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(54) METHOD AND MEANS FOR CONTROLLING AN ELECTROLYSIS CELL

VERFAHREN UND MITTEL ZUR STEUERUNG EINER ELEKTROLYSEZELLE

PROCÉDÉ ET MOYENS POUR COMMANDER UNE CELLULE ÉLECTROLYTIQUE

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Description

[0001] The present invention relates to a method and means for controlling an electrolysis cell for production of aluminium. The invention applies a non-linear model predictive control system (NMPC), where a model of the process is applied to predict the future behaviour of the process. Further, an estimator function is applied to produce estimates of process data in present time, based upon historical data.

[0002] The benefits of the presented invention are that one is able to control the electrolysis cell such that the process variations are reduced. By that on is able to operate the electrolysis cell closer to operational targets and process limits, and to achieve lower emission to the surroundings combined with stable and more efficient production.

[0003] The application of NMPC for controlling industrial processes is for instance known from the oil refinery industry, where this type of control has been widely applied.

[0004] However, a search conducted by the applicant did not reveal applications of non-linear MPC (NMPC) in the metallurgical industry. We recognize from (F.J.Stevens McFadden, JOM, February 2006) that it is mentioned linear MPC as an alternative to the investigated control scheme in controlling the non-alumina electrolyte variables in aluminium electrolysis cells based on a model identified from input-output data. An important difference between MPC and NMPC is that MPC uses a linear model, while NMPC uses a non-linear model. From a theoretical point of view, using a non-linear model changes the control problem from a convex QP (quadratic program) to a non-convex Non-Linear Program (NLP), which the solution of is much more difficult to obtain. When solving a non-convex NLP there is no guarantee that the global optimum can be found. This implies that the tuning of NMPC controllers may be very difficult, particularly for the case where there is model discrepancies.

[0005] EP 0211 924 discloses a method of controlling the alumina feed to reduction cells for producing aluminium. There is employed an adaptive control with parameter estimation and controller calculation based upon the separation theorem. As a process model there is used a linear model having two inputs and one output.

[0006] US patent 4,814;050 is representative for the state of the art linear controller that includes the use of an estimator that employs two sets of equations, namely, a time update algorithm that contains a dynamic model of the alumina mass balance of the cell and provides estimates of alumina concentration, and a measurement algorithm that uses a process feedback variable from the cell to modify the alumina estimate.

[0007] US 6 609 119 B1 relates to a neural control logic scheme based on prediction and pattern recognition techniques to control electrochemical processes such as aluminium electrolytic cells. The predictive capacity of feedforward neural networks is used to predict the future values of decision variables to be used by the cell's control logic, enabling the control logic to apply anticipated actions to cells in different conditions, thus avoiding anode effects and improving cell stability. The pattern recognition capacity of LVQ-type neural networks is used to provide a closed-loop control structure to the feeding of the cell as a function of cell resistance, alumina concentration and cell condition.

[0008] Controlling the alumina reducing process is challenging due to non-linear process characteristics, coupled mass and energy balance and few measurements.

[0009] While the control of Al_2O_3 is considered 'solved', the discussions in the literature in the last ten to fifteen years have been concerned about the control of the bath temperature and AlF_3 control. Common for these contributions is that the AlF_3 addition is calculated as a function of deviation from target acidity and/or target bath temperature.

[0010] It is well known in the aluminium community that both AlF_3 additions and the bath temperature have an influence on the acidity due to variation in side ledge thickness. The relationship between the bath temperature and the acidity is referred to as bath temperature-acidity correlation, or simply the correlation line.

[0011] In accordance with the present invention one (mathematical) model represents a theoretical representation of the Aluminium Electrolysis Cell. The modeling methodology in the present invention is based on First Principle. This means that the model describing the process is based on fundamental understanding of the physics that describe heat and mass transfer relations and basic physical property relations. Modeling by First Principle usually takes the form of non-linear differential equations, and hence results in a non-linear model. By using theory from chemistry and thermo-dynamics (First Principle), the mass and energy balance 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 variable 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.

[0012] 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.

[0013] Kalman filter state estimation is as such known from instance US patent 6757579. Kalman filter state estimation for the aluminium reduction cells is known from "Estimation of states in aluminium reduction cells applying extended kalman filtering algorithms together with a nonlinear dynamic model and discrete measurements" T.Saksvikronning, K.Vee, E.Gran (Light Metals 1976, pp. 275-286)

[0014] 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).

[0015] 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.

[0016] In accordance with the invention 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.

[0017] The abovementioned advantages and further advantages can be obtained by the invention as defined in claim 1-10.

The invention shall be further described by examples and figures where:

Fig. 1 discloses a sketch of the main features of an alumina reduction cell (Prebake)

Fig. 2 discloses prior art controlling of an electrolysis cell (anode beam adjustments for control of energy input, addition of AlF_3 and addition of Al_2O_3,

Fig. 3 discloses a NMPC controller

Fig. 4 discloses one estimate of current Control Variables

Fig. 5 is a diagram disclosing calculated future optimal input scenario (u)

Fig 6 is a diagram disclosing a computed new estimate of Control Variables based upon new measurements and inputs

Fig. 7 discloses a diagram representing the calculated new future optimal input scenario ($\underline{u}$).

[0018] The Hall-Heroult process for aluminium production.

The Hall-Heroult process, named after its inventors, is the most used method by which aluminium is produced industrially today. Liquid aluminium is produced by the electrolytic reduction of alumina (Al_2O_3) dissolved in an electrolyte, referred to as bath, which mainly consists of cryolite (Na_3AlF_6). A sketch of the alumina reduction cell is shown in Figure 1.

[0019] In the alumina reduction cell, hereafter referred to as the cell, one (Søderberg) or several (Prebake) carbon anodes are dipped into the bath. The alumina is consumed electrochemically at the anode.

[0020] As can be seen from Equation (1), the carbon anode is consumed during the process (theoretically 333 kg C/t Al).

$$\frac{1}{2}Al_2O_3 + 3NaF + \frac{3}{4}C \rightarrow AlF_3 + \frac{3}{4}CO_2 + 3Na^+ + 3e \qquad (1)$$

The lower part of the cell, the cathode, consists of a steel shell lined with refractory and thermal insulation. A pool of liquid aluminium is formed on top of the carbon bottom. The cathode, in the electrochemically sense, is the interface between the liquid aluminium and the bath, described by

$$AlF_3 + 3Na^+ + 3e \rightarrow Al + 3NaF \qquad (2)$$

and the total cell reaction becomes

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

[0021] Pure bath (Na_3AlF_6) has a melting point of 1011 °C. To lower the melting point, the liquidus temperature, aluminium fluoride (AlF_3) and calcium fluoride (CaF_2), to mention the most important ones, are added to the bath. The bath composition in a cell may typically be 6-13 *[wt%]* AlF_3, 4-6 *[wt%]* CaF_2, and 2-4 *[wt%]* Al_2O_3. Lowering the liquidus temperature makes it possible to operate the cell at a lower bath temperature, but at the expense of reduced solubility of Al_2O_3 in the bath, demanding good Al_2O_3 control. It should be mentioned that if the concentration of Al_2O_3 gets too low (less than approx. 1.8 wt%), the cell enters a state called anode effect. During anode effect, the cell voltage increases from the normal 4-4.5V up to 20-50V. Anode effect is a highly unwanted state, not only because it represents a waste of energy and a disturbance of the energy balance, but also because greenhouse gases (CF_4 and C_2F_6) are produced at the anode. Very often the anode effect requires a manual intervention of an operator.

[0022] The bath temperature during normal cell operation is between 940 °C and 970 °C.

