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Developing predictive empirical filtration models for advanced tailings handling

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Abstract

There has been a significant improvement in tailings dewatering techniques over recent years. However, the effects of tailings properties on the filtration process have not been vastly investigated. The different properties of tailings cause significant effects on the feasibility of filtration. Modifying or optimising filtration equipment for different tailings mixtures often requires testing procedures that involve high expenses. Therefore, an increasing demand has arisen to improve the prediction of tailings properties for efficient thickening and filtration using the available mineralogy and particle size data. Developing a suitable solution to do so is the focus of this paper. Experimental studying of tailings and their fractions helps to understand the empirical relationship of the physical properties of tailings, such as particle size distribution (PSD) and air permeability, to the filterability properties like average cake porosity and cake resistance. Also, it is vital to study how the changes of fine particle concentration affect these parameters of the tailings mixture. An algorithm developed based on the filterability of different particle size fractions of chosen minerals should be able to predict the filtration rate for a user-defined tailings blend. This type of model will be useful in evaluating the performance and economics of different tailings treatment models and studying the feasibility to produce tailings disposal solutions. It was discovered that separating fine fractions from tailings, significantly improves the filterability of the remaining portion. This opens up several further possibilities for advanced tailings handling systems. One possibility is to perform cost-efficient tailings filtration for the coarser fractions of the tailings and keep the fine fractions as slurry, which then mix with the filtration cake to form paste for surface disposal or backfill. This approach potentially allows mining companies to achieve paste rheology at lower opex and capex compared to the conventional paste thickener technology.

During the study a set of laboratory experiments were conducted to fraction the tailings and determine the empirical relationships between the physical and filterability properties of each fraction and their different mixtures. Development of a filterability parameter prediction model with the PSD data and known parameters of original tailings fractions allows the possibility of predicting new, untested materials. The accuracy of the predictions depends on the degree of similarity between the new material and the original tailings material used for empirical study in this stage. By inputting the filterability parameters, suspension properties and operation conditions, the developed filtration models are able to predict the filtration process parameters such as total filtration time, final filtration volume and final cake thickness, etc. The outcome of a validated predictive filtration model can be utilised to trade-off between filtered, thickened, paste and combined treatment of tailings by modifying the tailings feed.

Keywords: *tailings filtration, tailings dewatering, particle size distribution, tailings fractioning, filterability properties, predictive empirical filtration models, advanced tailings handling*

1 Introduction

When the recoverable metals and minerals have been extracted from the ore, the produced ‘waste’ solid material, together with the water used in the recovery process, are called tailings (Bista 2022). Tailings dewatering technologies improve the water recovery and make it possible to store tailings safely.

The most cost-effective alternative of tailings storage for most mine sites around the world is the conventional tailings impoundments where tailings slurries are constrained by a dam wall for permanent storage. Upstream dams, however, have caused several accidents in past years and are deemed less safe than centerline and downstream dams. These failures have brought about a re-evaluation of tailings storage, examining risk, the consequences of failure and the practices required to ensure the sustainable storage of mine waste.

Filtered tailings represent an alternative method for tailings management. The development of filtration technologies with large capacities supports tailings storage in an unsaturated state as compared to the slurry consistency in conventional tailings and/or ‘paste-like’ consistency in thickened tailings (Davies 2011). Filtered tailings generate negligible water seepages and significantly reduce the risks involved in the transportation of contaminants. They can be an excellent solution in situations where water conservation is the utmost important issue, the enhancement of economic recovery by tailings filtration is beneficial or space constraints for conventional tailings impoundments exist (Davies et al. 2010).

Determination of filtration properties is the most important step in developing a filtration process and designing new filtration equipment. Physical testwork has been the mainstay of filtration definition as theoretical modelling lacks the accuracy necessary. It is challenging to describe the fluid flow through a porous material and predict the behaviour of the filtration process precisely by a theoretical approach, due to the influences of a large variety of factors. Thus properly designed testing procedure is required where full, pilot or laboratory filtration units are utilised to determine the filtration properties (Safonov et al. 2021).

To conduct complete standard testwork a significant amount of slurry sample must be transported from the plant to a laboratory in a remote location or delivered to an adjusting pilot-scale test unit in the plant. Additionally, there can be limited availability of test material to perform the complete set of tests due to the gradual maturing of mining technology and the increasing cost of pilot testing (Palmer et al. 2010). As a result, test scales are reduced from pilot-scale to laboratory-scale with smaller sample sizes, which leads to implications associated with scale-up calculations and process modelling (Safonov et al. 2021).

The mineralogy of tailings and the particle size distribution (PSD) exhibit their own unique filtering behaviour, and filter suppliers have gained knowledge and experience in carrying out different projects to make efficient and reliable filter units (Vargas & Pérez Campomanes 2022). With this gained hands-on experience, filter suppliers, together with research universities, are actively developing new test procedures to design full-scale equipment by optimising the cost, testing time and sample size.

To predict changes in filterability with changes in mineral processing variables (such as grinding and ore variability), it is useful to develop an empirically validated filtration algorithm. This algorithm should be based on the filterability of different fractions of tailings’ PSD for selected minerals which could support predicting of the filtration behaviour of a user-defined slurry blend. Such developed filtration models can be used in pre-feasibility studies to evaluate the economic feasibility changes in process design and their implications on tailings management.

