

APPLICATION OF STOCHASTIC METHODS (GENETIC ALGORITHM-TABU SEARCH) TO IDENTIFY THE PARAMETERS OF MOHR COULOMB MODEL

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Received: 02 March 2020 / Accepted: 23 September 2020 / Published online: 01 January 2021

ABSTRACT

The problem of the choice of the parameters of soil is a difficult task, she requires many experiences. To answer this question, methods of identification of parameters, based on the principle of inverse analysis are developed who consist in adjusting a numerical model on observed experimental data. The objective of this work is to apply the principle of inverse analysis by using stochastic optimization methods (genetic algorithm and the genetic algorithm hybrid with tabu search) to identify the parameters (G , φ) of the constitutive soil model Mohr-Coulomb, from a real case of landslide of the Ciloc city of Constantine in Algeria. The Analysis of the results obtained showed that the best sets of parameters (G , φ) which minimize the deviation between the numerical model and the experiment are found by the genetic algorithm method.

Keywords: Inverse analysis; Stochastic methods; Identification of parameters; Landslide.

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doi: <http://dx.doi.org/10.4314/jfas.v13i1.6>

1. INTRODUCTION

The mechanical parameters introduced into the geotechnical calculations, in particular those realized by the finite element method, are often badly known. Added to this difficulty, the uncertainty on the solicitations and the boundaries conditions as well as the error that can

introduce the assumptions and approximations of the mechanical model to be used. The choice of the soil parameters is therefore a delicate task, it requires a lot of experiences and generally pose like a brake in the use of the finite elements method in geotechnics [1], in this context that is born the problematic of this article

The objective of this study concerns the identification of the parameters of the constitutive soil model Mohr Coulomb, the shear modulus (G) and the friction angle (φ), by the inverse analysis method. The inverse analysis procedure consists in calibrating a numerical soil model on experimental data by iterative modifications of the input parameter values of the model until the output values best reproduce the observed data, i. e. the calculation of the objective function called the error function, which quantifies the difference between experimental and numerical results. This difference is then minimized by two stochastic optimization methods. From this optimization are deduced new values for the parameters of the constitutive soil model. The process is repeated until the difference between the calculated values and the measured data is minimal [2].

In our work, we were interested in two stochastic optimization methods: the genetic algorithm (GA) and the hybrid genetic algorithm with the tabu search method (HGA). Genetic algorithms are stochastic optimization algorithms based on the mechanisms of natural selection. Their operation is extremely simple. We start with a population of initial solutions arbitrarily chosen. Their performance is evaluated using the error function. On the basis of these performances we create a new population of solutions using simple evolutionary operators: selection, crossover and mutation. This cycle is repeated until a satisfactory solution is found.

The second optimization method is the hybrid genetic algorithm with the tabu search method. Tabu search (TS) was invented by Glover [3]. The principle of this method is at each iteration the neighborhood of the current solution is examined. The algorithm registers the best solution among the neighbors, even if it is not as good as the current solution. The acceptance of less efficient solutions than the current solution avoids falling into a local optimum. To escape from turning in a circle between several solutions, the algorithm forbids the passage by recently visited solutions. In practice the method stores in a tabu list (T) the last solutions visited.

In order to test and evaluate the performances of the proposed optimization methods we have

developed two programs under Matlab 07 environment [4], The first program uses the genetic algorithm method and the second one uses the hybrid genetic algorithm method with the tabu search, these two programs were validated on the real case of landslide of the city ciloc of constantine in Algeria, for the purpose to identify the best sets of soil parameters (G , φ) which minimize the deviation between the numerical model and the experiment. A comparison and some conclusions at the end of this article to judge the relevance of the two stochastic optimization methods in solving this type of geotechnical problem. The numerical simulations were realized using the numerical calculation code Plaxis 2D [5].

2. THE SOFTWARE USED

2.1 Matlab 07

Matlab 07 software is a fourth generation programming language and a numerical analysis environment allows the development and execution of algorithms and visualization of data and also includes many functions, calculation or data processing, display , plots of curves, resolution of systems and algorithms of numerical calculations in the broad sense of the term [4].

