Jämsä-Jounela, Sirkka-Liisa; Oja, Marja

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MODELLING MODULE OF THE INTELLIGENT CONTROL SYSTEM FOR THE VARIABLE VOLUME PRESSURE FILTER

Sirkka Liisa Jämsä-Jounela*, Marja Oja**

*Helsinki University of Technology
Department of Chemical Technology
Laboratory of Process Control and Automation
Kemistintie 1. FIN-02150 Espoo
FINLAND
E-mail: sirkka-liisa.jamsa-jounela@aalto.fi

**Lappeenranta University of Technology
Department of Chemical Technology
P.O.Box 20 FIN-35851 Lappeenranta
FINLAND

Abstract: Artificial Intelligence methods like expert systems, fuzzy logic and neural networks have proved to be excellent tools for the control of mineral processes. This technology is currently being embedded directly into process equipment like flotation cells and dewatering filters. This paper presents the modelling module for a pressure filter. The modelling module of the intelligent system predicts filtration using the two-stage hybrid model. The first stage model is based on a numerical model for compressive cake filtration and the second stage model is the identified grey-box model based on the classical filtration model. The filtration parameters for the compressive cake filtration model were obtained from laboratory tests. The parameters for the classical filtration model are defined during filtration using the recursive least square identification method. The two-stage hybrid model of the on-line support system was tested in a full-size filter at a pilot plant.

INTRODUCTION

Artificial intelligence methods have attracted the growing interest of researchers in wide range of scientific and engineering fields. The number of applications has increased, and successful results have been widely reported. Artificial Intelligence methods like expert systems, fuzzy logic and neural networks have proved to be excellent tools for the control of mineral processes (Jämsä-Jounela, et al., 1996). This technology has recently been embedded directly into process equipment like flotation cells and dewatering filters.

This paper presents the intelligent control system designed for a variable-volume pressure filter. The system consists of the modelling, classification, economic, fault diagnosis and control modules. The modelling module utilises the simulation and real time models for predicting the filtration behaviour. The classification module utilises the neural network to classify the feed and states of the process. (Jämsa-Jounela, et.al., 1998)

The control and economic modules give suggestions for the most suitable set point values to the basic controllers in order to maintain the most economic and efficient operation of the filter. Fault diagnosis is an essential ingredient of an intelligent system. The aim of the fault diagnosis module is to indicate the undesired or unpermitted process states, and to take the appropriate actions for making the process more safe and economical. (Jämsä-Jounela, et.al., 1999)

The intelligent control system has been implemented using the PC based InTouch system (Wonderware). The additional parts of the control system have been made using the Microsoft Visual C++ 1.52. The simulations were carried out using the MatLab 4.2c.1 version.

The objective of this paper is to describe the modelling module of the intelligent system. The simulation models were constructed for compressive cake filtration at apparently constant pressure, which takes into account clogging phenomenon in the medium and the filter cake. These simulation models use commonly adopted equations for the compressive cake behaviour. These models are best suited for slightly compressible filter cakes. The models were first tested off-line by means of simulations. The experimental data obtained from the pilot test filter are compared with predictions given by the simulation model. The classical, constant-pressure filtration model using the recursive least square parameter identification method was evaluated on-line in pilot tests together with the simulation model.

FILTRATION THEORY

The classical cake filtration equation developed from Darcy's equation serves as the basis for most filtration models.

$$\frac{\Delta p}{\mu q} = \alpha_{av} m_c + R_m \tag{1}$$

where Δp is the total filtration pressure difference, μ the viscosity of the filtrate, q the superficial flow rate, α_{av} the average specific cake resistance, m_c the mass of dry cake per unit area, and R_m the medium resistance. The mass of dry cake is obtained

$$m_c = c\frac{V}{A} \tag{2}$$

where c is a pseudo concentration defined as the mass of dry solids per unit volume of filtrate, V the cumulative volume of filtrate, and A the filter area. The mass of dry solids can be calculated from the mass fraction of solids in the slurry s and the average cake concentration C_{av}.

$$c = \frac{1}{\dfrac{(1-s)}{s\rho} + \dfrac{1-C_{av}}{C_{av}\rho_s}} \tag{3}$$

where ρ is the density of the filtrate, and ρ_s the density of the solids. The compressive cake filtration model takes into account the fact that the cake concentration and average specific filtration resistance are functions of the cake thickness. The average cake concentration is obtained from a power law equation

$$C_{av} = C_0(1-m)\Delta p_{cake}^m \tag{4}$$

where C_0 and m are empirical constants, and Δp_{cake} is the pressure difference over the cake. Similarly the average specific cake resistance is obtained from

$$\alpha_{av} = \alpha_0(1-n)\Delta p_{cake}^n \tag{5}$$

where α_0 and n are empirical constants. Equations (4) and (5) are valid for slightly compressible cakes, including cakes obtained in the filtration of mineral slurries. The pressure difference over the cake is calculated from

$$\Delta p_{cake} = \Delta p - \mu q R_m \qquad (6)$$

When the particle size distribution of the slurry is broad and the fraction of small particles is large, clogging phenomenon can be very harmful. In industrial applications a new filter cloth loses its original permeability soon after it has been taken into use, and for a certain time afterwards the permeability of the cloth remains reasonably constant. The increase in filter medium resistance can be described by an empirical equation (Leu and Tiller 1983).

$$R_m = R_0\left[1 + (\lambda - 1)\left(1 - e^{-jm_{cake}^2}\right)\right] \qquad (7)$$

where R_0 is the clean medium resistance, and λ and j are empirical constants. As the cake grows the medium clogging stops and the cake becomes clogged. Tiller et al. (1981) assumed that the cake clogging can be described in terms of the average cake resistance and a specific function of the cake mass

$$a_{av}(glogged) = a_{av}\exp\left(\frac{m_c}{\eta}\right)^4 \qquad (8)$$

where η is an empirical constant.

