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Operator support system for pressure filters

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Abstract

Strong competition in the process industries is forcing the optimization of process operation at each production level, including the operation of process equipment. Overall optimization of process equipment requires an efficient control strategy based on process models and a fault diagnosis system in order to prevent equipment malfunctions. In this paper an integrated operator-support system for a pressure filter is presented. The system structure is modular and consists of classification, modelling, optimization, fault diagnostic, and remote support modules. Finally the test results from a pilot plant and an industrial environment are presented and discussed.

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Keywords:

Operator support system; Filtering; Pressure filters; Control strategy

1. Introduction

The recent toughening in competition in the process industry has set new requirements on production. Both the capacity and the controllability of the equipment have to be increased in order to improve the profitability of a plant. These requirements can partly be met by embedding intelligence in the equipment, thus providing the operators with more support in running the process more efficiently. The operator-support system (OSS) can perform a wide variety of tasks that help operators in their work: monitor the process, detect, isolate and diagnose faults, provide fault recovery guidance, and inform about the need for predictive maintenance. The OSS can thus be regarded as a system that reduces the operator's mental load. Apart from local solutions, OSSs can also include remote service centers. The analysis of certain difficult situations by experts can be of great help to the operator. The use of service centers

shortens the time used in troubleshooting, thus enabling more efficient use of the human resources of the production plant.

In mineral processing, advanced control methods and OSSs have been developed and excellent results have been reported (Jämsä-Jounela, 2001; Hodouin, Jämsä-Jounela, Carvalho, & Bergh, 2001). The application area has, however, been mainly in grinding and flotation. Very little effort has been put into developing these systems for the filtering process, and no attempts to develop OSS for this purpose have been reported.

This paper presents an OSS for a pressure filter. The aim of the system is to maximize the capacity of the filter and to find optimal operation parameters to ensure that the end product meets the quality criteria. Economical efficiency is improved not only by increasing capacity, but also by lowering the amount of energy consumed and by using fault diagnostic and remote support modules to decrease process downtime. The basic components of the integrated system are the dynamic models used to predict online the progress of the filtration, and to reflect the physical filtration phenomena in order to detect faults or abnormal process

conditions such as the clogging of the filtrate medium. The structure of the system is modular, which makes it updateable and expandable. The system consists of classification, modelling, optimization, fault diagnostic and remote support modules.

This paper is structured as follows: In Section 2, the mathematical model for the filtration process is formulated. In Section 3 the structure of the OSS is described, and in Section 4 the test results are presented and discussed.

The novelties of this paper are the development of online filtration model and the capacity-maximizing control strategy.

2. Description and modelling of the filtering process

2.1. Process description

The pressure filtration process is operated in cycles consisting of the following six stages:

1. *Feeding stage*: During the feeding stage slurry, i.e. a mixture of solids and liquid, is pumped into the horizontally oriented filtering chambers. The filtrate flows through the cloth used as filtering media, and cake forms on top of it.
2. *Pressing stage*: After the feeding stage, compressed air or pressurized water is pumped between the diaphragm and the ceiling of the chamber. The increasing pressure forces the diaphragm downwards, pressing the cake against the filtering cloth. Most of the liquid contained in the cake can be removed during the pressing stage.
3. *Cake washing*: In some applications it may be desirable to wash the cake to remove as much as possible of the original liquid from the cake. This stage is usually used when liquid instead of the cake is the product, e.g. when separating penicillin from the fungus producing it.
4. *Second pressing stage*: The second pressing stage is optional and used only if cake washing was utilized. The stage is performed exactly as in the first pressing stage, except the removed liquid is different.
5. *Drying stage*: Most of the liquid can be removed from the cake by pressing it, but not all. During the drying stage some of the remaining liquid is blown away by compressed air or, if necessary, by an inert gas. The gas is pressed into chambers between the diaphragm and the cake. The remaining moisture in the cake is removed by the gas flowing through the cake.
6. *Cake discharge and cloth washing*: When the cake is sufficiently dry, the plate pack is opened and the cloth is driven forward causing the simultaneous discharge of cakes from both ends of the filter. When the cloth

is moved it is washed using high pressure water sprays.

More detailed information about the Larox filter and the filtering process can be found in (Townsend, 2003).

