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A Kinetic Model for Conventional Flotation of Coal

UNITED STATES DEPARTMENT OF THE INTERIOR

UNITED STATES BUREAU OF MINES

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UNIT OF MEASURE ABBREVIATIONS USED IN THIS REPORT

g/kg	gram per kilogram	r/min	revolution per minute
L/min	liter per minute	μm	microliter
min	minute	%	weigh percent
min^{-1}	reciprocal minute		

A KINETIC MODEL FOR CONVENTIONAL FLOTATION OF COAL

By Frank J. Susko[1] and Don A. Stanley[2]

ABSTRACT

The U.S. Bureau of Mines has developed a computer model to describe a flotation process. Coal data from conventional flotation has been converted to a simple, two-parameter kinetic model developed by Reuter and van Deventer (1,2)[3]. Each set of coal data was represented by two constants, α and β, and an average flotation rate. The success of the model was demonstrated when the calculated and experimental recoveries showed good correlation. The two-parameter model allows complex data to be defined much more efficiently than traditional knowledge-based models.

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[3]Underlined numbers in parenthesis refer to items in the list of references at the end of this report.

INTRODUCTION

Currently, process control in use by the industry consists of maintaining setpoints for individual unit operations. The conventional form of process control does not adequately maintain these setpoints if there are changes in the feed. This is a particular concern to the mineral processing industry because the mineralogy of the feed can vary. The U.S. Bureau of Mines (USBM) has developed adaptive control processes which respond to complex problems such as changes in the feed. Researchers at the USBM have incorporated fuzzy logic and genetic algorithms into adaptive control routines (3,4). The result has been a very effective method of controlling both individual and multiple component unit operations. Examples are a cart-pole system (5), a pH experiment (6), a chaotic system (7) and an exothermic reaction (8).

Considerable work goes into developing the software associated with the adaptive control algorithms. A component of this effort is the development of computer models of individual unit operations. Numerous models exist for a wide variety of mineral processing operations. Examples include models for a flotation column (9), a hydrocyclone (10), a ball mill (11), a rapid flotation system (12), and a conventional flotation cell (13). Each of the above mentioned unit operations were represented by a series of complex equations. For example, the model which describes the conventional flotation system is based on the first order flotation rate equation (13):

$$\left(\frac{dC}{dt}\right) = - k\, C(t) \qquad (1)$$

where C is the concentration of hydrophobic particles in the cell at any time, t is time and represents the duration of the flotation test and k is the flotation rate constant. In order to model the flotation process, the flotation rate constant was related to the product of several probabilities. The probabilities, in turn, were defined by a very complex series of equations. The terms used in these equations included fluid, particle and bubble densities, particle and bubble size distributions, number of bubbles per unit volume, and dissipation energies (13). The result was a very complex model when the above mentioned parameters were used. There is, however, an alternative to using numerous fundamental parameters to model a unit operation.

Reuter and van Deventer proposed a two-parameter, knowledge-based kinetic model to simulate processes which do not have adequate fundamental models (2). This model could simulate both batch and continuous flotation operations and is applicable for all process conditions (reagent concentration, pH, particle density, etc.) (2). The model is described as "knowledge-based" because it consists of a generalized model and a database (1). The database is a collection of experimental data points, for example, concentration-time data from a flotation process. Each of these experimental data points is called an object or a pivot point. The generalized kinetic model was based on the first order rate equation:

$$\left(\frac{dC}{dt}\right) = - \alpha\, k\, (C(t) - C_0\, (1 - \beta)) \qquad (2)$$

where α and β are constants and C_0 is the original concentration of hydrophobic particles (2). When experimental data from the data base are utilized in equation 2, the values of α and β are 1. Equation 2 then resembles the first order flotation rate equation (equation 1). This equation is then used to solve for the flotation conditions such as concentration and flotation rate (2). The α and β constants come into play when there is no experimental data associated with a set of conditions. Information for conditions between the experimental data points can be gleaned by altering the values of α and β. Each set of process conditions would have a unique pair of α and β values associated with it (2). The Reuter and van Deventer model directly uses the experimental data to extrapolate to process conditions which exist between experimental data points. Hence, no curve fitting, such as the least squares method, would be required (2).