The bath is not consumed during the electrolytic process, but some is lost, mainly during vaporization. The vapour mainly consists of $NaAlF_4$. In addition some bath is lost by entrainment of small droplets, and water present in the alumina feed reacts to form HF. In order to protect the environment the gas is collected and cleaned in a gas scrubbing system. More than 98% of the AlF_3 is recovered in the scrubbing system and recycled back to the cells. In addition the content of sodium oxide (Na_2O) and calcium fluoride (Ca_2F) in the fed Al_2O_3 neutralize AlF_3. The neutralized amount is also a function of the penetration of sodium into the cathode, and hence the cell age. As an example a 170 kA cell emits about 60 equivalent kg AlF_3 pr. 24 hours, and uses approximately 2500 kg Al_2O_3 pr. 24 hours. The amount of AlF_3 due to neutralization for a 170 kA cell is between 0 and 20 kg per 24 hour (dependent of cell age). However, since most of the AlF_3 is recycled, the real consumption of AlF_3 is very small compared to the consumption of Al_2O_3.

[0023] At the sidewalls of the cathode there is a frozen layer, called side ledge, which protects the carbon sidewall from erosion. The composition of the side ledge is mainly pure Na_3AlF_6 with some CaF_2. The thickness of the side ledge is a function of the heat flow through the sides, which is a function of the difference in bath temperature and liquidus temperature. Since it is assumed that the side ledge composition is mainly Na_3AlF_6, this means that the total mass of cryolite in the bath varies, while the masses of AlF_3 and Al_2O_3 do not vary with the side ledge thickness. Further, since the concentration of an additive is the mass of the additive divided by the total mass of bath, the variation in the side ledge thickness introduces variation in the concentrations. Hence, the changes in the concentrations introduce changes in the liquidus temperature, which introduces changes in the superheat, affecting the side ledge thickness.

[0024] The challenge is thereby to ensure stable cell operations resulting in a stable protective side ledge, while minimizing energy input and maximizing production.

[0025] Given reasonable operational targets, it is an established operational practice 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. If the control of the alumina concentration is reasonably good, one has to focus on the bath temperature control and the AlF_3 control.

An increase in the bath temperature results in a lower acidity and an increase in the bath conductivity. According to previous studies in the open literature the variation in acidity is dominated by the variation in the bath temperature.

"Prior art" in process control of Aluminium Electrolysis Cell

[0026] To control the electrolysis cells there are two main hardware architectures, namely centralized or decentralised architectures. In the centralized architecture the process control input is calculated by a centralized computer and distributed to local controlling devices on each aluminium electrolysis cell. In the decentralized architectures a decentralized computer, usually located close to the aluminium electrolysis cell, calculates the process control input.

[0027] In controlling an electrolysis cell, there are, up till now, typically three main controlled variables: bath temperature, concentration of AlF_3 and concentration of Al_2O_3, and three control inputs: anode beam adjustments (controlling energy input), addition of AlF_3 and addition of Al_2O_3 (see figure 2)

[0028] The dynamics in reducing the mass of AlF_3 is slow (assumed no added soda), and the control of the concentration of AlF_3 has to deal with slow responses when changing the AlF_3 concentration.

[0029] 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.

[0030] The bath temperature is usually measured manually once a day or at least once a week. In some technologies, the bath temperature is possible to measure automatically. 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, only in conjunction with experiments.

[0031] The only continuous measurements is the bath pseudo resistance R_b defined as

$$R_b = \frac{U_{cell} - U_{ext}}{I} \qquad [\mu\Omega] \qquad (4)$$

[0032] 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.

[0033] Because the energy balance and the mass balance are coupled through the side ledge, the control of a cell must be considered as a non-linear multivariable control problem.

[0034] Although the control problem is a non-linear multivariable control problem, it is commonly solved as if it should be a linear non-multivariable problem. I.e. using linear, single loop controllers (i.e. one controller controls one process variable), typically one controller for alumina control, one for AlF_3 control and one for energy/bath temperature control.

[0035] The measurements act as input to the controllers; the alumina controller typically uses the pseudo resistance measurement; the AlF_3-controller uses a combination of AlF_3 and bath temperature measurements. The output from an AlF_3-controller could typically be $c1(Tb\text{-}TbRef) + c2(AlF_3\text{-} AlF_3ref)$, where $c1$ and $c2$ is technology specific constants. Some technologies also use the bath temperature measurement to adjust the energy input (voltage) applied to the cell.

[0036] Typically these linear single loop controllers do not "co-operate" (not a multivariable control scheme), although some technologies do use a slight coupling between AlF_3 control and energy/bath temperature control. Also these linear controllers are bounded by a lot of heuristic and rules.

[0037] Additional measurements, although commonly not used in automatic control, is the measurement of bath height, metal height and the mass of tapped metal.

The present invention process control of Aluminium Electrolysis Cell:

[0038] By Non-linear Model Predictive Control (NMPC) we understand the use of a non-linear dynamical model, state estimation (process variable estimation) and the solution of an online constrained non-linear optimisation problem to calculate the control inputs to the physical process. See also Fig. 3.

[0039] Figure 3 illustrates the building blocks in the invention. The block labelled "Process" is meant to illustrate the physical process - one instance of the aluminium electrolysis cell. To the "Process" one is able to apply process control inputs (mass and energy) and measure 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 labelled "Estimator" contains a mathematical model of the "Process". The "Process" is described by using "First Principle" modelling techniques, and results in several process parameters and process variables that are used in the estimation of the current value of the said variables. Also the model contains partial differential equations (PDE), which capture the time derivative of a selected sub-set of the process variables. This sub-set is called process states.

[0040] Since knowledge regard the process states and variables can be seen as simplified versions of the real truth, the discrepancy could be seen as uncertainty - here labelled "State Noise". Further the value of the process control inputs and the value of the measurements is also led as 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.

[0041] The estimated measurements, states and parameters are the output form the "Estimator", and serves as an input to the non-linear 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 senario (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 senario 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 senario would be calculated each time step (say each 5th minute), based up on 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. The optimal control input scenario is found by solving an optimisation criterion by minimizing it with respect to predicted process variables, among others. The predictions stem from using the non-linear dynamic model to predict the future values of the process variables. The optimiser used is an optimiser that is able to solve non-linear constrained problems (typically SQP). The non-linear process model in the "NMPC" block is in this embodiment of the invention the same as the non-linear model in the "Estimator" block.

[0042] In the description of this invention we will use the following terms: Definition 1:

1. Estimation: By estimation we understand that the value under consideration, the estimate, represent the said value at current time. Further the estimate is produced by the use of a mathematical model where the said value is adjusted based on historical data (measurements and/or process inputs) up till current time.
2. Prediction: By prediction we understand that the value under consideration, the predicted value(s), represents the future said value(s) ahead in time. Further the prediction is produced by the use of a mathematical model.

[0043] To describe this invention we define the following: Definition 2:

1. Process parameters: Process characteristics that do not vary with time (dimensions, enthalpy etc)
2. Process variables: Process characteristics that vary with time (bath temperature, alumina concentration, side ledge thickness etc.)
3. Process states: A subset of process variables that can be described with differential equations (bath temperature, side ledge thickness etc.)
4. Calculated variables: A subset of process variables, which is calculated from other process variables and/or integrated process states. For example the alumina concentration is the ratio between the mass of alumina in the bath and the mass of bath.
5. Measurements: Physically measurements of a subset of process variables.
6. Process inputs: Something (here: energy and mass) that can be fed to the physical process by the means of moving the process from one state to another state in a finite time.

[0044] We will also combine the content from Definition 1 and 2 to talk about estimated and predicted process variables, estimated and predicted states, estimated and predicted calculated variables and estimated and predicted measurements.

[0045] In NMPC a non-linear model of the aluminium electrolysis process is introduced. The (non-linear) model has two important purposes - one is to estimate the current value of important process variables and measurements of the process, the second is to be used to predict the future values of the process variables and measurements (see figure 7, to be further explained later).

[0046] In this proposed NMPC of an Aluminium Electrolysis Cell a dynamic mathematical model of the electrolysis process is used to estimate important process variables. The process variables could be variables that are not measured at all (side ledge thickness, mass of bath and metal, mass of AlF_3, mass of Al_2O_3, concentration of Al_2O_3) and process variables that are infrequently measured (concentration of AlF_3, bath height, metal height and bath temperature). Common for the process variables modelled is that estimates of the process variables are available almost continuously (for example each 5th minute).