2 Theory and literature

Predicting the filtration behaviour of a complex mixture of particles from their aggregate properties has failed to provide a reliable method. Models such as Darcy and Kozeni-Karmen exhibit behaviour as the resistance of flow through a series of pores. They can predict the effects of changes in pressure and cake thickness for a known mixture but are less effective when the material is unknown or the mixture changes.

$$Q = Bm\frac{A\,\Delta p}{\mu\,L} \tag{1}$$

$$\Delta p = K\frac{\mu\rho(1-\varepsilon)^2}{d^2\,\varepsilon^2} \tag{2}$$

$$\alpha_{\text{av}} = \frac{K(1-\varepsilon_{\text{av}})S_{\text{s}}^2\rho_{\text{s}}}{\varepsilon_{\text{av}}^3} \tag{3}$$

where:

Q = flow of filtrate.

Bm = permeability.

K = Kozeny constant.

A = area of the filter.

μ = viscosity.

L = cake thickness.

Δp = pressure.

α_{av} = cake resistance.

ε = void fraction.

It is proposed that by separating the solids into smaller fractions and defining the properties of those fractions that a better model for predicting the behaviour could be developed.

In previous studies by Huhtanen et al. (2013) derived good correlations between filterability and Blaine index. It was decided to investigate the behaviour of Blaine, specific surface area and void fraction against filterability of the mixture, separate fractions and mixtures in this study.

While filtration rate is the most studied parameter on an industrial-scale, cake moisture is also an important factor that is not well predicted with existing theories. In a saturated state the void fraction can be used to predict the mass fraction of liquid in cake. Most dewatered tailings are partially desaturated with liquid retained in the cake by capillary forces. Models on gas flow displacement and the relative permeability models indicate a correlation between void fraction and particle size, and air entry against particle size. These indicate that a component approach would be practical for predicting cake moisture. Surface properties are constant and moisture will vary with void fraction and particle size.

$$p_b = \frac{4.6\,(1-\varepsilon)\,\sigma}{\varepsilon\,d} \tag{4}$$

$$\Delta p = \frac{4\tau\cos\theta}{D} \tag{5}$$

where:

p_b = threshold pressure.

ε = void fraction.

σ = solids volume fraction.

d = particle diameter.

Δp = differential pressure.

θ = wetting angle.

τ = surface tension.

D = pore diameter.

For solids density, viscosity, specific surface area, void fraction and cake moisture values, a linear model of the change in the value of a particular parameter compared with a change in the concentration of the fine fraction is proposed. This is schematically shown in Figure 1. Thus if the masses of the components in the mixture and the values of the parameters of the components are known, it is possible to predict the value of the mixture parameter at any concentration of these components.

Mathematically, this can be expressed as a linear equation:

$$P_M = \frac{P_B - P_A}{100} C + P_A \tag{6}$$

where:

P_M = property value of a mixture.

P_A = property value of a component *A*.

P_B = property value of a component *B*.

C = percentage of component *B* in the mixture.

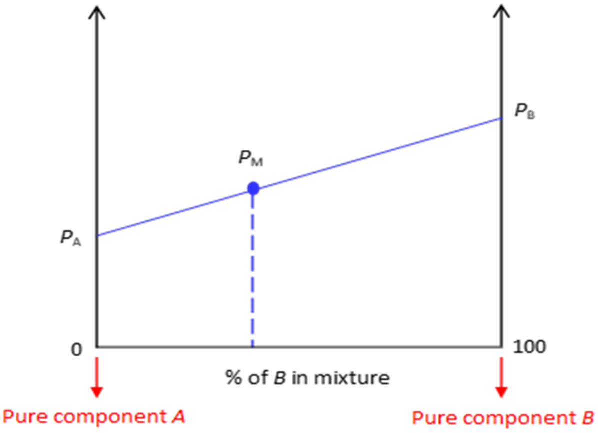


Figure 1 **Linear change of the parameter value of a mixture from the parameter value of a pure component (A) to the parameter value of a pure component (B)**

It can be assumed that this trend is also preserved when other coarse and fine fractions of the material are mixed. Therefore, for a mixture consisting of many components (fractions), the value of the mixture parameter can be determined if the masses of the fractions included in the mixture are known. This can be represented by the following equations:

$$P_M = \sum_{i=1}^{N} \frac{m_{F_i}}{m_M} P_{F_i} \tag{7}$$

$$m_M = \sum_{i=1}^{N} m_{F_i} \tag{8}$$

where:

i = index of a fraction in a mixture.

N = number of fractions that produces a mixture.

m_{Fi} = mass of *i*-th fraction.

m_M= mass of a mixture (mass of all fractions).

P_{Fi} = a value of property of *i*-th fraction.

The relationship of filtration rate or cake permeability is more complex, and an advanced prediction-based method was planned to develop the relationship utilising the parameters derived from the fractions and the available filtration models. (Grabowski & Wilanowicz 2010)

To test this theory two samples of mine tailings were prepared by splitting them into 7 fractions. The properties of the original material were then compared to that of the fractions and a series of mixtures of the fractions.

3 Experimental design

Experimental work was conducted on the tailings, fractions and mixtures to determine the empirical relationships between the physical properties (density, PSD, air permeability through packed beds of solids) and filterability parameters (average cake porosity ε_{av} and average specific cake resistance α_{av}), which mainly influence the filtration behaviour and the properties of the final filtration products. Laboratory experiments were conducted in laboratory facilities at Metso Outotec Pori Research Center and Lappeenranta-Lahti University of Technology LUT.

Two different tailings slurry samples from real production facilities were utilised as the initial material for the experiments. See Table 1.

Table 1 Initial tailings material

No.	Material name	Short description
1	NK tails	Powder material with a light grey colour. Particles look coarse like sand. Came in as slightly wet solids.
2	KV tails	Powder material with a darker grey colour. Particles are finer than NK tails. Came in the form of slurry.

