both measurements of alumina concentration, cell voltage, anode currents and correct input data, the alumina concentration is estimated using measurements of cell voltage, anode current distribution and the input data stored in the process database only. Based on the difference in modeled and measured output, the alumina model estimate is updated through an extended Kalman filter algorithm (Schei, 1997) implemented in Matlab.

Earlier results (Jakobsen et al., 2001) indicate that using the measurements of anode currents and voltage to update the model output in a Kalman filter did not improve the estimate of alumina concentration considerably for the fault free input case. Here the effect of using the Kalman filter for state estimation when the input feed rate to the model is faulty is investigated. For example, if one of the feeders is malfunctioning, the process control system may assume that the feed rate is normal while in fact severe disturbances in feed rate take place. This is the case for the experimental data set 1 and 2. Fig. 4 and Fig. 6 show how the estimate of alumina concentration for faulty input feed rate is improved through the Kalman filter. By examining the difference between the model output (no Kalman filter update) and the estimate from the Kalman filter as the actual alumina concentration in the cell decreases, an indication of abnormal alumina distribution is observed early enough in experimental run 1 and 2 to prevent the oncoming anode effect. The results for experimental run 3 were not so good. As is illustrated in Fig. 5, the estimate of alumina concentration was disturbed by an anode beam movement and did not follow the measured value accurately afterwards.

### 6. CONCLUSIONS AND DISCUSSION

The rather crude model for estimation of alumina concentration in an aluminium electrolysis cell
parameters and initial conditions are.

does give acceptable model response when the
parameters and initial conditions are fitted to the
experimental data. Since the model is reduced to
three control volumes and all mass transport is
modeled as dispersion, the problem of modeling
the unknown convection flow pattern in the cell is
eliminated. The two dispersion parameters are fit-
ted to the experimental data, indirectly describing
the effect of convection on alumina distribution.

Using the model for detection of abnormal feed
rates gave promising results. When the actual
concentration of alumina in the cell was low, the
effect of assuming an incorrect feed rate was reduced
when the concentration estimates were updated
through the Kalman filter. By examining the dif-
fERENCE between the model output and Kalman
filter estimate information about abnormal changes
in alumina distribution could be gained early
enough in some cases to prevent an oncoming
anode effect. However, some points proved to be
extremely important to get good results:

- As is seen in Fig. 7 good initial values for
  anode-cathode distance is important. Since
  anode-cathode distance directly influences the
  inter-electrode resistance and thereby cell
  voltage, a poor initial estimate will result in
  a difference between estimated and mea-
  sured cell voltage. The Kalman filter will try
to minimize the large prediction error by
adjusting alumina concentration. A bad
initial estimate for anode-cathode distance
might give a new estimate of alumina
concentration that differs significantly from the
actual value.

- Tuning of the Kalman filter matrices. The
two matrices V and W representing the
process and measurement noise respectively
must be supplied to the Kalman filter algo-
rithm. Tuning of these matrices are crucial
to get good results. If too much emphasis
is given to the measurements, the estimates
may reflect measurement noise not related to
alumina distribution. A problem with esti-
mator stability was observed for certain com-
binations of V and W. The cause of this insta-
BILITY is a topic for further work, but may well
be a combination of the strong nonlinearity
of the process and the rather crude model

- The effect of anode beam movement. The
model value of anode-cathode distance is not
updated in the Kalman filter and can only be
changed by moving the anode beam. Thus,
the anode current distribution could be
expected to remain relatively constant as all
anodes in a cell experience the same change
in anode-cathode distance. In practice how-
ever, this is often not the case. First, a move-
ment of the anode bream usually implies that
something is less than optimal in the cell
to begin with. Second, we lack information
of the processes going on in the electrolyte
that may affect anode current distribution.
For example, movement of the anode beam
may influence the flow pattern in the cell.
As is indicates in Fig. 5 a re-optimization of
the anode-cathode distance often seem to be
required after an anode beam movement.

6.1 Further work

The experiments considered in this paper all in-
volve rather large disturbances in feed rate that
seldom occur in normal operation. Further work
should involve validating the model against nor-
mal operation data focusing on detection of minor
feed disturbances and oncoming anode effects.

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Fig. 4. Detection of faulty feed rate, experimental run 1. Solid line represents model output for the correct input feed rate (feeder F1 closed down at $t = 1000$ sec). $-\cdot-\cdot$ gives model output for faulty feed rate (assume that both feeders have normal feed rate). $\cdots$ represents the alumina concentration estimate from the Kalman filter when the input feed rate is faulty.

Fig. 5. Effect of anode beam movement on alumina concentration estimate. The first plot shows measured cell voltage drop. The second plot shows the Kalman filter alumina concentration estimate for section 1 (solid line) and corresponding measured values (*) for experimental run 3.

Fig. 6. Detection of faulty feed rate, experimental run 2. Solid line represents model output for the correct input feed rate (feeder F1 and F2 closed down). $-\cdot-\cdot$ gives model output for faulty feed rate (assume that both feeders have a feed rate equal to 50% of normal feed rate). $\cdots$ represents the alumina concentration estimate from the Kalman filter when the input feed rate is faulty.

Fig. 7. The importance of initial anode cathode-distance. $-\cdot-\cdot$ and $\cdots$ are the Kalman filter estimates for two sets of initial values for anode-cathode distance for experimental run 1. The solid line is the fault free model output.