The cake thickness L can be calculated from

$$L = \frac{\Delta p_c^{1-n-m}}{a_0 \mu \rho_s C_{av}(1-n-m)}\frac{1}{q} \qquad (9)$$

The iterative solution is started with the assumptions that the applied filtration pressure acts over the filter cake, and that the filter medium is clean. The superficial flowrate q corresponding to a certain filtrate volume is obtained from Equation (1). The filtration time is calculated cumulatively from the start of filtration using small volume increments. Holdich (1994) introduced two spreadsheets for the simulation of apparently constant pressure filtration. The first one gives the throughput with time, and the second gives the cake concentration profiles.

MODELS FOR PREDICTIG THE FILTRATE VOLUME

The modelling module of the intelligent system utilises the simulation models for predicting the filtration behaviour. The first algorithm used in the calculation module is based on Equations 1-9. This algorithm developed for the revised compressive cake filtration model uses the volume increments as a step increment. First the algorithm assumes that the applied filtration pressure is consumed in cake. Then the pressure drop is divided between the cake and the medium using iterative solution for the Equations (1-9). The medium and cake clogging were negligible in test cases, therefore it is assumed that medium resistance is constant and that the cake clogging does not affect the average specific cake resistance.

In filtration of mineral slurries, c, a_{av}, and R_m may attain their final value quickly after a short start-up period. For practical purposes, the variation of these parameters can be neglected, when constant filtration lasts more than few minutes. Then in constant pressure filtration Equation (1) can be presented in the form

$$t = \frac{\mu c \alpha_{av}}{2A^2 \Delta p}V^2 + \frac{\mu R_m}{A \Delta p}V \qquad (10)$$

The second simulation algorithm (Holdich 1996) uses same initial assumptions as the first algorithm and calculates the filtrate volume using time increments as a step increment.

For real-time use of the models, the assumptions are made that only the time and filtrate volume are variable and that the specific cake resistance and dry cake mass per unit volume are constant. The equation (10) is written in the form

$$a * V^2 + b * V - t = 0 \qquad (11)$$

where the parameters a and b can be described as:

$$a = \frac{\mu\, \overline{\alpha}\, \overline{c}}{A^2 \Delta p} \qquad b = \frac{\mu\, R_m}{A\, \Delta p} \qquad (12)$$

This equation is valid over a small increment of time for the compressible cake, but for the incompressible cakes it can be used over the full filtration time as well. The method uses the recursive least square (RLS) method proposed in (Åström et al., 1984) to identify the parameters of Equation 11 as follows:

$$\begin{aligned} &\hat{\Theta}(N+1) = \hat{\Theta}(N) + K(N) \cdot \\ &\left[y_{N+1} - \Phi(N+1)\hat{\Theta}(N) \right] \\ &K(N) = P(N)\Phi^T(N+1) \cdot \\ &\left[1 + \Phi(N+1)P(N)\Phi^T(N+1) \right]^{-1} \\ &P(N+1) = \left[I - K(N)\Phi(N+1) \right] P(N) \end{aligned} \qquad (13)$$

where N is the time instant, y the output data vector, P the covariance matrix, θ the parameter vector, K the correction vector and Φ is a measurement data vector.

When this formula is applied to the identification of parameters a and b, the following recursive equations are given

$$\begin{aligned} &K(i) = \begin{bmatrix} k_1(i) \\ k_2(i) \end{bmatrix} = \begin{bmatrix} P_{11}(i) & P_{12}(i) \\ P_{21}(i) & P_{22}(i) \end{bmatrix} \begin{bmatrix} \Phi_1(i+1) \\ \Phi_2(i+1) \end{bmatrix} \\ &\left[1 + \begin{bmatrix} \Phi_1(i+1) & \Phi_2(i+1) \end{bmatrix} \begin{bmatrix} P_{11}(i) & P_{12}(i) \\ P_{21}(i) & P_{22}(i) \end{bmatrix} \begin{bmatrix} \Phi_1(i+1) \\ \Phi_2(i+1) \end{bmatrix} \right]^{-1} \\ &\begin{bmatrix} \theta_1(i+1) \\ \theta_2(i+1) \end{bmatrix} = \begin{bmatrix} \theta_1(i) \\ \theta_2(i) \end{bmatrix} + \begin{bmatrix} k_1(i) \\ k_2(i) \end{bmatrix} [y(i+1)] - \\ &\begin{bmatrix} \Phi_1(i+1) & \Phi_2(i+1) \end{bmatrix} \begin{bmatrix} \theta_1(i) \\ \theta_2(i) \end{bmatrix} \\ &\begin{bmatrix} P_{11}(i+1) & P_{22}(i+1) \\ P_{21}(i+1) & P_{22}(i+1) \end{bmatrix} = \\ &\left[\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} k_1(i) \\ k_2(i) \end{bmatrix} \begin{bmatrix} \Phi_1(i+1) & \Phi_2(i+1) \end{bmatrix} \right] \cdot \\ &\begin{bmatrix} P_{11}(i) & P_{12}(i) \\ P_{21}(i) & P_{22}(i) \end{bmatrix} \end{aligned} \qquad (14)$$

where the measurement vector is given by

$$\Phi(i) = \begin{bmatrix} \Phi_1(i) \\ \Phi_2(i) \end{bmatrix} = \begin{bmatrix} V(i) \\ V^2(i) \end{bmatrix} \qquad (15)$$

the output vector y (t) = t and the parameter vector is presented as

$$\theta = \begin{bmatrix} a \\ b \end{bmatrix} \qquad (16)$$

and the covariance matrix is then defined

$$P(i) = \begin{bmatrix} P_{11}(i) & P_{12}(i) \\ P_{21}(i) & P_{22}(i) \end{bmatrix} \qquad (17)$$