3.1 Different tailings fractions and mixtures preparation

To test the theory of modelling filtration properties based on the properties of their components, an experiment was proposed where samples of tailings were split into multiple fractions. The properties of the original sample and the properties of the fractions were measured.

To achieve the splitting of the sample into fractions, screening was used for the coarse fraction separation and hydrocycloning was used for the fine fraction separation. To separate the initial material into different coarse fractions, a set of dry sieves with several apertures (Table 2) and a sieve shaker (Haver EML 450 Digital) were used.

Table 2 Set of sieves used for fraction preparation

No.	Sieve aperture	Collected fraction on a sieve
1	200 µm	Fraction F1 (+200–inf)
2	100 µm	Fraction F2 (+100–200)
3	75 µm	Fraction F3 (+75–100)
4	50 µm	Fraction F4 (+50–75)
5	Bottom collector	Fraction F5 (+0–50)

After a series of preliminary experiments (separation tests) on the separation of the initial material by changing parameters such as load mass, vibration time and vibration strength, the optimal values of the parameters for separating a large batch of the initial material (separation project) were selected. The sieves need to be washed and dried after a series of separation batches as they were clogged, resulting in a reduction in separation efficiency.

It was possible to effectively separate the initial material up to F(+0 -50) by the use of dry sieves. To obtain finer fractions, a wet separation method using the Warman Cyclosizer was employed. Table 3 lists the set of fractions obtained through wet separation.

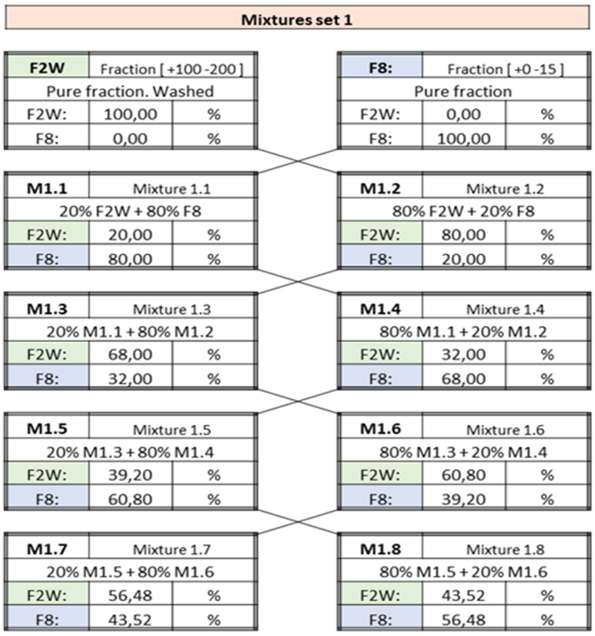
In order to investigate the filtration behaviour of mixtures of tailings of finer and coarser fractions, two sets of mixtures were prepared. Mixtures from some initial fractions were prepared to increase the number of tested materials having similar physicochemical properties and particle shape parameters but with different PSD. As a rule, each mixture comprised two different fractions – coarse and fine – with the most different PSD values. It was observed that separation of materials into fractions using dry sieves is not ideal as finer particles often remain attached to the coarser ones, resulting in inefficient separation. When forming mixtures, the coarser fractions are washed with tap water to remove the attached finer fractions.

Table 3 Set of fractions received after Cyclosizer separation

Cyclone number	Cut size (µm)*	Collected fraction
Retained on the 1st cyclone	(+44)	Fraction F6 (+33–50)
Retained on the 2nd cyclone	(+33–44)	
Retained on the 3rd cyclone	(+23–33)	Fraction F7 (+15–33)
Retained on the 4th cyclone	(+15–23)	
Retained on the 5th cyclone	(+11–15)	Fraction F8 (+0–15)
Passed the 5th cyclone	(+0–11)	

*Cut sizes were taken according to the Cyclosizer instruction manual by MARC Technologies Pty Ltd (2014)

To test the implications of recombining the fractions, and due to the large number of possible combinations, experimental design was used to determine which fractions should be recombined, and at what ratios. The finest fraction (F8) had the most significant influence on filtration and was included in all mixtures. F2W represents the coarser material and W means the sample was washed to remove the fine particles attached to the coarser particles. Figure 2 presents the strategy behind preparing mixtures with different fractions in different ratios for NK tails. Two mixture sets that consists of eight different mixtures per set were prepared, starting from the initial two tailings materials.



Mixtures set 1

F2W	Fraction [+100 -200]	
Pure fraction. Washed		
F2W:	100,00	%
F8:	0,00	%

F8:	Fraction [+0 -15]	
Pure fraction		
F2W:	0,00	%
F8:	100,00	%

M1.1	Mixture 1.1	
20% F2W + 80% F8		
F2W:	20,00	%
F8:	80,00	%

M1.2	Mixture 1.2	
80% F2W + 20% F8		
F2W:	80,00	%
F8:	20,00	%

M1.3	Mixture 1.3	
20% M1.1 + 80% M1.2		
F2W:	68,00	%
F8:	32,00	%

M1.4	Mixture 1.4	
80% M1.1 + 20% M1.2		
F2W:	32,00	%
F8:	68,00	%

M1.5	Mixture 1.5	
20% M1.3 + 80% M1.4		
F2W:	39,20	%
F8:	60,80	%

M1.6	Mixture 1.6	
80% M1.3 + 20% M1.4		
F2W:	60,80	%
F8:	39,20	%

M1.7	Mixture 1.7	
20% M1.5 + 80% M1.6		
F2W:	56,48	%
F8:	43,52	%

M1.8	Mixture 1.8	
80% M1.5 + 20% M1.6		
F2W:	43,52	%
F8:	56,48	%

Figure 2 Strategy for preparing mixture sets by mixing coarse and fine fractions

3.2 Material testing methods

The parameters of all those abovementioned samples were determined using several test methods and/or equipment. As both specific surface area (SSA) and filtration properties are correlated to the density, the densities of the initial material and fractions were measured by a Gay-Lussac DIN 12797 glass pycnometer (Sartorius 1999) whereas the densities of mixtures were determined by equations 9 and 10.