2.2 Plaxis 2D

Plaxis 2D is a two-dimensional program specially designed to perform strain and stability analyzes for different types of geotechnical applications. Real situations can be represented by a plane or axisymmetric model. The general algorithm of the plaxis code consists in solving a system of nonlinear equations according to an iterative process to determine the displacement values at the different nodes of the mesh, the stress field and the soil fracture states [5].

3. OPTIMIZATION PRINCIPALE

Based on the stresses imposed on the model and the assumed parameters for a soil model, a numerical answer is calculated. The numerical answer obtained is then compared with available experimental data. This comparison is translated by the calculation of the difference between the observed data and the calculated values, i. e. the calculation of the error function (F_{err}). This difference is then minimized by a stochastic optimization algorithm. From this optimization are deduced new values for the parameters of the constitutive soil model. The process is repeated

until the difference between the calculated values and the measured data is minimal [2]. The optimization principle is shown in Fig. 1.

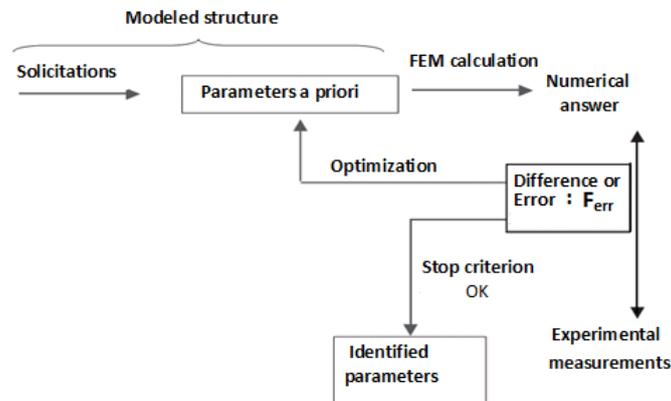


Fig.1. Optimization principle [2]

3.1. The Error Function

The choice of the error function (F_{err}) is crucial in inverse analysis [6]. Often in geotechnical engineering, the error function evaluates the difference between a numerically calculated curve, described by " U_{ni} ", and an experimental curve measured in situ, described by " U_{ei} " (see Fig. 2). For this study, the error function is defined as a scalar function, of a least square type as shown in Eq. (1):

$$F_{err} = \left(\frac{1}{N} \sum_{i=1}^N \frac{(U_{ei} - U_{ni})^2}{(0.01 + U_{ei})^2} \right)^{1/2} \tag{1}$$

Where:

N: is the number of measurement points; U_{ei} : is the experimental displacement at a measurement point i and; U_{ni} : is the numerical displacement at a measurement point i .

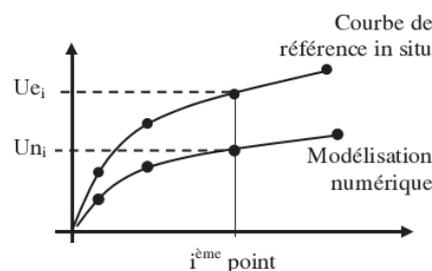


Fig.2. Estimation of the error on the solution between measured values U_{ei} and calculated values U_{ni} [2]

3.2 Optimization Algorithms

3.2.1 Optimization by the Genetic Algorithm

The genetic algorithm starts the search with a set of individuals. At each iteration of the search procedure, the best individuals are selected to survive and reproduce. The selection of individuals is based on their qualities which are measured from the error function. Then, the individuals (called parents) are selected to undergo crossover and mutation operators allowing the generation of another population of individuals (called children). Individuals in the new population will be assessed to replace a portion of the individuals in the current population [2]. The optimization process by the genetic algorithm is shown in Fig. 3

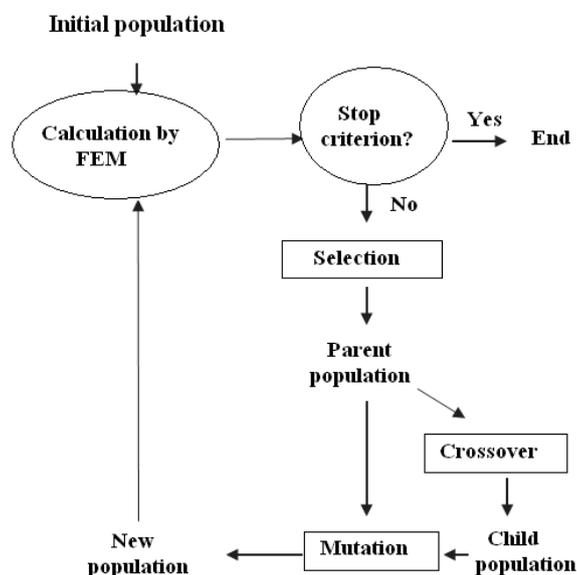


Fig.3. The optimization process by the genetic algorithm [2]

