EJGE

Parameter Identification of Creep Model of Rock Based on Modified PSO-LM Algorithm

Song Yong-jun*, Ren Jian-xi, Zhang Kun, Liu Chao-ke, Chen Xing-zhou

College of Architecture and Civil Engineering, Xi'an University of Science and Technology, Shaanxi, Xi'an 710054 China
**Corresponding author; e-mail: songyj79@163.com*

ABSTRACT

Identification of the creep parameter is one of the important research issues in the field of rock creep mechanics. Considered the defect of parameter identification in creep model which the particle swarm optimization (PSO) is convergence slowly, and prone to fall into local optimum solution, the Levenberg-Marquardt nonlinear least squares method (LM) is relied heavily on the initial value. Therefore, a new parameter identified method is proposed that it combined with linear decreasing weight particle swarm optimization(modified PSO) and LM method, which proceeds as: 1) the model parameters are identified by means of modified PSO firstly; 2) LM method is used to identify the model parameters by initial values from step 1. A case showed that the modified PSO-LM method could be effectively identified the parameters of rock creep model.

KEYWORDS: Rock mechanics; Creep model; Identification of parameter; Particle swarm optimization; LM algorithm

INTRODUCTION

Creep is one of the important mechanical properties of rocks which is closely related with the long-term stability of the rock mass engineering. Nowadays, with the development of construction projects, traditional rock creep model has already can't meet the needs of engineering construction, study of rock creep model has entered the stage of nonlinear. The correct identification of creep parameters has become the key scientific problems to be solved of rock nonlinear creep mechanics which has important theory value and practical significance(Sun, 2007). The workload and difficulty of identification increased sharply because of the parameters of nonlinear creep model has gradually more. With the speeding up of the mathematical algorithm and computer operation in recent years, intelligent algorithm gradually enter into people's vision and quickly applied to the identification of rock mechanics parameters, such as neural network, genetic algorithm, simulated annealing algorithm, support vector machine, ant algorithm and particle swarm optimization (pso) algorithm, etc. However, there are still many problems to be solved, such as results frequently trapped in local optimal solution rather than get the global optimal solution and so on. Gao and Zheng(2002) proposed the constitutive model identification method based on genetic algorithm method that analyzed the mechanism of rock and soil constitutive model identification; Chen et al.(2002) proposed the BP neural network model for the identification of creep constitutive model of rock and soil; Zhai et al.(2008) applied the genetic programming method to identify the creep model of rock mass; Li et al.(2008) proposed the chaotic particle swarm optimization algorithm by combined the chaotic mechanism and the PSO algorithm, and inverted unsteady parameters of rock creep constitutive model; Luo et al.(2009) applied PSO to invert model parameters, obtained a global suboptimal particles firstly, then executed least squares inversion, the results showed that the method can be applied to invert parameter of creep model; Liu et al.(2009) achieved the identification of creep constitutive model parameters of rock by means of improved particle swarm algorithm and FLAC; Peng and Xu (2011) inverted parameters of rock creep model by microevolution algorithm, the results indicated that microevolution algorithm can avoid the difficulty of select initial parameters, meanwhile, the calculation accuracy is also higher than the chaos particle swarm optimization algorithm.

Levenberg-Marquardt(LM) algorithm of Nonlinear least squares method is a nonlinear optimization method between Newton's method and gradient descent method, which has not only the merit of rapid convergence of Newton's method, but also overcome the shortcomings what can't effectively deal with non-positive definite and singular matrix; meanwhile, the method inherits the global search feature of gradient descent which greatly reduced opportunities of the objective function fall into a local minimum. However, parameter identification and curve fitting of the method relied heavily on the initial value, identification of parameter is still likely to fail if initial value can't be estimate effectively.

Taking all these factors, the article combined with linear decreasing weights PSO and LM nonlinear least squares method on the basis of the existing algorithm, identified parameter of creep test results, and verified the feasibility of the algorithm to identify the creep model parameters.

PRINCIPLE OF PSO ALGORITHM

Particle Swarm Optimization (PSO) is proposed by Dr. Eberhart and Kennedy in 1995, which is a global optimal algorithm of simulate foraging behavior of birds. The solution of every problem is called "particles" in the PSO algorithm, every particle is a potential solution in the search space. First of all, the solution of scale N is initialized to a flock of random particles in the D-dimensional solution space, and then seek the optimal solution by iterate step by step. In the process of iterate optimization, the particles constantly update their current location by track two "best solutions". A solution is found the optimal solution p_i by particle itself so far (ie, solution of minimum mean square of the ith particles in each iteration), the other one is found the optimal solution p_g in the whole particle swarm so far (ie, solution of minimum mean square of all particles in each iteration).