$$C_{\mathrm{sl,w}} = \frac{m_{\mathrm{s}}(1-MC_{\mathrm{w}})}{m_{\mathrm{sl}}} \tag{9}$$

$$\rho_{\mathrm{s}} = \frac{\rho_{\mathrm{sl}} C_{\mathrm{sl,w}} \rho_{\mathrm{l}}}{\rho_{\mathrm{l}} - \rho_{\mathrm{sl}}(1-C_{\mathrm{sl,w}})} \tag{10}$$

where:

$C_{\mathrm{sl,w}}$ = the suspension concentration determined by the mass fraction (kg/kg).

m_{sl} = the suspension mass (kg).

m_{s} = the mass of the solids (kg).

MC_{w} = the solids moisture content (kg/kg).

ρ_{s} = the true solid density (kg/m^3).

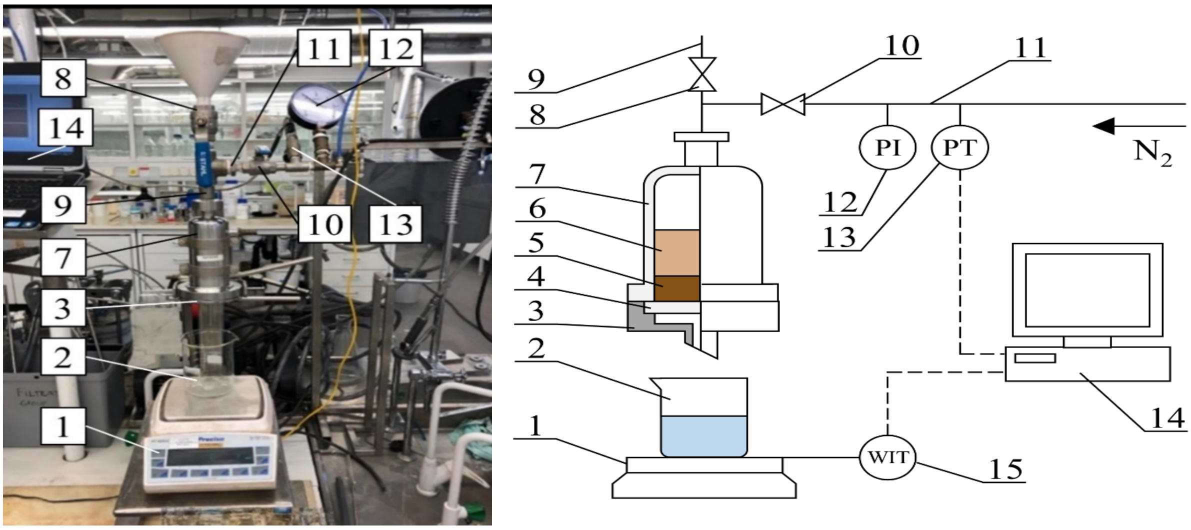
ρ_{sl} = the suspension density (kg/m^3).

The air permeability of a packed bed of particles is proportional to their fineness and, therefore, the SSA. Blaine's method, which exemplifies this principle, was used to determine the air permeability of each tailings sample following the ASTM standard procedure (ASTM International 2018). The testing procedure includes three consecutive stages: (1) determination of the bed porosity ranges, (2) air permeability tests with the standard and test materials, and (3) calculation of the SSA.

By using a fully automatic Mastersizer 3000 particle size analyser, made by Malvern Instruments Ltd, with a Hydro MU adapter, the PSDs of the samples were determined to a precision range of 0.01–3,500 µm. The Fraunhofer approximation theory was used to determine the PSD of the materials. (Malvern Instruments Ltd 2013)

3.3 Filtration experiments

The filterability parameters of the materials were determined by performing standard constant pressure filtration tests with a laboratory Nutsche filter. Pall T-120 cellulose discs were used as the filter medium. An image and schematic view of the filtration system are shown in Figure 3.



(a) (b)

Figure 3 Image (a) and schematic view (b) of the laboratory filtration system: (1) laboratory analytical scale, (2) glass beaker for the filtrate, (3) filter bottom removable part, (4) replaceable filter medium, (5) cake, (6) suspension, (7) laboratory-scale Nutsche filter, (8) valve on suspension pipe, (9) inlet pipe for suspension, (10) gas valve, (11) pipeline for gas supply, (12) pressure gauge, (13) pressure sensor and transmitter, (14) a computer with data acquisition system and (15) weight transmitter

Before the tests a 1,000 mL suspension was prepared in a small, stirred tank. The tests were performed by taking a suspension volume of 300 mL from the mixing tank and pouring it into the filter chamber. To avoid quick settling of the solids, the filter was pressurised immediately after the slurry had been introduced by using nitrogen gas at the specific pressure difference to cause filtration to start. The pressure differences of 0.2, 0.4 and 0.6 MPa were used. The mass of the filtrate that accumulated onto the scale was constantly recorded by a data acquisition system. At the end of each filtration test the cake thickness was measured and the cake was discharged from the chamber. The mass of the cake was weighed, and dried in an oven with a constant temperature of 105°C. After 24 hours the weight of the cake was measured again to determine the moisture content.