3.2.2 Optimization by the Hybrid Genetic Algorithm

Genetic algorithms are expensive in the calculation time, because they manage several solutions simultaneously. In order to improve the quality of solutions and accelerate the convergence of genetic algorithm (GA), it is interesting to hybridize the genetic algorithm with a local search algorithm. The role of the local search method is to explore in depth a particular area and to guide the search for the genetic algorithm in this area. With each generation of the genetic algorithm, the tabu search method is introduced after the crossover operation using the

intensification operator to find the best neighbor for each solution found [7]. The result will be a new, optimized population that will continue to evolve through other genetic operations to produce new generations that are better adapted to the problem. The optimization process by the hybrid genetic algorithm is shown in Fig. 4.

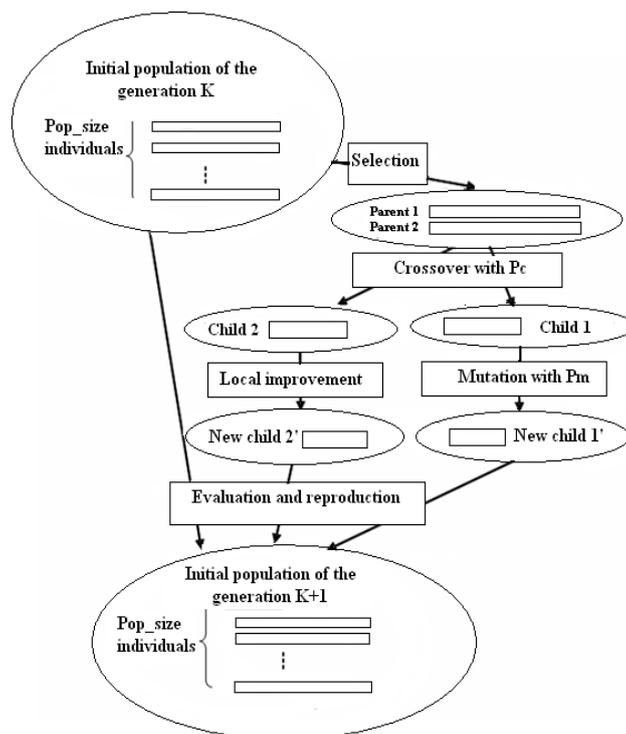


Fig.4. The optimization process by the hybrid genetic algorithm [7]

4. NUMERICAL MODELING OF THE STUDY SITE

The study site is the Ciloc city of Constantine in Algeria. The Ciloc city is located on a sloping area which suffered a landslide over a hundred metres in 1987. This slope is located at the foot of the building B (see Fig. 5). A geophysical reconnaissance campaign carried out in 1980 clarified the nature of the slope. On the surface, clays are present over a thickness of 8 m, followed by sand and gravel, probably heavily impregnated with water, which themselves rest on marls. Positions S2, S3 and S9 represent the location of the inclinometric soundings (see Fig. 6). In this work, we are interested in the horizontal displacements given by the inclinometer S9 [8].

The mechanical characteristics of the soils constituting the Ciloc slope refer to the work of

Mokhbi *et al.* 2008 [9]. Table 01 summarizes the physico-mechanical characteristics of each layer, these characteristics correspond to the Mohr Coulomb model (MC), chosen for calculation in plaxis. The numerical model of Ciloc is presented in figure 7, it has a width of 272m, and a minimum height of 23m and maximum height of 49m. The meshing of this model is done by triangular elements at 15 nodes. It consists of 219 elements, 1871 nodes and 2628 stress points (see Fig. 8). Figures 09 and 10 represent respectively. The level of the water table and the location of the landslide

In this work, we propose a numerical modeling, using the numerical calculation code Plaxis 08 for the analysis of the plane deformation problem, in order to identify two parameters of the soil. According to the works of Benaissa *et al.* 1989 [10], the most influential parameters on soil behaviour were: the shear modulus (G) and the friction angle (φ) of the 1st layer of the numerical model were therefore initially chosen for identification. These values are initially used to define the data used for the inverse analysis. Subsequently, the shear modulus (G) and the friction angle (φ) are assumed to be unknown. A priori values are given to the unknown parameter to simulate the associated direct problem, using the numerical calculation code Plaxis until the difference between the results of the numerical calculation (numerical curve) and the inclinometric measurements (experimental curve) is minimum (see Fig. 11).