IMPLEMENTATION OF THE MODELLING MODULE

The modelling module consists of the five submodules: parameter input, calculation, identification, drawing, and equation module. The parameter-input module is divided into two parts, the measurement and the constant parameter parts as presented in Figure 1.

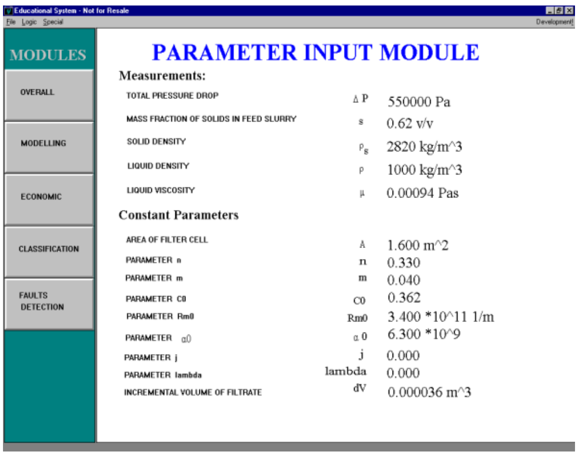

Figure 1. Parameter input module

The measurements part gives process parameters: the setpoint for the filtration pressure and the slurry characteristics. The constant parameters part gives the filter dependent parameters as filtration area and incremental volume of filtrate and also the experimentally measured model parameters for the slurry.

The calculation module presents the main measurements, the simulated results based on the selected model and the results of the real time model. Figure 2 shows the results for the constant time increments: measurements, the simulated results of the second model and the results of the third model calculated with the real time parameters a and b.

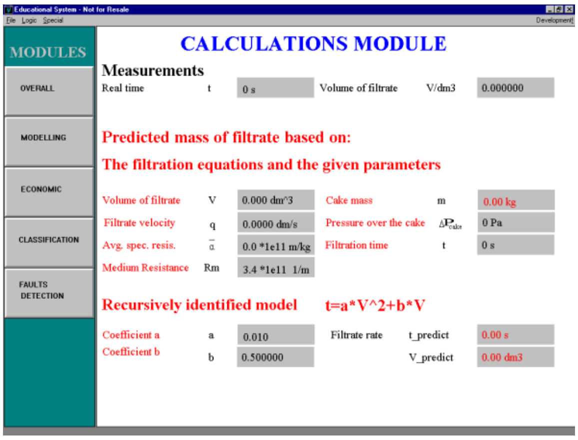

Figure 2. Calculation module

In the identification module the parameter data vector, the measurement data vector, the output data vector and the covariance vector are given as the inputs for the RLS method. The function returns the new parameter vector and the covariance matrix.
The identification module is presented in Figure 3.

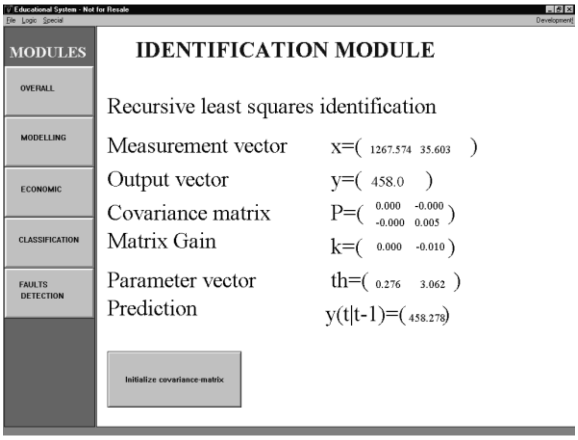

Figure 3. Identification module

The convergence of the covariance matrix and the parameter saturation during identification can be followed using the on-line trends of the parameters in the identification module and in the drawing module. The drawing module is shown in Figure 4. After parameters a and b are saturated, the model can predict the subsequent filtrate volume very accurately in real-time using the RLS algorithm. The first figure in the drawing module shows the differences between the measured and calculated filtrate volume using the identified parameters. The second figure in the drawing module shows the comparison between the simulated and the measured filtrate volume. The last four small figures describe the behaviour of the covariance matrix.

