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A NONLINEAR MODEL BASED CONTROL STRATEGY FOR THE ALUMINIUM ELECTROLYSIS PROCESS

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Abstract

Important factors for the aluminium industry for succeeding in reducing greenhouse gas emissions and increase energy efficiency is not only the speed in which the organization is able to utilize new knowledge, but also the development and use of new advanced process control systems. New advanced process control systems imply utilizing state of the art process control systems as e.g. Nonlinear Model Predictive Control (NMPC). Although the conventional control structures are dominating the aluminium industry, several authors have addressed advanced process control structures for controlling the Hall-Heroult process. This includes the adaptive control of alumina addition, 9 -Box Matrix Control, LQG Control, Model Predictive Control and control structures involving the Neural network approach.
Recently Hydro has been active in developing an NMPC control structure for controlling the Hall-Heroult process. The Hydro NMPC control structure and results from operational practice on Hydro's HAL275 and Hal4e cells are presented.

Introduction

An important factor for succeeding in reducing greenhouse gas emissions and increase energy efficiency in aluminium production is the use of new advanced process control systems and increased process knowledge. New advanced process control systems imply utilizing state of the art process control systems as e.g. Nonlinear Model Predictive Control (NMPC). NMPC is not a well defined term, but in our context NMPC means the use of a nonlinear mechanistic model, state estimation, and the solution of an online constrained nonlinear optimization problem.

Controlling the alumina reducing process is challenging due to nonlinear process characteristics, coupled mass and energy balance, and few measurements. The scope of this paper is to present experiences with Hydro's NMPC strategy for controlling an aluminium electrolysis cell.

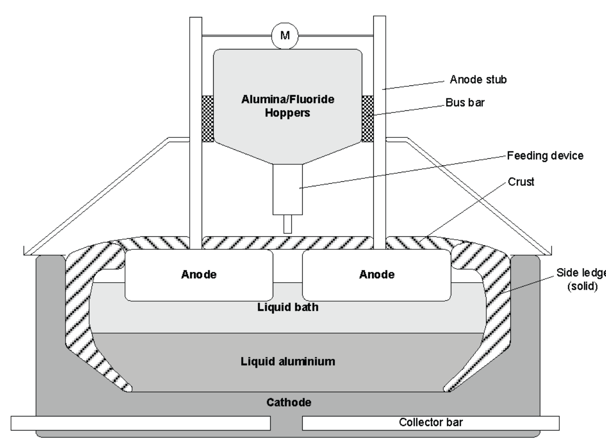
An important challenge in an NMPC application is connected to the estimator, in that the complexity and efficiency of the NMPC is closely related to the quality of the estimates produced by the estimator. This paper mainly highlights these issues. The paper is organized by a short introduction to the Hall-Heroult process. Then follows a short introduction to the NMPC control philosophy and the use of an estimator herein. Finally, results and experiences from operational practice on Hydro's HAL275 and Hal4e technology are presented and discussed.

The Hall-Heroult process

The Hall-Heroult process is the dominating process for producing aluminum today ([1]). The fundamentals of the process are to dissolve Al_2O_3 in molten cryolite (also known as electrolyte or bath), and electrically reduce complex aluminum containing ions to pure aluminum. The overall electrochemical reaction in the electrolyte is

$$2Al_2O_3+3C \rightarrow 4Al+3CO_2 \qquad (1)$$

where carbon is fed to the reaction as consumable anodes. By the use of various additives, in particular AlF_3, the operating temperature of the electrolyte can be lowered from 1010°C to approximately 960°C. Both decreased temperature and increased excess AlF_3 is believed to be beneficial for the amount of metal produced (current efficiency) and the energy consumption. As molten cryolite is very corrosive, the only component of an acceptable cost presently capable of coexisting with it over time is frozen cryolite. It is therefore necessary to maintain a layer of frozen cryolite (side ledge) to prevent the carbon walls from eroding. In order to maintain the side ledge there has to be a substantial heat loss through the side ledge and the carbon walls of the cell. The cell voltage applied is typically 4.3V, and the electric current through the cell is typically 150 - 350kA. A sketch of a cell is shown in Figure 1.