3.3.1 Average cake porosity

Based on the cake thickness and mass of the completely dry cake, the average cake porosity was calculated as:

$$\varepsilon_{\text{av,cd}} = 1 - \frac{m_{\text{dc}}}{\rho_s L A} \tag{11}$$

where $\varepsilon_{\text{av,cd}}$ is the average cake porosity (m^3/m^3), L is the measured thickness of the cake (m) and A is the cross-sectional area of the filter chamber (m^2). For compressible cakes the average cake porosity depends on the applied pressure difference according to the power law. Therefore, after conducting filtration tests at a set of pressure differences (0.2, 0.4 and 0.6 MPa) it was possible to determine the parameters of this dependence (Equation 12).

$$\varepsilon_{\mathrm{av}} = \varepsilon_0 \left(\frac{\Delta p}{\Delta p_0}\right)^{\lambda} \tag{12}$$

where:

ε_0 = an empirical coefficient (m^3/m^3).

λ = an empirical coefficient (–).

Δp = the difference between absolute pressures of the gas above the suspension and below the cake (Pa).

Δp_0 = the standard pressure difference (Pa).

Δp_0 = 10^5 Pa.

3.3.2 Average specific cake resistance

Average cake resistance α_{av} and filter media resistance R_m are two of the most important parameters that affect the filtration process and can be determined after the filtration tests. Filtration tests were conducted under a constant pressure difference so that the general filtration equation can be reduced into the following linear equation, considering Δp as a constant (Wakeman & Tarleton 2005).

$$\frac{t}{V_{\mathrm{f}}} = \frac{\mu_{\mathrm{l}}\alpha_{\mathrm{av}}c}{2A^2\Delta p}\cdot V + \frac{\mu_{\mathrm{l}}R_{\mathrm{m}}}{A\Delta p} = aV_{\mathrm{f}} + b \tag{13}$$

$$c = \frac{C_{\mathrm{sl,w}}\rho_{\mathrm{l}}}{\left(1 - C_{\mathrm{sl,w}}\frac{m_{\mathrm{wc}}}{m_{\mathrm{dc}}}\right)} \tag{14}$$

where:

t = the filtration time (s).

V_f = the volume of filtrate (m^3).

μ_l = a liquid dynamic viscosity (Pa·s).

$C_{sl,w}$ = a suspension concentration given by mass fraction (kg/kg).

c = filtration concentration (kg/m^3).

a and b = parameters of a line.

Utilising the experimental data it is possible to plot the dependency $t/V_f = f(V_f)$. This relationship is linear according to Equation 13 and gives a straight line when graphed. Therefore the slope of this line (parameter *a*) and the intersection with the y axis (parameter *b*) can be determined. As the other parameters are known, the unknown α_{av} and R_m values can be determined. It is possible to use an automatic iterative calculation method to determine these two parameters more accurately by considering the pressure difference fluctuations (Safonov 2021).

For compressible cakes the average specific cake resistance depends on the applied pressure difference according to the power law. Therefore, after conducting filtration tests at a set of pressure differences (0.2, 0.4 and 0.6 MPa), it was possible to determine the parameters of this dependence:

$$\alpha_{\mathrm{av}} = \alpha_0 \left(\frac{\Delta p}{\Delta p_0}\right)^{N} \tag{15}$$

where:

α_0 = an empirical constant (m/kg).

N = an empirical constant (cake compressibility coefficient).

Δp = the difference between absolute pressures of the gas above the suspension and below the cake (Pa).

Δp_0 = standard pressure difference (Pa).

Δp_0 = 10^5 Pa.

4 Results

4.1 Physical properties of the initial materials, fractions and mixtures

True densities of the initial materials and fractions were determined using a pycnometer, and the densities of the prepared mixtures were calculated using Equations 9 and 10. PSDs for each sample were found by a laser diffraction experiment. The Blaine index was used to determine the SSA for each sample, and these were proportional to the air permeability.

4.2 Filterability properties of the tested materials

From the filtration tests conducted by the laboratory Nutsche filter for the sample materials prepared it was possible to determine the filterability parameters. The average cake porosity ($\varepsilon_{av,cd}$), based on the cake moisture ratio and filter cake dimensions, was calculated for each material using three different pressures. The results for the average bed porosities of NK materials are presented in Figure 4 and the average specific cake resistances determined for NK materials are shown in Figure 5.

It is clearly visible from Figure 5 that the finest F8 (+0–15) fraction with particle size less than 15 µm influences the overall cake resistance the most. The difference of the cake resistance made by this finest fraction is significant compared to other fractions and valid for both types of tailings material tested. This observation is also true of the KV material test results.

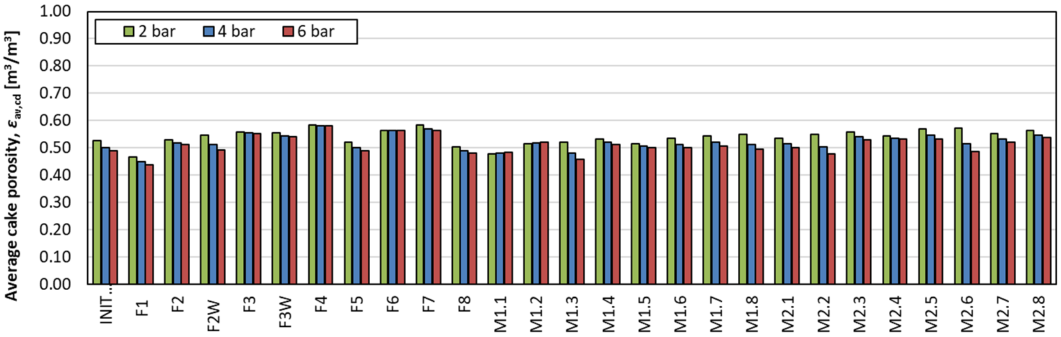


Figure 4 Determined average bed porosities in three different pressures for NK materials