Fig.5. The Location of the landslide at the foot of the building B [11]

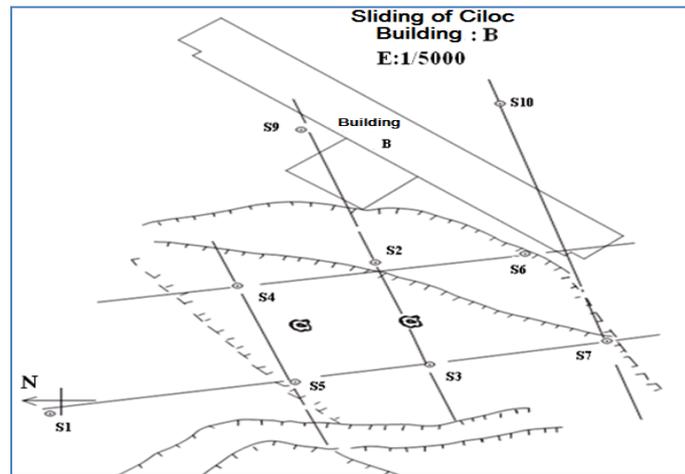


Fig.6. The polls of geological reconnaissance [9]

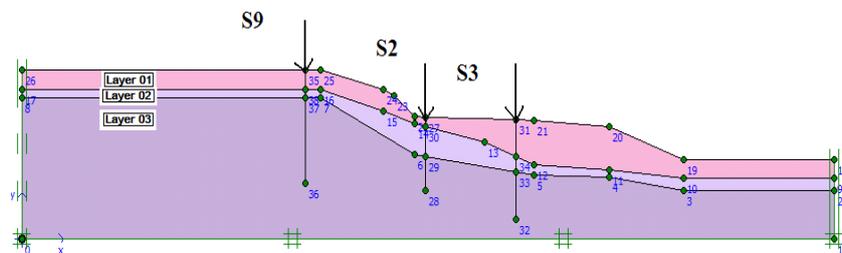


Fig.7. The Numerical Model

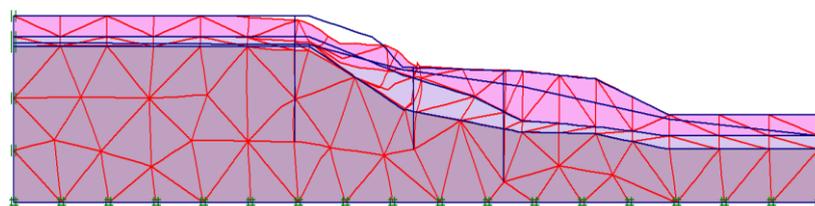


Fig.8. Deformed mesh

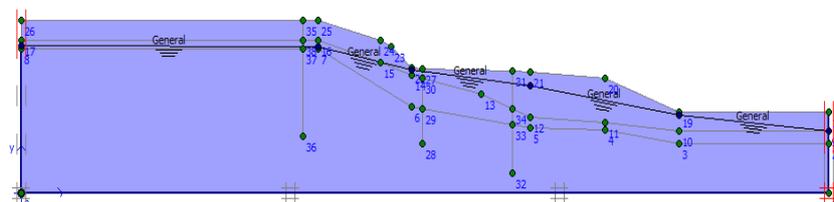


Fig.09. The level of the water table

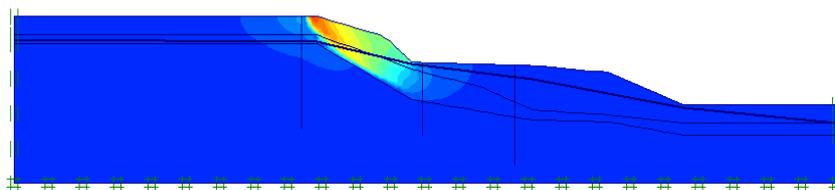


Fig.10. The location of the landslide

Table 1. The physico-mechanical characteristics of the Soil layers [9]