2.2. Modelling of the filtration process

A model for forming of the cake, i.e. the filtration process has been derived for a single chamber, constant-pressure filter. The starting point for the model is Darcy's Eq. (1):

$$Q = k \frac{A \Delta p}{\mu l}, \quad (1)$$

where Q is the the accumulation rate of filtrate ($\text{m}^3 \text{s}^{-1}$), k is a constant, permeability of the cake (m^2), A is the the area of filtration (m^2), Δp is the total filtration pressure difference (Pa), μ is the viscosity of the filtrate ($\text{kg m}^{-1} \text{s}^{-1}$), and l is the thickness of the cake (m).

Eq. (1) can be formulated to use the overall filtering resistance, R (m^{-1}):

$$Q = \frac{A \Delta p}{\mu R}. \quad (2)$$

The overall resistance can then be divided into two resistances, one caused by the cake and the other caused by the filtering cloth

$$Q = \frac{A \Delta p}{\mu(R_c + R_m)}, \quad (3)$$

where R_c is the the resistance of the cake (m^{-1}), and R_m is the the resistance of the cloth (m^{-1}).

The cloth resistance is usually assumed to be constant, and the cake resistance to be a function of the thickness of the cake. Solving (3) for Δp and assuming that the overall pressure difference consists of the pressure difference over the cake and over the filtering medium, Δp can be expressed as (4)

$$\Delta p = \frac{\mu Q}{A}(R_c + R_m) = \Delta p_c + \Delta p_m. \quad (4)$$

An acceptable calculation precision is usually achieved by assuming that the pressure difference over the cake is equal to the overall difference.

For non-compressible cakes, the resistance can be expressed with the cake resistance coefficient and its magnitude

$$R_c = \alpha_{av} w, \quad (5)$$

where α_{av} is the avearge cake resistance coefficient (m kg^{-1}), and w is the weight of the cake per area (kg m^{-2}).

From Eqs. (3) and (5) the accumulation rate of the filtrate, Q , can be written as

$$Q = \frac{A \Delta p}{\mu \alpha_{av} w + \mu R_m}. \quad (6)$$

The mass of dry cake can be calculated if the amount of filtered slurry and its concentration of solids are known

$$wA = cV, \quad (7)$$

where V is the cumulative amount of filtrate (m^3), and c is the concentration of solids in the slurry (kg m^{-3}).

By combining (6) and (7), an equation for the accumulation rate of filtrate, Q , can be written as

$$Q = \frac{A \Delta p}{\mu \alpha_{av} c V / A + \mu R_m}. \quad (8)$$

The accumulation of filtrate at a certain point in time is known to be

$$Q = \frac{dV}{dT}. \quad (9)$$

Eq. (8) can then be reformulated as

$$\begin{aligned} \frac{dV}{dt} &= \frac{A \Delta p}{\mu \alpha_{av} c V / A + \mu R_m} \Rightarrow \\ \frac{dt}{dV} &= \mu \alpha_{av} c \frac{V}{A^2 \Delta p} + \frac{\mu R_m}{A \Delta p}. \end{aligned} \quad (10)$$

If the filtration pressure is constant, (10) can be integrated as

$$\int_0^t dt = \frac{\mu \alpha_{av} c}{A^2 \Delta p} \int_0^V V dV + \frac{\mu R_m}{A \Delta p} \int_0^V dV, \quad (11)$$

$$t = \frac{\mu \alpha_{av} c V^2}{2 A^2 \Delta p} + \frac{\mu R_m}{A \Delta p} V. \quad (12)$$

All the terms in (12), except time and the cumulative amount of filtrate, are constants. For the sake of convenience, (12) can be written as

$$t = aV^2 + bV, \quad (13)$$

where dummy variables a and b are:

$$a = \frac{\mu \alpha_{av} c}{2 A^2 \Delta p}, \quad b = \frac{\mu R_m}{A \Delta p}. \quad (14)$$

The values of the a and b parameters can be calculated if the average specific cake concentration, α_{av} , and the concentration of solids in the slurry, c , are known.

