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Use of a landslide problem for the identification parameters in geotechnics

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Soil behavior has been widely studied. However, methods for identifying parameters of soil behavior models have not been given equal importance. Identifying these parameters has posed a challenge for geotechnical calculations. Inverse analysis has emerged as an approach that aims to solve this problem by seeking to identify the optimal values of the desired parameters by minimizing the gap between the responses simulated by the model and in situ observations. The objective of this study has been to apply the principle of inverse analysis by exploiting the power of two optimization algorithms, the genetic algorithm and the hybrid genetic algorithm with tabu search method, in order to identify two parameters of the Mohr-Coulomb soil model, the cohesion and the friction angle. Both algorithms have been validated on a landslide case at the Boulakroud site in Skikda, Algeria. The results obtained have shown that the hybridization of the genetic algorithm with the tabu search method has proved to be more efficient, allowing a faster convergence towards the exact optimum of the problem. Conversely, the genetic algorithm alone has required a longer computation time to reach an optimum close to the exact optimum.

Keywords: Cohesion, Friction angle, Inverse analysis, Mohr coulomb, Optimization algorithms

1 Introduction

The simulation of complex soil behavior relies on a variety of constitutive models. The reliable use of these models in calculations requires the precise identification of their parameters. These parameters are usually obtained by tests, which can be carried out in the laboratory on samples of limited dimensions, such as triaxial or oedometer tests, or from in situ tests, such as pressuremeter or penetrometer tests. However, the identification of the parameters of a soil behavior model from laboratory tests is extremely complex, mainly due to the problems of accuracy of soil samples collected in the field and the significant modifications resulting from drilling and extraction. Although in situ tests avoid these reworking problems, they do not directly give the constitutive parameters of the soil layers, which are often estimated by empirical correlations[1]. Despite these challenges, geotechnical tests, whether conducted in the laboratory or in situ, provide experimental curves that can be used to estimate soil layer parameters through inverse analysis, which involves fitting a constitutive model to these experimental curves[2]. Several researchers such as Marseguerra *et al.* (2003)[3] have studied inverse analysis to identify soil constitutive parameters from measured displacements in the soil[4]. Their studies highlight the ability of this technique to estimate parameters that are difficult to identify using conventional methods. Inverse analysis works by minimizing the gap between experimental observations and predictions of a numerical model of soil behavior, through iterative adjustment of the model parameters[5]. Quantifying this gap using an objective function, often called an error function, converts the parameter identification process into an optimization problem. Fino and Calvelo (2005)[6], point out that simultaneous optimization of all parameters can lead to indeterminate or incorrect solutions, making it necessary to limit the number of optimized parameters. Despite this precaution, the optimization process can sometimes stop before reaching the desired optimum [7].

The objective of this study is to apply the principle of inverse analysis to identify two key parameters of the Mohr-Coulomb model, namely cohesion (c) and friction angle (φ) which are considered unknown. To achieve this objective, two programs developed with Matlab 07 were used to implement an identification process based on two stochastic optimization algorithms: a genetic algorithm and a hybrid genetic

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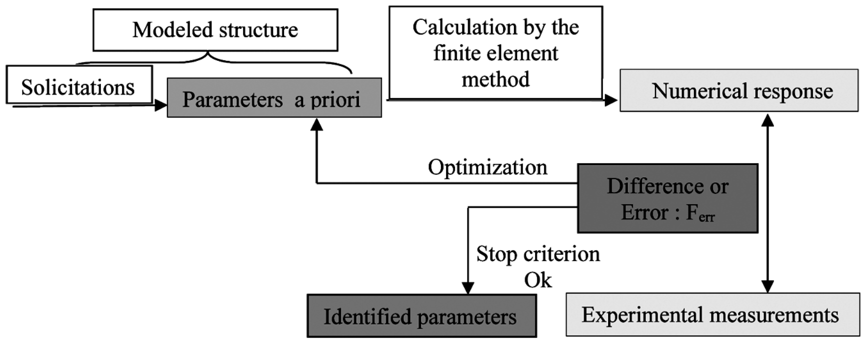

Fig. 1 — Flowchart of the identification method.

algorithm with tabu search method. The validity of these two programs was tested on a landslide problem at the Boulakroud site in Skikda, Algeria. In order to find the optimal values of these parameters that allow a better fit between the experimental curve and the predictions from the numerical simulations carried out with the Plaxis 2D software.

