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Robust HPGR model calibration using genetic algorithms

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ABSTRACT

Mathematical modeling and simulation techniques are widely used to design and optimize comminution circuits in mineral processing plants. However, circuit performance predictions are prone to errors due to inaccurate calibration of models used in simulations. To address this problem, the authors applied a method based on genetic algorithms (GA) for estimation of HPGR (high pressure grinding rolls) model parameters. In this research, a simulation algorithm was developed and implemented in MATLAB™ based on published HPGR models to test and demonstrate GA application for model calibration. The GA toolbox of MATLAB was used to obtain the optimal values of HPGR model parameters. The authors successfully validated simulator predictions against HPGR data sets at laboratory and industrial scales. The results indicate that GA is a robust and powerful search method to find the best values of HPGR model parameters that lead to more reliable simulation predictions.

1. Introduction

Comminution circuits have the highest level of energy consumption in mineral processing plants. Therefore, improving design and operation of comminution devices to optimize performance and energy consumption are always an important part of manufacturers and process engineers' researches. HPGR is the result of basic changes in roller crushers due to Schönert (1986). Subsequently, the comminution mechanism was changed in the new crusher due to its high pressures (Schönert, 1979, 1986). The high throughput of HPGR units and their low specific energy consumption made them increasingly suitable for use in comminution circuits.

With respect to modeling of high pressure grinding rolls, the most considerable works were done by Morrell and co-workers (Morrell et al., 1997; Daniel and Morrell, 2004). Recently, Torres and Casali (2009), following the work done by Morrell and Daniel, developed a new method for modeling of HPGR. In the model presented by Daniel and Morrell, outputs of drop-weight apparatus are used for ore characterization and their model is fitted to laboratory data through limiting the number of model parameters. In next step, the obtained model parameters are kept constant and used in a scale-up procedure to predict the performance of full-scale units. But in Torres and Casali new method, established functional expressions of breakage and selection functions are used for this purpose and also there is no scale-up procedure involved. In HPGR units, comminution mechanism basically differs from that of media mills due to the high pressure applied on particles. For this reason, the breakage and selection functions obtained using media mills such as a ball mill or a rod mill and other devices cannot be used for simulation of HPGR units. As a solution, these parameters can be estimated simultaneously by fitting the measured data with corresponding models. Considering a normalizable breakage function and only the first two terms of the logarithmic polynomial expression used to define selection function, there will be totally six parameters which must be back calculated from actual HPGR data sets in order to determine breakage function and selection functions.

A programming environment equipped with powerful search tools for function optimization is a prerequisite for model fitting purposes. In a previous paper, successful application of genetic algorithm search method to optimize comminution circuits was reported by Farzanegan and Vahidipour (2009). Therefore, MATLAB environment and also its genetic algorithms toolbox were selected for implementation of HPGR simulation model, optimal calibration of model parameters and finally prediction of HPGR product size distribution in an open circuit.

2. Description of HPGR model

Authors programmed the HPGR mathematical model explained by Torres and Casali (2009) as the main part of simulator structure. This model includes a set of equations that is based on ore characteristics, equipment dimensions and operating conditions. Given the required input, the model is able to predict throughput, power consumption and particle size distribution of HPGR product.

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The equations are based on physical phenomena that control the operation: mass balances for throughput estimation, physics equations for the power consumption and population balance model for prediction of particle size distribution of product.

In this study, authors used particle size distribution sub-model to predict HPGR product size distribution under various operating conditions, because product size distribution is an important result of modeling and optimization researches.

2.1. Particle size distribution model

In models presented by Daniel and Morrell (2004) and Torres and Casali (2009), comminution between rolls includes two stages: single-particle comminution (pre-crushing) and particle-bed comminution (Fig. 1). The particles coarser than a definite size are broken in single-particle compression zone in which comminution is done directly by rolls surfaces, as would occur in conventional roller crushers. The definite size is equal to the length of the boundary line between the two comminution zones and is called critical distance, x_c, (Klymowsky et al., 2002). In HPGR units, the main process of particle breakage takes place in the particle-bed compression zone which has been depicted in Fig. 1.

The distance between rolls surfaces, $s(\alpha)$, can be calculated geometrically as a function of angle α using the following equation:

$$s(\alpha) = s_0 + D(1 - cos\,\alpha) \tag{1}$$

where s_0 is the least distance between rolls (rolls gap) and D is roll diameter. The value of x_c can be obtained using the following equation:

$$x_c = s(\alpha_{IP}) = s_0 + D(1 - cos\,\alpha_{IP}) \tag{2}$$

where α_{IP} is the angle that refers to the beginning of inter-particle compression zone. The theoretical throughput, G_s (t/h), treated by an HPGR can be calculated using mass conservation law. Eq. (3) is used for calculation of throughput as a function of angle α(Torres and Casali, 2009):

$$G_s = 3600\rho(\alpha)s(\alpha)LUcos(\alpha) \tag{3}$$

where $\rho(\alpha)$ is ore band density at angle α (t/m^3), L is roll length (m) and U is peripheral velocity (m/s). Under steady-state conditions, flow rates (t/h) of the beginning and the end of compression zone are equal. In addition, the flow rate is equal to throughput. Therefore, using Eqs. (1) and (3) and also considering that $\rho(\alpha_{IP}) = \rho_a$ and $\rho(\alpha = 0) = \delta$, Eq. (4) is obtained in which the unknown value is inter-particle compression angle (α_{IP}):

$$\rho_a D cos^2\,\alpha_{IP} - \rho_a(s_0 + D)cos\,\alpha_{IP} + \delta s_0 = 0 \tag{4}$$

where δ is ore band density in extrusion zone and ρ_a is feed bulk density. The solution to Eq. (4) results in two roots values that only the higher one is the acceptable value for the angle (the smaller root gives too high angles). The acceptable value for $cos\,\alpha_{IP}$ can be calculated by the following equation:

$$cos\,\alpha_{IP} = \frac{1}{2D}\left[(s_0 + D) + \sqrt{(s_0 + D)^2 - \frac{4s_0\delta D}{\rho_a}}\right] \tag{5}$$

The particles coarser than x_c are comminuted in single-particle compression zone and the product size distribution of this zone is calculated by the following equation (Torres and Casali, 2009):

$$P_i^{SP} = \sum_{l=1}^{N} b_{il} f_l^{SP} \tag{6}$$

where b_{il} is non-cumulative breakage function, f_l^{SP} is the mass fraction in size class l entering the single-particle compression zone (class of size $x > x_c$) and N is the number of size classes coarser than x_c.