The average specific cake concentration can be obtained from:

$$\alpha_{av} = \alpha_0 (1 - n) \Delta p_c^n, \quad (15)$$

where α_0 and n are empirical constants and Δp_c is:

$$\Delta p_c = \Delta p - \frac{\mu Q R_m}{A}. \quad (16)$$

The concentration of solids in the slurry, c , is:

$$c = \frac{1}{(1 - s)/(s\rho) + (1 - C_{av})/(C_{av}\rho_s)}, \quad (17)$$

where s is the mass fraction of the solids in the slurry, ρ is the density of the filtrate (kg m^{-3}), and ρ_s is the density of the solids (kg m^{-3})

and the average cake concentration, C_{av} , can be calculated from:

$$C_{av} = C_0 (1 - m) \Delta p_c^m, \quad (18)$$

where C_0 and m are empirical constants.

The duration of the feeding stage is a function of the filtrate volume and, when the desired volume is known, the time taken to reach this volume can be determined if the parameters a and b are known. The parameters a and b can be identified online using the recursive least-squares method as proposed by Jämsä-Jounela, and Oja, (2000).

3. The support system

The support system is designed to help operators to monitor the filtration process and to optimize the capacity and operating costs of the pressure filter. The support system is implemented as software consisting of the optimization, classification, modelling, fault diagnostic, and remote support modules described in this section. The user interface of the software is shown in Fig. 1.

The control objective of the support system is to maximize the production capacity. Maximization is performed by optimizing the durations of the individual stages of the production cycle while, at the same time, maintaining the quality of the product, i.e. the moisture content of the cake at the desired level. Another objective is to run the process in an economical way

Fig. 1. Screen capture of the support system software.

by monitoring and displaying the operating costs of the filtering process. If the same quality and quantity of final product can be achieved with different operating strategies, the strategy with the lowest costs is chosen. The production costs are calculated from the consumption of electricity.

The most important disturbance in the process is the varying composition of the feed. The effect of varying feed composition on the filtration process is mitigated using a classification module, which detects changes in the feed type. The classification is performed on the basis of measurements that describe the physical properties of the slurry, and it is implemented (Jämsä-Jounela, Laine, & Ruokonen, 1998) by means of an artificial neural network, the Kohonen self-organizing map (SOMs) (Kohonen, 1990). The optimal durations of the individual stages depend on the properties of the feed, and are optimized separately for every slurry type.

3.1. Optimization of the different stages of the cycle

The optimization module optimizes for every feed type the duration of the feeding, pressing and drying stages of the filtration cycle separately.

3.1.1. The feeding stage

In the feeding stage the goal is to continue feeding for a long enough time for the chambers of the filter to become filled with slurry. However, overfilling the chambers must be avoided because this could cause problems during the next operation cycle. The optimal increase in the mass of the filter during the feeding stage is calculated using information about the desired moisture content of the cake, the densities of the components in the slurry, the volume of the chambers and the volume of the dry cake (see Fig. 2). The time when the feeding should be stopped can be calculated when the optimal mass for the filter and parameters a and b of the recursive model described earlier in Eq. (13) have been determined. The structure of the feeding stage optimization strategy is presented in Fig. 2.

3.1.2. The pressing stage

The aim in the pressing stage is to remove as much liquid as possible from the cake and to get the cake dense enough for the drying stage. If the cake is not pressed hard enough, it may break during the drying stage. If the cake cracks, the pressurized air used for drying flows mainly through the cracks, the cake will not dry properly and the desired moisture level of the cake cannot be achieved. The pressing stage can be divided into two separate sub-stages with durations of $t_{p,1}$ and $t_{p,2}$ (Kämpe, 1999). At first, the excess liquid on top of the cake is pressed through the cake and filtering medium. The cake is then further pressed in order to achieve the density required in the drying stage. During

Fig. 2. The feeding stage optimization strategy. K is the moisture of the cake (%), m_F the mass of the cake (kg), m_{Fk} the mass of the dry substance of the cake (kg), ρ_c the density of the dry substance (kg m^{-3}), V_c the volume of the dry substance (m^3), V_F the volume of the chambers of the filter (m^3), ρ_l the density of the liquid (kg m^{-3}), m_l the mass of the liquid in the filter (kg), m_c the set point for the dry cake mass (kg), and m_{Fsp} the set point for the mass of the filter at the end of the feeding stage (kg).

the second sub-stage the amount of filtrate coming from the filter is much smaller than during the first sub-stage. As a result, the transition from the first sub-stage to the second can be seen from the rate at which filtrate accumulates. Parameter values of $t_{p,1}$ and $t_{p,2}$ are updated online with the optimization algorithm. The strategy for optimizing pressing stage is shown in Fig. 3.