The USBM developed a knowledge base model based on Reuter and van Deventer's work. Data from the conventional flotation of coal was used for this study. Each data set consisted of pairs of residence times and percent recovery data. A flotation rate was calculated for each pair of time-recovery data set. An average flotation rate was then calculated to represent the conditions for that particular set of flotation conditions. Using Reuter and van Deventer's two-parameter kinetic equation (equation 2), values for α and β were determined with the help of a genetic algorithm (4). Each set of process conditions had a unique pair of α and β values plus an average flotation rate associated with it (2). Rather than using a series of time and recovery data to represent a particular set of flotation conditions, data was reduced to values for α, β and an average flotation rate. Converting complex knowledge into a simpler form made manipulating the data on the computer much more efficient.

MINERAL, REAGENTS AND EXPERIMENTAL PROCEDURE

Conventional flotation tests were performed on a coal sample obtained from the feed stream of a coal cleaning operation. Table 1 lists the particle size analysis for the sample as well as the composite assay. Prior to the flotation process, each sample was conditioned with fuel oil at 1.0 g/kg of ore. Methyl isobutyl carbinol (MIBC) was added at 0.1 g/kg ore to stabilize the bubbles. The coal sample was obtained as a slurry at a pH of 8.5. The original pH was maintained throughout the flotation testing.

Tests were carried out in a conventional flotation cell set at 1,100 r/min and air was introduced at 4 L/min. One test was run at 3% solids while another was run at 5% solids. Samples of the flotation concentrate were taken at intervals ranging up to 10 min to determine the flotation kinetics. The original ore and all samples were analyzed using the rough ash technique (14). The remainder of the sample was assumed to be coal. Sulfur analysis was not considered for these tests.

Table 1. - Particle size analysis and composite assay of the coal sample

Coal size range, μm	Mass, %[1]	Ash, %	Coal, %	Coal distribution, %
Plus 38	32.04	5.31	94.69	42.69
Minus 38	67.96	40.08	59.92	57.31
Composite	100.00	28.94	71.06	100.00

[1]All percentages are on a weight basis.

RESULTS AND DISCUSSION

Figure 1 plots the recovery versus residence time for the conventional flotation tests run at 3 and 5% solids. The data appears to fit equation 1, the first order flotation rate equation. In order to further analyze the data, equation 1 was solved for the flotation rate constant:

$$k = -\left(\frac{1}{t}\right) \ln (1 - R) \qquad (3)$$

where R is the recovery of hydrophobic particles and is defined as the ratio of the concentration of hydrophobic particles at time t (C(t)) over the original concentration of hydrophobic particles (C_0). Using equation 3, a flotation rate constant was calculated for each pair of time and concentration data. Table 2 lists the experimental recoveries (R) and the calculated flotation rates (k) at various residence times (t) for the conventional flotation tests run at 3 and 5% solids. The average calculated flotation rate constant is 0.333 min^{-1} for the test run at 3% solids and is 0.425 min^{-1} for the test run at 5% solids.

The next step was to represent the data in table 2 as objects. To do this, equation 2 was solved for the recovery:

$$R_{calc} = \beta \left(1 - e^{-\alpha k_{avg} t} \right) \qquad (4)$$

where R_{calc} is the calculated recovery and k_{avg} is the average flotation rate constant. The values for α and β were determined using a genetic algorithm regression method (3,4). This method searches for best values of the constants for the Reuter-van Deventer equation that most closely calculates the experimental recovery for each test. The genetic algorithm determines the optimum values of α and β which produce the least amount of error between the experimental and calculated recovery. Using this mathematical technique, the complex time and recovery data was reduced to two constants, α and β, and an average flotation rate constant (k_{avg}). These values as well as the mean squared error from the genetic algorithm regression method for the conventional flotation tests run at 3 and 5% solids are listed in table 3. The very small values for the mean squared error indicates a good correlation between the experimental and calculated values of the recovery. The results are listed in table 4. Figure 2 is a plot of the experimental and calculated recoveries versus the residence time in the flotation cell and also demonstrates the good correlation between the experimental and calculated values.

