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Evaluation of slurry settling rate using fuzzy rule-based modeling

By

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Abstract

The pressure acid leach process is the most widely used method of metal extraction from laterite ores. The self-weight settling rate of the ore slurries governs the throughput of the process and is improved by adding synthetic polymers. The charge density, molecular weight, and dosage of the polymers are the key factors influencing the settling rate of the slurries. This interdisciplinary paper uses the geotechnical understanding of hindered sedimentation for a mining engineering application. A conceptual fuzzy rule-based model was developed to evaluate the initial hydraulic conductivity of polymer-modified laterite ore slurries. Identification of control parameters and selection of the model architecture (fuzzy rule-base) were based on expert judgement. The developed model was trained and validated using bench-scale settling test data. The model reasonably predicts the initial hydraulic conductivity of polymer-added laterite ore slurry with a coefficient of determination of 0.75. Rank correlation coefficient based sensitivity analyses indicated that charge density was the most significant polymer parameter followed by molecular weight and then by dosage. Charge density accounted for more than 97% of variability in the initial hydraulic conductivity estimates for both anionic and cationic polymers.

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1. Introduction

The pressure acid leach process is the most widely used method for extracting nickel and cobalt from laterite ores due to its high recovery, low environmental risk, and economic viability [1]. This mining process requires that the ore slurries settle at a rapid rate under self-weight. Synthetic polymers are added to the feed for improved slurry settling rates thereby increasing system efficiency in terms of process throughput [2]. Given a consistent composition of colloids (size distribution, mineralogy, and surface charges) and water (pH, ions concentration, and electrical conductivity), the settling rate of laterite ore slurries is governed by polymer parameters: charge density (*C*); molecular weight (*M*); and dosage (*D*). The collide-water-polymer interactions are highly complicated and result in an insufficient mechanistic understanding of the settling process [3].

Polymer performance is usually assessed using bench-scale settling tests. Due to expensive and time-consuming procedures, the test programs are mostly unsystematic and incomprehensive thereby generating limited amount of useful data [4]. This precludes the application of data intensive techniques such as neural networks or multiple regressions for performance prediction [5]. Vaguely known polymer parameters add further complexity to this non-linear problem. For example, the actual values of *C* and *M* are seldom known as manufacturers only provide their ranges [6]. Although *D* is known within experimental error, the adsorbed polymer amount is always uncertain and the resulting discrepancy is not quantifiable [2]. Therefore, there was an exigent need to develop a conceptual model with the following features: (a) independent of test results; (b) based on the opinion of experts with reasonable process understanding; (c) captures the vagueness and uncertainty in polymer parameters; and (d) sufficiently robust to predict the intricate colloid-water-polymer interactions. These requirements could be addressed by adopting a fuzzy rule-based modeling approach that translates qualitative information into numerical interpretation using linguistic reasoning.

Based on the geotechnical understanding of hindered sedimentation, this interdisciplinary paper presents a conceptual fuzzy rule-based model to evaluate the settling rate of a typical laterite ore slurry modified with synthetic polymers. Expert opinion from the mining and the chemical industry was used to develop the model by establishing fuzzy *if-then* rules. Thereafter, the model was trained and validated using data from bench-scale settling tests. Finally, sensitivity analyses were performed to delineate the relative significance of polymer parameters on the settling rate of laterite ore slurries.

2. Geotechnical Phenomenology

Figure 1 gives the results of bench-scale settling test in the form of solid-liquid interface height versus time for a typical laterite ore slurry [7]. The initial rapid decrease in interface height, known as hindered sedimentation, refers to the settling of a spatial network of soil particles without measurable effective stresses [8]. The swift slurry settling gradually decreased with time as the material acquired a soil-like character. This stage of slurry settling is known as self-weight consolidation and commences when the solid grains are in contact thereby transmitting effective stresses [9]. The slurry exhibited a smooth transition between the two distinct settling regimes. The slope of the initial straight-line portion of the settling curve that represents hindered sedimentation was used to determine the initial hydraulic conductivity (k_i) as follows [10]:

$$k_i = V_s \left[\frac{\gamma_w (1 + e_i)}{\gamma_s - \gamma_w} \right] \tag{1}$$

The k_i of laterite ore slurry without polymers measured 0.124 cm/sec. This corresponds to a median settling rate for such heavy materials and must be improved using polymers [7].