The final product of HPGR is composed of two different particle size distributions (Klymowsky et al., 2002; Daniel and Morrell, 2004; Patzelt et al., 2006). Lubjuhn (1992) explained this phenomenon when he found that the pressure profile exerted over the rolls is similar to a parabola, as it is shown in Fig. 2.

Following this approach, the force depending roll where the pressure is applied was divided into N_B blocks. In each one, a different compression on the pressure profile is applied. The product of single-particle compression zone rejoins with the materials that are equal or lesser than x_c and will be comminuted in particle-bed compression zone. The product of particle-bed compression zone is the final product and is calculated using the following equation:

$$P_{i,k} = \sum_{j=1}^{i} A_{i,j,k} exp\left(-\frac{S_{j,k}}{v_z} z^*\right) \tag{7}$$

and

$$A_{ij,k} = \begin{cases} 0 & i < j \\ \sum_{l=j}^{i-1} \frac{b_{i,l} S_{l,k}}{S_{i,k} - S_{j,k}} A_{lj,k} & i > j \\ f_i^{IP} - \sum_{l=1}^{i-1} A_{il,k} & i = j \end{cases} \tag{8}$$

where $P_{i,k}$ is remained mass on ith screen on block k, v_z is the downward velocity of flake, f_i^{IP} is the fraction in size class of the mineral going to particle-bed compression zone, z^* is the vertical distance from beginning of particle compression bed zone to extrusion zone. Also $S_{j,k}$ is the selection function value of size class i in block k. The parameter z^* is calculated geometrically as follows:

$$z^* = \frac{D}{2} sin(\alpha_{IP}) \tag{9}$$

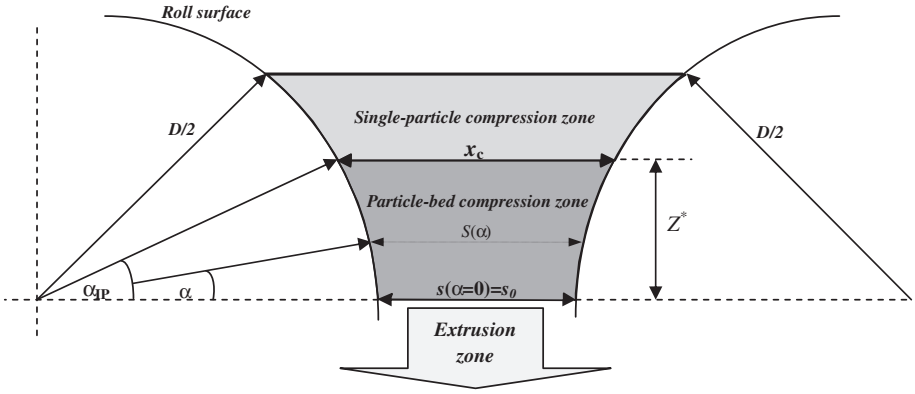

Fig. 1. A schematic diagram showing various parts and important dimensions between rolls.

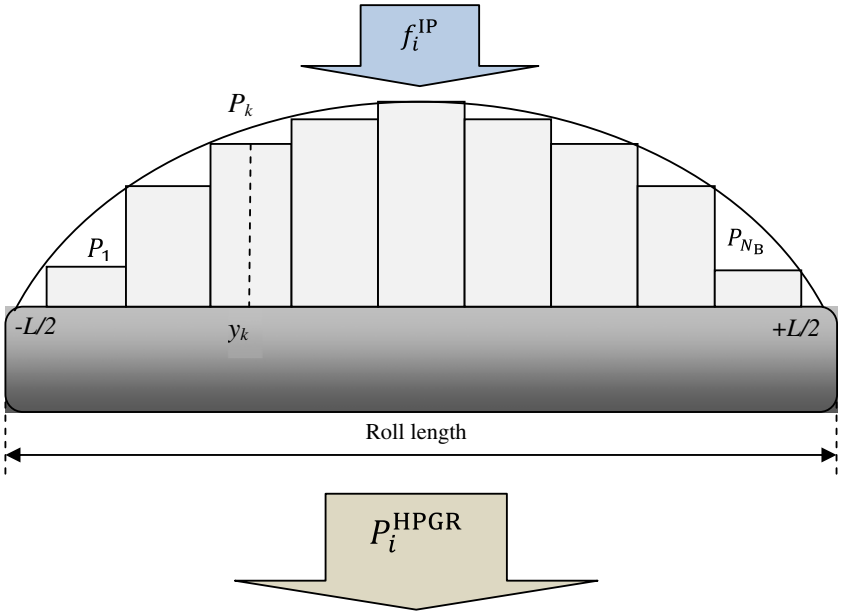

Fig. 2. Pressure profile applied over the roll in particle-bed compression zone.

