Parameter Optimization for Model Computation of Pipeline Critical Deposition Velocity using Improved SFLA Algorithm

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***Abstract* — In pipeline transportation of slurry, the existing calculation models of critical deposition velocity face the problem of different model forms only suitable for specific conditions. To address this problem, this paper uses improved "shuffled frog leaping algorithm" (SFLA) to optimize the parameters of the computational model in order to calculate critical deposition velocity. This has been found to be more suitable for the specific conditions in the western region of china. Through experimental simulation, the results show that the accuracy of the calculated results obtained by the parameter optimized model of improved SFLA is more accurate than the previous calculation models, which proves the feasibility of the proposed model.**

Keywords-pipeline; critical deposition velocity; SFLA

I. INTRODUCTION

Pipeline transportation of slurry is a kind of transport mode, which is used to transport solid liquid mixture as main service. Compared with other transports, it is not only has obvious economic benefit, but also has less environmental pollution. So it achieved rapid development. The application of this technology in China began in the 1950s. At that time, for the purpose of experimental research, China tried to establish a short distance pipeline to transport slurry in remote mining away from the city[1].Since the last century 80's, with the rapid development of China's industry, the development of basic material resources such as mineral and coal are growing. Meanwhile, many domestic research institutes and design units set off a boom in the test analysis and theoretical study of pipeline transportation. At present, China has built a lot of slurry pipeline, such as Jianshan pipeline, Wengfu pipeline and Dahongshan pipeline, etc [2,3].

Although the advantage of slurry pipeline transportation is outstanding, how to determine the critical deposition velocity is still a difficult problem. Because the slurry is a mixture of solid and liquid in pipeline, it can lead to the deposition of solid particles under the condition of low flow rate, and eventually making the pipe blocked. Although the particles can be fully suspended in the case of high transport flow velocity, it can make a proportionally increased resistance with the square of the velocity of flow in a certain diameter. Critical deposition velocity of pipeline is the economic speed that ensures the solid material not plug the pipeline, and it has a great relationship with the safe and reliable operation of the pipeline [4]. Since 20th Century, many experts and scholars at home and abroad have carried out a lot of experimental research and theoretical exploration, and also put forward the calculation model of critical deposition velocity [5-8]. The calculation models of critical deposition velocity which is more famous contain Durand model, Wasp model, Shook model and so on.

However, due to the pipeline transport technology which involves many disciplines is very complex, and the models that they have put forward are based on the specific experiment conditions, there is a problem of narrow application and large calculation error when the calculation model faced with other complex criteria. Therefore, it is necessary to revise the parameters of the calculation model according to the specific conditions. Because parameter optimization of the model is equivalent to the nonlinear optimization problem, the traditional method with the way of experience is difficult to get the optimal solution. In recent years, the rise of the shuffled frog leaping algorithm (SFLA) is a relatively new search swarm intelligence algorithm based on collaborative groups[9], and it combines the advantages of particle swarm optimization algorithm with the advantages of memetic algorithm, which has the advantages of simple concept, few parameters, fast calculation speed and so on[10-11]. It was initially used to solve the problem of combinatorial optimization of water supply pipe network [12], and then received wide attention from scholars at home and abroad. At present, the Improved SFLA algorithm has been applied in the field of short-term hydrothermal scheduling, continuous optimization problem, multi-phase model for multi-depot vehicle routing problem, and the k-shortest path problem,etc[13-18]. This paper studied the existing experience models and found out some main factors that affect critical deposition velocity of slurry pipeline. Then, the improved SFLA algorithm was used to optimize the parameters of the model in order to fit a more suitable model for calculating critical deposition velocity for the specific conditions in the western region of china.

II. BASIC SHUFFLED FROG LEAPING ALGORITHM

A. The Principle of SFLA Algorithm

As is shown in Fig.1, the standard shuffled frog leaping algorithm contains the following basic idea: In a population consisting of m sub-groups, there are many frogs. Meanwhile, on the basis of combining the ideas of other frogs within groups, each sub group of frogs is searched within the group and constantly approached to the optimal solution. When the information in each sub group is exchanged after a round, the different sub groups of the population will be exchanged for global information. And then again the local search rules of the frog to find food. It is in this way that all frogs are constantly evolving and developing themselves. When the convergence condition is reached, the search will be terminated.