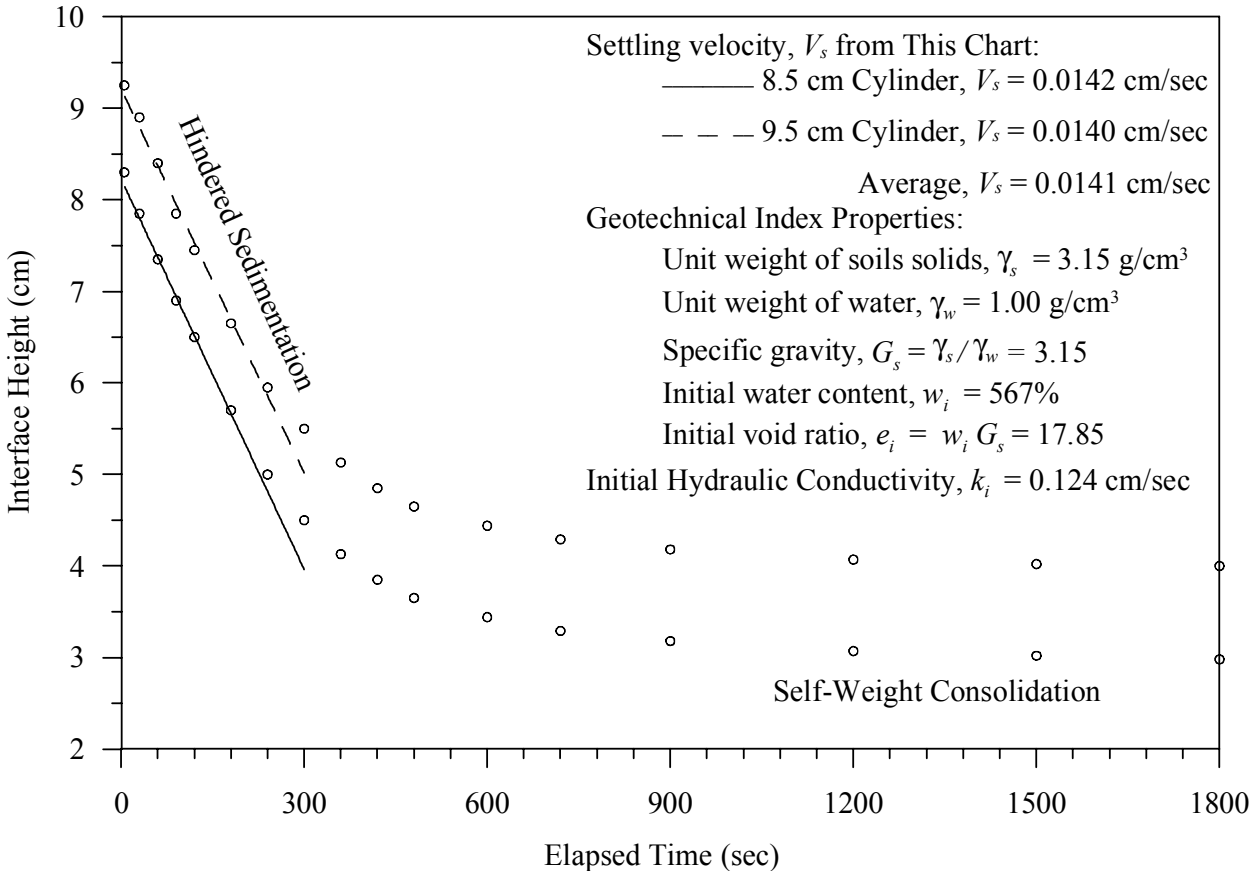

Figure 1: Bench-scale settling test data

3. Theoretical Background

Fuzzy numbers describe imprecise information by correlating an uncertain quantity (x) with a membership function ($\mu(x)$) defined over [0,1] interval. The relationships are represented by *if-then* rules of the form "*If* antecedent proposition *then* consequent proposition". In a linguistic model, the rule (R_i) can be written as follows [11]:

$$R_i: \quad \textit{If } x \text{ is } A_i \textit{ then } y \text{ is } B_i; \quad i = 1, 2 \ldots K \tag{2}$$

Input (x) and output (y) are linguistic variables whereas A_i and B_i are linguistic constants. The truth-value (real number) of the propositions depends on similarity between variables and constants. Collectively, the rules and the constants form the knowledge base of the model. To restrict the simultaneous occurrence of x and y, the fuzzy conjunction ($A_i \wedge B_i$) is computed by a *minimum* operator (t-norm) on the Cartesian X-Y product space for all possible (x, y) as follows:

$$R_i = A_i \times B_i, \quad \text{that is, } \mu_{Ri}(x, y) = \mu_{Ai}(x) \wedge \mu_{Bi}(y) \tag{3}$$

The fuzzy relation R represents the entire model and is given by the disjunction (union or maximum, that is, s-norm) of the K individual relations of the R_i rule as follows:

$$R = \bigcup_{i=1}^{K} R_i, \quad \text{that is, } \mu_R(x, y) = \max_{1 \le i \le K} \left[\mu_{Ai}(x) \wedge \mu_{Bi}(y) \right] \tag{4}$$

For an input fuzzy value $x = A'$, an output value B' is given by the following composition:

$$\mu_{B'}(y) = \max_{X} \left[\mu_{A'}(x) \wedge \mu_R(x, y) \right] \tag{5}$$

After substituting $\mu_R(x, y)$ from Eq. (4) and rearranging, the above expression is as follows:

$$\mu_{B'}(y) = \max_{1 \le i \le K} \left(\max_{X} \left[\mu_{A'}(x) \wedge \mu_{Ai}(y) \right] \wedge \mu_{Bi}(y) \right) \tag{6}$$

Denoting $\beta_i = \max_{X} \left[\mu_{A'}(x) \wedge \mu_{Ai}(y) \right]$ is the *degree of fulfillment* of the i^{th} rule antecedent, the resulting output fuzzy set of the linguistic model is of the following form:

$$\mu_{B'}(y) = \max_{1 \le i \le K} \left[\beta_i \wedge \mu_{Bi}(y) \right] \tag{7}$$