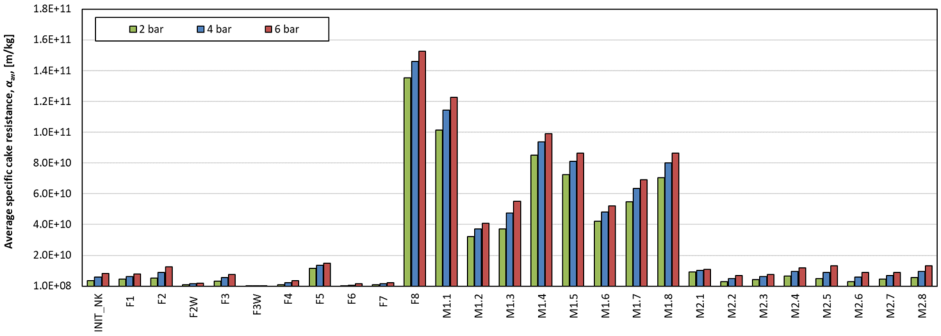


Figure 5 Determined averaged specific cake resistance for three different pressures for NK materials

Another interesting observation made was that the average cake resistance for the coarse fractions (F1 or F2) are higher compared to the fine fractions (F6 or F7) for NK tails. The reasoning attributes this to the imperfect fractionation of the dry vibrating sieves. In this separation technique, the fine particles stick to the coarser ones and vibrating is not enough to separate them. Finer fractions, F6 and F7, were obtained using hydrocyclone separation, thus their cake resistances were lower. However, the washing of coarse fractions resulted in significant reductions in average specific cake resistances.

5 Simulation

The results are encouraging and indicate that the methodology could be used to predict the properties of a mixture, and also form the basis of simulation and tool development.

Tailings by their nature are a mixture of minerals that grind at different rates and form various shapes. As a consequence of milling, the density, size and shape of particles all have an influence on filtration properties. (Hunger & Brouwers 2009) The parameters we measured were utilised to predict the behaviour of the filtration performance of a new mixture. The density of particles in the fractions varied, with denser material in the coarse fractions. Recombination of the densities of fractions into the predicted density of the mixtures followed the linear mixture model (Figure 6).

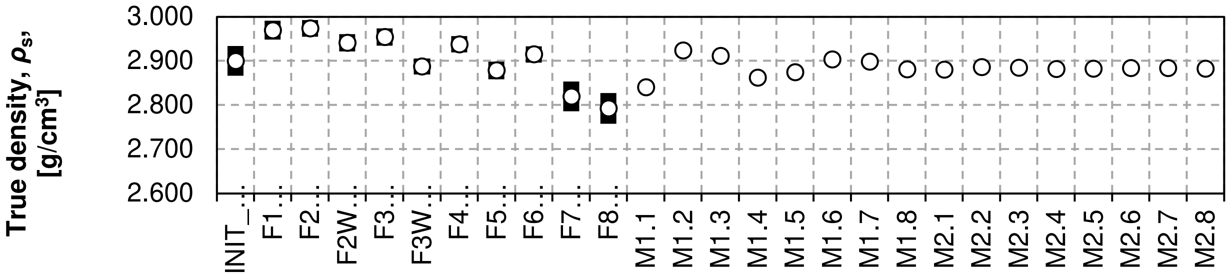


Figure 6 Density measurements

SSA was measured by laser diffraction (Figure 7), nitrogen adsorption and the Blaine index. As expected, it increased with a decrease in particle size. The recombination of the surface areas of fractions into the predicted surface area of the mixture followed the linear mixture model.

Bed porosity (Figure 8) was measured after filtration, and increased with a decrease in particle size (with a low point at 20 to 30% fines). The recombination of the bed porosity of fractions is not entirely linear, however, the area of interest is the higher fraction of fines. For the upper end, the predicted bed porosity of the mixture followed the linear mixture model if a constant void fraction was applied for the lower end.