State of the ith particle is signified by X_i, that is

$$X_i = (x_{i1}, x_{i2}, \cdots \ x_{id}), \quad i = 1,2,\cdots \ N \tag{1}$$

Velocity of particle i is defined as the moving distance of particles in each iteration, namely

$$V_i = (v_{i1}, v_{i2}, \cdots \ v_{id}), \quad i = 1,2,\cdots \ N \tag{2}$$

Flight speed of particle i ($i = 1,2,\cdots \ N$) at D-dimensional subspace($i = 1,2,\cdots D$) is adjusted according to the following formula:

$$v_{id} = wv_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{3}$$

Position of particle is adjusted by the following formula:

$$x_{id} = x_{id} + v_{id} \tag{4}$$

The above two formulas,

c_1、 c_2—Acceleration constant, generally take a value of 2.

r_1、 r_2—Random number in the range [0, 1]

w—Inertia weight.

Algorithm of w value linearly decrease is called linear decreasing particle swarm algorithm, formula of w value is as follows:

$$w = w_{\max} - \frac{(w_{\max} - w_{\min})}{M} \times m \tag{5}$$

The above formula,

$w_{\max}$—Maximum weight,

$w_{\min}$—Minimum weight,

m—The current iterated steps,

M—set the maximum iterated steps,

Usually taken as: $w_{\max}$ =0.9, $w_{\min}$ =0.4。

the basic process of linearly decreasing particle swarm algorithm is as follows:

Step 1： Initialize particles：position and velocity of the particle is randomly generated in D-dimensional problem space;

Step 2： Evaluate particles：For every particle, it is stored current position and fitness value in p_i and optimal individual position and fitness value of all p_i in p_g ;

Step 3： Update particles: change the velocity and position of the particle according to formula (3) and (4) ;

Step 4： Update inertia weight value according to the formula (5) ;

Step 5： The fitness value of every particle is compared with its experienced the best place, then The better value is set as the current best position, Meanwhile, compared all the current values of p_i and p_g , and then updated the p_g value;

Step 6： Stop condition: loop back to step 3 until termination condition is met.

PRINCIPLE OF PARAMETER IDENTIFICATION

The parameters to be solved of creep test has denoted as X , objective function can be used the following formula:

$$F(X) = \sum_{i=1}^{n} (\varepsilon_i(X, t_i) - \varepsilon_i)^2 \tag{6}$$

The above formula,

n —Data number ;

$\varepsilon_i(X,t_i)$ —Calculated value at t time from the theoretical formula ;

ε_i —Test data (strain) at t time.

The purpose of creep model parameters identification is that objective function tended to be minimum by iterate repeatedly.

THE CASE ANALYSIS

In order to validate the proposed algorithm, creep test data and improved Burgers rheological model of Literature [10] is verified, the specific methods are as follows:

1. Firstly, creep parameters of different stress level is identified preliminary by the linear decreasing PSO algorithm.

(1) The compiled the fitness function file (M-file) is stored in the MATLAB workspace to prepare for the call, and the test results are imported the M-file; fitness function (ie, objective function) is used to be formula (6), wherein, $\varepsilon_i(X,t_i)$ is calculated value at t time from the theoretical formula , the formula is as follows:

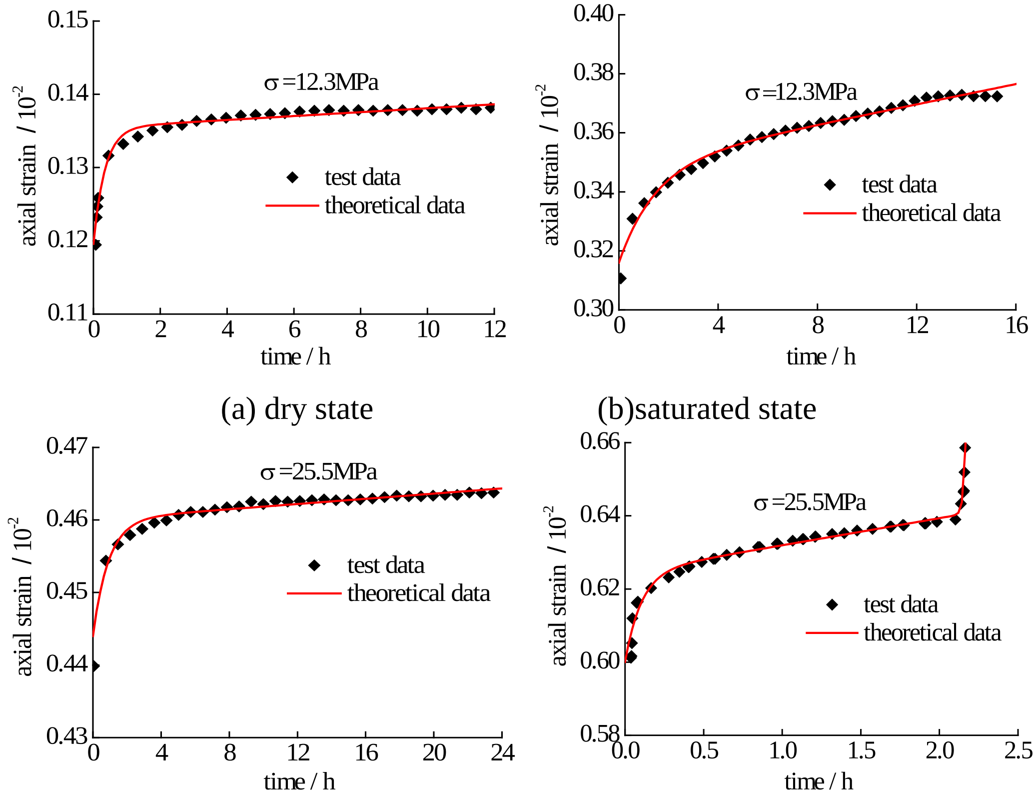
$$\varepsilon_i(X,t)=\frac{\sigma_i}{E_1}+\frac{\sigma_i}{\eta_1}t+\frac{\sigma_i}{E_2}\left[1-\exp\left(-\frac{E_2}{\eta_2}t\right)\right] \qquad \sigma\le\sigma_\infty \tag{7}$$

$$\varepsilon_i(X,t)=\frac{\sigma_i}{E_1}+\frac{\sigma_i}{\eta_1}t+\frac{\sigma_i}{E_2}\left[1-\exp\left(-\frac{E_2}{\eta_2}t\right)\right]+\frac{\sigma_i-\sigma_\infty}{\eta_3}t \qquad \sigma>\sigma_\infty,\quad t\le t^* \tag{8}$$

$$\varepsilon_i(X,t)=\frac{\sigma_i}{E_1}+\frac{\sigma_i}{\eta_1}t+\frac{\sigma_i}{E_2}\left[1-\exp\left(-\frac{E_2}{\eta_2}t\right)\right]+\frac{\sigma_i-\sigma_\infty}{\eta_3}e^{(t-t^*)^n}t \qquad \sigma>\sigma_\infty,\quad t>t^* \tag{9}$$

(2) Call main program[11] of linear decreasing PSO is identified preliminary creep parameters in MATLAB. The calculated process of PSO algorithm is as follows: every particle is randomly distributed within the limited search space, then a fitness value of the particle can be obtained according to the formula (6). Every particle is successive iterated based on the procedure of set , the calculated minimum fitness value of each particle is affirmed as a historical optimum value, replaced former value in turn, until find the smallest fitness value, which is the optimal value of history. For this test, identification of the parameter is terminated when the number of iteration reach 1000 or fitness value is less than 100, and parameters of linear decreasing PSO algorithm $w_{\max}$ 、 $w_{\min}$ 、 c_1 、 c_2 successively taken as 0.9, 0.4, 2, 2 in turn.

2. The identified result of linear decreasing PSO algorithm is regarded as the initial value from step 1, then LM nonlinear least squares is used to invert the model parameters by the initial value. this process is realized by means of the software Origin. Firstly, the inverted result from step 1 is input in the fitting screen of Origin, then inverted accurately by means of Levenberg-Marqud algorithm. typical fitting curves are shown in Figure 1, the corresponding creep parameters are shown in Table 1.