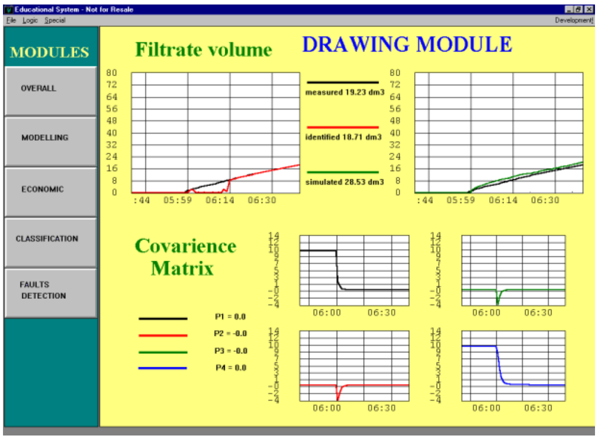

Figure 4. Drawing module

EXPERIMENTAL EQUIPMENT AND MATERIALS

The understanding of solid-liquid separation is important in evaluating the performance of filters in the existing facilities.

Laboratory tests

The empirical parameters for the filtration model were measured separately using a laboratory-scale piston press filter. The test filter has been designed for testing different kinds of mineral slurry, which may need high filtration pressures, and industrially applied filter cloth materials. The test filter has a slurry feeding system and a computer-controlled piston press filter and data collection system. The filter can be filled automatically with high concentration slurries (20% - 30% by volume), and can be operated in two different modes: constant pressure mode (Oja et al 1994) and gradual pressure increase mode (Oja and

Nyström 1995). The laboratory test filter is presented in Figure 5 and the respective technical data are given in Table 1.

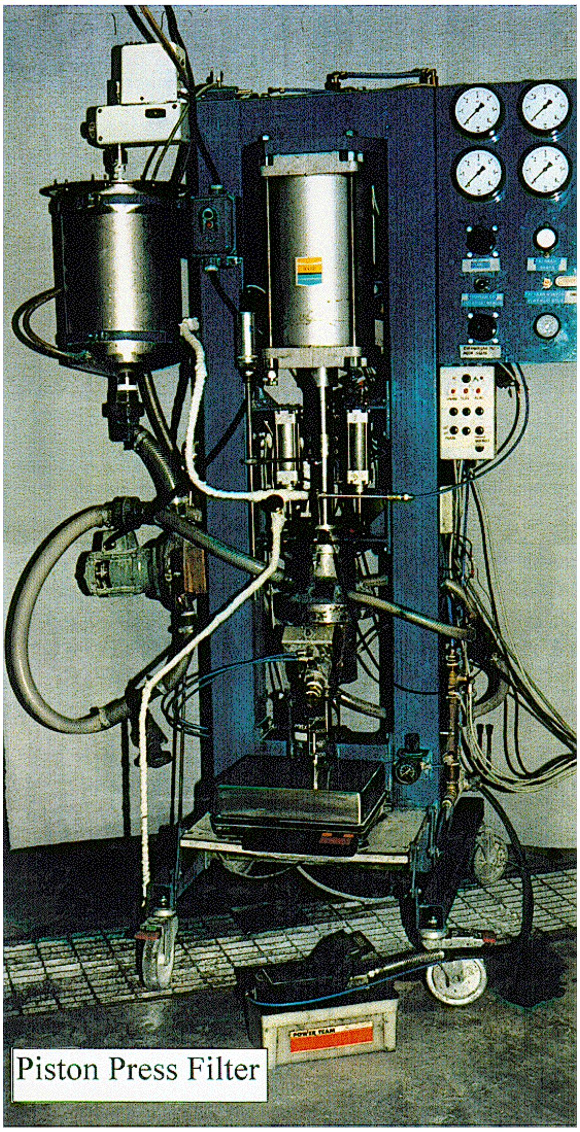

Figure 5. The laboratory test filter.

Table 1. Technical data of the test filter

Technical data	
Horizontal filter area	78.5 cm^2
Pressure ranges	
Filtration	0.3 - 20 bars
Expression	0.3 - 20 bars
Air drying	1- 5 bars
Max. filter chamber height	70 mm
Data collection	
• Applied piston pressure	
• Pressure below the filter medium	
• Applied work cylinder pressure	
• Piston level	
• Mass of filtrate	
• Flow rate of drying air	
• Conductivity of the slurry	

The experimental procedure used in the measurements was divided into the following steps:

Pre-treatment of the slurry: The slurry is first produced by mixing and recycling outside the filter chamber. The slurry pump warms up the slurry. The temperature of the slurry is kept constant by cooling the slurry tank.

Preparations: The piping below the filter medium is filled with water and the wetted filter cloth is placed on the filter medium support. Data collection parameters and operating parameters were selected. The required chamber height is defined and the filter is closed.

Filling: The inner wall of the filtration chamber and the piston are raised in order to open the two feeding ports, which are located just above the filter medium. The slurry flows into the chamber and raises the piston. When the piston has risen to the preset position, the inner wall is pushed down automatically.

Filtration: When the feed ports are closed, the filtration is started by a preset filtration pressure profile. The filtrate is collected on the weighing scale through a check valve.

Expression: The pressure transmitter of the filtration chamber works only when in contact with a liquid. Thus when filtration is completed the control system of the filter starts the expression automatically using a preset expression pressure and continues up to the preset expression time.

Cake drying: After expression, the check valve is opened and the filling water is drained from the piping. The piston is raised and the air or steam-drying period is started. Experience has shown that it is better to use manual control during piston lifting in order to avoid cake cracking.

End of the cycle: After the test, the filter is opened, the filter cake removed and the filter washed. The filter is now ready for the next test.

Pilot test filter

The experimental tests were performed with a Larox PF 1.6 variable volume pressure filter. In this filter, a plate pack forms the horizontal layered filter chambers on the top of each other. The Larox PF 1.6 test filter contains only one filter chamber, but otherwise it has the same operations and control as the industrial filters. The effective filter area of the filter is 1.6 m^2.