The fuzzy set *defuzzification* using the quality ordered weights (w_l) yields a crisp output (Y_i^{mod}). Denoting l as the number of output granules, $\mu_{B'l}(y)$ as the output membership for each granule (Eq. 7), and B_o^l as the respective crisp values, defuzzification is done as follows [12]:

$$Y_i^{mod} = \sum_{l=1}^{m} \mu_{B'l}(y) \times B_O^l \times w_l \tag{8}$$

The model is fine-tuned on test data to determine w_l. This training is done by linear optimization of mean absolute error (MAE) that is defined by an objective function, $min[abs(Y_i^{obs} - Y_i^{mod})/n]$, where Y_i^{obs} is observed value, Y_i^{mod} is modeled value (Eq. 8), and n is number of observations.

4. Initial Hydraulic Conductivity Modeling

Figure 2 gives a conceptual framework for k_i modeling of polymer-modified laterite ore slurries. The identification of input parameters (C, M, and D) and the selection of model architecture (fuzzy rule-base) were based on extensive consultations with the mining and the chemical industries. A multiple inputs-single output (MISO) model was developed for k_i prediction. The model was trained on the bench-scale settling test data by linear optimization. Rank correlation coefficient-based sensitivity analyses were performed to identify the percent contribution of input parameters in k_i variability.

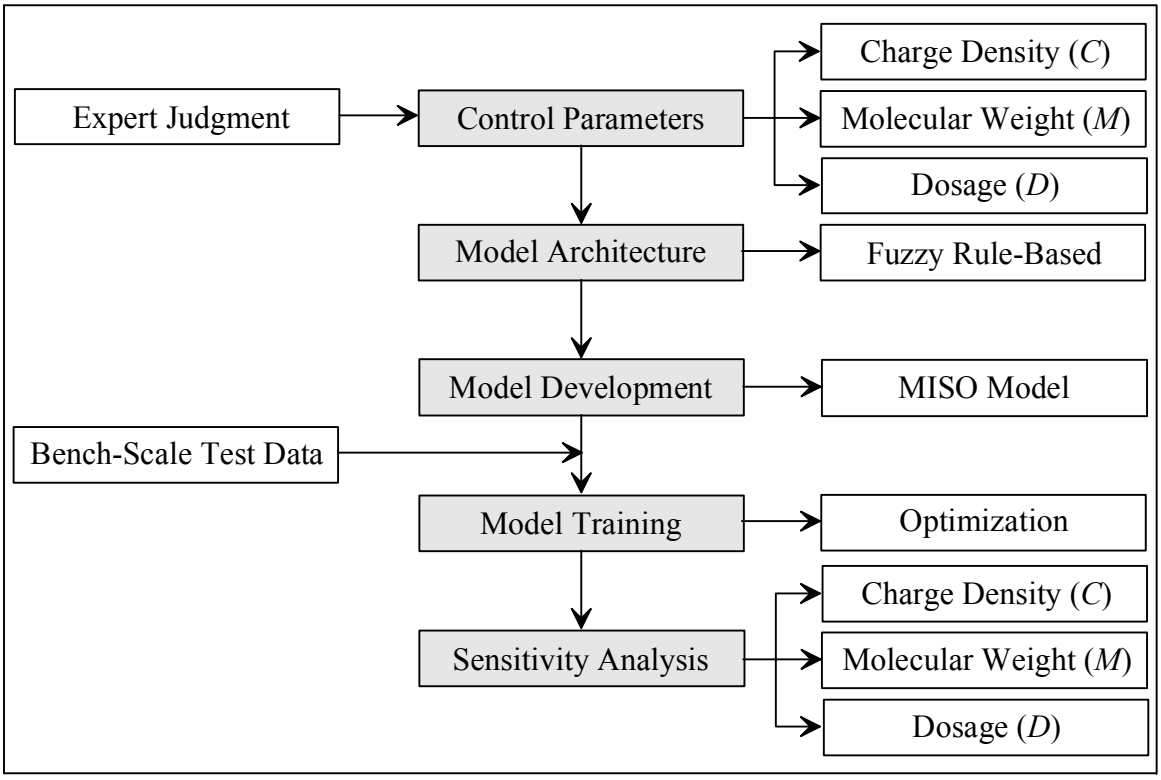

Figure 2: Conceptual framework for k_i modeling

Figure 3 gives the model inputs (C, M, and D) defined as linguistic constants (triangular fuzzy numbers, TFN). These control parameters used two granules (A_i) of *low* and *high* for both anionic and cationic polymers. The variation in C and M among the two polymer types indicates the variability during their commercial-scale production [6]. These uncertainties led to a higher level of uncertainty in the amount of adsorbed polymer at a given D. The granule definitions captured the k_i uncertainty associated with different combinations of the investigated input parameters.