3.1.3. The drying stage

In the drying stage the object is to dry the cake to the desired moisture level as fast as possible. As for the pressing stage, the drying stage can also be divided to two sub-stages with durations of $t_{p,1}$ and $t_{p,2}$. In the first stage the liquid between the particles is blown out, and in the second sub-stage the air flow removes moisture from the surface and pores of the particles. Again, the transition between sub-stages can be seen from the change in the rate of accumulating filtrate. The values of $t_{p,1}$ and $t_{p,2}$ are optimized online with the algorithm presented in Fig. 4.

Fig. 3. The pressing stage optimization strategy. $V_s(t)$ is the accumulative volume of the filtrate coming from the filter (m^3), t is the time instant from the beginning of the pressing stage (s), $t_{p,max}$ the maximum length of the pressing stage (s), $m.a.p.$ the minimum accumulation rate during the pressing stage ($\text{m}^3 \text{s}^{-1}$), $t_{p,1}$ the time when accumulation rate falls under the minimum (s), $t_{p,2}$ the optimized extra pressing time (s), $t_{p,end}$ the suggested total length of the pressing stage (s), and $t_{pressing}$ the time when pressing will be stopped (s).

After the filtration cycle samples are collected from the cake and analysed in laboratory for moisture content. If the measured moisture of the cake is smaller than required, $m.a.p.$, $m.a.d.$, $t_{p,2}$, and $t_{d,2}$ parameters are modified to allow a shorter production cycle. If the moisture does not meet the criteria, the same parameters are modified to make the cycle last longer in order to produce dryer product. After either modification, the parameter values in an optimization database are updated (see Fig. 5).

3.2. Fault diagnostic module

As is commonly known, the main tasks of the fault diagnosis system are subdivided into fault detection by analytic and heuristic symptom generation, and fault

Fig. 4. The drying stage optimization strategy. $V_s(t)$ is the accumulative volume of the filtrate coming from the filter (m^3), t is the time instant from the beginning of the drying stage (s), $t_{d,max}$ the maximum length of the drying stage (s), $m.a.d.$ the minimum accumulation rate during the drying stage ($\text{m}^3 \text{s}^{-1}$), $t_{d,1}$ the time when accumulation rate falls under the minimum (s), $t_{d,2}$ the optimized extra drying time (s), $t_{d,end}$ the suggested total length of the drying stage (s), and t_{drying} the time when drying will be stopped (s).

diagnosis. The fault diagnosis system consists of a diagnostic application and databases containing information about normal operating conditions, faults, their symptoms and probabilities, and maintenance. The diagnostic application is divided into change detection, symptom generation, diagnosis, decision and action phases (Isermann, 1997).

3.2.1. Change detection

Measurement signals and the signals from the actuator state sensors and transmitters are evaluated by comparing them with the normal behaviour database. During the feeding stage, the feeding pressure and the accumulation of filtrate are compared to their typical values. The model for accumulation of the filtrate volume during the feeding stage is also used;

Fig. 5. Optimization database update strategy. $m.a.p.$, $m.a.d.$, $t_{p,2}$, and $t_{d,2}$ are parameters that determine the length of pressing and drying stages.

parameters a and b are identified using the recursive least-squares method, and if after the settling time the parameter values abruptly change, an abnormal situation is detected. Differences between parameters and their normal values or high parameter variation after settling indicate process disturbances or equipment malfunctions.

3.2.2. Symptom generation

Observed differences between process measurements and their normal values and the abnormal behaviour of the model parameters a and b are converted into symptoms.

3.2.3. Diagnosis

If symptoms are generated during the current filtration cycle, fault diagnosis is performed. The active symptoms are compared against symptoms of known faults. Information about the probabilities of failures in the process equipment is used in the diagnosis. The current age of each part is compared against the average lifetime of the part in the maintenance database. This gives the system a third piece of information describing the estimated part wear. A relative probability for each possible fault is calculated from these three values.

3.2.4. Decision

The decision part of the fault diagnosis system decides the appropriate action needed to maintain the operation, to avoid damage or accidents, and to decrease

running costs. The heuristic knowledge can also be updated after the operator has confirmed the correct diagnosis of the fault. This enables the system to learn each filter individually.