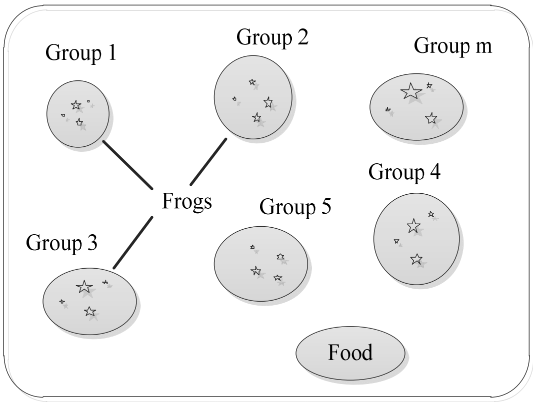

Figure 1. Schematic diagram of SFLA

B. *The Mathematical Model of SFLA*

The initial population is generated by randomly generated patterns, and they are made up of F solutions. Each of the sub groups contained n frogs, and satisfied $F = S \times n$ .Then, we sort these frogs in descending order of the fitness value. The frog's classification is performed according to the following rules. First frog is divided into a first sub group, the second frog is divided into second sub groups, the s frog is divided into s sub group s, and the S+1 frog are divided into first sub group .And so on, until the end of all the frogs division.

In each sub groups, the best and worst of the fitness value is expressed as X_b and X_w respectively. In addition, the frog which has the best fitness value in a population is expressed as X_g . Then the local search operation is performed for each of the sub groups of the X_w frog. Thus, the worst frogs in sub group can be updated at each iteration, and the update strategy is as follows:

$$\mathrm{D_i} = rand() \cdot (X_{bi} - X_{wi}) \tag{1}$$

$$X_w{}' = X_w + D_i, (-D_{\max} \le D_i \le D_{\max}) \tag{2}$$

Where rand () indicates the number of random numbers between [0, 1], and $D_{\max}$ indicates that the maximum value allowed for the frogs. After the update, if the fitness value of the obtained frog $X_w{}'$ is better than that of the original frog X_w, then X_w will be replaced by $X_w{}'$. If there is no improvement, then exchange X_b for X_g and execute local search process. If there is still no improvement, then a new location will be randomly generated to replace the original X_w. We repeat the update operation constantly until it reaches the local iteration number within a group. After that, all the sub groups within the frog will be mixed and sorted, and then continue to do the local search. Repeating the above steps until the algorithm reach the end of the defined convergence condition.

C. *Improved SFLA Algorithm*

Through the update model of worst frog, it can be found that the effect of step size $\mathrm{D_i}$ on the updated value is constant. This approach can not only reduce the convergence rate of the algorithm, but also easily lead to a local optimal solution. Based on this, in order to improve the search efficiency of the algorithm, the inertia weight is introduced into the Improved SFLA algorithm based on the update strategy of PSO algorithm. The strategy of formula (2) is updated as follows:

$$X_w{}' = X_w + wD_i, (-D_{\max} \le D_i \le D_{\max}) \tag{3}$$

Where w is the inertia weight.

Although the traditional method of inertia weight which uses the strategy of decreasing with the increase of the number of iterations is simple and intuitive, the local search is a nonlinear complex process, and the linear decline of inertia weight is difficult to accurately reflect the whole search process. Therefore, this paper uses the following nonlinear decreasing inertia weight:

$$w = (w_{\max} - w_{\min})^{\sqrt{(t/k)}} + w_{\min}{}^2 \tag{4}$$

Where $w_{\max}$ is the maximum inertia weight; $w_{\min}$ is the minimum inertia weight; t is the product of the number of iterations of the current sub population and the current iteration of the entire group; k is the total number of iterations for the sub population. Because the inertia weight decreased in a nonlinear way, it meets the requirements of large inertia weight in the initial evolution process, and less inertia weight in the later evolution process.

III. ANALYSIS OF CRITICAL DEPOSITION VELOCITY MODEL

In general, critical deposition velocity is related to the nature of the material being transported, the physical characteristics of the slurry, and the physical characteristics of the carrier. So far, many experts and scholars at home and abroad have carried out a thorough study on critical deposition velocity. But these models have very big difference in the form and parameters, and only apply to the specific conditions. The followings are well-known calculation models published so far[6-8].