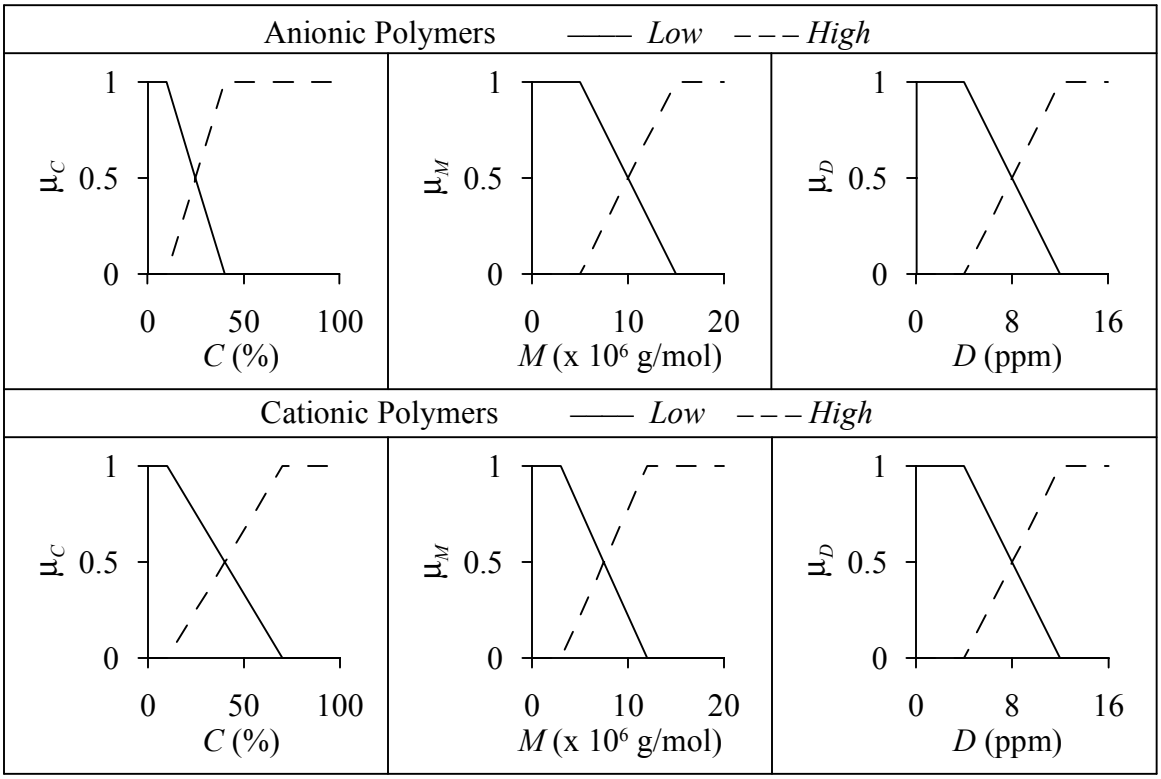

Figure 3: Model inputs in the form of linguistic constants

Table 1 summarizes the rule-base for the conceptual model. The rules were of the following general form (extension of Eq. 2 for MISO models):

$$R_i: \quad \textit{If } x_1 \text{ is } A_{1i} \textit{ and } x_2 \text{ is } A_{2i} \textit{ and} \ldots \textit{and } x_p \text{ is } A_{pi} \textit{ then } y \text{ is } B_i \qquad i = 1, 2 \ldots K \qquad (9)$$

The ranges of linguistic constants were assigned based on the anticipated data uncertainty. Rule 1 interprets that *if* charge density, molecular weight, and dosage are *low*, *then* initial hydraulic conductivity is *low*. This output is the same for Rule 2 despite the use of a *high D*; *C* and *M* remain unaltered. The variation among rules for anionic and cationic polymers was due to their variable interactions with the slurry [3].

Figure 4 outlines the k_i model for anionic polymers with assumed *C*, *M*, and *D*. The various steps including fuzzification, estimating degree of fulfillment, rules aggregation, and defuzzification are described to make an inference from the model. In this example, model inputs: $C = 20$, $M = 8$, and $D = 5$ were fuzzified on their respective scales (Figure 3). All rules were fired and their degrees of fulfillment (β_i) were obtained. By aggregating the rules using Eq. 6, memberships (μ_{ki}) for *low*, *medium*, and *high* output fuzzy numbers were estimated to be 0.67, 0.30, and 0.33, respectively; the memberships represented the heights of the output granules. A crisp output (k_i^{mod}) of 0.178 cm/sec was obtained by defuzzification (Eq. 8).

Table 1: Rule-base for the model

Polymer Type	Rule No., R_i	*If*	Charge Density, C	*and*	Molecular Weight, M	*and*	Dosage, D	*then*	Initial Hydraulic Conductivity, k_i
Anionic	R_1	*If*	*low*	*and*	*low*	*and*	*low*	*then*	*low*
	R_2	*If*	*low*	*and*	*low*	*and*	*high*	*then*	*low*
	R_3	*If*	*low*	*and*	*high*	*and*	*low*	*then*	*medium*
	R_4	*If*	*low*	*and*	*high*	*and*	*high*	*then*	*medium*
	R_5	*If*	*high*	*and*	*low*	*and*	*low*	*then*	*high*
	R_6	*If*	*high*	*and*	*low*	*and*	*high*	*then*	*high*
	R_7	*If*	*high*	*and*	*high*	*and*	*low*	*then*	*high*
	R_8	*If*	*high*	*and*	*high*	*and*	*high*	*then*	*high*
Cationic	R_1	*If*	*low*	*and*	*low*	*and*	*low*	*then*	*low*
	R_2	*If*	*low*	*and*	*low*	*and*	*high*	*then*	*low*
	R_3	*If*	*low*	*and*	*high*	*and*	*low*	*then*	*high*
	R_4	*If*	*low*	*and*	*high*	*and*	*high*	*then*	*low*
	R_5	*If*	*high*	*and*	*low*	*and*	*low*	*then*	*low*
	R_6	*If*	*high*	*and*	*low*	*and*	*high*	*then*	*medium*
	R_7	*If*	*high*	*and*	*high*	*and*	*low*	*then*	*medium*
	R_8	*If*	*high*	*and*	*high*	*and*	*high*	*then*	*high*