[0047] While the measurements as described above in "Prior art" are, at the best, used as input to some single loop linear controller, **all** the measurements are used in NMPC to drive the estimated process variables such that better estimates of the process variable can be calculated. The technique used is found in the literature as Kalmanfiltering, including the linear Kalmanfilter, Augmented Kalmanfilter, Extended Kalmanfilter, Augmented Extended Kalmanfilter, the Sigmapoint/Unscented Kalmanfilter and Ensamble Kalmanfilter. Another approach is to use Moving Horizon Estimation (MHE), since the delayed measurements are then effectively handled. For example the results of the measurement of the acidity usually is available some hours after the actual measurement took place. By using MHE the measurement is placed on the right place in the time window and hence contribute to a more correct current estimate.

[0048] It is important to realize that time varying estimates are available also between the infrequent measurements.

[0049] The NMPC uses the estimate from the estimator described above as a starting point (where we are). By comparing the estimate with selected set points (where we want to go) on a given set of process variables, the NMPC controller calculates the future control path in an optimal manner by the use of the model. The 'future' could be the next 24 hours. The first optimal control is then applied to the physical process. This scheme is then repeated each nth minute (n to be determined) (see Fig. 7).

[0050] A major difference from "Prior Art" is that the input to the controller is entirely based on estimated values, and not measured values directly. Further the controller utilizes the nonlinearity of the process, the coupling between the process variables, and the process dynamics together with process and controller constraints, and finds an optimal process control input, which is put onto the physical process. Also, in this embodiment of the invention the use of the NMPC is to directly calculate the process control inputs, and not some set points to secondary control loops or systems

[0051] In one embodiment of the present invention the model used has 9 estimated process states, 7 measurements, 3 main and 10 additional process control inputs and some estimated process parameters. Further there is defined some calculated process variables.

[0052] The estimated process states are the side ledge thickness, bath temperature, mass of dissolved alumina in the bath, mass of dissolved aluminium fluoride in the bath, metal mass, the distance between the lower anode surface and the cathode, cathode temperature, mass of alumina sludge and mass of cryolite in the cell.

[0053] The measurements are the pseudo resistance, line current, bath temperature, concentration of aluminium fluoride, metal height, bath height and cathode rod temperature.

[0054] The main 3 process control inputs are the addition of alumina and aluminium fluoride and the anode movement. The additional 10 process control inputs are information about the discrete events anode change, tap of metal, addition/removal of bath, crust covering, covering crust by alumina, addition of soda, crust brake, anode effect and anode problems.

[0055] The parameter estimated could be any, one or several, of the parameters needed to describe an aluminium electrolysis cell, but in present embodiment of the invention only the heat loss through the is estimated. The other parameters are considered known and constant.

[0056] The most important calculated variables are mass of bath, alumina concentration, acidity, pseudo resistance, liquidus temperature, super-heat and anode-cathode distance.

[0057] In the Kalmanfilter context the uncertainty related to the estimated process states and measurements is assumed Gaussian and additive. The uncertainty in the control inputs is assumed Gaussian and relative.

[0058] The NMPC controller:

The NMPC controller is used to control the Aluminium Electrolysis Cell and the aim is to control the energy and mass balance. Since there are three process inputs available (addition of alumina, addition of aluminium fluoride and anode movement) one can only expect to control three process variables to a desired value (set point). In the NMPC framework the process input is termed manipulated variables (MV).

[0059] One of the challenges is then to select those three process variables that allow one to best control the mass and energy balance. In this embodiment of present invention the following three process variables are chosen: alumina concentration, bath temperature and side ledge thickness. These process variables are referred to as controlled variables or CVs, and is a sub set of all the process variables. Further the three process variables referred is associated with a reference (or a desired) value.

[0060] In addition to these process variables, the mass of fluoride in the bath, the anode-cathode distance (ACD) and the superheat is also included in the CV, but without reference values. They are however assumed having a value between some determined minimum and maximum limits (see Table 3). Also it is important to note that the pseudo resistance has no dedicated reference value in this embodiment of the invention. The NMPC is allowed to use the resistance value necessary to maintain the energy balance.

[0061] The idea behind the selection of these process variables as CVs is that once the alumina concentration, the bath temperature and the side ledge thickness are determined the superheat is determined. When the superheat is determined, the liquidus temperature is determined and by that the mass of fluoride. Further the ACD is included in the CV in order to have the possibility to constrain the ACD because of safety related issues. For example it is considered as a serious safety concern if the anodes should leave the bath (high ACD).

[0062] The output from the Kalmanfilter as previously described is the best estimate of the current state of the process variables, and is used by the NMPC to define a starting point for the calculations to come. The NMPC calculates an optimal future process input scenario $U(t_k)$, $U(t_{k+1})$, ...,$U(t_{k+Nu})$ in order to achieve the set point for the CVs within a chosen future discrete time of length N (prediction horizon). Here t_k is the present time (now) and t_{k+1}, ..., t_{k+Nu} is the forward discrete time in the control horizon. *Nu* is the length of a control horizon, where *Nu* <= *N*. The interval t_k *to* t_{k+N} forms the prediction window. However, only the first calculated process input $U(t_k)$ from the optimal future process input scenario is put into effect on the physical process itself. This scheme is then repeated for example each 5th minute.

[0063] Since the process variables and measurements cannot be measured in advance or ahead in time, a model of the process is used to predict the future time behavior of the physical process. The prediction model used in this invention is the same model as the model used in the estimator previously described, but now without the possibility to update the state estimates from measurements.

[0064] In order to achieve the optimal future input sequence (*U*) a criterion to be minimized is defined. The criterion or Cost Function, J, to be minimized by the optimizer within the NMPC can in general be any function, but is usually like

$$J = f(Z, Z_{ref}, W, U, \Delta U, \text{Constraints}) \tag{5}$$

where *Z* is the future prediction of the controlled variables (CV), Z_{ref} is the desired values or reference values of *Z*, *U* is the future process input scenario, ΔU is the difference between the present and the previous process input scenario and *W* is some weight matrices or functions used to penalize combinations of *Z*, Z_{ref}, *U* and/or ΔU (see below for further explanation). By the term *Constraints* it should be understood methods for constraint handling if some constraints are violated.

[0065] In an embodiment of this invention the criterion to be minimized is defined as

$$J' = \frac{1}{2}\left(Z - Z_{ref}\right)^T Q\left(Z - Z_{ref}\right) + \frac{1}{2}\Delta U^T S \Delta U + \text{Constraints} \tag{6}$$

[0066] In Equation (6) ^{T} means the transpose. The vector *Z* is composed of the future prediction of the controlled variables (CV). Z-Z_{ref} means the deviation. The vector *U* is the future input scenario of all manipulated variables (MV), while ΔU is the difference between the present and the previous input scenario.

[0067] The Q and S in Equation (6) are all positive semi-definite and diagonal matrices, i.e. contains only positive or zero weights. Related to Equation (5), Q and S can bee seen as incorporated in W.

[0068] The purpose of the weight matrix *Q* is to control the behavior of the NMPC controller. Obviously increasing the weights in *Q* will increase the importance of controlling the CV to its set point and therefore reduce the set point deviation. By choosing different weights for the different CVs, one controls the priority between them. In this process the most important one is to achieve the desired alumina concentration, then the bath temperature and finally the side ledge thickness. This is reflected in the *Q* matrix with a large value in *Q* related to the alumina concentration, lower on the bath temperature and lowest on the side ledge thickness (see Table 3).

[0069] The term *S* in Equation (6) controls the cost of the use of the process inputs. Increasing the weights in *S* will suppress the use of the MV and relax the use of it. For example, with reference to Table 2 below, it is cheap to use alumina, a bit more costly to use anode movement and very expensive to use aluminium fluoride to achieve the desired set points.

[0070] One challenge with NMPC is that if the prediction horizon is long, the computational load may become very high, and one is not guarantied that an optimal solution is available when needed. In order to drastically reduce the computational load, one can parameterize the points where the CV is evaluated against the reference values and also parameterize the process input scenario. The latter is referred to as input blocking.