For the cumulative breakage function elements, B_i, the following functional expression (Eq. (10)) is used (Austin and Luckie, 1972):

$$B_i(x_i) = \alpha_1 \left(\frac{x_i}{x_1}\right)^{\alpha_2} + (1-\alpha_1)\left(\frac{x_i}{x_1}\right)^{\alpha_3} \tag{10}$$

where α_1, α_2, and α_3 are model parameters. For calculation of non-cumulative breakage function elements, $b_{i,j}$, Eq. (11) can be used:

$$b_{ij} = \begin{cases} B_{i-1+j} - B_{i-j+2} & i > j \\ 1 - \sum_j b_{ij} & i = n \\ 0 & i \leqslant j \end{cases} \tag{11}$$

To represent selection function, Herbst and Fuerstenau (1980) have proposed the following logarithmic functional expression:

$$ln\left(\frac{S_i^E}{S_1^E}\right) = \zeta_1 ln\left(\frac{\bar{x}_i}{\bar{x}_1}\right) + \zeta_2 \left(ln\left(\frac{\bar{x}_i}{\bar{x}_1}\right)\right)^2 \tag{12}$$

where ζ_1, ζ_2 and S_1^E are model parameters that should be calculated. To obtain selection function value for each block, $S_{i,k}$, Eq. (13) (Herbst and Fuerstenau, 1980) is used, assuming a parabola pressure profile exerted over the rolls:

$$S_{i,k} = \frac{P_k}{H_k} S_i^E \tag{13}$$

where H_k is the hold up of each block and P_k is power consumption of block k that changes by each block. The hold up of each block k is calculated using the following equation:

$$H_k = \frac{1}{N_B} G_s \frac{z^*}{3600U} \tag{14}$$

where G_s is throughput (t/h) and can be calculated in extrusion zone using the following equation:

$$G_s = 3600 \delta s_0 L U \tag{15}$$

According to pressure profile exerted over the rolls (Lubjuhn, 1992), the power consumption of each block k is calculated using the following equation (Torres and Casali, 2009):

$$P_k = 2F \sin\left(\frac{\alpha_{IP}}{2}\right) U \frac{\left(L^2 - 4y_k^2\right)}{\sum_{j=1}^{N_B}\left(L^2 - 4y_j^2\right)} \tag{16}$$

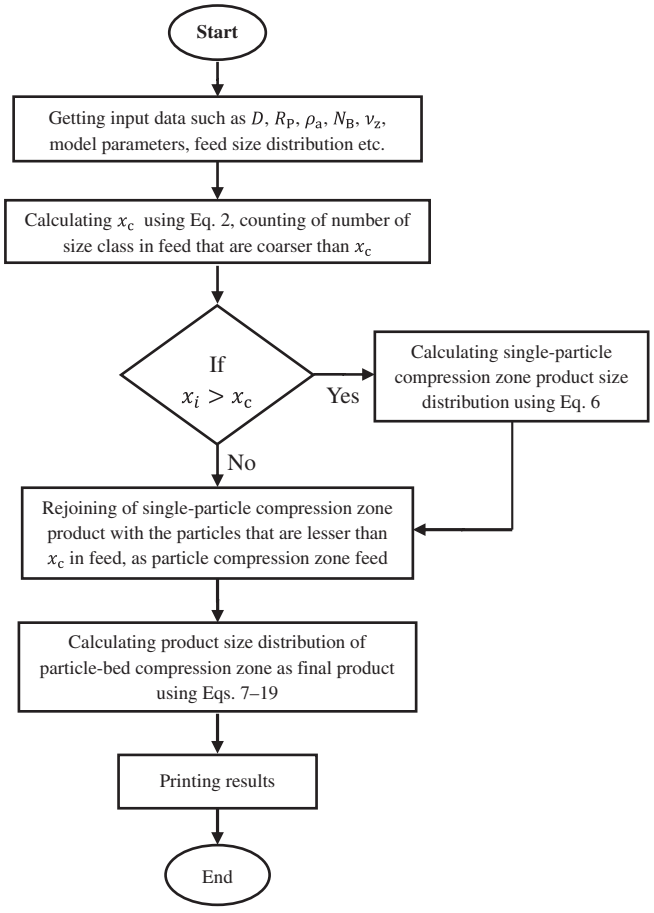

Fig. 3. Simplified flowchart of HPGR simulator under MATLAB.

where y_k (m) is center position of block k which is geometrically calculated using the following equation (see Fig. 2):

$$y_k = \frac{L}{2N_B}(2k - N_B - 1) \tag{17}$$

Moreover, F is compression force (kN) and is presented in the following equation (Torres and Casali, 2009):

$$F = 100R_p\frac{D}{2}L \tag{18}$$

where R_p is roll pressure (bar).

Finally for calculation of particle size distribution of total product, P_i^{HPGR}, Eq. (19) is used:

$$P_i^{HPGR} = \frac{1}{N_B}\sum_{k=1}^{N_B} P_{i,k} \tag{19}$$

where P_i^{HPGR} is the remained mass on ith screen and N_B is the number of blocks.

3. HPGR model in MATLAB language

As mentioned earlier, model parameters including α_1, α_2, α_3, ζ_1, ζ_2 and S_1^E should be estimated by fitting the model to experimental data set. Since there are six variables as model parameters that should be changed simultaneously in curve fitting process, a powerful search pattern is needed to alter variables, calculate model predictions with new values and compare the model predicted results with experimental data sets. The work done by other researchers (Farzanegan and Vahidipour, 2009) showed that GA search method is an excellent tool for optimization and minimizing the fitness function written by user as a MATLAB file.

Therefore, authors implemented HPGR model equations in MATLAB language due to its optimization toolboxes particularly GA to search for the best-fit model parameters. Flowchart of this program is shown in Fig. 3 and a screen capture of results is presented in Fig. 4.

This program simulates HPGR performance in an open circuit. By importing input data and executing the program, HPGR product size distribution will be computed under defined operating conditions, as it is shown in Fig. 4.

4. Simulation validation

Validation of the program is based on the published Rio Tinto historical laboratory and industrial-scale data sets reported in a previous research project by Daniel (2002). The laboratory tests were done using an HPGR unit with rolls having a diameter and length equal to 250 mm and 100 mm, respectively. In addition, the industrial-scale tests results are based on an HPGR unit with rolls having a diameter and length equal to 2200 mm and 1000 mm, respectively.

Three data sets from a laboratory-scale unit (data sets Nos. 1–3) and three data sets from an industrial-scale unit (data sets Nos. 4–6) were used for validation purpose. One data set of each laboratory and industrial-scale data sets was randomly selected for model fitting and calculation of model parameters for associated HPGR unit and feed. As the type of treated material by both laboratory and industrial HPGR units was the same, therefore the authors tried to calculate one set of breakage function parameters for all data sets and two sets of selection function parameters, one for laboratory data sets and one for industrial data sets. These model parameters were calculated by fitting the model to experimental data using simulation program and GA tool for optimizing the fit. In next step, the optimal model parameters were considered as constant values in model equations and were used for prediction of the two remained data sets.