The model was trained on the data comprising of 16 bench-scale settling tests for anionic polymers; test results are given later in this paper. While the data was limited for robust training, it was sufficient to develop a conceptual model that incorporated both subjective (expert judgment) and objective (test data) information and that can be improved with additional data. The training was conducted by solving the objective function, that is, by minimizing MAE. This allowed the determination of the quality ordered weights (w_l). The constraints on w_l were heuristically defined as $0.1 \leq w_L \leq 0.4$, $0.5 \leq w_M \leq 1$, and $1.5 \leq w_H \leq 2$. Using the optimized quality ordered weights of $w_L = 0.12$, $w_M = 0.53$, and $w_H = 1.2$ for defuzzification, the trained model utilized both expert judgment and bench-scale settling test data.

Sensitivity analyses were used to understand the relative significance of input parameters on the model output and to quantify the change in output due to input variability. To estimate the contribution of each input parameter to the output variance, rank correlation coefficients were determined. These coefficients estimated the degree of association between two random variables and linearly correlated model inputs and output. From the ranges defined in Table 1, the input parameters (C, M, and D) were randomly generated assuming uniform distributions. The random values of the input parameters were fuzzified and subsequently inferenced using the rule-based algorithm explained earlier. Likewise, the crisp model outputs were ranked.

Model Inputs

C (%) = 20 M (x 10^6 g/mol) = 8 D (ppm) = 5

1. Fuzzification

$\mu_C^L = 0.67$; $\mu_C^H = 0.33$ $\mu_M^L = 0.70$; $\mu_M^H = 0.30$ $\mu_D^L = 0.92$; $\mu_D^H = 0.08$

2. Rules Firing - estimating the degree of fulfillment (β_i)

R_1: *min* (0.67, 0.70, 0.92) → $\beta_1 = 0.67$

R_2: *min* (0.67, 0.70, 0.08) → $\beta_2 = 0.08$

R_3: *min* (0.67, 0.30, 0.92) → $\beta_3 = 0.30$

R_4: *min* (0.67, 0.30, 0.08) → $\beta_4 = 0.08$

R_5: *min* (0.33, 0.70, 0.92) → $\beta_5 = 0.33$

R_6: *min* (0.33, 0.70, 0.08) → $\beta_6 = 0.08$

R_7: *min* (0.33, 0.30, 0.92) → $\beta_7 = 0.30$

R_8: *min* (0.33, 0.30, 0.08) → $\beta_8 = 0.08$

3. Rules Aggregation - estimating the membership

$\mu_{ki}^L = max(\beta_1, \beta_2) = max(0.67, 0.08) \rightarrow 0.67$

$\mu_{ki}^M = max(\beta_3, \beta_4) = max(0.30, 0.08) \rightarrow 0.30$

$\mu_{ki}^H = max(\beta_5, \beta_6, \beta_7, \beta_8) = max(0.33, 0.08, 0.30, 0.08) \rightarrow 0.33$

$k_i = (\mu_{ki}^L, \mu_{ki}^M, \mu_{ki}^H) = (0.67, 0.30, 0.33)$

4. Defuzzification - determining the output

$k_i^{mod} = \mu_{ki}^L \times L_O \times w_L + \mu_{ki}^M \times M_O \times w_M + \mu_{ki}^H \times H_O \times w_H$

Centroids of k_i x 10^{-3} cm/sec (Output TFN)

$L_O = 42$; $M_O = 167$; $H_O = 292$

Quality Ordered Weights

$w_L = 0.12$; $w_M = 0.53$; $w_H = 1.2$

$k_i^{mod} = 0.178$ cm/sec (Crisp)

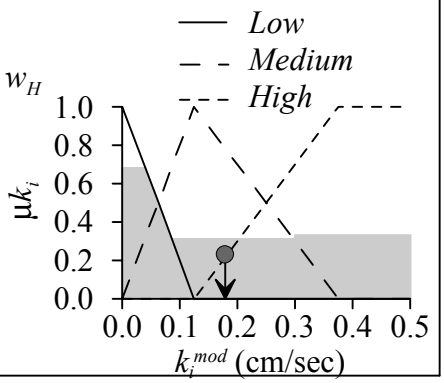

Figure 4: Model outline for anionic polymers

4. Data Collection

Table 2 gives the average values of polymer parameters and bench-scale settling test data. Based on 2^4 factorial design, *C*, *M*, and *D* were tested at two levels for the acrylamide-based anionic and cationic polymers, provided by Ciba Specialty Chemicals Inc., Canada. The *low* and *high* polymer dosages corresponded to 4 mg/L (53 g/ton) and 12 mg/L (159 g/ton), respectively, based on dry mass of polymer and solids in the slurry. Two sets of test data were obtained for improved accuracy. A fresh concentrated stock solution was prepared for each test by dissolving the polymers in distilled water. To preclude the effect of polymer aging, this solution was instantly diluted to a test solution and immediately used.