The filtration procedure used in the pilot test filter was divided into the following phases:

Pretreatment of the slurry: The slurry is first produced by mixing it in the feeding tank of the pilot filter. Before the actual experimental runs, the slurry was first filtered and the obtained cake resuspended into filtrate.

Automatic pressure cycle: After a filtration cycle, the test filter is open and closing the filter begins a new cycle. The data collection begins when the filter is closed. The pressure sensor in the feed line measures the feeding and filtration pressures, as well as the drying air pressure, and a pressure sensor in the feed line of the pressing water measures the expression pressure.

The automatic filtration cycle can have six steps. In this study the optional steps, cake washing and post wash expression, were omitted. The steps included in the study were feeding, expression, drying and cake discharge.

Feeding: The slurry is pumped into the filter chamber, and filtering begins by applying the pumping pressure. In this study the applied pressures were four and seven bars. The pumping times were from five to ten minutes.

Expression: After pumping, the feeding valve is closed and the diaphragm is filled with pressurized water. Squeezing produces more filtrate and completes the filtration. Expression was continued for one to two minutes.

Drying: After expression, the air-drying valve is opened and air is blown into the filter chamber. The pressurized air raises the diaphragm and dries the cakes further. The air drying time in this study was two minutes.

Cake discharge: The filter is opened and movement of the filter cloth discharges the cake. After the discharge, the filter cloth is washed and the filter is ready for the next cycle.

Materials

The slurry used in the first test series was a copper concentrate slurry. The concentration of the copper concentrate slurry was 60 % by weight (34 % by volume), the mean particle size 35 µm and the median particle size 20 µm. The density of the dry material is 1820 kg/m^3.

The second test series was a calcium carbonate slurry. The concentration of the slurry was 40 % by weight (20 % by volume), the mean particle size 6.6 µm and the median particle size 5.7 µm. The density of the dry material is 2700 kg/m^3.

RESULTS OF THE LABORATORY TESTS

The filtration parameters were measured on the original slurry and on the slurry made by suspending the filter cakes in the filtrate in order to estimate the effects of recycling. Experimental laboratory data (Table2) showed that the test slurries did not block the cakes or the medium during the tests. The laboratory filtration test gives the mass of the dry cake, filtrate volume and the height of the cake at the end of the filtration period. The concentration of the feed was measured separately for each filtration test.

The structure of the cakes obtained from the recycled copper concentrate slurry was denser than the structure of the cakes of the original slurry. This can be seen from the increased specific cake resistance and from the initial cake concentration. The mean particle size of the slurry did not change during recycling.

The filtration model requires also the medium resistance value. Industrial filter cloths are not uniform and the sides of the cloth may be tighter than the centre. The measured resistance of the filter cloth varied from 0.2 10^{11} to 10.9 10^{11} 1/m, and the mean value of 3.4 10^{11} 1/m was used in the model calculations.

Table 2. Compressibility data.

	Original slurry	Recycled slurry
Copper concentrate filter cakes		
α_0	1.7 10^9 m/kg	6.3 10^9 m/kg
n	0.41	0.33
C_0	0.37	0.39
m	0.04	0.04
Calcium carbonate filter cakes		
α_0	5.8 10^{10} m/kg	4.5 10^{10} m/kg
n	0.10	0.10
C_0	0.21	0.21
m	0.08	0.08

SIMULATION RESULTS

The applicability of the models was tested with history data of the pilot test filter. The main purpose of the pilot tests was to verify the filtration models. Therefore the industrial size test filter (Larox PF 1.6) was filled to maximum cake thickness in order to obtain constant pressure conditions. The simulation results of the proposed models were compared with measured values of 15 copper concentrate tests and with 50 calcium carbonate tests.

Figure 6 shows a typical filtration curve with measured pressure difference. The data reveals interesting facts about the course of the filtration. The frequency of the pump changes after a short period, when a diaphragm pump feeds the slurry to the filtration chamber. Figure 7 shows the expected linear behaviour after the startup period. The filtration curve of the expression period shows the time when no more liquid can be removed from the cake with the applied pressure. The filtration curve jumps up at the beginning of the drying period (t=1400 s), when the drying air blows away the filtrate, which was collected in the space below the filter cloth. The time difference between this jump in the filtrate curve and the first measurement of the drying air pressure gives the estimate for time delay.

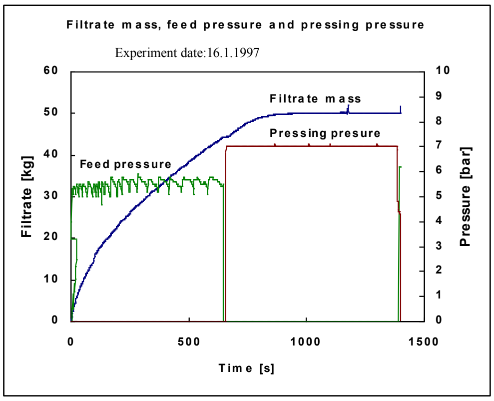

Figure 6. Mass of filtrate, feed pressures and pressure as a function of time.