(a) dry state (b)saturated state

(c) dry state (d) saturated state

Figure 1: Fitted curves of creep tests

It can be seen that experimental results are coincide with identified theoretical value by means of modified PSO—LM algorithm from figure 1 and table 1. And so, the PSO—LM method could be effectively identified the parameters of rock creep models.

Table 1: Creep model parameters

state	σ_1 /MPa	E_1 / GPa	η_1 / GPa·h	E_2 / GPa	η_2 / GPa·h	η_3 / GPa·h	n	R^2
dry	12.3	10.28	4603.57	77.71	26.74			0.983
	20.4	5.93	2602.40	91.53	24.32			0.953
	25.5	5.74	14235.37	158.87	144.52			0.943
saturated	12.3	3.89	715.17	37.28	54.61			0.989
	20.4	3.99	1841.38	77.74	98.81			0.993
	25.5	4.25	343.78	104.07	10.78	2.85E8	77.12	0.977

CONCLUSIONS

Identification of model parameter often leads to failure due to the defects of parameter identification that the PSO is prone to fall into local optimum solution and the LM is rely heavily on the initial value. For obtain global optimal solutions, this article combined the above two methods, the model parameters of the model are identified by linear decreasing PSO algorithm firstly, the inverted results are regarded as initial values, then LM method is used to invert accurately by initial values. The method is applied to parameters identification of improved Burgers rheological model and hierarchical load creep test of carbonaceous slates, the identified results showed that experimental results are coincide with identified value by modified PSO—LM method, and so the method is feasible.

REFERENCES

1. Sun Jun. Rock Rheological Mechanics and its advance in engineering applications[J]. *Chinese Journal of Rock Mechanics and Engineering*, 2007, 26(6)∶1081–1106.
2. Gao Wei, Zheng Ying-ren. Identification of the geomaterial constitutive model based on genetic algorithm[J]. *Chinese Journal of Rock Mechanics and Engineering*, 2002, 21(1): 9-12.
3. Chen Yuan-jiang, Pan Chang-liang, Cao Ping, et al. Identification of rheological constitution model of rock and soil based on artificial neural network[J]. *The Chinese Journal of Nonferrous Metals*. 2002, 12(5): 1027-1034.
4. Zhai Shu-hua, Li Wen-xiu, Gao Qian, et al.. Identification of rheological constitutive model of rock based on genetic programming[J]. *Journal of Hebei University (Natural Science Edi tion)*. 2008, 28(6): 578-582.
5. Li Zhi-jing, Zhu Zhen-de, Zhou Wei-hua, et al.. Back analysis of non-stationary parameters of rock creep model based on chaos particle swarm optimization algorithm[J]. *Journal of Hohai University(Natural Sciences)*. 2008, 36(3): 346-349.
6. Luo Run-lin, Ruan Huai-ning, Zhu Chang-xing. Parameter inversion of rock creep model based on PSO-least square method[J]. *Journal of Liaoning Technical University (Natural Science)*. 2009, 28(5): 750-753.
7. Liu Wen-bin, Liu Bao-guo, Liu Zhong-zhan,et al. Parameter identification of creep constitutive model of rock based on modified PSO algorithm[J]. *Journal of Beijing Jiaotong University*. 2009, 33(4): 140-143.
8. Peng Ru-fa, Xu Xiao-jian. Microevolution Algorithm for inversion of non-stationary parameters in rock creep model[J]. *Journal of Yangtze River Scientific Research Institute*. 2011, 28(6): 50-54.
9. Kennedy J, Eberhart R. Partical Swarm Optimization[C]. *Proc IEEE lnt Conf on Neural Networks*, 1995, 1942-1948.
10. Song Yong-jun, Lei Sheng-you. Study on creep properties and constitutive model of carbonaceous slates under dry and saturated states[C]. *Proceedings of the 3rd ISRM Young Scholars' Symposium on Rock Mechanics*, Xi'an, China, 2014, 77-81.
11. Gong Chun, Wang Zheng-lin. Proficient in MATLAB optimization calculation (the second edition) [M]. Beijing: *Electronic Industry Press*, 2012.

Editor's note. This paper may be referred to, in other articles, as:
Song Yong-jun, Ren Jian-xi, Zhang Kun, Liu Chao-ke, and Chen Xing-zhou: "Parameter Identification of Creep Model of Rock Based on Modified PSO-LM Algorithm" *Electronic Journal of Geotechnical Engineering*, 2016 (21.16), pp 5389-5395. Available at **ejge.com**.