Table 2: Average values of polymer parameters and bench-scale settling test data

Polymer Type	Charge Density, C (%)	Molecular Weight, $M \times 10^6$ (g/mol)	Dosage, D (ppm)	Initial Hydraulic Conductivity, k_i^{obs} x 10^{-3} (cm/sec)	
				8.5 cm Cylinder	9.5 cm Cylinder
Anionic	10	5	4	7	7
	10	5	12	15	15
	10	15	4	88	85
	10	15	12	99	102
	40	5	4	234	234
	40	5	12	394	423
	40	15	4	263	292
	40	15	12	372	409
Cationic	10	3	4	11	12
	10	3	12	14	14
	10	12	4	409	445
	10	12	12	5	5
	70	3	4	7	8
	70	3	12	197	204
	70	12	4	179	182
	70	12	12	394	438

The stock solution was prepared by weighing 0.5 g of dry powdered polymer in a clean dry 250 mL beaker. Then, 1 mL of methanol (for anionic polymers) or acetone (for cationic polymers) was added as the powder was swirled for an even distribution. Next, 99 mL of distilled water was added and a magnetic stirrer rod was immersed in the beaker. The beaker containing the above ingredients was put on a stirring machine for 1 hour at a moderate speed of 12 rpm. Finally, the stock solution was diluted to 0.05% test solution for dosing by adding 10 mL of the former to 90 mL of distilled water. Thus, 1 mL of the test solution contained 0.5 mg of dry polymer. When divided by the total volume of the slurry (L), this gave the amount of 1 mL of test solution in the slurry in mg/L. To get the polymer dosage volume (in mL), the desired amount in mg/L of slurry was divided by the amount of dry polymer in 1 mL of the test solution.

Test samples were prepared by mixing the required dosage from the test solution with the known volume of the slurry at 15% initial solids concentration (by weight). The desired polymer volume was introduced to the slurry by a graduated plastic syringe. To minimize floc breakage, ingredients were mixed using a steel plunger that was rotated at a rate of 12 rpm for 5 minutes. The slurry was poured into the graduated cylinder up to a known height (8.5 cm and 9.5 cm) and was allowed to settle under gravity. The solid-liquid interface movement was captured at equal

time intervals using a camcorder with macro lenses for up to 7 times image magnification. The camcorder was connected to a computer that stored the captured frames in a digital format. After test completion, the enlarged digital frame files were carefully viewed and the observed data were recorded as interface height versus time; k_i was determined as explained in Figure 1.

5. Results and Discussion

Figure 5 gives the results of model training and validation by plotting the observed test data as a function of the predicted model data. The coefficient of determination (R^2) estimated 0.75 for the available data. The discrepancy in the predicted and the observed k_i values is primarily attributed to the limited amount of test data used for model training. The scatter can be decreased with increasing the number of training data. Further, the difference between the two tests (using 8.5 cm cylinder and 9.5 cm cylinder) on the same materials was more pronounced at high k_i (Table 2). This is attributed to the limited number of available data points in the initial straight-line part of the settling curves for the fast moving slurries. The associated observational error can be minimized by using automated digital sensors during testing.