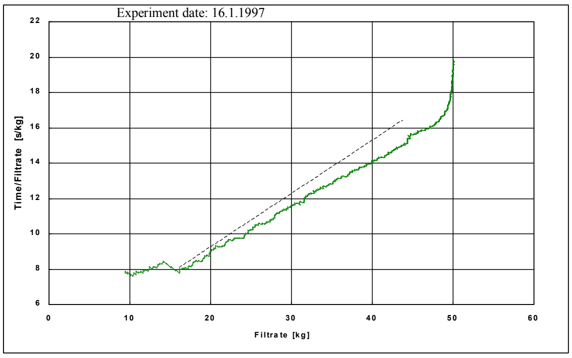

Figure. 7. t/V for the experiment shown in Figure 6.

Figure 8 and 9 show the results of the measured and predicted filtrate volumes of the copper concentrate and calcium carbonate. The solid line represents the actual values of the process measurements, and the dashed line shows the prediction using the first simulation algorithm. The model did not use any measurements to update its predictions.

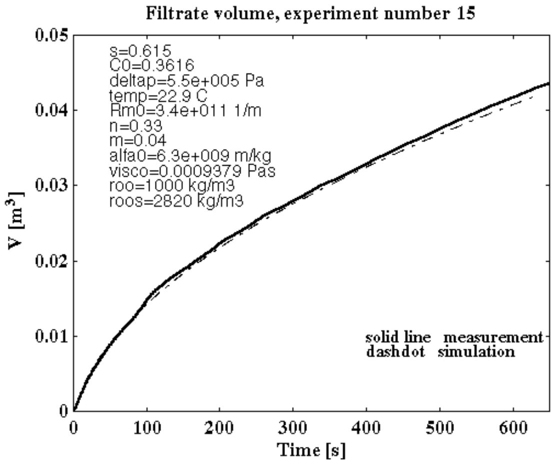

Figure 8. Measured and predicted filtrate volume based on the simulation model for the copper

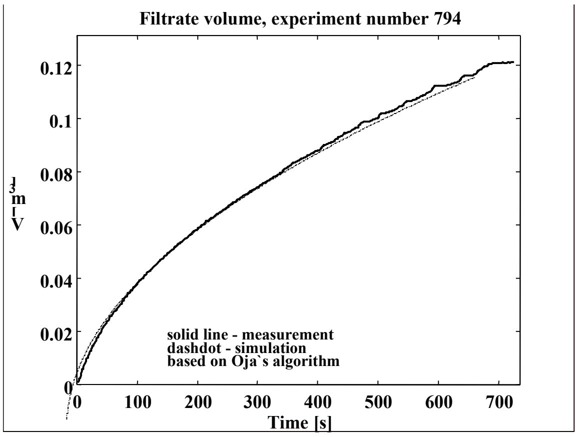

Figure 9: Measured and predicted filtrate volume responses for calcium carbonate

The measured filter volume of the experiment presented in Figure 9 together with the predictions by the numerical model for compressive cake filtration and the identified model are presented in Figure 10. The "identified" curve of Figure 10 shows the prediction of the filtrate volume at t=200 s. The identified model when information is included about the measurements can be seen to converge on the true process values better than the model alone.

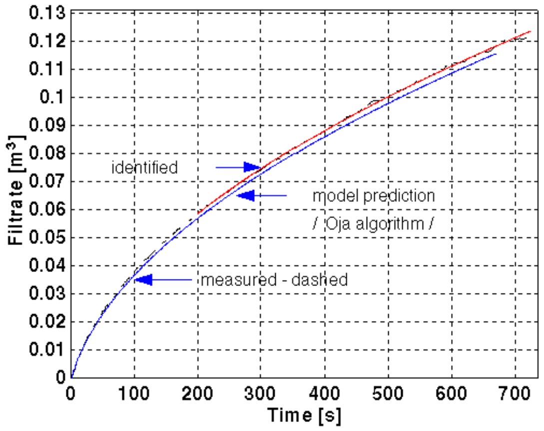

Figure 10. Measured and predicted filtrate Experimental run number 794

Figure 11 illustrates the behaviour of the identified parameters a and b during the filtration process. The responses indicate that the parameters have attained stable values at approximately t=100s, which can also be seen from the behaviour of the covariance matrix elements in Figure 12. After the time instant t=360 s the instability of the parameters behaviour can be observed. Due to the identified uncertainty in a and b and the elements of the covariance matrix, less reliance can be placed on the dynamic model after the time t=360 s.

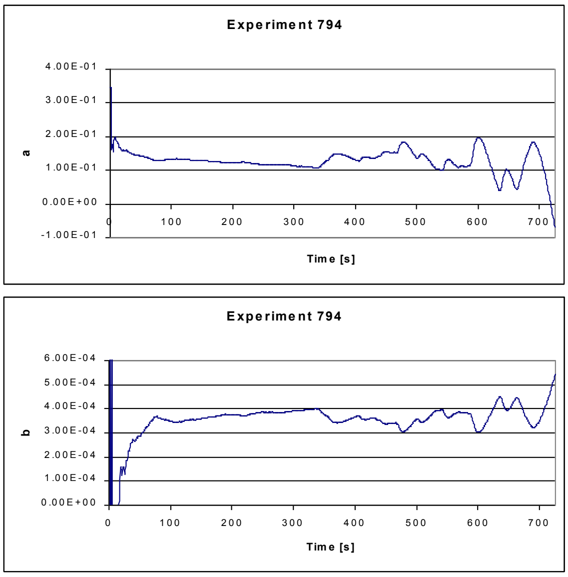

Figure 11. Behaviour of the identified parameters a and b during the filtration.