[0071] In this embodiment of the invention there is used a prediction horizon of 12 hours. With 5 minutes sample interval and three MVs, on could have had 144 x 3=432 MV-values to be calculated for the prediction horizon. By saying that the input value could only change at selected sample numbers in the prediction horizon and are considered constant (blocked) in between, the size of the optimization problem is drastically reduced. This technique is known as 'input blocking'. See also Table 1 for further reference. In this invention the problem is reduced from calculating 432 MV-values to calculating 13 for the selected prediction horizon.

[0072] The following table shows the future sampling times when a new control value is calculated. The control values are held constant (blocked) between these sampling times. Control values are not calculated each sample in the future (input blocking) due to high computational load, but the result is a good approximation.

Table 1: Input blocking - selected samples

No	Input	Type	Selected samples (sample numbers of 143)
1	Alumina feed	Feedback	0, 4, 10, 24, 48, 96
2	Aluminium fluoride feed	Feedback	0, 72
3	Anode movement for MPC	Feedback	0, 12, 24, 48, 96

[0073] In this embodiment of the invention the points where the CV is evaluated against the reference are freely selected (see Table 4). The parameterization of the input scenario may be selected individually for each MV (see Figure 7).

[0074] Further one has the possibility to put a limit on *Z,U* and $\Delta \underline{U}$. In equation (6) the *"Constraints"* is the handling when states and/or inputs violate maximum or minimum values.

[0075] The pseudo code for the algorithm becomes

Repeat: (typical each 5th minute)

Estimate the current process variables based on updated measurements and control inputs.
Extract the CV from the estimate (figure 5).
Calculate optimal future process input scenario $U(t_k, t_{k+1}, \ldots t_{k+n})$ according to the criteria *J'*
Apply only $U(t_k)$ to the physical process
k=k+1

End repeat

[0076] The algorithm is also illustrated in figure 4 to 7.

[0077] Figure 4 illustrates that in the time t_k (now) a new updated estimate of the CV's is available. The updated estimate of the CV's is a subset of the estimate of the process variables. The estimate of the process variables is the output available from the estimator (Kalmanfilter). Z_{ref} illustrates the set point for the CV. MV illustrates the manipulated variables as defined earlier.

[0078] Figure 7 illustrates that in the time t_k (now) the future optimal process control input scenario is calculated for the prediction window defined. Only $U(t_k)$, the first process input combination for the optimal process control input scenario, is put onto the physical process. The current estimate of the process variables forms the starting point used in the prediction of the future time behavior of the process. The predicted CV is an extracted subset of the predicted time behavior of the process variables as given by the prediction model. Also the figure illustrates the control horizon and the prediction horizon. The control horizon could be smaller or equal to the prediction horizon. The control horizon stems from the cases when using input blocking. In such a case when the control horizon is smaller than the prediction horizon, it is assumed that the future optimal process control input value in the interval t_{k+Nu+1} to t_{k+N} is equal to $U(t_{k+Nu})$.

[0079] Figure 6 illustrates that in the time t_k (now) a new updated and corrected estimate of the CV's is available based on new measurements and inputs.

[0080] Figure 7. illustrates that in the time t_k (now) a new future optimal input sequence is calculated for the prediction window defined based on the new updated CV. Only $U(t_k)$, the first process input combination for the optimal future input sequence, is put onto the physical process. The updated predicted CV is an extracted subset of the predicted time behavior of the process variables as given by the prediction model. The dotted lines are the one from the last sample. Then repeat from Fig. 6.

[0081] The following table shows the tuning of the parameters related to the MV's in the optimization criterion:

Table 2: Parametertuning related to the MV's

No	Input	Type	UMin	uMax	duMax	S
1	Alumina feed	Feedback	0	12	1.5	0.1
2	Aluminium fluoride feed	Feedback	0	1.36	1.36	1800
3	Anode movement for MPC	Feedback	-20	20	8	20

[0082] The following table shows the tuning of the parameters related to the CV's in the optimization criterion:

Table 3: Parametertuning related to the CV's

No	Variable name	Z_{min}	Z_{max}	Q	Setpoint
1	Alumina concentration	2.3	4.5	250	3.0
2	Bath temperature	952	970	10	958.0
3	Side ledge thickness	20	160	0.4	100.0
4	Mass of fluoride	500	1600	0	N/A
5	Anode-cathode distance	0.02	0.04	0	N/A
6	Super heat	3.0	15.0	0	N/A

[0083] The chosen prediction horizon is typically 12 hours long. This has proven to give good results both on simulator and during online tests. This horizon is long enough that most variables have settled at the end of it.

[0084] The different controlled variables have different settling times, and are thus tuned differently in the prediction horizon. The controller is tuned such that the added alumina mainly controls alumina concentration, anode movement mainly controls the temperature and the addition of aluminium fluoride mainly controls the side ledge thickness. However, interactions and coupling between the variables are taken into account despite this tuning

[0085] The following table shows which sampling times the value of each output variable (CV) are taken into account in the optimization criterion.

Table 4: Parameterizing of the CV's

No	Variable name	Active samples
1	Alumina concentration,	3:6:144
2	Bath temperature	24:6:144
3	Side ledge thickness	48:6:144
4	Mass of fluoride	12:6:144
5	Anode-cathode distance,	12:6:144
6	Super heat	12:6:144

[0086] Here 3:6:144 means that the 1th value selected is sample nr 3, then each 6th up till sample nr 144 (12 hours). The idea behind the parameterization is that the CV is not changing faster than that the process dynamics is captured within the parameterization. By this, a selection of the sampling times is used and hence reduces the application's memory usage.

[0087] It should be understood that the above mentioned embodiment is non exhaustive. Other estimated process states, measurements, periods, intervals, main control inputs, additional control inputs, estimated process parameters and calculated process variables than those mentioned can be realized in accordance with the present invention. This may be realized by new methods of measurement, or by more sophisticated ways of modeling the cell's behavior.
For instance, new types of measurements such as heat loss from the top, chisel bath contact, automatic measurements of bath temperature and automatic bath and metal height measurements can be applied to improve the performance of the estimator and hence the performance of the controller.

[0088] Even heat loss through the side could be applied as an active control input by means of heat exchangers linked to energy recovery.

[0089] Further, some activities in the future can be modeled and compensated for. By for instance modeling the anode change and metal tap the impact on the process can be predicted in the prediction horizon, and hence be compensated for.

[0090] Further, the controller can be integrated in both decentralized and centralized control system architectures where said computer will have a software program dedicated to each pot or electrolysis cell due to the individual character of said cells.

[0091] The NMPC could be used to control the complete plant when dynamic current load is an issue.

[0092] The set point could be optimized such that the whole plant (all cells) could be operated in an optimum manner to lower the power consumption in defined periods during the day.

Claims

1. A method of controlling an electrolysis cell of Hall-Heroult type for aluminium production by process control inputs of energy and mass, comprising measurement of one or more process variable(s) for establishing a set of historical data for modelling a set of process variable(s) that vary with time including at least one of alumina concentration, bath temperature or side ledge thickness, where the said measured value(s) is led to an estimator for estimation of the current value of said one or more process variable(s) followed by prediction of the value of same process variable(s) and/or other process variable(s) in the future, where said predicted value(s) is used in the calculation of future control input scenarios,
wherein,
the prediction of the process variable(s) is performed in accordance with a non-linear dynamic model of the aluminium electrolysis process based upon First Principle to achieve an optimal future process input scenario $U(t_k)$, $U(t_{k+1})$, ...,$U(t_{k+Nu})$ in order to reach the set point for the controlled variables (CVs) for at least one of alumina concentration, bath temperature or side ledge thickness within a chosen prediction horizon and that the estimation of the said current value of one or more process variable(s) is performed by Kalman filtering techniques or Moving Horizon principles.

2. A method in accordance with claim 1,
wherein,
a process control input is directed to the cell at time intervals where the period T is about 5 minutes.

3. A method in accordance with claim 1,
wherein,
the calculation of future control input scenarios is performed at time intervals where the period T is about 5 minutes.