Parameter	Layer 01: Clays	Layer 02: Gravelly sand	Layer 03 : Marls
γ_d (KN/m ³)	17	15	18
γ_{sat} (KN /m ³)	19.5	17.5	21.5
C (KN /m ²)	15	8	55
φ (°)	12	21	22
G (KN /m ²)	376	385	1154
ν	0.33	0.30	0.30

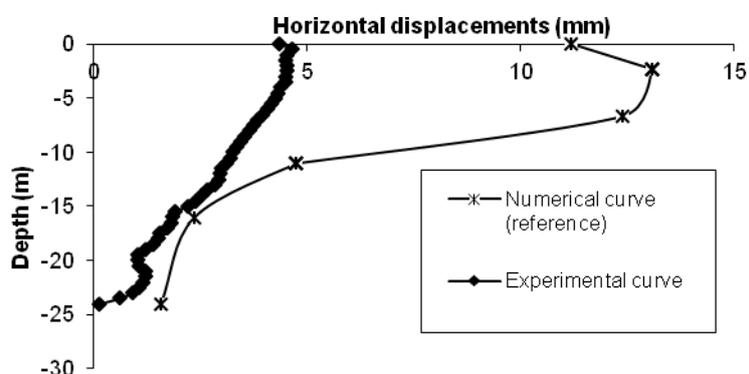


Fig.11. Horizontal displacement of the inclinometer S9 according to the depth.

◆: Experimental measurements to be optimized; ✕: A priori modeling of the measurements

5. VALIDATION OF THE OPTIMIZATION METHODS

In order to test the convergence and efficiency of the two proposed optimization methods we developed two programs under Matlab 07. The first program uses the genetic algorithm method and the second uses the hybrid genetic algorithm method with the tabu search, these two programs are validated on the numerical model of the real problem of landslide of the city ciloc

of constantine in Algeria, in order to identify two parameters of the constitutive soil model Mohr Coulomb, the shear modulus (G) and the friction angle (φ). Prior values are given to the unknown parameters to simulate the numerical model, using the numerical calculation code Plaxis 08, until the difference between the result of the numerical calculation and the experimental data is minimal. It should be noted that the identification only concerns the shear modulus (G) and the friction angle (φ) of the first layer of the reference model cited in table 01.

5.1 Genetic Algorithm method

The optimization by genetic algorithm program is therefore equivalent to a parameter estimation process of the constitutive soil model. The genetic algorithm parameters used in the different tests are cited in Table 02.

Table 2 . Parameters of the genetic algorithm

Parameter	Value
Number of individuals	N=30 individuals
Number of generation	k=100
Length of the bit chain	l=18 bits
Probability of crossover	$P_c = 0.6$
Probability of mutation	$P_m = 0.05$

The genetic algorithm program is based on the following eight steps:

Step 01: Create an initial population $P(k) = 30$ individuals = $[N_1 (G_1; \varphi_1), \dots, N_{30} (G_{30}; \varphi_{30})]$

Step 02: Evaluate the adaptation of each individual using the error function (as shown in Eq. (1))

Step 03: Is there any convergence? Any convergence if the experimental curve is well reproduced or the convergence of the population towards a single individual for the parameters (G; φ): If the algorithm does not converge towards a solution, the procedure is stopped after a maximum number of iterations (after 100 iterations).

-If yes, display the results

-If not go to step 4

Step 04: Select the best individuals of the initial population $P(k)$ with a low error function to obtain the parent population: $P(k) = 30$ individuals \rightarrow Parent individuals = $1/3 P(k)$;

Step 05: Code the parent individuals (decimal \rightarrow binary).

Step 6: Cross the parent population in two random points with a crossover rate $P_c = 0.6$ to obtain the child population (as shown in Fig.12), then apply a mutation rate $P_m = 1/l = 1/18$ (as shown in Fig.13), to obtain a new population $P(k+1)$. Where l : the length of the bit chain in an individual.

Step 7: Decode the new population $P(k+1)$ (binary \rightarrow decimal).

Step 8: Evaluate the adaptation of the new individuals $P(k+1)$ using the error function and go to Step 3.