Table 2. - Experimental recovery and calculated flotation rates for conventional flotation tests run at 3 and 5% solids (from eq. 3)

	Residence time, min				
	0.0	1.0	2.0	5.0	10.0
3% SOLIDS					
Experimental recovery, % coal . . .	0.0	0.318	0.546	0.802	0.900
Calculated flotation rate[1], min^{-1} . .	0.0	0.382	0.395	0.323	0.230
5% SOLIDS					
Experimental recovery, % coal . . .	0.0	0.412	0.637	0.861	0.931
Calculated flotation rate[1], min^{-1} . .	0.0	0.532	0.506	0.394	0.267

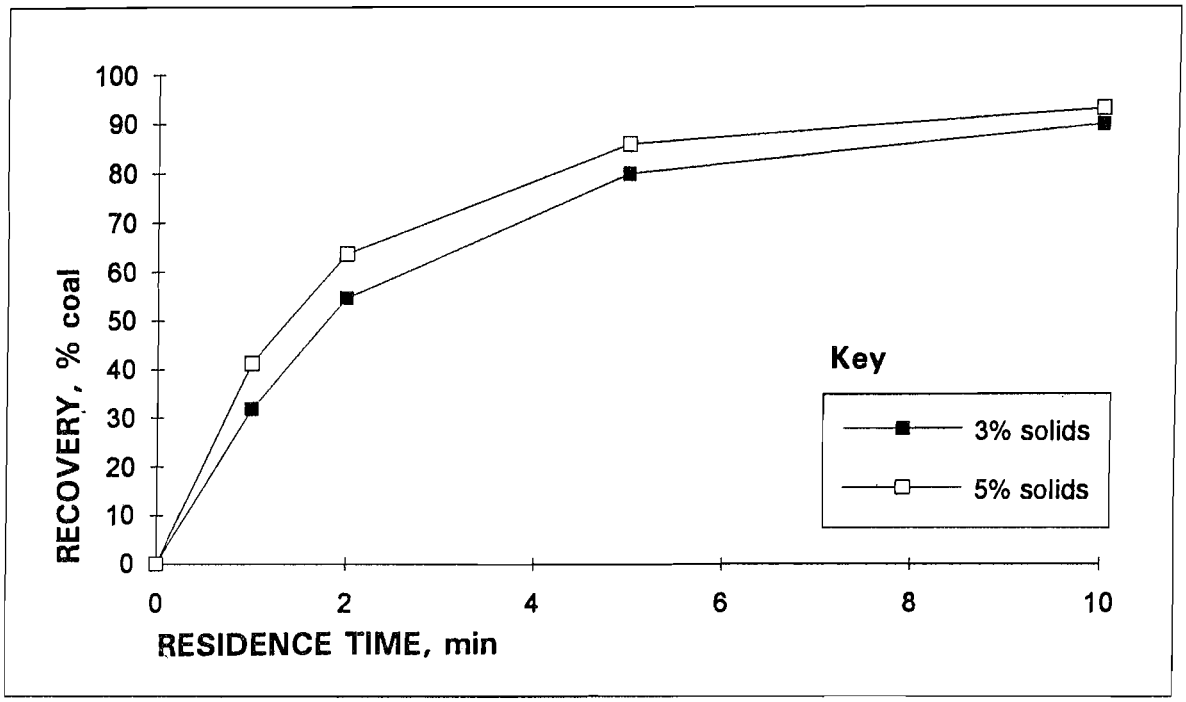
Table 3. - Values for α, β, k_{avg} and the mean squared error for conventional flotation tests run at 3 and 5% solids

	3% solids	5% solids
α	1.248	1.396
β	0.932	0.919
k_{avg}	0.333	0.425
mean squared error	0.000016	0.000083

Table 4. - Experimental recovery and calculated flotation rates for conventional flotation tests run at 3 and 5% solids (from eq. 4)