4. A method in accordance with claim 1,
wherein,
the calculation of future control input scenarios i s performed in accordance with the following cost function equation J;

$$J = f(Z, Z_{ref}, W, U, \Delta U, \text{Constraints})$$

where;

Z is the future prediction of the controlled variables (CV),

Z_{ref} is the desired values or reference values of Z,
U is the future process input scenario,
ΔU is the difference between the present and the previous process input scenario,
W is some weight matrices or functions used to penalize combinations of Z, Z_{ref}, U and/or ΔU,
and the term *Constraints* relates to methods for constraint handling if some constraints are violated.

5. A method in accordance with claim 1,
wherein,
the calculation of future control input scenarios i s performed in accordance with the following cost function equation J';

$$J' = \frac{1}{2}\left(Z - Z_{ref}\right)^T Q\left(Z - Z_{ref}\right) + \frac{1}{2}\Delta U^T S \Delta U + \text{Constraints}$$

where; ^{T} is the transpose,
Z is a vector composed of the future prediction of the controlled variables (CV),
Z-Z_{ref} means the deviation,
U is a vector related to the future input scenario of all manipulated variables (MV),
ΔU is the difference between the present and the previous input scenario,
Q and S are all positive semi-definite and diagonal matrices, i.e. contains only positive or zero weights.

6. A method in accordance with claim 1,
wherein, the model compares the estimated current value(s) of process variable(s) with selected set points on a given set of process variables.

7. Means for controlling an electrolysis cell for aluminium production of Hall-Heroult type by process control inputs of energy and mass, comprising means for measurement of one or more process variable(s) for establishing a set of historical data for modelling a set of process variable(s) that vary with time including at least one of alumina concentration, bath temperature or side ledge thickness, where the said measured value(s) is led to an estimator for estimation of the current value of said one or more process variable(s) followed by prediction of the value of same process variable(s) and/or other process variable(s) in the future, where said predicted value(s) is used to calculate future input control scenario by means of a calculator,
wherein,
the prediction of the process variable(s) is performed in accordance with a non - linear dynamic model of the aluminium electrolysis cell based upon First Principle to achieve an optimal future process input scenario $U(t_k)$, $U(t_{k+1})$, ..., $U(t_{k+Nu})$ in order to reach the set point for the controlled variables (CVs) for at least one of alumina concentration, bath temperature or side ledge thickness within a chosen prediction horizon and that the said current value of one or more process variable(s) is estimated, where the estimator is a Kalman filter or a Moving Horizon estimator.

8. Means in accordance with claim 7,
wherein,
the process controlling means is an integrated part of a local pot controller.

9. Means in accordance with claim 7,
wherein,
the process controlling means is an integrated part of a central controller.

10. Means in accordance with claim 9,
wherin,
the process controlling means has software dedicated to each individual pot (cell).

Patentansprüche

1. Verfahren zur Steuerung einer Elektrolysezelle vom Hall-Heroult-Typ zur Aluminiumproduktion durch Prozesssteuerungseingaben von Energie und Masse, welches die Messung einer oder mehrerer Prozessvariabler zur Erstellung eines Satzes von historischen Daten zur Modellierung eines Satzes von Prozessvariablen, welche über die Zeit

variieren, umfasst, darunter wenigstens eines von Aluminiumoxidkonzentration, Badtemperatur oder Seitenwanddicke, wobei die gemessene(n) Variable(n) einem Schätzer zur Schätzung des aktuellen Wertes der einen oder mehreren Prozessvariablen zugeführt wird (werden), gefolgt von der Vorhersage des Wertes derselben Prozessvariablen und/oder einer anderen Prozessvariablen (anderer Prozessvariabler) in der Zukunft, wobei der (die) vorhergesagte(n) Wert(e) bei der Berechnung zukünftiger Steuerungseingabeszenarien verwendet wird (werden), wobei
die Vorhersage der Prozessvariablen gemäß einem nichtlinearen dynamischen Modell des Aluminiumelektrolyseprozesses durchgeführt wird, basierend auf dem Ersten Prinzip, um ein optimales zukünftiges Prozesseingabeszenario $U(t_k)$, $U(t_{k+1})$, ... ,$U(t_{k+Nu})$ zu erzielen, um den Sollwert für die gesteuerten Variablen (Controlled Variables, CVs) für wenigstens eines von Aluminiumoxidkonzentration, Badtemperatur oder Seitenwanddicke innerhalb eines gewählten Vorhersagehorizonts zu erreichen, und wobei die Schätzung des aktuellen Wertes einer oder mehrerer Prozessvariabler durch Kalman-Filtertechniken oder Prinzipien des bewegten Horizonts durchgeführt wird.

2. Verfahren nach Anspruch 1,
wobei
eine Prozesssteuerungseingabe der Zelle in zeitlichen Abständen zugeführt wird,
wobei die Periode T ungefähr 5 Minuten beträgt.

3. Verfahren nach Anspruch 1,
wobei
die Berechnung zukünftiger Steuerungseingabeszenarien in zeitlichen Abständen zugeführt wird, wobei die Periode T ungefähr 5 Minuten beträgt.

4. Verfahren nach Anspruch 1,
wobei
die Berechnung zukünftiger Steuerungseingabeszenarien gemäß der folgenden Kostenfunktionsgleichung J durchgeführt wird:

$$J = f(Z, Z_{ref}, W, U, \Delta U, \text{Nebenbedirgungen})$$

wobei:

Z die Zukunftsvorhersage der gesteuerten Variablen (CV) ist,
Z_{ref} die gewünschten Werte oder Referenzwerte von Z sind Z,
U das zukünftige Prozesseingabeszenario ist,
ΔU die Differenz zwischen dem gegenwärtigen und dem vorhergehenden Prozesseingabeszenario ist,
W gewisse Gewichtsmatrizen oder -funktionen sind, die verwendet werden, um Kombinationen von Z, Z_{ref}, U und/oder ΔU mit Strafen zu versehen,
und der Begriff *Nebenbedingungen* sich auf Verfahren zur Handhabung von Nebenbedingungen, falls gewisse Nebenbedingungen verletzt werden, bezieht.

5. Verfahren nach Anspruch 1,
wobei
die Berechnung zukünftiger Steuerungseingabeszenarien gemäß der folgenden Kostenfunktionsgleichung J' durchgeführt wird:

$$J' = \frac{1}{2}\left(Z - Z_{ref}\right)^T Q\left(Z - Z_{ref}\right) + \frac{1}{2}\Delta U^T S \Delta U + \text{Nebenbedingungen}$$

wobei: ^{T} die Transponierte ist,
Z ein Vektor ist, der aus der Zukunftsvorhersage der gesteuerten Variablen (CV) besteht,
Z-Z_{ref} die Abweichung bedeutet,
U ein Vektor ist, der sich auf das zukünftige Eingabeszenario aller manipulierten Variablen (MV) bezieht,
ΔU die Differenz zwischen dem gegenwärtigen und dem vorhergehenden Eingabeszenario ist,
Q und S alle positiv semidefinite Matrizen und Diagonalmatrizen sind, d. h. nur positive oder Nullgewichte enthalten.

6. Verfahren nach Anspruch 1,
wobei das Modell den (die) geschätzten aktuellen Wert(e) einer/von Prozessvariablen mit ausgewählten Sollwerten auf einem gegebenen Satz von Prozessvariablen vergleicht.