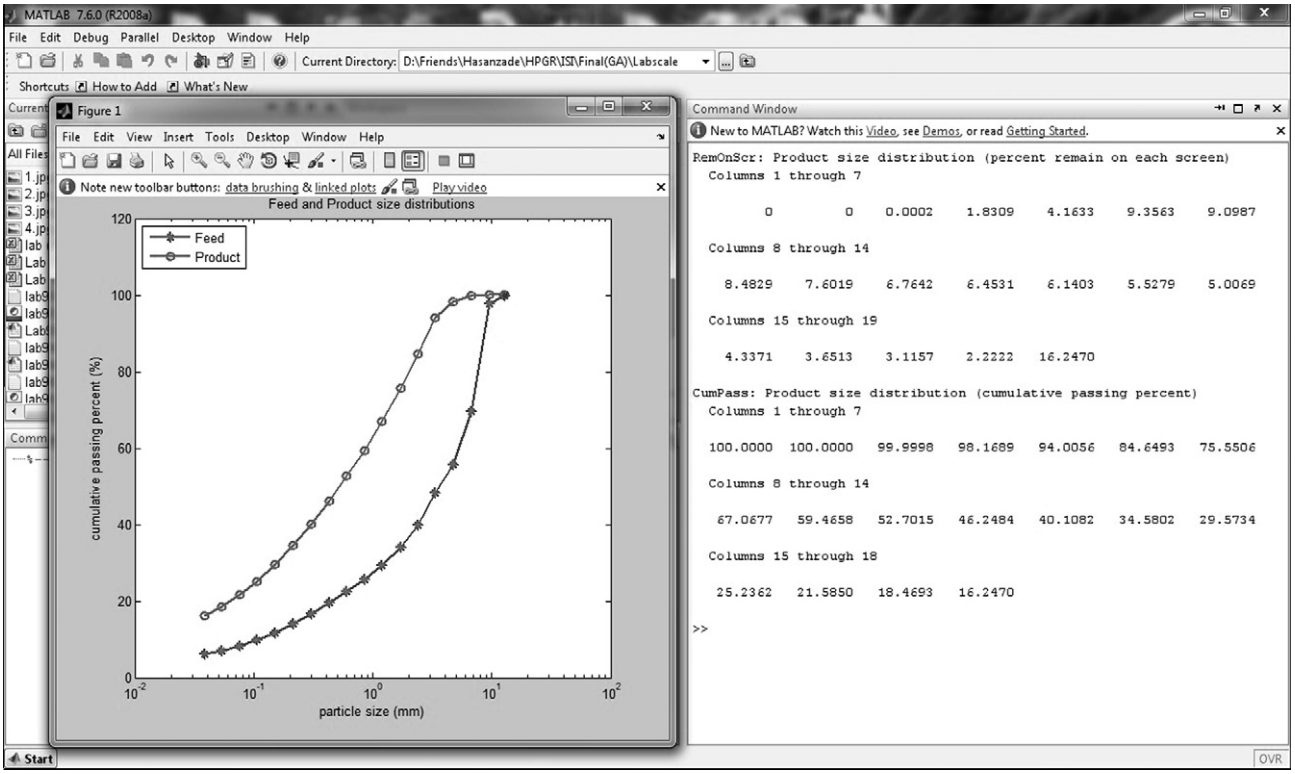

Fig. 4. Screen capture of simulation program running.

4.1. Genetic algorithms

Genetic algorithm and direct search toolbox has increased capability of optimization and numeric computing in MATLAB environment. Holland (1975) introduced the basics of genetic algorithms. Since then a lot of research has been done to develop more robust and efficient algorithms. Succinctly, GA is a search algorithm that mimics natural selection and evolution in genetics.

While in simple optimization algorithms, the search process starts with only a single possible solution, in GA a set of possible solutions called individuals is used to initiate the search. The set of individuals is called a population. Individuals are like chromosomes in natural genetics context that are composed of several genes. Best individuals are selected based on their fitness value to become parents of new children. This procedure is repeated over generations using various GA operators until a single individual takes over the population as the final and best solution.

It is noted that in other search algorithms used to solve optimization problems, an initial guess is normally required, which may significantly affect converging to a final solution. Effectively, GA