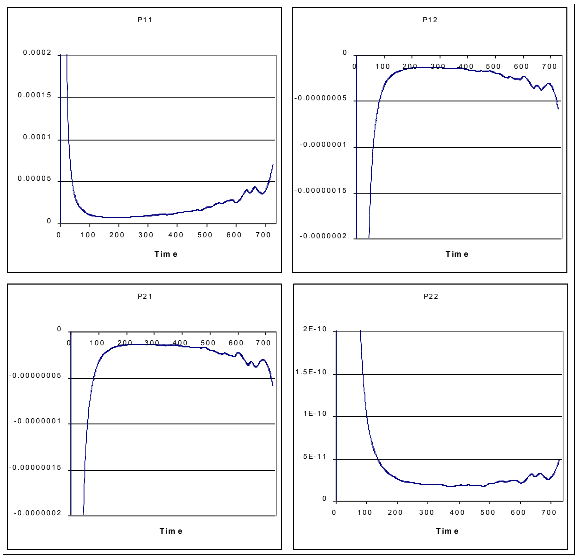

Figure 12. Behaviour of the elements of the covariance matrix of the RLS- model (Experiment 794).

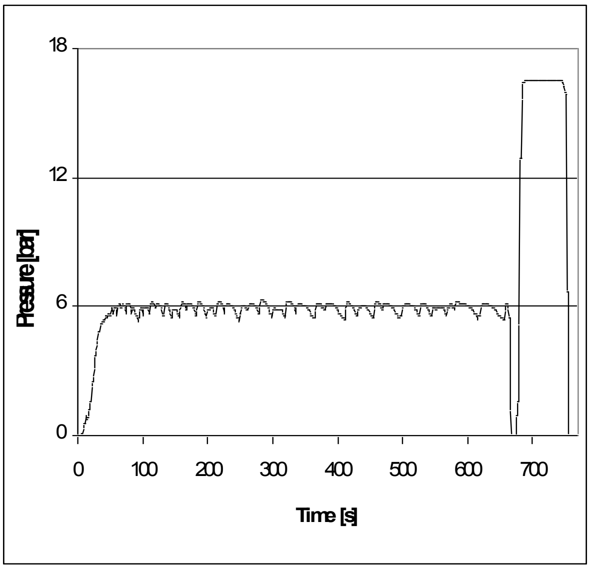

Figure 13. Behaviour of the feed and pressing pressure in experiment 794.

Figure 13 describes the behaviour of the feed and pressing pressure during the same experiment. The figure shows that the pressing stage starts at time t = 650 s. This is also clearly evident from the dynamic behaviour of parameters a and b in Figure 11. After the same time instant there is considerable uncertainty in the filter performance parameters. The values of the covariance matrix elements also start to deviate considerably from the steady state values after the start of the pressing stage.

Based on the results, the mathematical models of the compressive cake filtration are good enough to predict the first critical stage of filtration with sufficient accuracy. After the identified parameters are saturated, the RLS identification algorithm can be used for filtrate prediction during the time period t = 100s to t = 360 s. After the time instant of 360 s the filter is not operating optimally.

Figure 14 shows the predicted results of the shorter filtering cycle that is normally used in industrial applications. The behaviour of the model parameters a and b is stable after t=100 s (Figure 15 & 16) which can also be discovered from the behaviour of the elements of the covariance matrix in Figure 17. In optimal operating conditions the filtration models can be used in an on-line support system to predict filtration behaviour in an industrial set-up.