7. Mittel zur Steuerung einer Elektrolysezelle vom Hall-Heroult-Typ zur Aluminiumproduktion durch Prozesssteuerungseingaben von Energie und Masse, welche Mittel zur Messung einer oder mehrerer Prozessvariabler zur Erstellung eines Satzes von historischen Daten zur Modellierung eines Satzes von Prozessvariablen, welche über die Zeit variieren, umfasst, darunter wenigstens eines von Aluminiumoxidkonzentration, Badtemperatur oder Seitenwanddicke, wobei die gemessene(n) Variable(n) einem Schätzer zur Schätzung des aktuellen Wertes der einen oder mehreren Prozessvariablen zugeführt wird (werden), gefolgt von der Vorhersage des Wertes derselben Prozessvariablen und/oder einer anderen Prozessvariablen (anderer Prozessvariabler) in der Zukunft, wobei der (die) vorhergesagte(n) Wert(e) verwendet wird (werden), um ein zukünftiges Eingabesteuerungsszenario mittels eines Rechners zu berechnen,
wobei
die Vorhersage der Prozessvariablen gemäß einem nichtlinearen dynamischen Modell der Aluminiumelektrolysezelle durchgeführt wird, basierend auf dem Ersten Prinzip, um ein optimales zukünftiges Prozesseingabeszenario $U(t_k)$, $U(t_{k+1})$, ...,$U(t_{k+Nu})$ zu erzielen, um den Sollwert für die gesteuerten Variablen (Controlled Variables, CVs) für wenigstens eines von Aluminiumoxidkonzentration, Badtemperatur oder Seitenwanddicke innerhalb eines gewählten Vorhersagehorizonts zu erreichen, und wobei der aktuelle Wert einer oder mehrerer Prozessvariabler geschätzt wird, wobei der Schätzer ein Kalman-Filter oder ein Schätzer zur Schätzung auf bewegtem Horizont ist.

8. Mittel nach Anspruch 7,
wobei
das Prozesssteuerungsmittel ein integrierter Bestandteil einer lokalen Zellensteuereinheit ist.

9. Mittel nach Anspruch 7,
wobei
das Prozesssteuerungsmittel ein integrierter Bestandteil einer zentralen Steuereinheit ist.

10. Mittel nach Anspruch 9,
wobei
das Prozesssteuerungsmittel für jede einzelne Zelle zugeordnete Software enthält.

Revendications

1. Procédé de contrôle d'une cellule d'électrolyse de type Hall-Héroult pour une production d'aluminium par des entrées de contrôle de processus d'énergie et de masse, comprenant la mesure d'une ou plusieurs variables de processus pour établir un ensemble de données historiques afin de modéliser un ensemble de variables de processus qui varient au cours du temps, comprenant au moins un paramètre parmi la concentration d'alumine, la température de bain et l'épaisseur du bord latéral, où lesdites valeurs mesurées sont conduites à un estimateur pour l'estimation de la valeur actuelle desdites une ou plusieurs variables de processus, suivie par la prédiction de la valeur des mêmes variables de processus et/ou d'autres variables de processus futures, où lesdites valeurs prédites sont utilisées dans le calcul de scénarios futurs d'entrée de contrôle,
dans lequel
la prédiction des variables de processus est mise en oeuvre conformément à un modèle dynamique non linéaire du processus d'électrolyse de l'aluminium basé sur le Premier Principe pour obtenir un scénario futur d'entrée de processus optimal $U(t_k)$, $U(t_{k+1})$, ..., $U(t_{k+Nu})$ de manière à atteindre le point de consigne pour les variables contrôlées (CV) pour au moins un paramètre parmi la concentration d'alumine, la température de bain et l'épaisseur du bord latéral dans un horizon de prédiction choisi, et dans lequel l'estimation de ladite valeur actuelle d'une ou plusieurs variables de processus est mise en oeuvre par des techniques de filtrage de Kalman ou des principes d'horizon mobile.

2. Procédé selon la revendication 1,
dans lequel
une entrée de contrôle de processus est dirigée vers la cellule à des intervalles temporels où la période T est d'environ 5 minutes.

3. Procédé selon la revendication 1,
dans lequel
le calcul de scénarios futurs d'entrée de contrôle est mis en oeuvre à des intervalles temporels où la période T est d'environ 5 minutes.

4. Procédé selon la revendication 1,
dans lequel
le calcul de scénarios futurs d'entrée de contrôle est mis en oeuvre conformément à l'équation de fonction de coût J suivante :

$$J = f(Z, Z_{ref}, W, U, \Delta U, \text{Constraints})$$

où :

Z est la prédiction future des variables contrôlées (CV),
Z_{ref} correspond aux valeurs désirées ou aux valeurs de référence de Z,
U est le scénario futur d'entrée de processus,
ΔU est la différence entre les scénarios d'entrée de processus actuel et antérieur, W correspond à certaines fonctions ou matrices de pondération utilisées pour pénaliser des combinaisons de Z, Z_{ref}, U et/ou ΔU,
et le terme *Constraints* a trait à des procédés de traitement de contrainte si certaines contraintes sont violées.

5. Procédé selon la revendication 1,
dans lequel
le calcul de scénarios futurs d'entrée de contrôle est mis en oeuvre conformément à l'équation de fonction de coût J' suivante :

$$J' = \frac{1}{2}\left(Z - Z_{ref}\right)^T Q\left(Z - Z_{ref}\right) + \frac{1}{2}\Delta U^T S \Delta U + \text{Constraints}$$

où :

^{T} est la matrice transposée,
Z est un vecteur composé de la prédiction future des variables contrôlées (CV), $Z\text{-}Z_{ref}$ est un moyen de déviation,
U est un vecteur relatif au scénario futur d'entrée de toutes les variables manipulées (MV),
ΔU est la différence entre les scénarios d'entrée actuel et antérieur,
Q et S sont toutes des matrices positives semi-définies et diagonales, c'est-à-dire contenant uniquement des pondérations positives ou nulles.

6. Procédé selon la revendication 1,
dans lequel le modèle compare les valeurs actuelles estimées de variables de processus à des points de consigne sélectionnés sur un ensemble donné de variables de processus.

7. Moyen de contrôle d'une cellule d'électrolyse de type Hall-Héroult pour une production d'aluminium par des entrées de contrôle de processus d'énergie et de masse, comprenant un moyen de mesure d'une ou plusieurs variables de processus pour établir un ensemble de données historiques afin de modéliser un ensemble de variables de processus qui varient au cours du temps, comprenant au moins un paramètre parmi la concentration d'alumine, la température de bain et l'épaisseur du bord latéral, où lesdites valeurs mesurées sont conduites à un estimateur pour l'estimation de la valeur actuelle desdites une ou plusieurs variables de processus suivie par la prédiction de la valeur des mêmes variables de processus et/ou d'autres variables de processus futures, où lesdites valeurs prédites sont utilisées pour calculer un scénario futur de contrôle d'entrée à l'aide d'un calculateur,
dans lequel
la prédiction des variables de processus est mise en oeuvre conformément à un modèle dynamique non linéaire de la cellule d'électrolyse à aluminium basé sur le Premier Principe pour obtenir un scénario futur d'entrée de processus optimal $U(t_k)$, $U(t_{k+1})$, ..., $U(t_{k+Nu})$ de manière à atteindre le point de consigne pour les variables contrôlées (CV) pour au moins un paramètre parmi la concentration d'alumine, la température de bain et l'épaisseur du bord latéral dans un horizon de prédiction choisi, et dans lequel ladite valeur actuelle d'une ou plusieurs variables de

processus est estimée, où l'estimateur est un filtre de Kalman ou un estimateur à horizon mobile.

8. Moyen selon la revendication 7,
dans lequel
le moyen de contrôle de processus est une partie intégrée d'un contrôleur de pot local.

9. Moyen selon la revendication 7,
dans lequel
le moyen de contrôle de processus est une partie intégrée d'un contrôleur central.

10. Moyen selon la revendication 9,
dans lequel
le moyen de contrôle de processus comporte un logiciel dédié pour chaque pot (cellule) individuel.