Figue1: The figure illustrates a cell for producing liquid aluminium.

In a modern plant of today 100-300 cells are placed and connected in series. There are three control inputs to the process, anode beam adjustments (controlling energy input), addition of AlF_3 and addition of Al_2O_3, and three controlled variables, electrolyte temperature (also known as bath temperature), concentration (or mass) of AlF_3 and concentration of Al_2O_3. A cell is regularly excited since liquid aluminium is tapped and some of the anode blocks are changed on a daily basis. This induces severe disturbances in the energy balance, and it implies that the operating conditions will vary significantly and hence provoke nonlinear cell effects. The process has strong internal couplings, for instance between the mass and energy balance through the side ledge. The coupled mass and energy balance combined with nonlinear process characteristics and few measurements, makes the Hall-Heroult process challenging to control ([2], [3], [4]).

Although conventional control structures, like PID-variants combined with heuristics, are dominating the industry, several authors have addressed advanced process control structures of control variables regarding the Hall-Heroult process. This includes adaptive control of alumina addition ([5]), 9 -Box Matrix Control ([6]), LQG Control ([7], [4]), Model Predictive Control (MPC) ([8]) and control structures involving the Neural network approach ([9]).

Recently Hydro have been active in developing an advanced control structure, by initiating an NMPC project that has resulted in a patent application for NMPC control of the Hall-Heroult process ([10]).

Motivation

Given reasonable operational targets, it is believed that minimizing the process variations around target values results in good process operations in the sense of minimum pollution to the environment, maximum production and minimum expenditure. Used in the context of the alumina reduction cell the focus should be on achieving low anode effect frequency, good gas scrubbing efficiency and low deviation from target when it comes to alumina concentration, bath temperature and acidity.

The dynamics in reducing the mass of AlF_3 is considered slow, and the control of the concentration of AlF_3 has to deal with slow responses when changing the AlF_3 concentration. The dynamics in the mass of Al_2O_3 is fast, and the control of the concentration of Al_2O_3 has to deal with quick responses. The control of the concentration of Al_2O_3 is usually considered as an isolated problem.

The bath temperature is usually measured manually once a day or at least once a week. The concentration of AlF_3 (acidity) is typically measured manually once or twice a week, while the concentration of Al_2O_3 is not normally measured at all, and only in conjunction with experiments. The continuous measurements are the pseudo bath resistance R_b and continuous measurement of a temperature in the cathode (T_{cat}). R_b is used as an input for the anode beam adjustment, and acts as a control variable in conjunction with the energy input to the cell. Because the energy balance and the mass balance are coupled through the side ledge (see e.g. [11]), the control of a cell must be considered as a nonlinear multivariable control problem.

Experimental conditions

All the results referred to in this paper are from the development phase of the control strategy. The control strategy was developed mainly on Hydro's HAL275 technology, but has recently been ported to and tested on Hydro's Hal4e cell technology.

Towards a novel control philosophy

In this work a (mathematical) model represents a theoretical representation of the Aluminium Electrolysis Cell, where the modeling methodology is based on First Principle. This means that the model describing the process is based on fundamental understanding of the physics such as heat and mass transfer relations and basic physical property relations. Modeling by First Principle usually takes the form of nonlinear differential equations, and hence results in a nonlinear model. By using theory from chemistry and thermodynamics, the mass and energy balances of the cell is described in such a manner that the time behavior of a chosen set of process variables and the relationship between them can be determined or estimated. The chosen set of process variables modeled is typical the side ledge thickness, mass of liquid bath and metal, concentration and mass of AlF_3, concentration and mass of Al_2O_3, mass of sludge, bath temperature, cathode temperature, various heat flows, bath and metal height and pseudo resistance, to mention the most important ones.