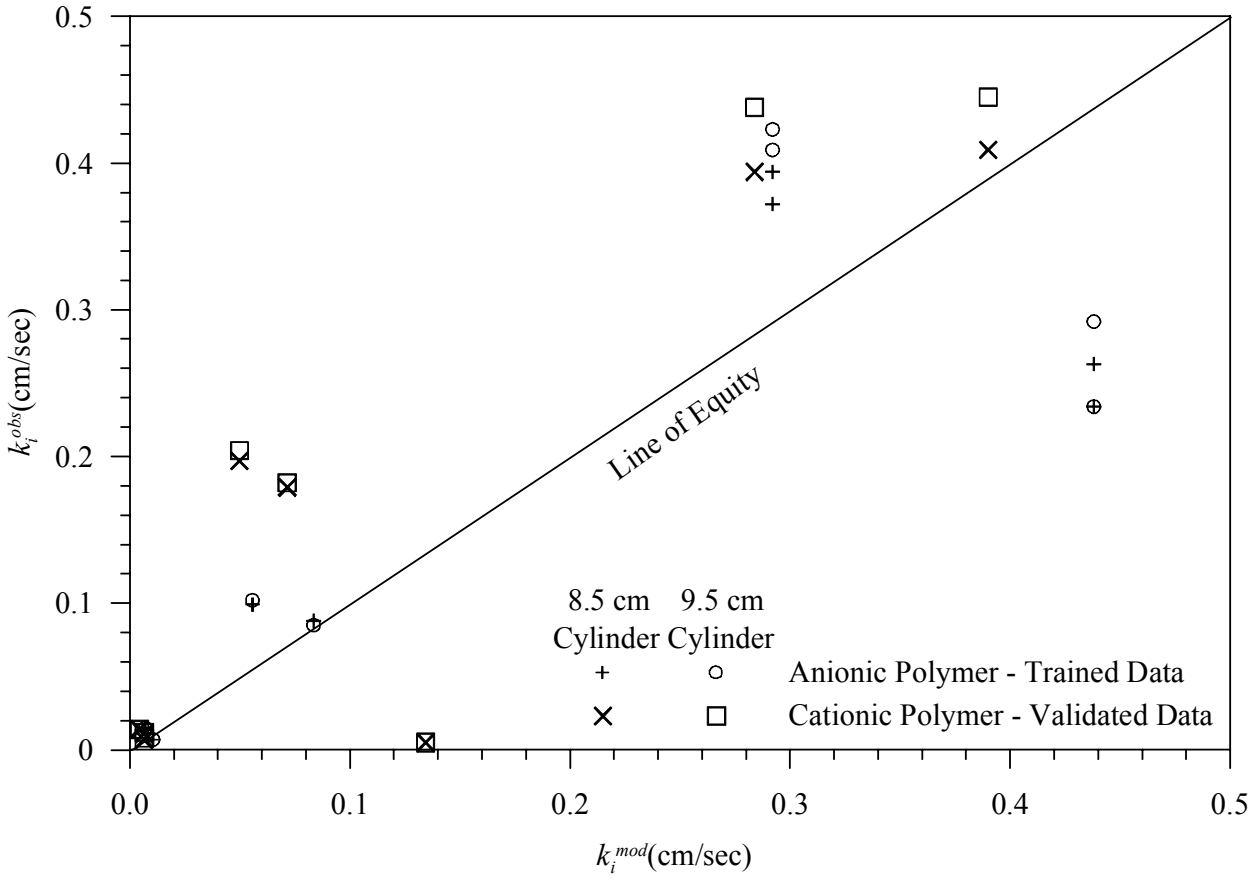

Figure 5: Model training and validation using test data

The main source of repeatable experimental error was polymer addition and mixing with the slurry that was undergoing self-weight settling. The resulting turbidity and eddies offered difficulty in deciphering the solid-liquid interface movement. In the absence of a distinct interface, observational bias marginally contributed in overestimating the settling rate. Figure 5 illustrates that most of the observed data plotted on or above the line of equity. The bias associated with such systematic errors can be minimized by adding the polymers with the slurry stream prior to settling [4].

Figure 6 gives the ranks of C, M, and D plotted against the k_i ranks thereby determining the rank correlation coefficients. The output variability was used to determine the percent contribution of each input parameter using the method described in [5]. Table 3 summarizes the statistics for sensitivity analyses based on the model. The scatter in the generated data was lowest for C followed by M and then by D. The highly significant input parameters showed trends, which account for variability in the output. For both anionic and cationic polymers, C was the most significant factor accounting for more than 97% of variability in the output estimates. Followed by M and then by D, this predominance of polymer charge density on the settling rate of laterite ore slurry was expected.