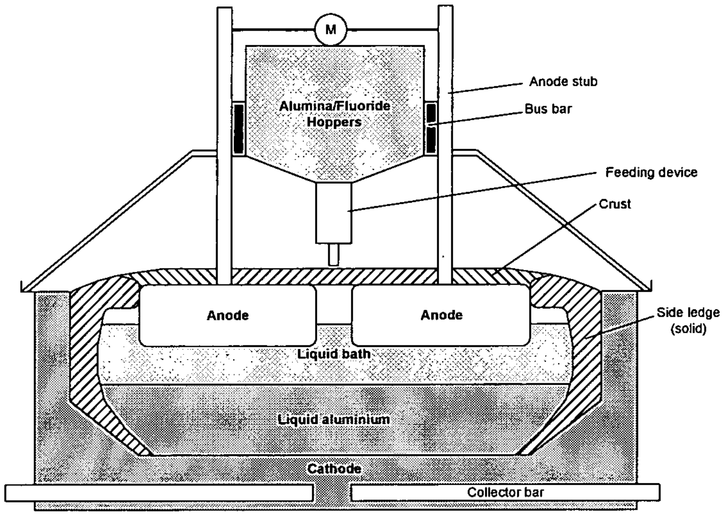
M
Alumina/Fluoride Hoppers
Anode stub
Bus bar
Feeding device
Crust
Anode
Anode
Side ledge (solid)
Liquid bath
Liquid aluminium
Cathode
Collector bar

Fig. 1

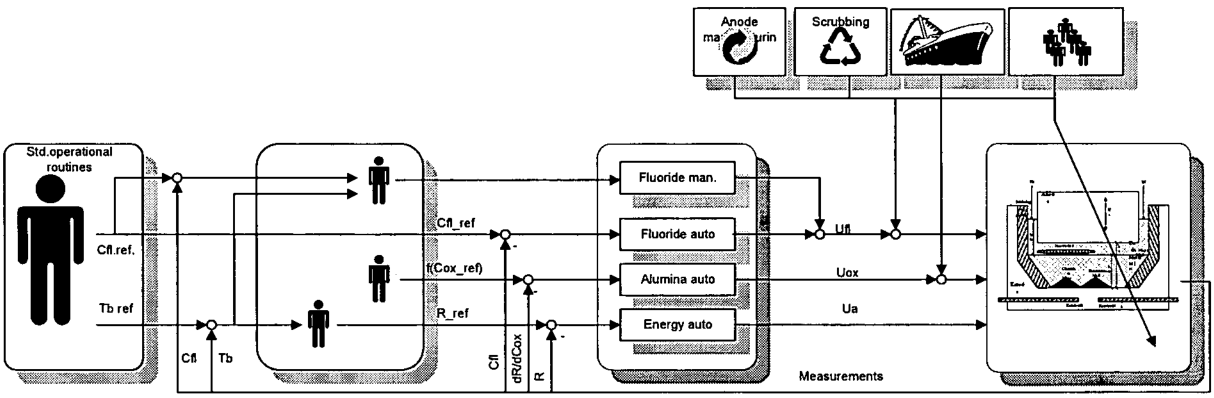
Anode
Scrubbing
Std.operational routines
Cfl.ref.
Tb ref
Cfl
Tb
Cfl_ref
f(Cox_ref)
R_ref
Cfl
dR/dCox
R
Fluoride man.
Fluoride auto
Alumina auto
Energy auto
Ufl
Uox
Ua
Measurements

Fig. 2

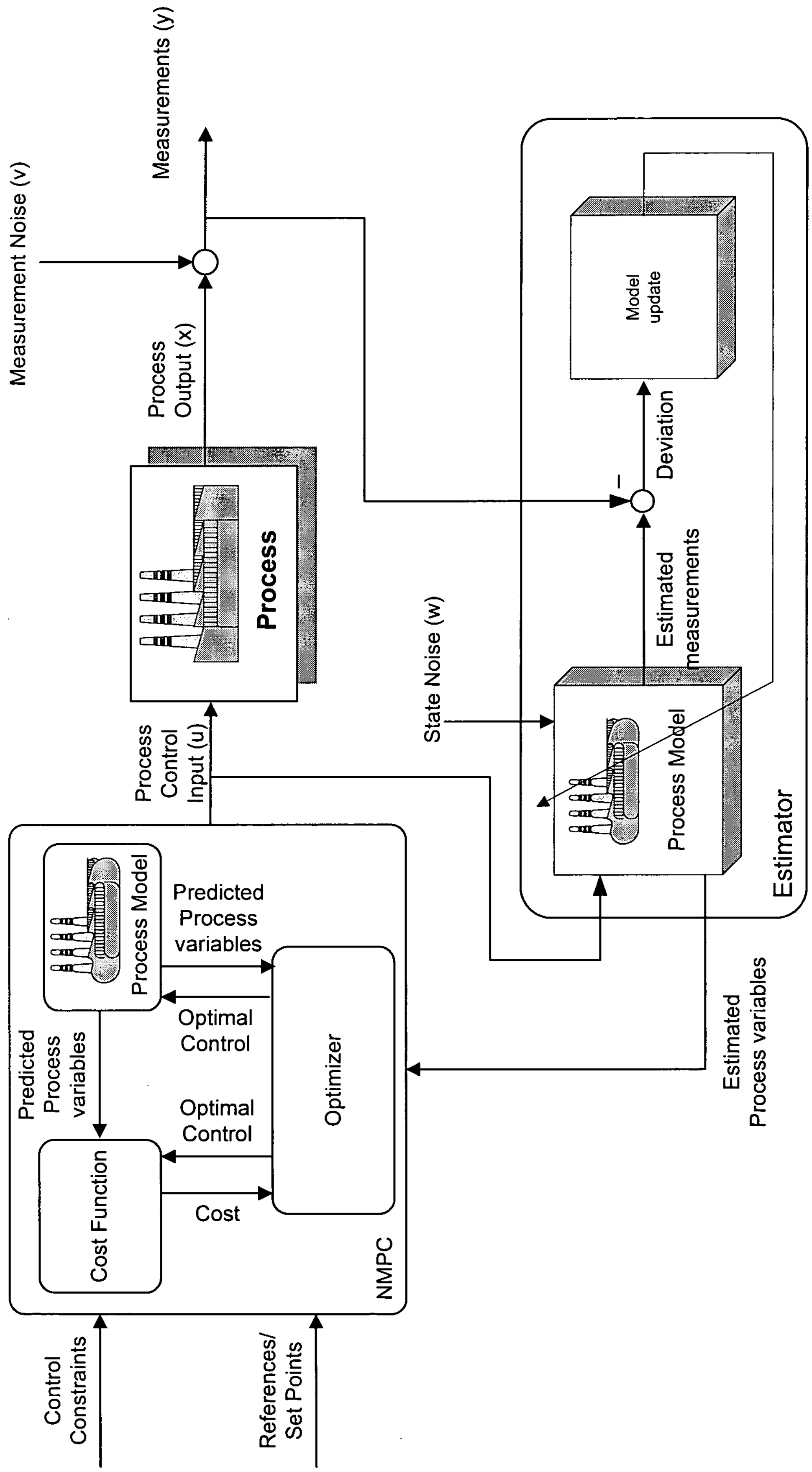
Measurement Noise (v)
Measurements (y)
Process Output (x)
Process
Process Control Input (u)
State Noise (w)
Estimated measurements
Deviation
Model update
Process Model
Estimator
Estimated Process variables
Process Model
Predicted Process variables
Optimal Control
Optimizer
Predicted Process variables
Cost Function
Optimal Control
Cost
NMPC
Control Constraints
References/ Set Points

Fig. 3

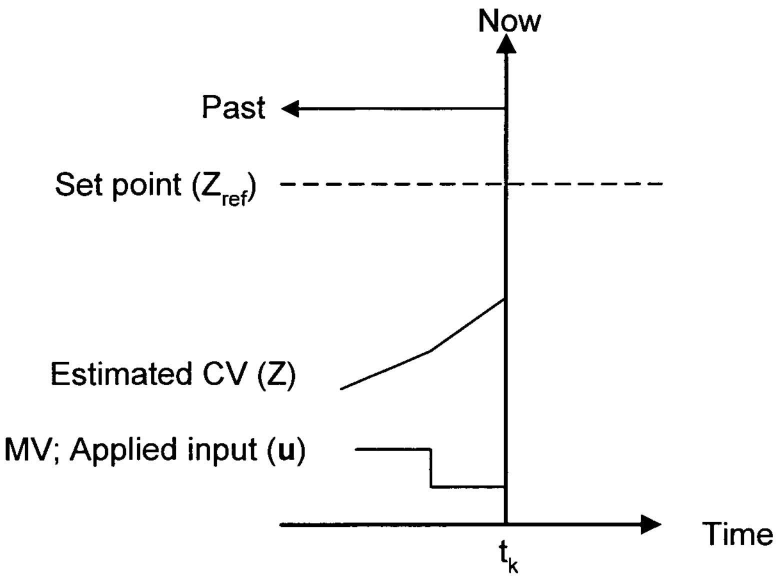
Now
Past
Set point (Z_{ref})
Estimated CV (Z)
MV; Applied input (**u**)
Time
t_k