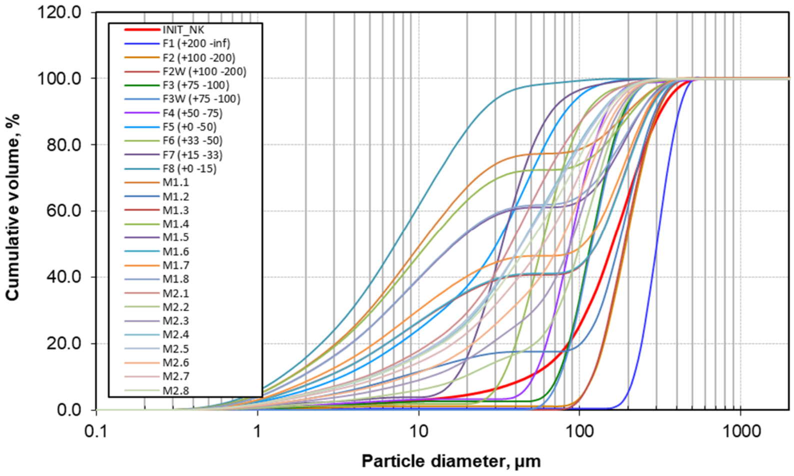


Figure 7 Laser diffraction measurement of PSD and SSA

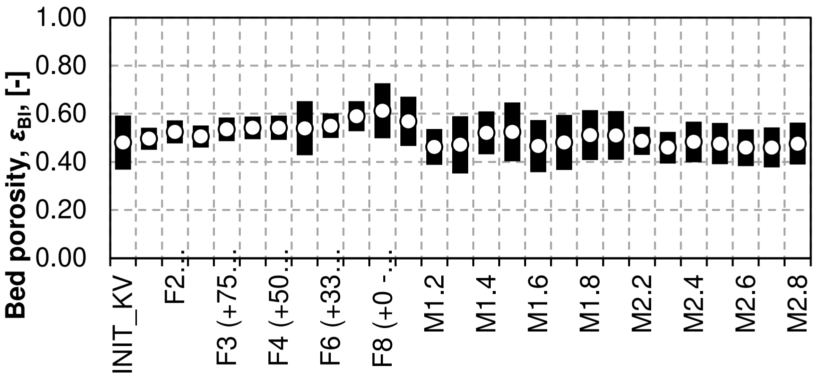
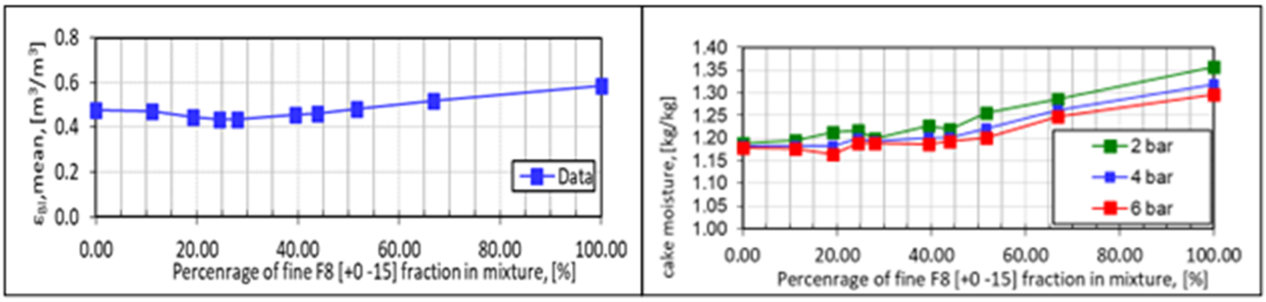


Figure 8 Determined bed porosities for KV materials

Cake moisture ratio (cake mass in kg/cake solid mass in kg) was determined after filtration of the mixtures, and increased with a decrease in particle size. The recombination of the cake moisture of fractions into the predicted cake moisture of the mixture followed the linear mixture model for a benchmark fixed drying time. Variations in the filtration sequence could be utilised to modify the cake moisture but the benchmark gave a good indication of the achievable cake moisture.



(a) (b)

Figure 9 Correlation of the percentage of fines to (a) the bed porosities and (b) the cake moisture

Within the limitation of the separation methods utilised in the experiment, the major factors influencing the filtration behaviour of a tailings sample if divided into different size fractions could be used to predict the filtration behaviour of a different mixture of the same material.

Average cake resistance α_{av} was measured for all fractions and mixtures. While the relationship is not linear it is a function of the above parameters. Therefore models such as Darcy and Kozeni-Karmen, utilising the data predicted from the parameters above, should be used to predict cake resistance.

The results are unique to the material tested and, with the limited range of materials tested, are not suitable for predicting an unknown tailings sample. The results are effective in determining the implications of changes in particle size for a measured material.

6 Tool development

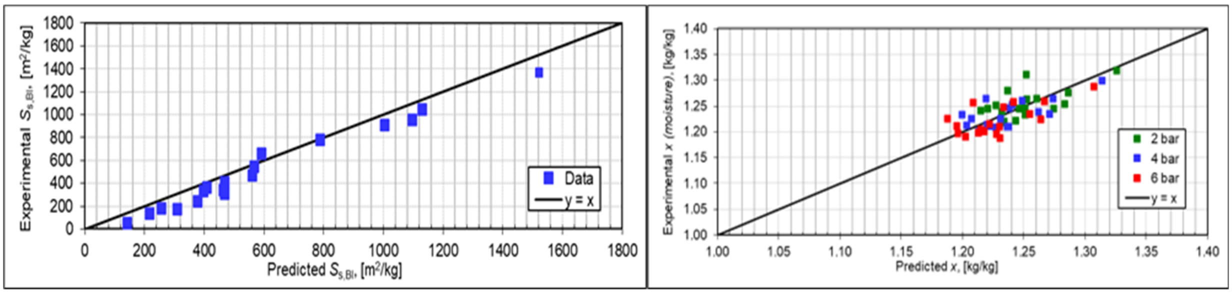
Once the properties of the fractions of the original test sample are known, the performance of a different mixture of the same fractions can be predicted. The desired PSD of a simulation material is broken down to the masses of fractions that form the original test material.

6.1 Particle swarm optimisation is an intelligent algorithm

The application for making decomposition of the test material based on knowledge about its PSD and the PSDs of containing fractions, and then predicting the test material filterability parameters, was developed in Visual Studio using Visual Basic programming language. The application interface consists of a set of tabs (Fractions data, Mixture generation, Search settings, Mixture decomposition and Parameters prediction) on which various parameters, which are necessary for prediction of the filterability parameters, are determined.