Parent 1	00 0100 111	\rightarrow	Child 1	00 1011 111
Parent 2	11 1011 000	\rightarrow	Child 2	11 0100 000
	Before			After

Fig.12. Representation of a crossover in two points

011001
 \downarrow
 011011

Fig.13. Representation of a mutation of bits in a chain

5.1.1 Results and Discussion

After several executions of the genetic algorithm program with different values of the parameters that has been previously described. Fig. 14 shows that the optimization process by genetic algorithm (GA), presents a very large decrease in the error function value from the first generation, characterizing the identification of a set of approximate solutions from the first generations. Then, it progressively evolves between generation (02) and generation (11) until all parent individuals are equal to the same combination of parameters. This characterizes the convergence of the algorithm. Finally, the identified optimum of the problem is the following combination of parameters:

$G = 621$ kPa and $\varphi = 9.5^\circ$

The calculation of the standard deviation on each combination of parameters makes it possible to estimate the optimum of the problem. This definition of the optimum of the problem shows

that the evaluation of the values of the parameters G and ϕ is very close to the optimal solution. In addition, Moreover, these parameter combinations ensure a satisfactory reproduction of the experimental measurements as illustrated by Fig. 15.

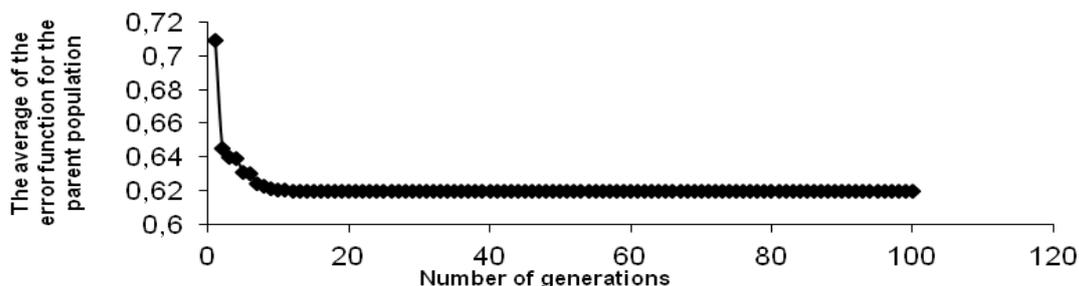


Fig.14. Evolution of the average of the error function on the parent population according to the generations of a genetic algorithm

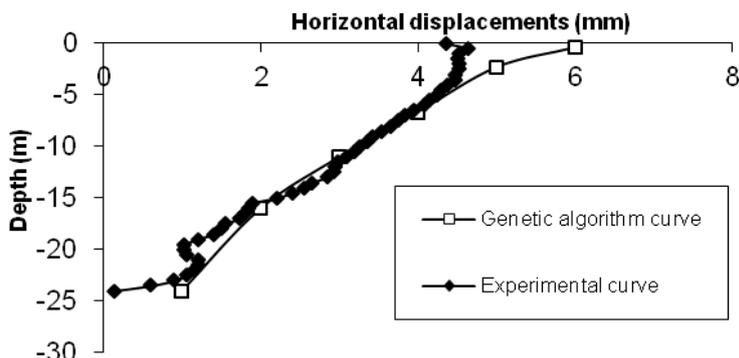


Fig.15. Horizontal displacement of the inclinometer S9 according to the depth.

◆: Experimental measurements to be optimized; □: Modeling of measurements after optimization by the genetic algorithm

5.2 Hybrid Genetic Algorithm method

The application of the hybrid genetic algorithm program on this problem is guided by a number of parameters that influence the success or not of the algorithm, these parameters are cited in Table 03:

Table 3. Parameters of the hybrid genetic algorithm

Parameter	Value
Number of individuals	N= 30 individuals
Number of generation	k = 100
Length of the bit chain	l = 18 bits
Probability of crossover	P _c = 0.6
Probability of mutation	P _m = 0.025
Size of the tabu list	T = 3

The hybrid genetic algorithm program is based on the following ten steps:

Step 01: Create an initial population $P(k) = 30$ individuals = $[N_1 (G1; \varphi1), \dots, N_{30} (G30; \varphi30)]$

Step 02: Calculation of an adaptation value for each individual using the error function (as shown in Eq. (1))

Step 03: Selection of a pair of parent individuals with a low error function.