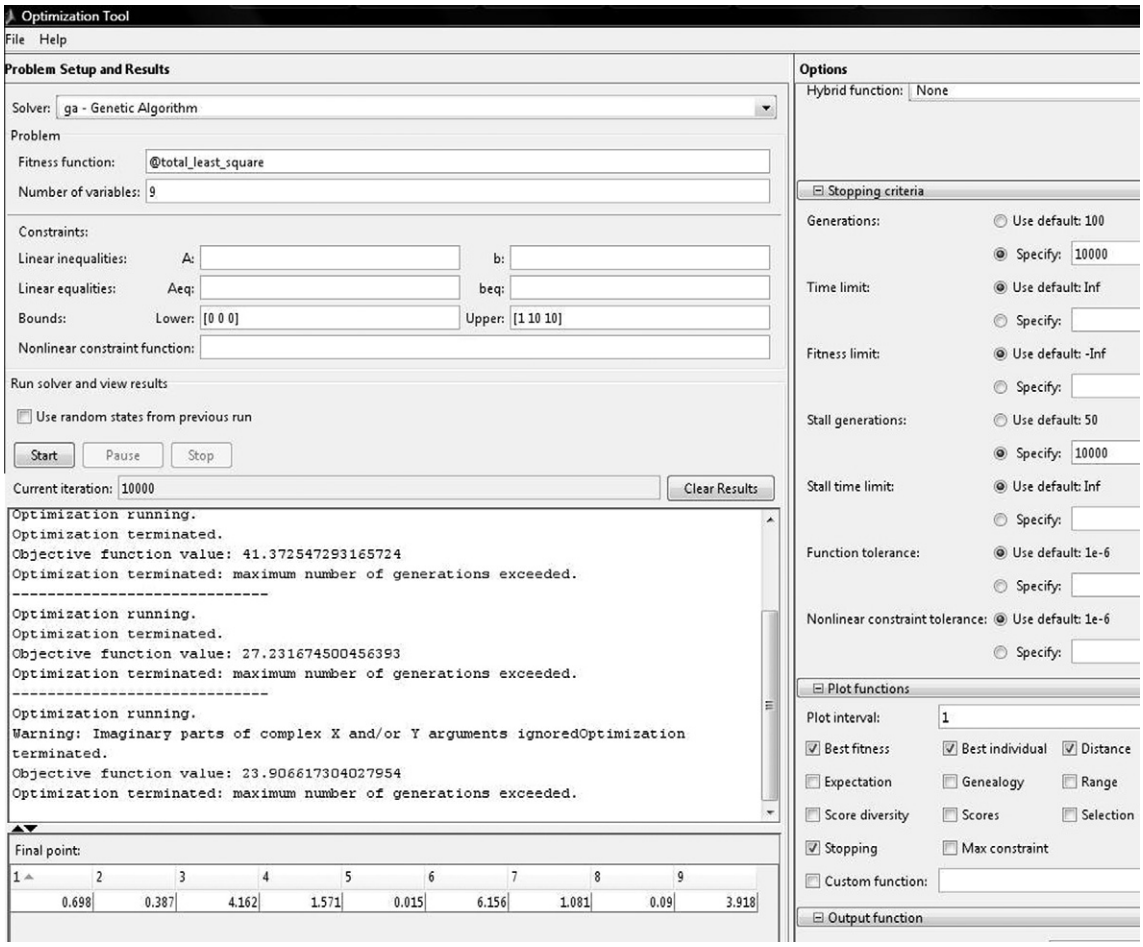

Fig. 5. GA Optimization tool window of MATLAB.

Table 1
Summary of results and stopping criteria for model fitting using GA; breakage function parameters constraints: $0 \leqslant \alpha_1 \leqslant 1$, $0 \leqslant \alpha_2 \leqslant 10$ and $0 \leqslant \alpha_3 \leqslant 10$.

			Stopping criteria		Breakage function parameters			Laboratory selection function parameters			Industrial selection function parameters			Goodness of fit
			Generations	Stall generations	α_1	α_2	α_3	ζ_{11}	ζ_{21}	S_{11}^E	ζ_{12}	ζ_{22}	S_{12}^E	SSE
Step 1		Run 1	1000	1000	0.593	0.389	1.334	0.822	−0.024	2.041	0.716	0.056	2.161	44.27
		Run 2	2000	2000	0.212	0.478	0.521	1.728	0.170	4.244	0.771	0.072	1.917	41.37
		Run 3	5000	5000	0.918	0.383	2.775	1.546	−0.088	5.413	1.325	0.119	3.983	27.23
		Run 4	10000	10000	0.698	0.387	4.162	1.571	0.015	6.156	1.081	0.09	3.918	23.91
Step 2	Laboratory	Run 1	1000	1000	–	–	–	1.699	0.044	6.941	–	–	–	13.79
		Run 2	2000	2000	–	–	–	1.952	0.104	8.799	–	–	–	12.85
		Run 3	5000	5000	–	–	–	2.120	0.141	10.363	–	–	–	12.44
	Industrial	Run 1	1000	1000	–	–	–	–	–	–	0.879	0.051	2.625	10.76
		Run 2	2000	2000	–	–	–	–	–	–	1.114	0.087	3.572	10.06
		Run 3	5000	5000	–	–	–	–	–	–	1.029	0.074	3.186	9.96