In many cases the symptoms observed by the system are not enough to determine the source of the fault. In such cases the system has to obtain more information through guided symptom generation. Symptoms for all possible fault cases, including the detected symptoms, are retrieved from the fault database. The system displays to the operator the possible fault cases and their symptoms and asks him/her to supply the additional information needed to make the decision about the fault (Jämsä-Jounela, Paavola, Kuitunen, & Kämpe, 1999; Jämsä-Jounela, Vermasvuori, Haavisto, & Kämpe, 2001).

Remote support module is an independent component of the fault diagnosis system; it transmits data about observed symptoms and faults in the diagnostic database when a request for data is sent to it. The module provides a secure and reliable way of transferring data from the filter to experts. If the process behaves abnormally or if there are some hardware problems, the experts can quickly analyse the data to offer a solution to remedy the situation. The remote support module consists of an SQL database server that is connected to a pressure filter, a Microsoft Internet Information Server (IIS), workstations, and a LAN network. The workstations are connected to each other either over the Internet or via modems. For security reasons the Internet connection has been secured by means of a Virtual Private Network (VPN) and access to the local network is restricted by a firewall.

4. Testing the support system

Testing the support system was organized in a stepwise manner. First, the applicability of the filtration model was tested using a pilot filter. The empirical parameters for the model were determined using a laboratory-scale piston pressure filter, and the predictability of filtering behaviour was then evaluated using historical data from the pilot filter. Second, the performance of the fault diagnosis module was tested. Finally, the capacity maximizing control strategy was studied in a real industrial environment.

4.1. Measuring the empirical values using a laboratory-scale piston press filter

Before the filtration model can be used online, the initial values of the empirical parameters, α_0 , n , C_0 , and m in Eqs. (15) and (18) have to be determined. A laboratory-scale piston press filter was used for measuring the parameters. As these parameter values depend

Table 1

Compressibility data

	Copper concentrate	Calcium carbonate
α_0	$1.7 \times 10^9 \text{ m kg}^{-1}$	$5.8 \times 10^{10} \text{ m kg}^{-1}$
n	0.41	0.10
C_0	0.37	0.21
m	0.04	0.08

on the properties of the filtrated material, they are determined separately for each type of filtered slurry. In this test the parameters were determined for two types of slurry, a copper concentrate slurry and a calcium carbonate slurry. The parameter values are shown in Table 1.

The filtration model also requires 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, R_m , varied from 0.2×10^{11} to $10.9 \times 10^{11} \text{ m}^{-1}$, and the mean value of $3.4 \times 10^{11} \text{ m}^{-1}$ was used in the model calculations.

4.2. Testing the filtration model

The applicability of the model in Eq. (13) was tested with the process history data from the pilot test filter: a Larox PF 1.6 variable volume pressure filter. In this filter, a plate pack forms the filter chambers that are layered horizontally on 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 filter was filled to maximum cake thickness in order to obtain constant pressure conditions. The simulation results of the model were compared with the measured values of 15 copper concentrate tests and 50 calcium carbonate tests. The measured volume of the filtrate in one filtration cycle, together with the prediction given by the model, are presented in Fig. 6.

The prediction curve of the RLS model in Fig. 6 shows the prediction of the filtrate volume at $t = 200 \text{ s}$. The model identified using the RLS method can be seen to converge on the measured process values. Fig. 7 illustrates the behaviour of the identified parameters a and b during the same filtration cycle as shown in Fig. 6. The responses indicate that the parameters have attained stable values at approximately $t = 100 \text{ s}$. The instability of the parameters' behaviour can be observed after the time instant $t = 360 \text{ s}$. Due to the identified uncertainty in a and b , less reliance can be placed on the dynamic model after the time $t = 360 \text{ s}$, thus indicating that the prediction at time instant $t = 200 \text{ s}$ was justified.

The model was tested in real-time use for 2 weeks at the pilot plant. The results of the long terms tests were

Fig. 6. Measured and predicted amounts of filtrate.

Fig. 7. Behaviour of the identified parameters a and b during the filtration.

good and encouraged further development of the system for industrial use.

4.3. Testing the fault diagnosis module

After the validation of the filtration model, the fault diagnosis module of the system was tested using the same 1.6 pilot filter. Especially the applicability of the filtration model to detect abnormal situations was evaluated. Different faults were induced in the filtering system: low feeding pressure, significant and rapid changes in the feed density, and clogging of the filtering medium.