Step 04: Code the parent individuals (decimal \rightarrow binary).

Step 05: Crossing of the two parents with a probability $P_c = 0.6$ to generate two children.

Step 06: Mutation of a child with a probability $P_m / 2$.

Step 07: Apply the intensification operator which is a parameter of the tabu search procedure, such as a local improvement operator (best neighbor choice) to the other child generated by the crossover operator not chosen by the step 5 for the mutation. A new individual is obtained.

Step 08: Repeat steps (3), (4), (5), (6), and (7) until the new population $P(k + 1)$ occurs.

Step 09: Decode the new population $P(k + 1)$ (binary \rightarrow decimal).

Step 10: Evaluate the adaptation of the new individuals $P(k + 1)$ using the error function and go to Step 03.

5.2.1 Results and Discussion

The hybrid genetic algorithm program is first launched to identify the two parameters of Mohr Coulomb (G and φ). The evaluation of the solutions is based on the error function. Fig. 16 presents the evolution of the average of the error function on individuals composing the parent population during the process of optimization by hybrid genetic algorithm. This time it appears that starting from an initial population uniformly distributed over all the search space of the

parameters, from the first iteration a zone of solutions of the search space is identified. Then, as the identification is refined to the optimum of the problem after only five iterations, the identified optimum of the problem, is the following combination of parameters:

$$G = 656 \text{ kPa and } \varphi = 9.5^\circ$$

The optimization procedure by the hybrid genetic algorithm method is faster but in this case can not converge to the correct solution of the problem because of the mechanism of the tabu search which records the best solution among the neighbors even if it is worse than the current solution to avoid falling into a local optimum. That is to say that the combinations of parameters obtained do not sufficiently produce the experimental measurements. As illustrated by Fig. 17.

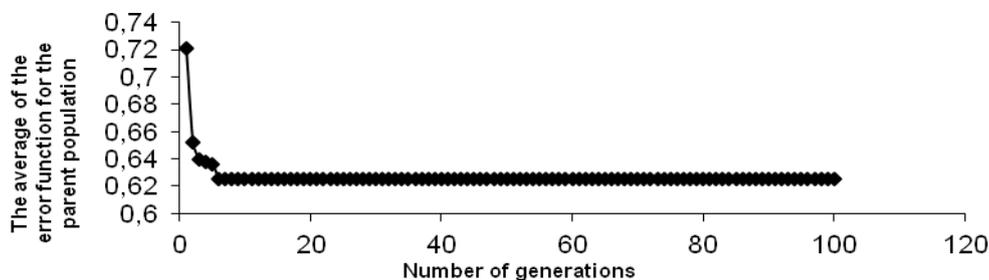


Fig.16. Evolution of the average of the error function on the parent population according to the generations of a hybrid genetic algorithm

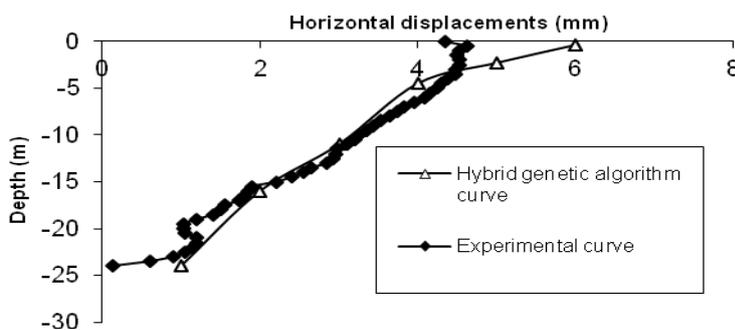


Fig.17. Horizontal displacement of the inclinometer S9 according to the depth.

◆: Experimental measurements to be optimized; Δ: Modeling of measurements after optimization by hybrid genetic algorithm

6. COMPARISON OF RESULTS

The horizontal displacement of the slope as a function of the depth obtained by the numerical

curve and the two stochastic optimization curves (GA and HGA) are compared with those obtained experimentally by the inclinometer measurements. This comparison shows that our numerical curve has a very large deviation from the experimental curve and the other two optimization curves (see Fig. 18), this difference can be due to the uncertainties on the stresses and the boundary conditions as well as the error that can introduce the assumptions and approximations of the mechanical model used that are not taken into account in numerical modeling, so the numerical curve is indeed an approximation far from satisfactory of the actual behaviour of the slope.