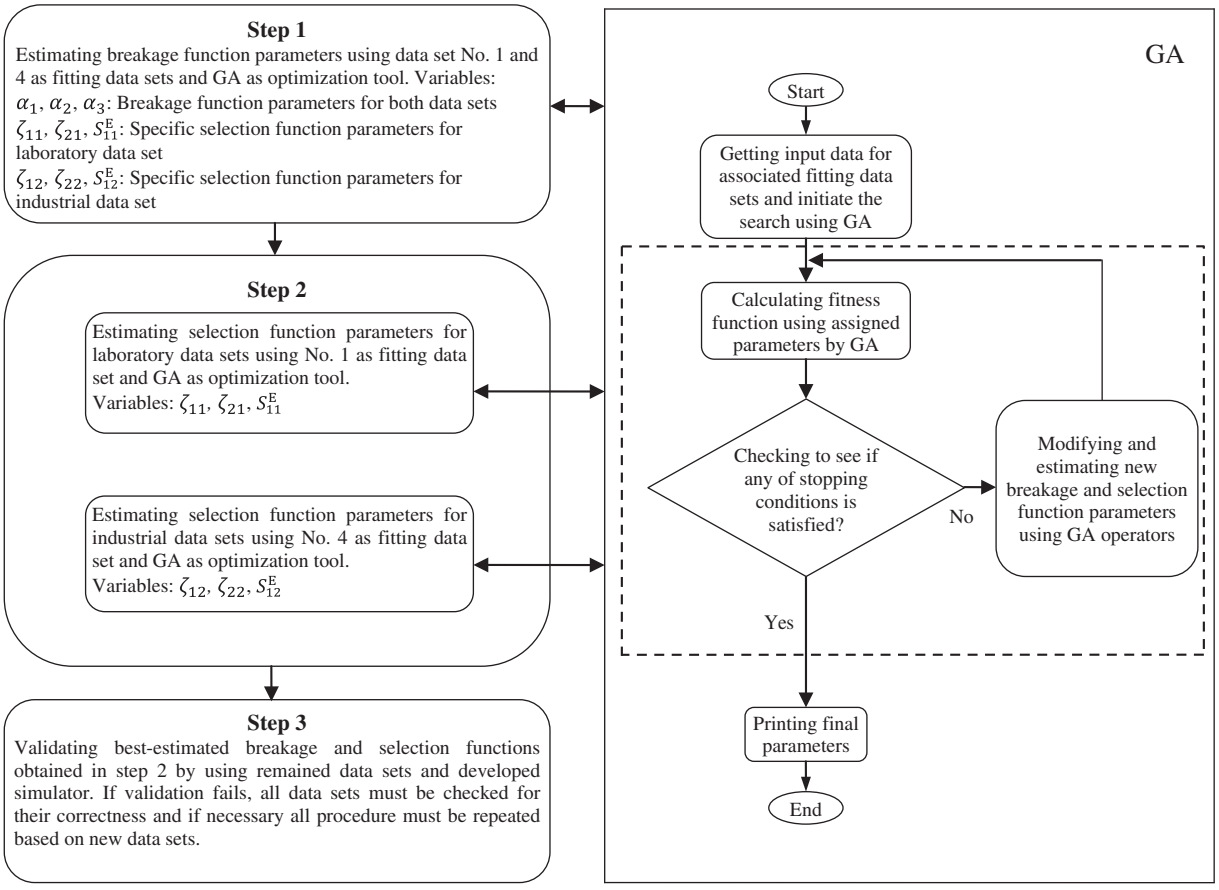

Fig. 6. Calibration procedure.

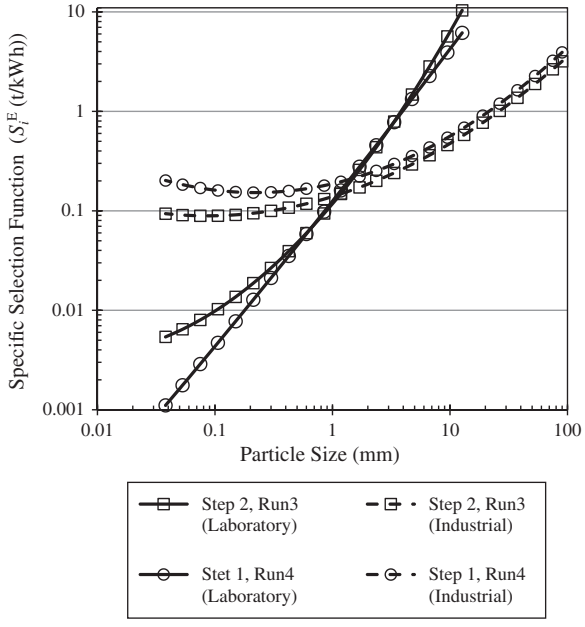

Fig. 7. Specific selection functions obtained in the best runs of both calibration steps.

search is based on exploring the whole solution space in every generation. This helps avoiding the problem of being trapped in local maxima or minima during search process. There are two main reasons for this: (1) the initial population, being randomly generated,

Table 2
The best-estimated model parameters using GA.

Data set No.	Model parameters					
	α_1	α_2	α_3	ζ_1	ζ_2	S_1^E
1	0.698	0.387	4.162	2.120	0.141	10.363
4	0.698	0.387	4.162	1.029	0.074	3.186

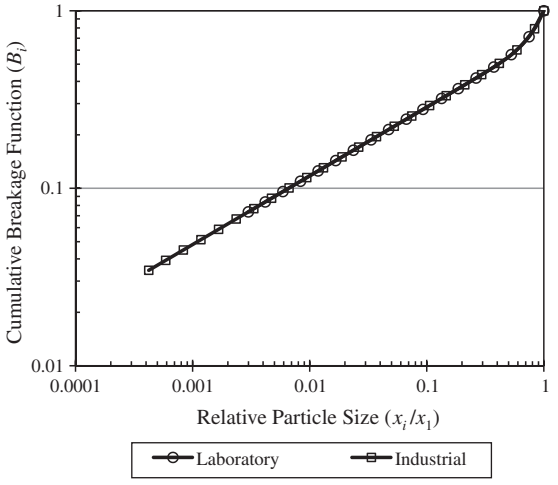

Fig. 8. Best-estimated breakage functions for both laboratory and industrial-scales data sets.

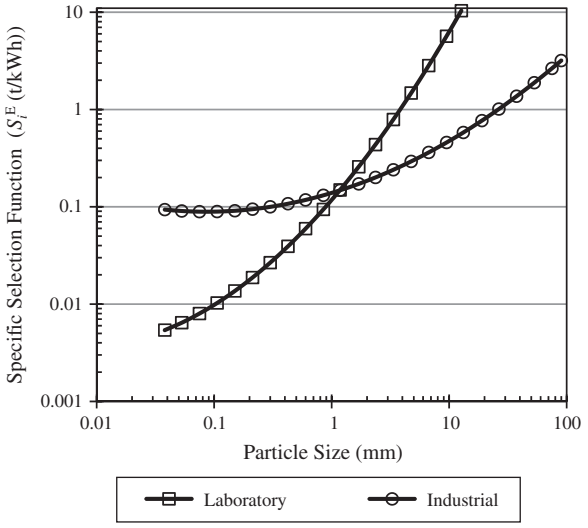

Fig. 9. Best-estimated selection functions for both laboratory and industrial-scales data sets.

Table 3
Variable operating conditions for the laboratory-scale HPGR unit.

Data set No.	Variables			
	Roll pressure, R_P (bar)	Rolls gap, s_0 (m)	Roll velocity, U (m/s)	Flake density, δ (t/m^3)
1	55.00	0.00429	1.5	2.62
2	51.79	0.00269	2.5	2.15
3	89.00	0.00254	3.1	2.19

Table 4
Variable operating conditions for the industrial-scale HPGR unit.

Data set No.	Variables			
	Roll pressure, R_P (bar)	Rolls gap, s_0 (m)	Roll velocity, U (m/s)	Flake density, δ (t/m^3)
4	38	0.02962	1.98	2.16
5	34	0.02341	1.97	2.20
6	41	0.03407	0.96	2.22

Table 5
Constants in laboratory and industrial-scale data sets.

	Constants			
	Roll diameter, D (m)	Roll length, L (m)	Bulk density, ρ_a (t/m^3)	Feed size, d_{80} (m)
Laboratory scale	0.25	0.1	1.8	0.0078
Industrial scale	2.20	1.0	1.8	0.0500

will sample the whole solution space rather than a small or specific area of the solution space; (2) variation-inducing operations, i.e. crossover and mutation, prevent the algorithm being trapped in one part of the solution space. These benefits have made GA method very powerful as a model calibration tool, particularly, when so many search variables are involved.