Wasp model:

$$V_d = 3.40 C_v^{0.22} \left(\frac{d}{D}\right)^{\frac{1}{6}} \left[2\,\mathrm{gD}\left(\frac{\rho_s - \rho}{\rho}\right)\right]^{\frac{1}{2}} \tag{5}$$

Where d is the particle size; D is the diameter of the pipeline; ρ_s is the material density; ρ is the liquid density; C_v is volume concentration; g is the gravity acceleration.

Newitt model:

$$V_d = 13.88 C_v^{0.11}(1-C_v)^{0.25}(\frac{d}{D})^{0.5}[2\mathrm{gD}(\frac{\rho_s-\rho}{\rho})]^{\frac{1}{2}} \quad (6)$$

Where d is the particle size; D is the diameter of the pipeline; ρ_s is the material density; ρ is the liquid density; C_v is volume concentration; g is the gravity acceleration.

Yotsukura model:

$$V_d = 1.87(\frac{d}{D})^{\frac{1}{6}}\sqrt{2\mathrm{gD}(\frac{\rho_s-\rho}{\rho})} \quad (7)$$

Where d is the particle size; D is the diameter of the pipeline; ρ_s is the material density; ρ is the liquid density; g is the gravity acceleration.

Shook model:

$$V_d = 2.43(\frac{C_v^{1/3}}{C_D^{1/4}})\sqrt{2\mathrm{gD}(\frac{\rho_s-\rho}{\rho})} \quad (8)$$

Where C_v is volume concentration; C_D is resistance coefficient; D is the diameter of the pipeline; ρ_s is the material density; ρ is the liquid density; g is the gravity acceleration.

By comparing the calculation models of many experts and scholars in this field, we find that the volume concentration, pipe diameter, particle size, material density and liquid density are the most commonly used parameters in the calculation of critical deposition velocity. Thus it reflects that the main factors affecting critical deposition velocity include the above parameters. Furthermore, critical deposition velocity is directly proportional to the one second power, one third power or one sixth power of the ratio of the particle size and pipe diameter in many calculation models, and it remained in the range of 0 to 1.Meanwhile, the relationship between the value of critical deposition velocity and the ratio of the density of material and the density of liquid is mainly one second power, and the proportional relationship is also maintained in the range of 0 to 1. In addition, the relationship between the value of critical deposition velocity and volume concentration is also very different. For example, in the Wasp model, it is proportional to the 0.22 power of the volume concentration. But in the Turian model, it is proportional to the 0.11 power of the volume concentration. Through comparative analysis, we can find that the proportion of relationship is still maintained in the range of 0 to 1.If the above calculation model is used to calculate critical deposition velocity, there can be a large error. The main reason causing this problem is that the experts and scholars have different factors to consider in their specific experimental conditions, and the target object is not entirely consistent. So it is needed to correct the parameters of the model in order to find out the model for the specific conditions.

Through the analysis of the existing research, this paper draw a conclusion that the volume concentration, pipe diameter, particle size and the ratio of the density of material and the density of liquid are mainly relate to critical deposition velocity. At the same time, because the Wasp model is a good description of the relevance, this paper intend to use a rheological data of pipeline company in the western region of china to modify the parameters of the Wasp model, and then fitting out a model for calculating the critical velocity deposition that is suitable for the specific condition of the western region of china. The model to be constructed is as follows:

$$V_d = \mathrm{a}C_v^{\mathrm{b}}(\frac{d}{D})^c[2\mathrm{gD}(\frac{\rho_s-\rho}{\rho})]^z \quad (9)$$

Where a, b, c and z are the parameters to be determined, and the Improved SFLA algorithm is used to determine its value.

IV. CONCLUSIONS APPLICATION OF IMPROVED SFLA ALGORITHM TO OPTIMIZE THE PARAMETERS OF CRITICAL DEPOSITION VELOCITY

In fact, the optimization of the parameters of critical deposition velocity model can be equivalent to a nonlinear optimization problem. If the traditional optimization method is used, not only the computation is very complex, but also the solution is probably not the global optimal solution. In this paper, the improved SFLA algorithm is used to optimize the Wasp model, and the objective function is the minimum value of the sum of the squares that fitted values of model subtract with measured values. That means we need to construct the following objective function of optimization criteria:

$$\mathrm{m}inG(x) = \sum_{i=1}^{n}(\mathrm{a}C_v^{\mathrm{b}}(\frac{d}{D})^c[2\mathrm{gD}(\frac{\rho_s-\rho}{\rho})]^z - y_i)^2 \quad (10)$$

Where a, b, c and z are the parameters that need to be determined by improved SFLA algorithm; y_i is the measured value of critical deposition velocity. The SFLA that is used to establish the optimization model architecture is shown in Fig.2.