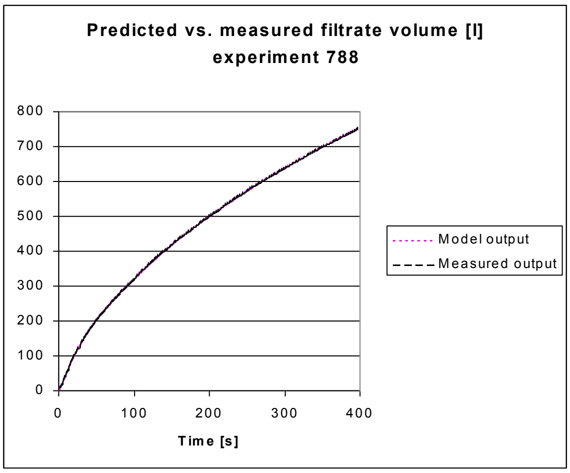

Figure 14. Predicted vs. measured filtrate volume in experiment 788

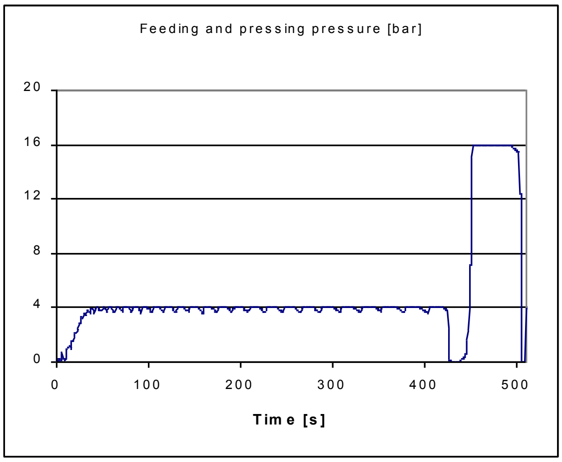

Figure 15. Feed and pressing pressures in experiment 788

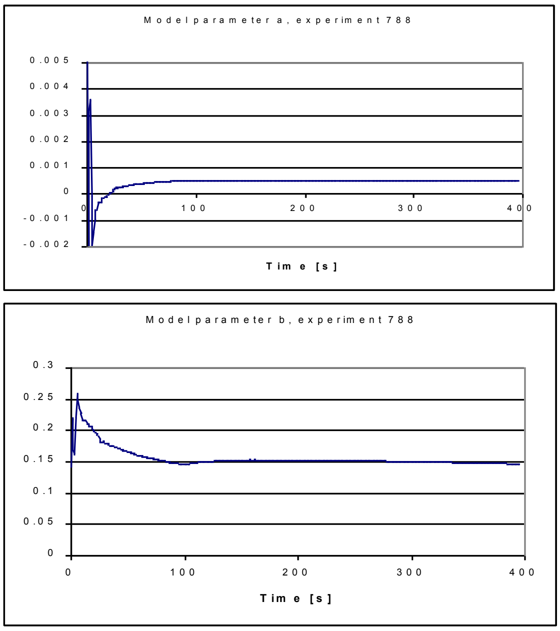

Figure 16. Model parameters a and b in experiment 788

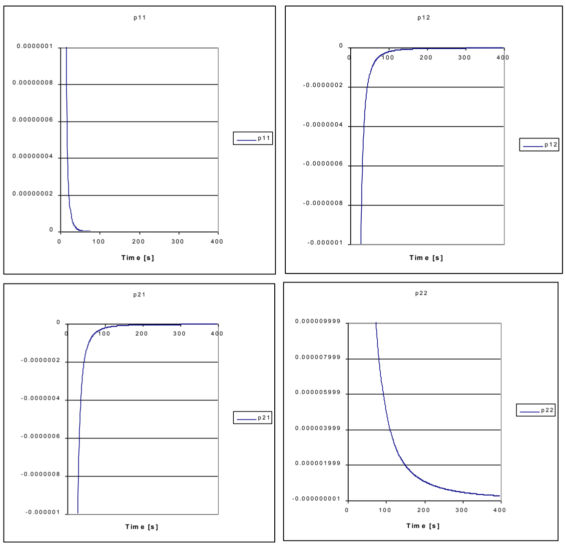

Figure 17: Elements of covariance matrix

RESULTS OF THE REAL -TIME APPLICATION

For real-time use it was decided to implement the two-stage hybrid model which combines the physical and grey-box model. According to the experimental results, the mathematical models of the compressive cake filtration are good enough to predict the first “critical” stage of the filtration with sufficient accuracy. After the identified parameters are saturated, the RLS identification algorithm can be used for filtrate volume prediction. In the last experiments, the system was tested in real-time use for two weeks at the pilot plant.

The results of the long terms tests were good. The on-line prediction results can be used to monitor the operation of the pressure filter and to support the decision making of the plant operator. The display of the real-time intelligent control system, as shown during the long-term tests, is presented in Figure 18.

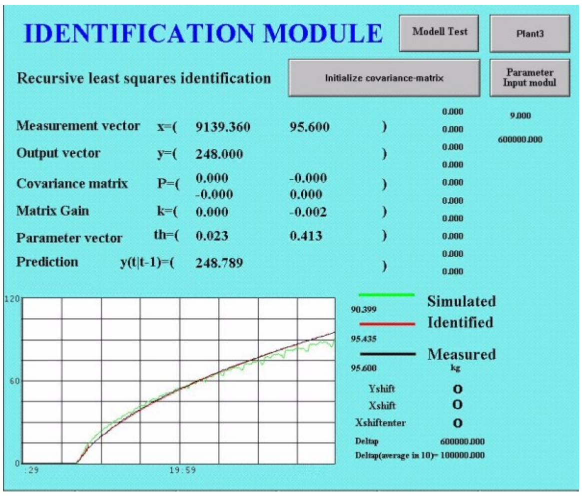

Figure 18. Prediction results on the system interface.

CONCLUSIONS

In the mineral industries, the filtration characteristics of slurries can change periodically due to varying operating parameters of the plant, system conditions and physical characteristics. The current demands for cost effectiveness and better cake-dewatering have increased the use of membrane filter presses. Present-day automation technology for monitoring filter performance permits high level control with modern artificial intelligence methods. The expert system has, however, to be customised separately for each filter and application.

An intelligent control system for a pressure filter has been designed and the modelling module of this system is described in this paper. Two different filtration models have been implemented to predict the filtration behaviour on-line. The mechanistic filtration model for the first critical filtration stage and the grey-box model together with the RLS-identification method for the succeeding stages. The results of the prediction of the performance of the pilot pressure filter are reported by means of simulations and experimental tests carried out at the pilot plant. The results confirmed that the filtration models can be used in an on-line support system to predict filtration behaviour in an industrial set-up. Further work will be directed towards developing the other modules of the intelligent control system.

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NOMENCLATURE

A	Filtration area, m^2
M_c	mass of dry cake per unit area
L	cake thickness
N	time instant
P	covariance matrix
K	correction vector
Q	superficial flowrate, m^3/s
R_m	filter medium resistance, m^{-1}
R_0	clean medium resistance, m^{-1}
T	time, s
Y	output data vector
V	cumulative volume, m^3
α	specific cake resistance, m/kg
α_{avg}	average value of specific cake resistance, m/kg
μ	filtrate viscosity, Pa s
ρ	density of the filtrate, kg/m^3
θ	parameter vector
Φ	measurement data vector

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