The model represents an idealized framework, and will to a certain degree deviate from the physical process due to model uncertainty. In order to make the model work in a non-ideal framework, estimation techniques known as Kalmanfiltering is used ([12]).

Kalman filter state estimation for the aluminium reduction cells is known from [13]. By using Kalmanfiltering techniques, the model uncertainty is adjusted for based on the information available in the measurements of process variables (a sub-set of all the process variables) and the process inputs. The measurements are typically the pseudo resistance, bath temperature, cathode temperature, liquid bath and metal height and the concentration of AlF_3. The process inputs are typically the line current, added masses, anode movements and events (anode effect, metal tap, liquid bath tap/addition, anode change). Based on the information available via the inputs and measurements, the outcome of the model adjustment is a more accurate estimation of the chosen set of process variables at the given time instance. By this, hardly measurable and non-measurable process variables can be estimated and predicted and used in a controller, making it possible to achieve better control of mass and energy balance of the aluminium electrolysis cell. By nonlinear Model Predictive Control (NMPC) we understand the use of a nonlinear dynamical model, state estimation (process variable estimation) and the solution of an online constrained nonlinear optimization problem to calculate the control inputs to the physical process. The structure of the NMPC controller is depicted in Figure 2.

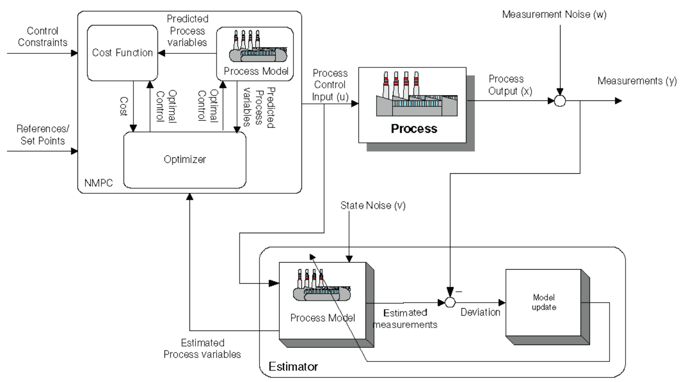


Figure 2: The figure indicates the layout of the NMPC controller as applied by Hydro.

The block labeled Process is meant to illustrate the physical process - one instance of the Aluminium electrolysis cell. The Process is operated by applying process control inputs (mass and energy) and by measuring some process outputs. The measurement could only be done up to a certain level of accuracy. The level of inaccuracy is described as Measurement Noise. The block labeled Estimator contains a mathematical model of the Process. The Process is described by using First Principle modeling techniques and results in several process parameters and process variables. The model also contains differential equations, which capture the time derivative of a selected sub-set of the process variables. This sub-set is called process states.

Since knowledge regarding the process states and variables can be seen as simplified versions of the true process, the discrepancy could be seen as uncertainty - here labeled State Noise. The value of the process control inputs and the value of the measurements are inputs to the Estimator. Based on the knowledge of the process control inputs and measurements, the purpose of the Estimator is to calculate an estimate of the current process variables (process states, estimated parameters and measurements). Further, the estimated measurements are compared to the physical measurements, and the deviation is used to adjust the model such that the deviation is minimized. This technique is referred to as a Kalmanfilter estimation technique ([12]).

The estimated measurements, states and parameters are the output from the Estimator, and serves as an input to the nonlinear model predictive control (NMPC) block. The NMPC block uses a sub set of the estimated process variables (CV), usually in conjunction with some reference values and constraints, to calculate the optimal future process control input scenario (MV) in order to move the process from the current working point (given by the estimate), to the working point given by the reference values. The optimal future process control input scenario would typically be within a finite future time frame. Since the strategy is operating in the discrete time frame, the optimal future process control input scenario would be calculated each time step (say each 5th minute), based upon updated process variable estimates, which also are available each time step. However, only the first value of the future process control input scenario is put onto the physical process. This is illustrated in Figure 3.