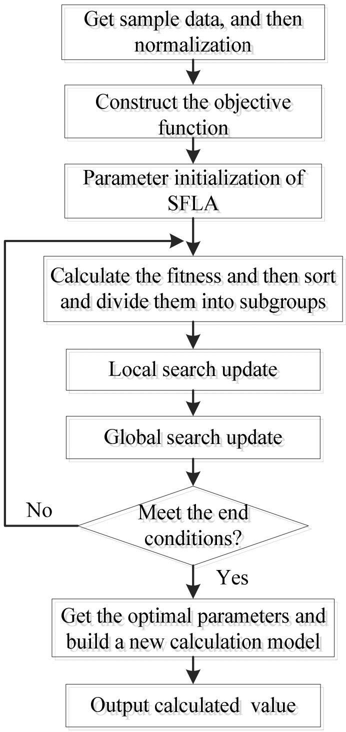

Figure 2. Architecture of parameter optimization model of SFLA

The detail steps by using improved SFLA optimization algorithm to solve the parameters of model are as follows:

1) Parameters are initialized. The value scopes of a, b, c and z are set according to the experience. In addition, the number of frogs in frog population, the number of sub groups, the number of frogs within each sub group, the total number of mixed iteration, and the total number of iterations within each sub group are need to be set .

2) Calculate objective function value of each frog, and then all the frogs are sorted in descending order according to the objective function value. In addition, all the frogs are divided into m sub groups, and each sub group contains n frogs.

3) Determine the objective function of the best individual, the worst individual and the global optimal individual. Then constantly update frogs for the worst of each sub group based on the updated strategy.

4) The frogs are sorted in descending order according to the value of the objective function, and then sub groups are mixed in order to replace the original group. In addition, the X_g is updated with the best solution in the population after sorting.

5) Check whether the algorithm satisfies the termination conditions. If the condition is met, then stop the calculation, and output information about the optimal objective function value. Otherwise, go to the step two.

V. PRACTICAL ANALYSIS

In this experiment, 60 sets of rheological data of iron ore concentrate pipeline in the western region of china are used as training samples, and 7 sets of data are selected as the test sample. Test sample is shown in tab.1. By using the parameters optimization algorithm in this paper to optimize the Wasp model, the model can be corrected.

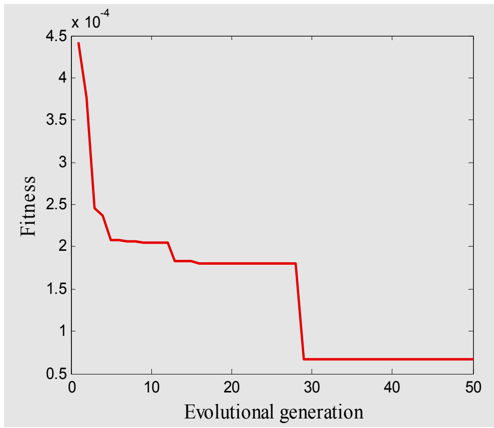

Figure3. Fitness values along with the increasing of the iteration number

TABLE 1. TEST DATA FOR THE OPTIMIZATION MODEL OF CRITICAL DEPOSITION VELOCITY MODEL

No.	Pipe diameter D / mm	Particle size $\overline{d}$ / μm	Density ratio S	Volume Concentration C_V / %	Measured value V_{dc}/ms^{-1}
1	253	147	4.769	27.8	1.520
2	253	147	4.931	26.2	1.498
3	253	147	4.936	27.2	1.532
4	253	147	4.837	29.1	1.517
5	253	147	4.856	28	1.505
6	253	147	4.829	30.6	1.527
7	224.5	147	4.872	29.6	1.533

First of all, the parameters of the improved SFLA algorithm and the values of a, b, c and z are needed to be determined. The setting ranges of parameters in this paper are as follows: the total number of frogs in the frog population is 600; the number of sub groups is 20; the number of frogs within each sub group is 30; the number of iterations within each sub group is 30; the total number of mixed iteration is 50. The range of the model parameters settings is: $a \in [0,10]$, $b \in [0,1]$, $c \in [0,1]$, $z \in [0,1]$ .After the parameter optimization by using improved SFLA algorithm, the obtained parameter is as follows: a=2.0641, b=0.41375, c=0.058995, z=0.20949. Then, these four parameters were input the Wasp model to calculate critical deposition velocity of 7 sets in test data. The optimization results of improved

SFLA algorithm is shown in Fig. 3, and the calculation results of test data are shown in Fig.4 , Tab.2 and Tab. 3.