Table 6
Summary of measured and predicted product size distribution for laboratory-scale HPGR unit.

Screen Size (mm)	Cumulative passing (%)			
	Data set No. 2		Data set No. 3	
	Measured	Predicted	Measured	Predicted
12.70	100.00	100.00	100.00	100.00
9.50	100.00	100.00	100.00	100.00
6.70	100.00	99.99	100.00	100.00
4.75	99.85	99.16	99.94	99.80
3.35	97.92	96.27	98.74	98.56
2.36	89.87	87.70	93.73	93.48
1.70	78.84	78.21	85.13	85.96
1.18	68.80	68.96	76.31	77.18
0.85	60.51	60.76	69.01	68.67
0.60	54.21	53.68	62.26	60.96
0.42	47.66	47.06	55.74	53.65
0.30	41.24	40.90	49.19	46.82
0.21	35.37	35.41	42.56	40.68
0.15	30.02	30.46	36.15	35.14
0.11	25.49	26.18	31.13	30.32
0.08	21.55	22.57	26.45	26.22
0.05	17.90	19.49	22.24	22.70
0.04	16.12	17.27	19.19	20.10

Table 7
Summary of measured and predicted product size distribution for industrial-scale HPGR unit.

Screen size (mm)	Cumulative passing (%)			
	Data set No. 5		Data set No. 6	
	Measured	Predicted	Measured	Predicted
90.000	100.00	100.00	100.00	100.00
75.000	100.00	100.00	100.00	100.00
53.000	98.65	99.94	97.79	99.94
37.500	97.64	99.27	93.73	96.26
26.500	95.90	94.03	90.02	90.92
19.000	89.79	87.72	83.80	84.65
13.200	81.92	80.49	76.10	77.61
9.510	73.25	72.99	69.24	70.35
6.700	65.90	65.83	62.55	63.43
4.750	59.35	59.15	56.62	56.98
3.350	53.40	53.05	50.98	51.10
2.360	48.33	47.83	45.77	46.08
1.700	44.35	43.29	41.73	41.72
1.180	40.50	39.10	37.80	37.70
0.850	37.92	35.60	35.19	34.35
0.600	35.24	32.33	32.60	31.22
0.425	32.41	29.17	29.74	28.18
0.300	29.42	26.14	26.81	25.27
0.212	26.18	23.38	23.78	22.60
0.150	23.35	20.81	20.82	20.13
0.106	20.84	18.57	18.47	17.96
0.075	18.75	16.65	16.39	16.11
0.053	16.53	14.96	14.41	14.48
0.038	15.34	13.56	12.98	13.14

4.2. Fitness function

To use GA toolbox of MATLAB, a fitness function with a specific structure is needed which must be written as a separate file by the user in MATLAB language. This file includes the function that should be minimized. The fitness function file will be loaded by passing its handle in optimization tool window. As it is shown in Fig. 5, user must select "ga-genetic algorithm" as solver. Also user can define some constraints such as lower and upper limits of variables that should be changed by GA. Moreover, many options can be changed according to conditions. In this study, the values of some stopping criteria including maximum number of generations

and stall generations were changed in various runs (Table 1) to make sure that the value of fitness function is as close as possible to the true global minimum and errors in predicted product size distributions are within the acceptable range.

The developed fitness function includes HPGR simulation model discussed earlier which can predict the product particle size distribution. For this purpose, breakage and selection functions (model parameters) must be known. These parameters were considered as unknown variables during model fitting procedure by GA. The measured product size distributions were inserted in fitness function to calculate the fitness function (also known as objective function) after predicted product size distributions become available. The sum of the squared of errors (SSE) between measured and predicted product size distributions is calculated as the value of fitness function. GA tries to minimize the value of fitness function by changing of model parameters as variables. The final state of variables when a minimum fitness function value is achieved, are considered as the best estimate of model parameters. Once a successful calibration procedure is completed, these parameters will be used as known parameters for later simulation trials.

5. Results and discussions

As it was mentioned earlier, one of each laboratory and industrial-scale data sets was randomly selected for using in fitness function and calculation of model parameters. Model parameters were optimally estimated based on the algorithm depicted in Fig. 6.

At first step, both laboratory and industrial fitting data sets were used for estimation of breakage function parameters. Therefore, one set of breakage function parameters (for both data sets) and two sets of selection function parameters (one for the laboratory-scale data set and another one for the industrial scale) were considered as variables in fitness function. The breakage function parameters were obtained by minimizing fitness function using GA. This step was repeated for confirmation of reproducibility of the breakage function parameters. At next step, the obtained breakage function parameters were used as constants in fitness function and the selection function parameters were considered as variables again. Then these parameters were separately estimated for each laboratory and industrial data sets. Results of all aforementioned steps were shown in Table 1.

Using the breakage function estimated in step 1, calibration procedure was continued to separately estimate selection functions of laboratory and industrial data sets in step 2. Fig. 7 shows that selection function values found in both steps.

Those sets of parameters for laboratory and industrial-scale data sets which generated the least fitness function values, presented as Sum of Squared of Errors (SSE) in Table 1, were chosen as the best estimates for breakage and selection functions. The final selected parameters are presented in Table 2.

Figs. 8 and 9 show the best-estimated breakage and selection functions, respectively. The accuracy of the best-estimated parameters was then checked by using remaining data sets Nos. 2, 3, 5 and 6.

Afterward, the obtained parameters were used in above-mentioned program (as it is shown in Fig. 4) to predict product size distributions. The data sets that will be predicted are the ones remained from each laboratory and industrial-scale HPGR data sets. It means that by using one data set parameters, another two data sets were predicted successfully. It should be noted that in each group of laboratory and industrial-scale data sets, HPGR unit and its associated feed are kept constant and only operating conditions were changed during simulation. The conditions for each data set are given in Tables 3 and 4. In following data sets, data sets Nos. 1 and 4 were selected for model fitting and calculation of model parameters.