Fig. 4

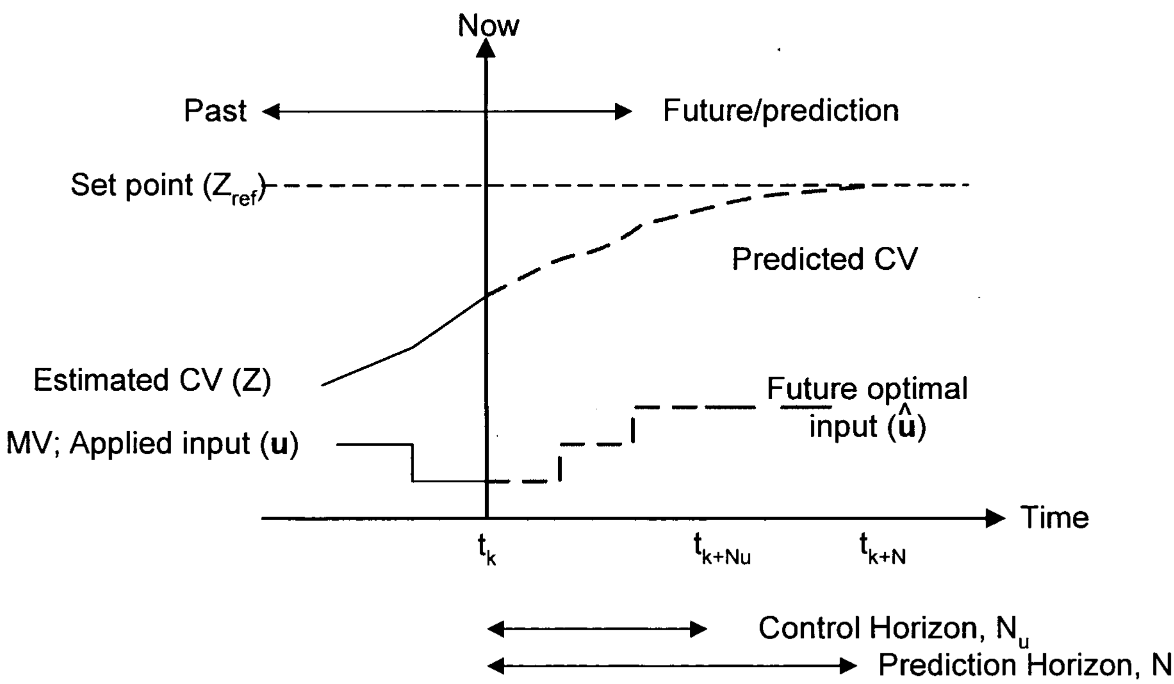
Now
Past
Future/prediction
Set point (Z_{ref})
Predicted CV
Estimated CV (Z)
Future optimal input ($\hat{\mathbf{u}}$)
MV; Applied input (**u**)
Time
t_k
t_{k+Nu}
t_{k+N}
Control Horizon, N_u
Prediction Horizon, N

Fig. 5

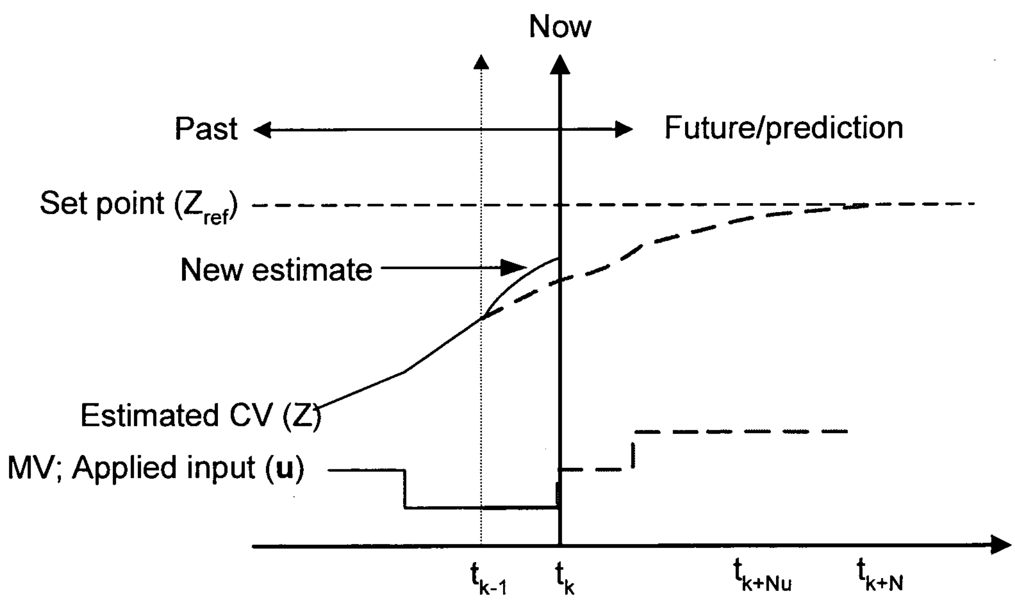
Now
Past
Future/prediction
Set point (Z_{ref})
New estimate
Estimated CV (Z)
MV; Applied input (**u**)
t_{k-1}
t_k
t_{k+Nu}
t_{k+N}

Fig 6

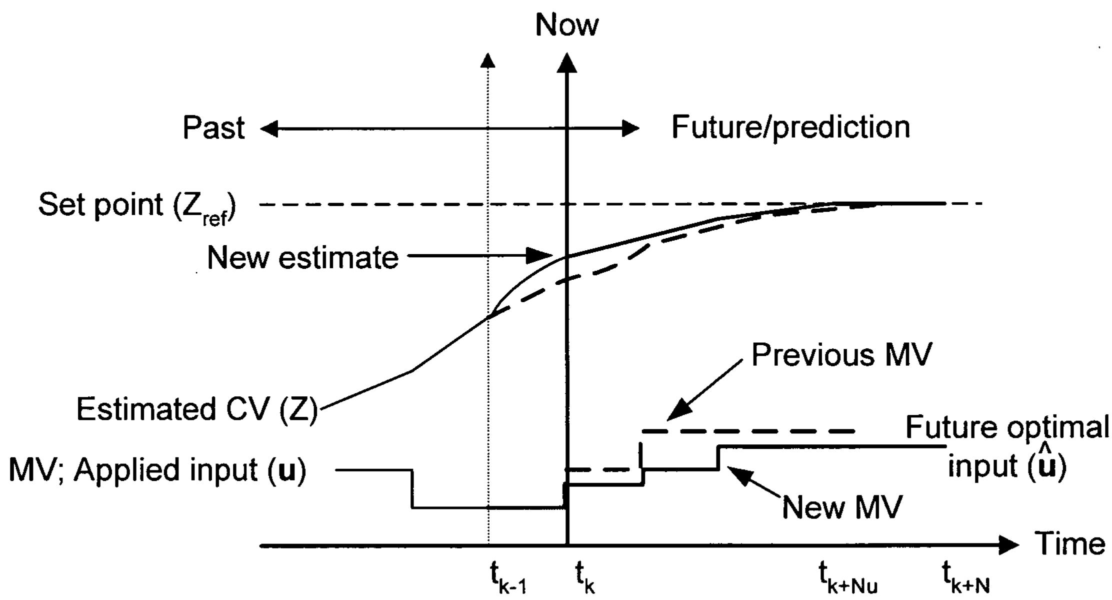
Now
Past
Future/prediction
Set point (Z_{ref})
New estimate
Previous MV
Estimated CV (Z)
Future optimal input ($\hat{\mathbf{u}}$)
MV; Applied input (**u**)
New MV
Time
t_{k-1}
t_k
t_{k+Nu}
t_{k+N}

Fig. 7

REFERENCES CITED IN THE DESCRIPTION

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