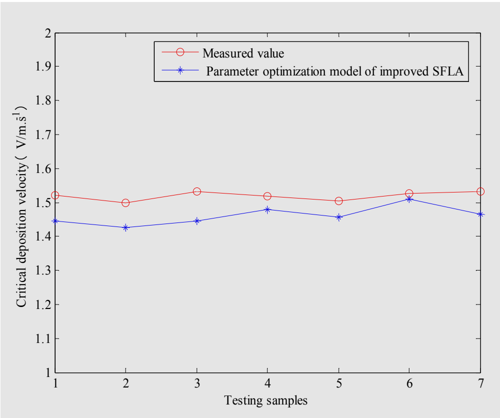

Figure 4. Comparison between calculation results of improved SFLA parameter optimization model and measured values.

It can be seen that the calculated values of the model that parameters optimized by improved SFLA algorithm is very close to the measured values from Fig.4. As is shown in Table 2, the maximum relative error of the 7 sets of samples is only 5.65%, and the sum of relative error is only 26.71%. In order to evaluate the efficiency of the model, the Yotsukura model, Newitt model and Wasp model are all used to calculate and compare critical deposition velocity values. As is shown in Tab.3, the calculated values of the Wasp model have a large difference between the measured values, and the maximum relative error is 115.99%.

TABLE.2 CALCULATION RESULTS OF TEST DATA

No.	Measured value V_{dc}/ms^{-1}	Parameter optimization model of SFLA	
		Calculated value V_c/ms^{-1}	Relative error %
1	1.520	1.445	4.91
2	1.498	1.425	4.93
3	1.532	1.445	5.65
4	1.517	1.479	2.49
5	1.505	1.458	3.15
6	1.527	1.509	1.19
7	1.533	1.466	4.39

The obtained results are not good when compared with parameter optimization model of improved SFLA. Meanwhile, the maximum relative error of the calculated values of Newitt model and Yotsukura model are 23.81% and 59.21% respectively, and the sum of relative error are 159.67% and 383.42% respectively. So the practical effects are not ideal. It shows that the parameter optimization model of SFLA is better than the above model.

TABLE 3. COMPARISON OF THE CALCULATED VALUES AND THE MEASURED VALUES OF DIFFERENT MODELS

No.	Measured value V_{dc}/ms^{-1}	Wasp model		Newitt model		Yotsukura model	
		Calculated value V_{dc}/ms^{-1}	Relative error %	Calculated value V_{dc}/ms^{-1}	Relative error %	Calculated value V_{dc}/ms^{-1}	Relative error %
1	1.520	3.204	110.78	1.158	23.81	2.335	53.64
2	1.498	3.230	115.59	1.182	21.12	2.385	59.21
3	1.532	3.258	112.69	1.183	22.77	2.386	55.78
4	1.517	3.265	115.25	1.169	22.93	2.356	55.32
5	1.505	3.246	115.66	1.172	22.16	2.362	56.95
6	1.527	3.298	115.99	1.168	23.50	2.354	54.15
7	1.533	3.164	106.38	1.175	23.38	2.275	48.37

VI. CONCLUSIONS

Critical deposition velocity is an important parameter in the design of slurry pipeline. Through the calculation of calculation model, it can be able to evaluate the economic reliability of the slurry pipeline. However, most of the calculation models that have been published so far are very narrow in the application, and the results obtained by the experts and scholars are based on their specific experimental conditions. Because the traditional method with the way of experience is not easy to get the optimal, it is necessary to explore a more suitable method for nonlinear parameter optimization, in order to solve the parameters in the model. Aiming at this problem, this paper studied the existing experience model and found out some main factors that affect critical deposition velocity of slurry pipeline. Then, the improved SFLA algorithm was applied to the optimization of the parameters of critical deposition velocity model by using the rheological data of pipeline in the western region of china. The experimental results show that the accuracy of the parameter optimization model of improved SFLA is improved when compared with the original Wasp model. At the same time, it also has a greater advantage when compared with the other calculation models. This proves the feasibility of the calculation model in the western region of china under the specific conditions.

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