In all above data sets, other operating conditions and feeds of both laboratory and industrial-scale HPGR were kept constant. These constant values are shown in Table 5.

After importing input data and changing operating conditions in HPGR simulation program, the program can be executed to obtain the product size distribution under new operating conditions. The predicted and measured product size distributions for the open circuit tests have been presented in Tables 6 and 7.

Figs. 10 and 11 show that predicted particle size distributions can be well compared to the measured product size distributions. It must be noted that in order to be confident about the truth of validation tests, it was checked that sufficient disparity to be existed between data sets used for model fitting and validation steps.

As it is clear in Figs. 10 and 11, in both laboratory and industrial-scale data sets, using of new approach and HPGR simulator program resulted in predicted product size distributions that are in close agreement with measured ones. In these data sets, it should be noted that operating conditions were simultaneously varied, but obtained results show that this approach can truly govern and predict product size distributions. Moreover, although one data set was used for model fitting and calculating of model parameters, the results show that the obtained parameters can successfully be considered as constant for prediction of product size distribution of an HPGR unit and its associated feed under various operating conditions. Also it shows that these parameters are dependent on HPGR dimensions and feed characteristics and can be used for simulation and optimization of circuits in next steps.

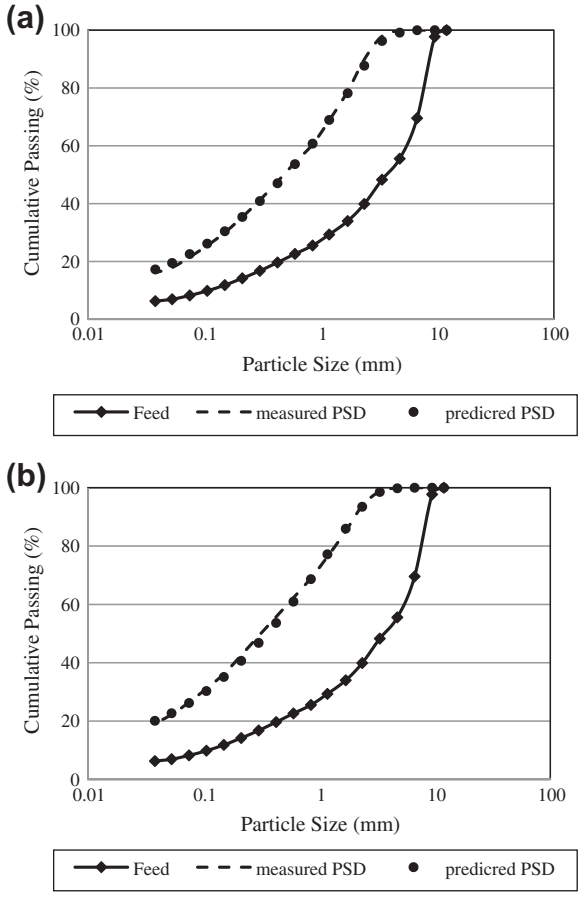

Fig. 10. Measured and predicted product size distribution curves for laboratory-scale HPGR. (a) Data set No. 2 (b) Data set No. 3.

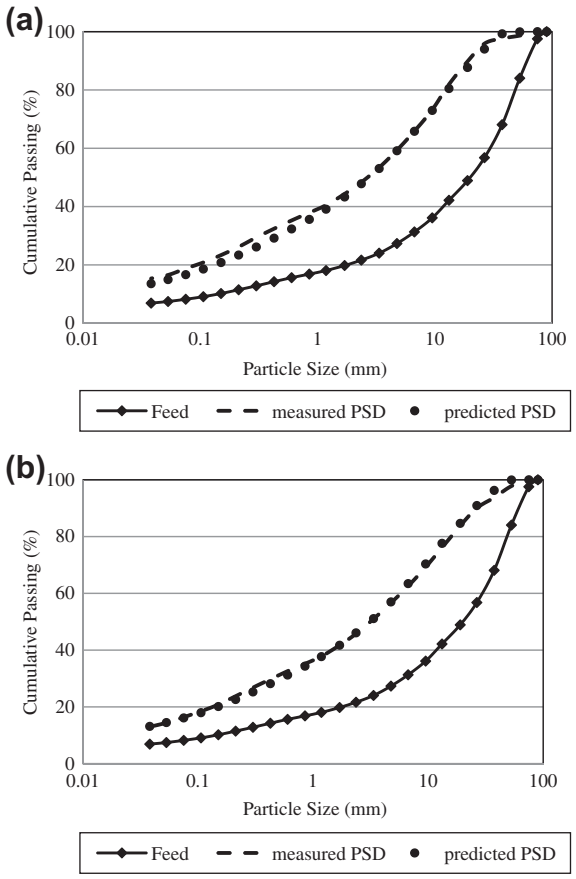

Fig. 11. Measured and predicted product size distribution curves for industrial-scale HPGR. (a) Data set No. 5 (b) Data set No. 6.

In summary, the modeling and calibration approach taken in this research was shown to be suitable for successful simulation of HPGR units at laboratory and industrial scales. In compare with other models reported in literature, this modeling approach can facilitate determination of fundamental grinding equation parameters using proposed back-calculation method instead of laboratory tests. Therefore, the demonstrated methodology can be used by plant engineers for optimization of operating variables such as rolls speed and applied pressure to achieve a pre-defined grinding performance.

6. Conclusions

A new numerical approach based on GA search for prediction of HPGR product size distribution was investigated. The obtained results showed that the employed technique can accurately back calculate model parameters and predict product size distribution of HPGR in an open circuit. Implementing of HPGR model in MATLAB environment made it possible to use Genetic Algorithm. Combining GA search method with HPGR simulation algorithm provided a robust numerical tool that can be used successfully for calculating of breakage model parameters. To predict HPGR product size distribution in closed circuits, the simulation algorithm has been also developed in ANSI C programming language and will be used as a module in BMCS comminution software. This GA-based numerical approach was validated by experimental data sets and was shown that is reliable for prediction of HPGR product size distribution in an open circuit under various operating conditions.

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