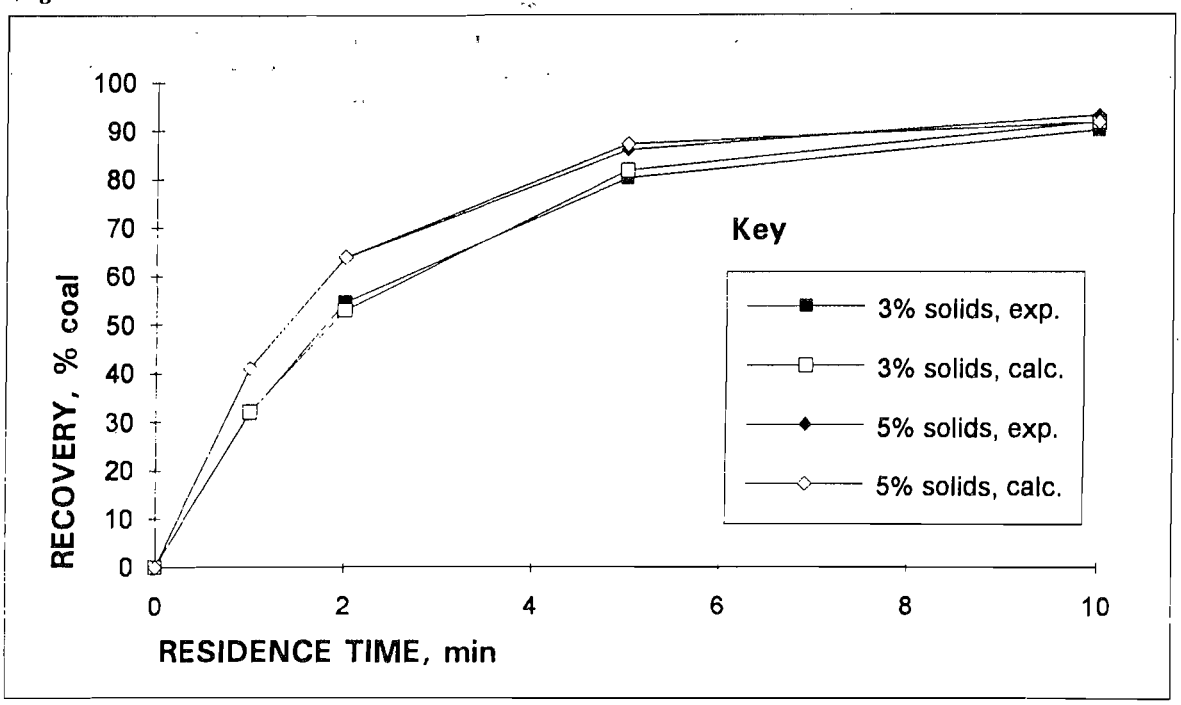
	Residence time, min				
	0.0	1.0	2.0	5.0	10.0
3% SOLIDS					
Experimental recovery, % coal . . .	0.0	0.318	0.546	0.802	0.900
Calculated flotation rate[1], min^{-1} . .	0.0	0.320	0.530	0.818	0.918
5% SOLIDS					
Experimental recovery, % coal . . .	0.0	0.412	0.637	0.861	0.931
Calculated flotation rate[1], min^{-1} . .	0.0	0.411	0.638	0.872	0.916

Figure 1



Recovery versus residence time for the conventional flotation tests run at 3 and 5% solids.

Figure 2



Experimental and calculated recovery versus residence time for the conventional flotation tests run at 3 and 5% solids.

CONCLUSIONS

Using a method developed by Reuter and van Deventer (1,2), complex data from the conventional flotation of coal was converted to a simple, two-parameter model. Two sets of data were defined by two constants, α and β, and an average flotation rate. The results indicated a very good correlation between the experimental and calculated recoveries. The mean squared error between the experimental and calculated recoveries were >0.0001. Using this technique, complex information can be represented in a much more concise way. This would facilitate the manipulation of the data in computer models.

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