Based on the test results, these specific fault situations can be observed from the dynamic behaviour of the model parameters. During normal operation the parameter values settle to near constant values but, in abnormal cases, the values of the parameters keep

Fig. 8. Development of the amount of filtrate under normal operating conditions (solid line) and when the feeding pressure is low (dashed line).

Fig. 10. The behaviour of parameter b during the normal feeding stage (solid line) and in the low pump pressure experiment (dashed line).

Fig. 9. The behaviour of parameter a during the normal feeding stage (solid line) and in the low pump pressure experiment (dashed line).

changing. This fault detectability can, for example, be clearly seen in an experiment in which the feeding pressure was lower than that in normal operation and, as a result, the flow of filtrate was smaller than normal. This natural consequence of a low feeding pressure is shown in Fig. 8. During the test cycle parameters a and b behave rather differently compared to the normal situation. The evolution of the value of parameter a in normal operation and in this low pressure experiment is illustrated in Fig. 9, and the corresponding behaviour of parameter b in Fig. 10.

In the other tested fault situations, the parameter values behaved abnormally in a similar manner and the diagnostic module was able to successfully detect and identify, using the generated symptoms, all the problem cases used in the testing (Kämpe, 1999).

4.5. Testing the filtration model offline with a multi-chamber filter

After the tests with the pilot filter, the applicability of the model to predict the progress of filtration was tested for a large multi-chamber filter. The data used in the testing were acquired offline with the remote support module from a real industrial-size filter, the Powerex PF60/60, with 10 chambers and a total filtration area of 60 m². The gathered data represented 2 weeks of normal production operation of the filtration plant. The filtrated slurry was magnesium silicate hydroxide.

4.5.1. Testing the constant pressure model

The model presented in Eq. (13) is derived for a single-chamber, constant feeding pressure filter. The suitability of this model for a multi-chamber filter with variable feeding pressure was studied first.

The model prediction and the measured amount of filtrate, as well as the evolution of model parameters a and b in one testing experiment, are presented in Fig. 11. The parameter values settle at $t = 120$ s and are then used to predict the progress of the filtration process as shown in the figure.

The duration of the feeding stage in this test equipment is, however, approximately 65 s and the stability of the model parameters cannot be attained in time to predict the progress of filtration during feeding. A significant variation in the feeding pressure was observed when the data from the experiments were studied in more detail. Based on these findings the model had to be modified to include the information about the variable pressure.

Fig. 11. (Left) The predicted (black) vs. measured (grey) amount of filtrate and (right) the behaviour of parameters a (grey) and b (black).

Fig. 12. Gradual increase in feeding pressure during the feeding stage.

4.5.2. Testing the variable pressure model

In industrial-sized filters the feeding pressure is raised gradually; a sudden increase in pressure can damage the equipment and make the slurry flow into the chambers too rapidly, causing significant wear and tear in the plumbing. A typical progressive change in feeding pressure used with the PowerexPF60/60 is shown in Fig. 12. The model in Eq. (13) was modified to use the current value of the measured pressure difference over the cake and the filtering medium, Δp_v , as follows:

$$t = \frac{a_p}{\Delta p_v} V^2 + \frac{b_p}{\Delta p_v} V, \quad (19)$$

where dummy variables a_p and b_p are:

$$a_p = \frac{\mu \alpha_{av} c}{2A^2}, \quad b_p = \frac{\mu R_m}{A}. \quad (20)$$

The new modified model was tested next. The predicted and measured amounts of filtrate, as well as the behaviour of the new model parameters a_p and b_p for the first 120 s, are shown in Fig. 13. The parameters of the modified model have smaller variations than the parameters of the original model presented in Fig. 11. The new model is usable after a time instant $t = 80$ s, as shown in Fig. 13.

Fig. 13. (Left) The predicted (black) vs. measured (grey) amount of filtrate and (right) the evolution of parameters a_p (grey) and b_p (black).

Even though the model parameters attain their constant values sooner than the parameters of the original model, this modified model was not fast enough for predicting the progress of the feeding stage, which continues for only 65 s. The model had to be modified to exclude the delayed filtrate measurement.