The results obtained by applying the two optimization processes also show that the optimization curve by genetic algorithm (GA) is a little closer to the experiment than the hybrid genetic algorithm optimization curve (HGA). That is, the best parameter sets that minimize the difference between the model and the experiment are found by the genetic algorithm method.

The comparison in this article is based not only on the quality of the results obtained by the two optimization methods but also on the speed of convergence, the speed of convergence of the error function for the two different optimization methods towards the global optimum of the sliding problem shows that the hybrid genetic algorithm converges faster than the genetic algorithm since the latter converges at the 5th iterations while the genetic algorithm (GA) converges after 11 iterations. Therefore, we can conclude that the genetic algorithm method (GA) has found a better result than the hybrid genetic algorithm method (HGA) but in a longer convergence time.

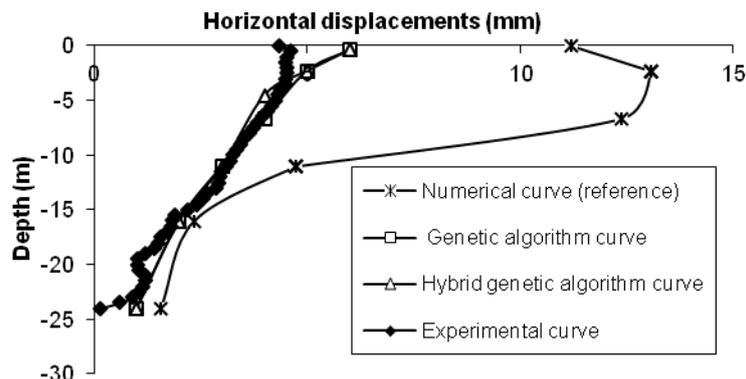


Fig.18. Horizontal displacement of the inclinometer S9 according to the depth.

- ◆: experimental measurements to be optimized; ✕: A priori modeling of the measurements;
- : Modeling of the measurements after optimization by the genetic algorithm; △: Modeling of the measurements after optimization by the hybrid genetic algorithm

7. CONCLUSION

The objective of this study is the validation of two stochastic optimization methods by genetic algorithm and hybrid genetic algorithm using two programs developed under Matlab 07. These two programs are validated on the numerical model of the real landslide problem of the city Ciloc of constantine in Algeria, in order to identify the best sets of two parameters of the constitutive soil model Mohr Coulomb, the shear modulus (G) and the friction angle (φ), which minimize the deviation between the numerical model and the experiment.

The result obtained by applying the genetic algorithm method shows that from an initial population uniformly distributed over the search space, the optimum was obtained after 11 generations for 100 generations of the genetic algorithm program. However, the improvement was faster and more efficient with the hybrid genetic algorithm, where the optimum was obtained after only 05 generations for all generations.

The comparison of the performance of two stochastic methods (GA and HGA) shows that the genetic algorithm optimization curve is a little closer to the experience than the hybrid genetic algorithm optimization curve. That is, the best sets of parameters that minimize the deviation between the model and the experiment are found by the genetic algorithm method. For this reason can be said that the genetic algorithm method alone is robust allows to identify a

satisfactory optimum. This optimum presents a good reproduction of the experimental data, but expensive in calculation time. On the contrary, the hybrid genetic algorithm method is faster but in some cases cannot converge to the right solution of the problem because of the tabu search mechanism which registers the best solution among the neighbors even if it is worse than the current solution to avoid falling into a local optimum.

So, we can conclude that the Genetic Algorithm (GA) method found a better result than the Hybrid Genetic Algorithm (GAH) method but in a longer convergence time.

Despite the large number of evaluations of the objective function required by stochastic methods, these methods constitute a class of approximate methods adaptable to a very large number of optimization problems. They have been shown to be highly effective in providing good quality approximate solutions for a large number of optimization problems and real applications. For this reason the study of these methods is currently in full development.

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How to cite this article:

Moussaoui M. Application of stochastic methods (genetic algorithm-tabu search) to identify the parameters of Mohr coulomb model. J. Fundam. Appl. Sci., 2021, 13(1), 89-106.