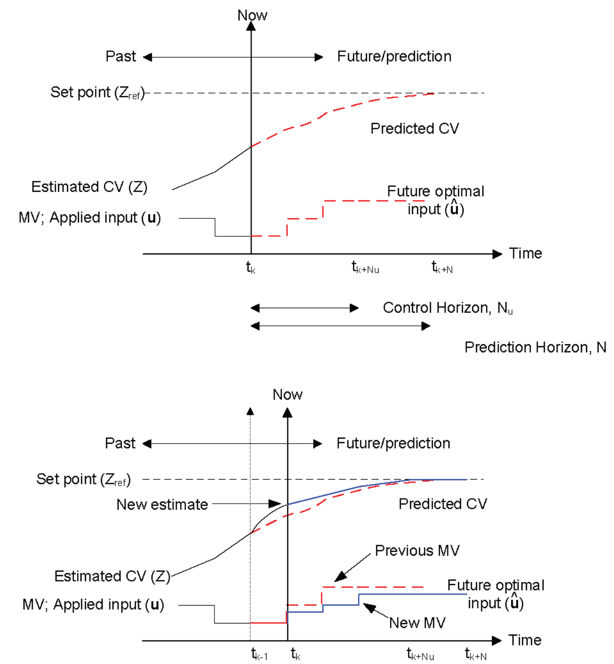


Figure 3: The figure illustrates the NMPC principles.

The optimal control input scenario (MV) is found by solving an optimization criterion by minimizing it with respect to predicted process variables, among others. The predictions stem from using the nonlinear dynamic model to predict the future values of the process variables. The optimizer used is an optimizer that is able to solve nonlinear constrained problems (typically an SQP algorithm). The nonlinear process model in the NMPC block is in this work the same as the nonlinear model in the Estimator block.

Results and discussion

An important challenge in an NMPC application is connected to the estimator, in that the complexity and efficiency of the NMPC is closely related to the quality of the estimates produced by the estimator. This is illustrated in Figure 4, where data from one of the early tests of NMPC in closed loop control of the Hall-Heroult process is shown.

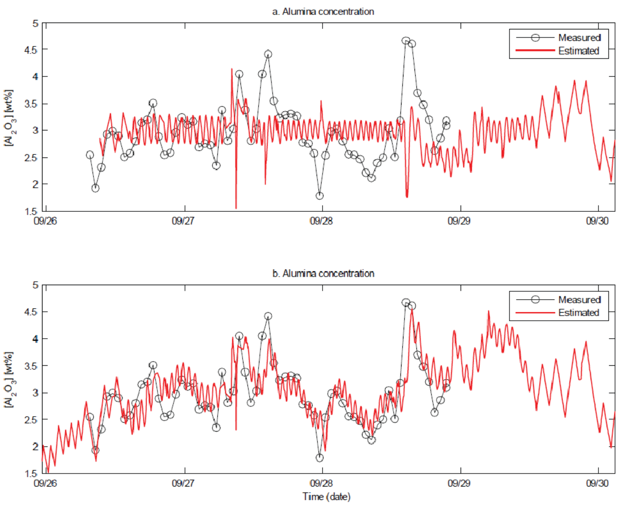


Figure 4: The figure shows measured and estimated alumina concentration for different tuning (a) and (b) of an estimator for the Hall-Heroult process. Note that the measured alumina concentration is not available to the estimator.

Figure 4 clearly illustrates that the performance of the estimator is crucial for the expected performance of the NMPC application. As plot a. in Figure 4 shows, the alumina concentration was poorly estimated, but as plot b. in Figure 4 shows, by retuning of the estimator, it was possible to achieve good estimation of the alumina concentration. However, the quality of the estimates may not only depend on the accuracy of the model, but also of the estimating method selected and how process knowledge is applied. This is illustrated in Figure 5.