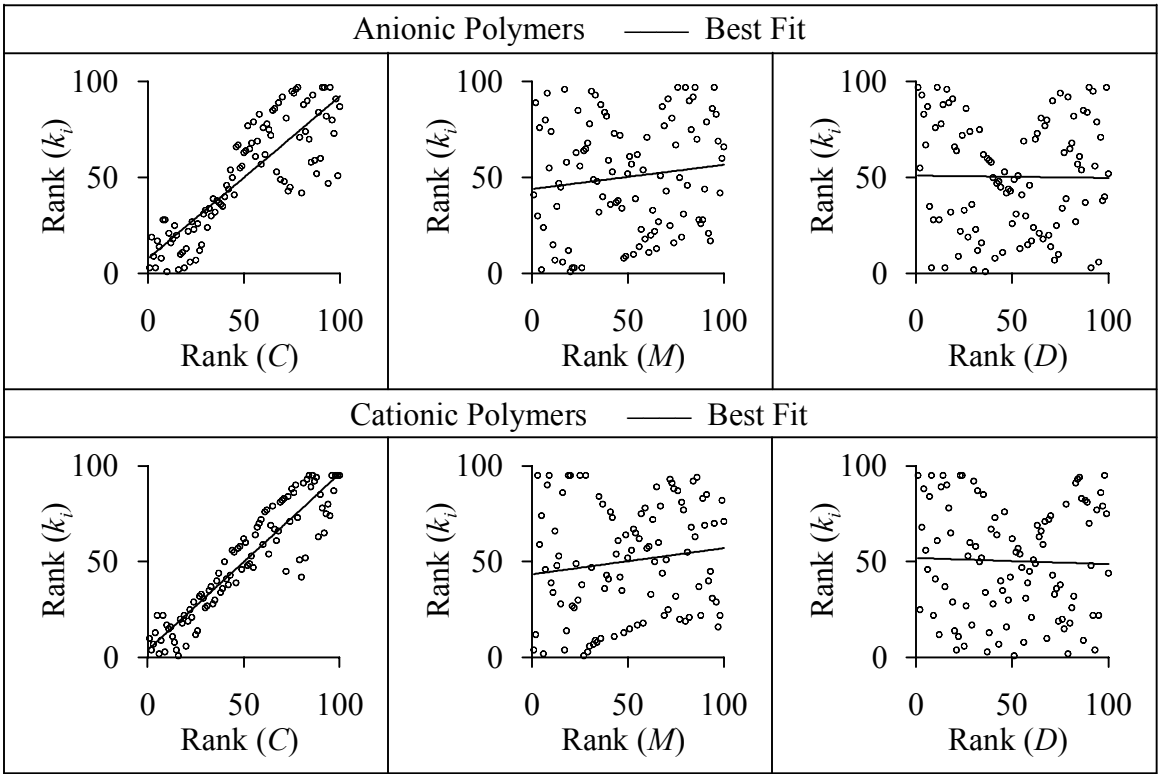

Figure 6: Sensitivity analyses

Table 3: Summary statistics of sensitivity analyses

Polymer Type	Statistical Estimates	Charge Density, *C*	Molecular Weight, *M*	Dosage, *D*
Anionic	Coefficient of Determination, R^2	0.72	0.01	0.002
	Rank Correlation Coefficient (%)	97.28	2.70	0.02
Cationic	Coefficient of Determination, R^2	0.86	0.02	0.001
	Rank Correlation Coefficient (%)	97.62	2.27	0.11

The solids of the slurry were primarily iron oxides (goethite, hematite, and maghemite) and clay minerals (kaolinite and chlorite) whereas the water was at a pH = 7.0 having very low electrolyte concentration [7]. This composition allowed both anionic and cationic polymers to interact with the slurry. The negatively charged anionic polymers were attracted to the positively charged iron oxide surfaces whereas the positively charged cationic polymers were attracted to the negatively charged clay surfaces [1]. In both cases, the slurry was usually flocculated and the flocs settled at relatively higher velocities under self-weight thereby increasing k_i of the material. The type of flocculation depended on bond strength and floc size [13].

The charge density of a polymer refers to the number of unsatisfied charges on the polymer chain. Synthetic polymers with high *C* resulted in a stronger overall bond between the polymer and the colloid because the polymer could get attached to a single colloid at many points along its length [14]. Likewise, a single high *C* polymer was able to get bonded to a number of laterite particles thereby increasing the floc size. The same high *C* was responsible for holding the large size flocs intact. Conversely, strong bonds and large floc sizes were not formed when low *C* polymers were added to the ore slurry. Therefore, polymer charge was the most significant parameter in improving k_i of laterite ore slurries.

The molecular weight pertains to the total chain length of a polymer made up of an assemblage of a large number of the basic building block called a *monomer* [6]. The actual dimensions of ionic polymers in a slurry of known composition increase with charge density as high intra-molecular charge repulsions of the polymer chain tend to unfold the solvated coils [13]. The contribution of polymer molecular weight depends on charge density and is considered to be embedded in the later. Therefore, a good correlation of k_i was not obtained for polymer molecular weight.

Flocculation of laterite ore slurries depends on the type of adsorbed conformation of the polymer chains. At low dosages, each polymer chain is grafted onto a colloid by one segment

leading to a *mushroom* conformation. Conversely, the chains overlap and stretch out perpendicular to the colloid at high dosages thereby adopting the *brush* conformation. An optimum dosage is one at which the polymer chain is flat enough to be bonded to a colloid at more than one points but still precludes chain interference. The polymer chain at the optimum dosage assumes a *pancake* conformation. These conformations depend on the charge density and the molecular weight of the polymer used [14]. In this study, the term polymer dosage (D) was used to quantify the amount of polymer added to the slurry because the actual amount of polymer adsorbed onto the colloidal surfaces could not be determined. The bench-scale settling tests were conducted using the limiting values of the range of dosages (4 ppm and 12 ppm) but an optimum dosage for each combination of C and M was not determined.

Good correlations for M and D were not obtained because of the limited bench-scale settling test data. The relative significance of M and D on the settling rate of laterite ore slurry was considered to be part of C. The fuzzy rule-based technique adopted in this study, conceptually modeled the well-known parts of the process through expert judgment whereas the remaining less-known parts were predicted using sensitivity analyses. The model can be improved by conducting a large number of tests at constant values of C and by varying M and D over practical ranges. A comprehensive model should also include the composition of the solid and the liquid phases of the slurries as input parameters. Further, the fuzzy rule-based model developed in the current study can be modified for other material types.

6. Summary and Conclusions

The self-weight settling rate of laterite ore slurries is improved by adding synthetic polymers. The charge density, molecular weight, and dosage of the polymers are the key factors influencing the settling rate of soil slurries. This interdisciplinary paper used the geotechnical understanding of hindered sedimentation for a mining engineering application. A conceptual fuzzy rule-based model was developed to evaluate the initial hydraulic conductivity of polymer-modified laterite ore slurries. Based on expert judgement, the model correlated well with bench-scale settling test data and the predicted k_i of polymer-added laterite ore slurry gave an $R^2 = 0.75$. Rank correlation coefficient-based sensitivity analyses indicated that charge density was the most significant polymer parameter followed by molecular weight and then by dosage. Charge density accounted for more than 97% of variability in the k_i estimates for both anionic and cationic polymers. The predictions and the associated ranks of the conceptual model can be improved by increasing the number of test data for model training.

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