4.5.3. Testing the filter mass model

The delay in the measurement was found to be due to the structure of the testing equipment: during the tests with the Powerex PF60/60 the filtrate was collected in a tank and weighed in order to determine its volume. A significant delay was found between the instants when the filtrate flows out of the filter and when it reaches the tank.

The model was next modified to use the mass of the filter instead of the filtrate as follows:

$$t = a_m m_F^2 + b_m m_F. \quad (21)$$

The measured and predicted increase in mass of the filter during a feeding stage, as well as the values of parameters a_m and b_m , are shown in Fig. 14. The variances of parameters a_m and b_m are small and they settle to near constant values in 55 s. The predictions of the filter mass are accurate. As shown in Fig. 14, the model in Eq. (21) is usable after 55 s, and can be used early enough to predict the progress of filtration during the feeding stage.

The model in Eq. (21) was found to be the best for predicting the filtration phenomena during the feeding stage, and was selected to be used in the capacity maximizing control strategy.

4.6. Testing the capacity maximizing control strategy

In the final tests the capacity maximizing control strategy was studied in a real industrial setting with the Powerex PF60/60 filter. The tests consisted of 42 filtration cycles during which the durations of the pressing and drying stages were altered according to

Fig. 14. (Right) The predicted (black) and measured (grey) increase in mass of the filter during the feeding stage and (left) the parameters a_m (grey) and b_m (black).

Fig. 15. The estimates of the optimal feeding time during one testing day.

the optimization strategy: pressing time from 150 to 480 s and drying time from 270 to 330 s.

4.6.1. Testing the feeding stage optimization

The most important element in the capacity maximizing control strategy presented in Section 3.1 is to estimate the optimal duration for the feeding stage. The prediction is based on the modelling module. Throughout the testing period the suggested feeding times varied from 68 to 73 s. The proposed optimal feeding times for one testing day are shown in Fig. 15. These values were found to be good estimates for the optimal feeding stage duration. A 65 s feeding time already produced cakes of below optimum thickness.

4.6.2. Testing the pressing stage optimization

The pressing stage optimizing strategy presented in Section 3.1 was tested with 15 filtration cycles. During these test cycles the drying time was kept constant at 300 s, and a stepwise decrease in the pressing time without increasing the final cake moisture was noted. According to the test results, the final moisture levels of the cakes were higher when using pressing times of 285 and 300 s compared to the moisture levels obtained with 200 and 240 s pressing times. The results of the experiments are shown in Fig. 16.

Fig. 16. The effect of pressing time on cake moisture.

Fig. 17. The effect of drying time on cake moisture.

The results suggest that pressing the cake beyond optimal duration does not have a beneficial effect on the final cake moisture. Pressing should thus be used only to make the cake solid.

4.6.3. Testing the drying stage optimization

In the final tests the drying stage optimization strategy presented in Section 3.1 was tested. The effect of drying time on cake moisture was studied with 11 filtration cycles using six different drying times. The pressing time was kept constant at 200 s. The results presented in Fig. 17 show the clear correlation between the drying stage duration and the final cake moisture: increasing the duration of drying lowers the moisture content of the cakes.

The results suggest that the drying stage duration can be used to control the final cake moisture.

4.6.4. Impact of the maximizing control strategy on the whole filtration cycle

During the testing period the capacity-maximizing control strategy described in Section 3.1 made changes

to the durations of the pressing and drying stages, as reported in Sections 4.6.2 and 4.6.3. The optimized cycles were approximately 12 per cent shorter than the original ones, and the moisture level of the cakes remained at an acceptable level. The results were thus very promising as the production rate of the tested Powerex PF60/60 filter increased by almost 14 per cent.

5. Conclusion

Solid-liquid separation is an important unit process in mineral processing. However, little research has been made on the control and automation of the filtering process. In this paper an operator support system for a pressure filter is presented. The system is based on the mathematical model derived for the filtration phenomena in Section 2. The model is used to predict the progress of the filtration process, to detect faults in the filtering process, and is a part of a control strategy for maximizing the production capacity of the filter.

The system has been tested with two different filters, the Larox PF1.6 pilot filter and the industrial-sized Larox Powerex PF60/60. The test results indicate that the filtration model is accurate and the fault diagnosis module is able to detect process faults. Tests made in a real industrial environment showed that the capacity-maximizing strategy was able to raise the production rate of a Powerex PF60/60 filter by almost 14 per cent. These results encourage further development of the OSS for commercial use.

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