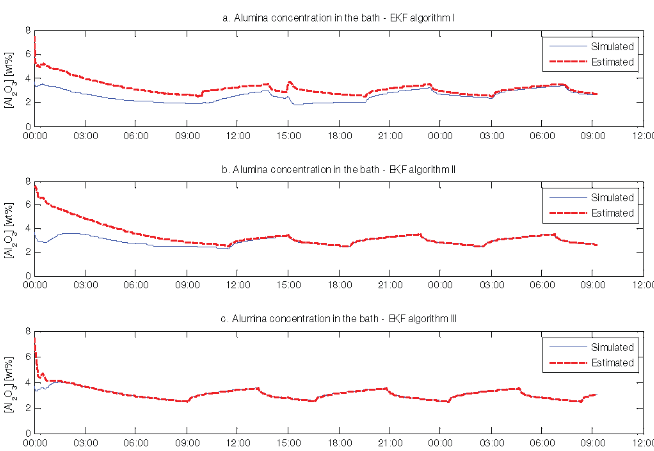


Figure 5: The figure illustrate the convergence speed (how fast the estimated curve approaches the simulated curve) for different estimator algorithms with respect to the same erroneous initial values. Subplot (a) shows the convergence properties for one type Kalmanfilter. Subplot (b) show the convergence properties for another Kalmanfilter algorithm and subplot (c) show the convergence properties for a third Kalmanfilter algorithm. The investigated case studied is the alumina concentration for the Hall-Heroult process. Note that the estimators do not have identical tuning.

As Figure 5 illustrates, knowledge about the performance of different Kalmanfilter algorithms may show important when selecting the right one for the Hall-Herout process. One would like to choose the algorithm that converges to the true solution as fast as possible.

Experience with the estimator algorithm on Hydro's Hal4e cells shows very good performance in estimating important process variables. An example is shown in Figure 6.

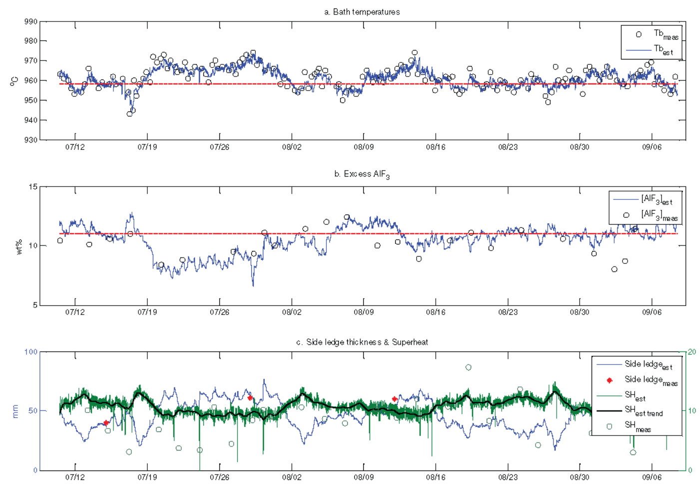


Figure 6: The figure shows the estimated and measured process variables (a.) bath temperature (Tb), (b.) excess AlF_3, (c.) superheat (SH) and side ledge thickness on a Hal4e cell.

By having a selection of the estimated process variables available, this is not only utilized by the NMPC application, but also by the organization in that they are able to follow up process variables previously not accessible. This eases the follow up of the cell behavior and contributes to increased and better process knowledge and organizational learning.

Conclusions

We have presented an NMPC control structure for controlling the Hall-Heroult process. We claim that the most important challenge in an NMPC application is related to adjusting the model behavior to process data through the estimator. Results from the developing phase of the NMPC application regarding estimator performance is presented, and shows that by carefully selecting the estimator algorithm and applying process knowledge with respect to the tuning of the estimator, very good estimates of important process variables can be achieved.

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