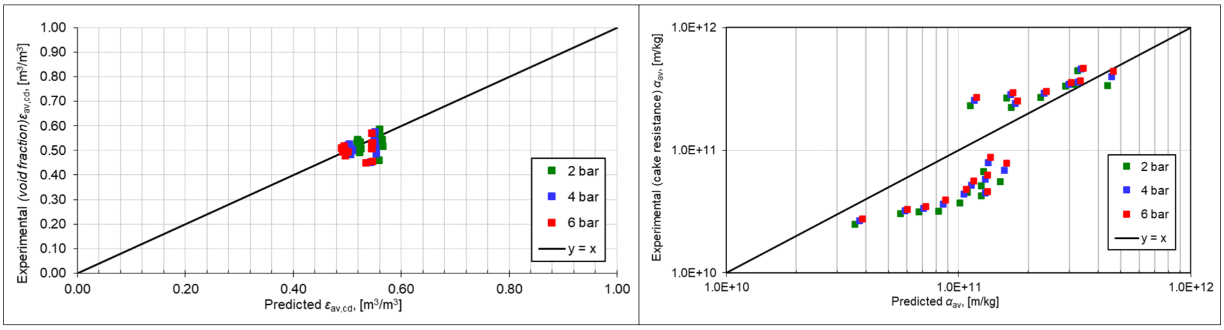
The performance of the developed application was tested on the real data: experimentally determined values of different parameters. Different plots on Figures 9 and 10 show the comparison between predicted and experimentally determined parameter values for materials.

As a conclusion it can be stated that knowing the material origin, the PSDs of material fractions, the experimentally determined fraction parameters and PSD of the target material, it is possible to predict the properties of the target material (including filterability properties). (Eberhart & Kennedy 1995)



(a) (b)

Figure 10 Experimental versus predicted (a) Blaine index and (b) moisture ratio of cake



(a) (b)

Figure 11 Experimental versus predicted (a) void fraction and (b) cake resistance

The final stage of the project was devoted to the development of a set of Unit DLL models in the HSC Sim process simulation software that solves the problem of predicting the filtration behaviour of the testing material. This was done by combining previously developed algorithms for predicting filterability parameters and for predicting filtering behaviour (based on filterability parameters) into a single easy-to-use flowsheet with an interface in HSC Sim. This can be shown schematically in Figure 12. Modelling the process in this system provides a number of significant advantages since the model can use various features of the software package, e.g. determining the parameters of material flows and the built-in database of substances.

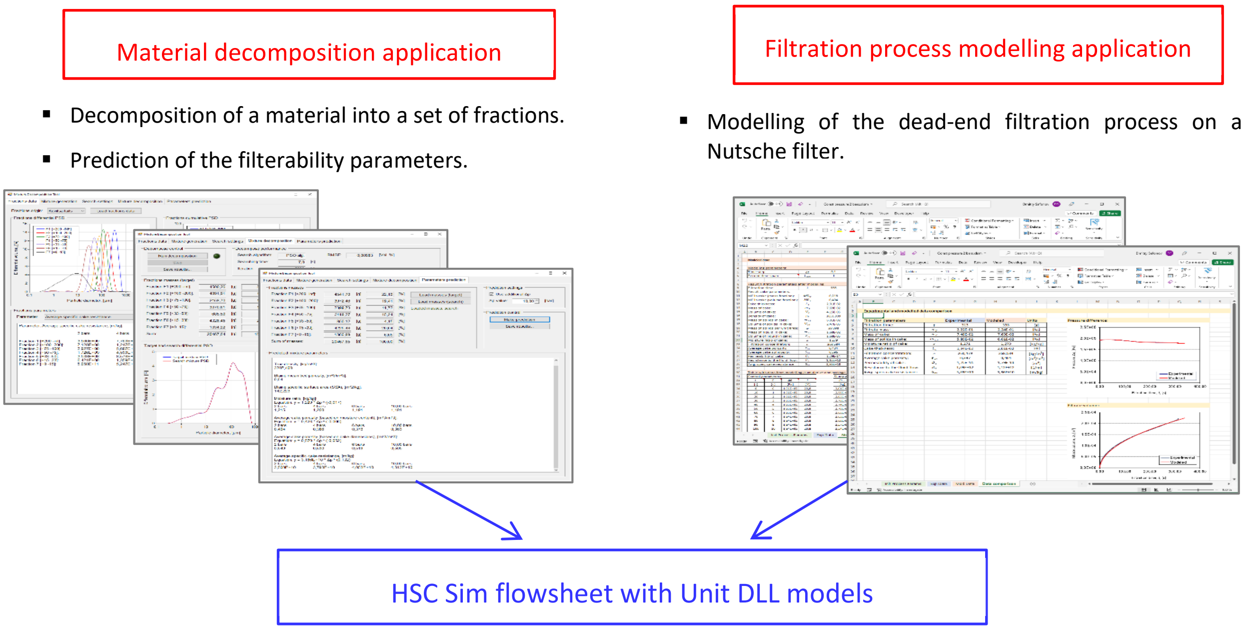


Figure 12 Schematic representation of the functionality of filtration behaviour prediction flowsheet in HSC Sim software

7 Conclusion

There were some limitations in the experimental work, particularly in the separation of the sample into fractions. The screening was imperfect, with some fines retained in the coarse fractions, and this may help explain the shift in Blaine index values between screen sorting and hydrocyclone sorting.

However, the methodology and the subsequent tool developed are an effective method for predicting the filtration behaviour of selected tailings samples where different particle size combinations can be simulated. It is expected that the method can also be utilised to simulate the implications of ore variability across a resource, and that the changes in behaviour caused by the clay content present in the sample can be predicted.

With further testing on different materials and the development of a minerals database of typical ores within HSC SIM, this methodology could be utilised to achieve scoping level accuracy for the prediction of filtration behaviour in untested materials.

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