2 Materials and Methods

Through this study, we aim to develop a method to identify two key parameters of the Mohr-Coulomb soil model: the cohesion (c) and the friction angle (φ) of the backfill layer of the studied site. These values are initially considered as unknown. Subsequently, a priori values are given to the unknown parameter to simulate a landslide problem on the Boulakroud site in Skikda, Algeria. The identification method begins with a definition of the stresses imposed on the soil model and the specification of its initial parameters. These data are then used to calculate a numerical response using the finite element calculation code Plaxis 2D. This answer is then compared to the experimental measurements provided by an inclinometer. The evaluation of the difference between the predicted values and the experimental measurements constitutes the error function, defined by Eq. (1). In order to minimize this error function, two programs developed under Matlab 07 were used to execute an optimization process based on two optimization algorithms: the genetic algorithm and a hybrid genetic algorithm with tabu search method. The result of this optimization is to obtain new values for the constitutive parameters of the soil model. This iterative method ends when the optimal values of these parameters are found in order to obtain a better agreement between the simulations and the measured data[8]. The flowchart of the identification method is shown in Fig. 1.

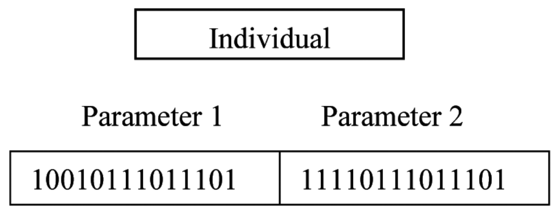

Fig. 2 — Binary coding of the parameters to be identified.

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

Where:
N =Total number of measurement points.
U_{ei}=Experimentally measured displacement
U_{ni}=Numerically calculated displacement

2.1 Optimization algorithms

2.1.1 Genetic algorithm

A genetic algorithm is an optimization approach based on the mechanisms of natural evolution described by Darwin. Its originality is due to the use of random selection to identify and explore the parts of the search space most likely to contain improvements [9]. Genetic algorithms exploit chance to direct their search in the sections of the search space where improvements are likely. In a genetic algorithm, we work with a population of individuals[10]. Each individual is a representation of a set of parameters, encoded as a bit string that includes all the information necessary to define a point in the search space (Fig. 2). Once the initial population is randomly created in the search space, each individual is evaluated in its environment and receives a numerical value from its error function. This evaluation is used to qualify each individual. Once each individual has been evaluated, the genetic algorithm directs the population to the best areas of the search space through three key steps: selection, crossover, and mutation.

Selection: During this stage, individuals are ranked based on the value calculated by the error function. Only the best-performing individuals, displaying the lowest values of this function, are retained to move on to the next generation. These selected individuals constitute the parent population.

Crossover: Crossover is a technique applied to a portion of the parent population. To perform a crossover, two individuals are randomly selected from the parent population. Then, portions of their respective bit strings are reversed. This operation produces two new individuals. These individuals constitute the child population as illustrated in Table 1.

Mutation: This operation as illustrated in Table 2 introduces random changes in the bit string of the individuals. By occasionally changing the value of a bit to create some diversity within the child individuals and the rest of the parent individuals not affected by the crossover. The new generation is then composed of these children and the retained parents.

This cycle of evaluation and evolution continues iteratively until the algorithm converges to an optimal solution. Figure 3 shows the research process chart of the genetic algorithm.

2.1.2 *Hybrid genetic algorithm*

Optimization by genetic algorithm alone proves to be a powerful tool for optimizing various geotechnical problems. It offers new opportunities for probabilistic finite element analysis of geotechnical structures. However, as pointed out by Zolfaghari *et al.* (2005)[11], the main disadvantage of genetic algorithms compared to other methods is the computing power required to carry out the optimization. The computational cost of an optimization by genetic algorithm is higher than that necessary for any other optimization method. For McCombie and Wilkinson (2002)[12], a genetic algorithm is a highly probabilistic method. The worse the problem is posed, the more the computational cost increases, so it is difficult to know in advance the number of evaluations necessary to identify the optimum. At present, hybrid methods are widely used for geotechnical studies[13, 14].

Table 1 — The crossover operator in binary coding.

Parent Individuals				
Parent A:	1100	110	10011101	11100
Pointsofcrossover :				
Parent B:	0110	001	01111011	00111
Child Individuals ChildA' :	1100	001	10011101	00111
Pointsofcrossover :				
ChildB' :	0110	110	01111011	11100

Table 2 — The mutation operator in binary coding.

Individual before mutation	
Individual:	11000011001110100111
Selected Bit:	
Individual after mutation	
Mutated individual:	1100001101**1**110100111
Mutated Bit:	

Overall, the hybrid method proposed in this study provides a balance between exploration and exploitation of the search space, leading to better identification of geotechnical parameters. It provides a more robust and efficient solution than using either method alone, because it combines their respective strengths to find the absolute minimum while minimizing the calculation time required. The optimization principle by hybridization of these two methods is done in two phases[15].

- The first phase is a direct application of the genetic algorithm. It begins with the random creation of an initial population. The selection operator chooses the best-performing parents using the error function. These parents are then subjected to the crossover operator to generate a population of children. Finally, the mutation operator is applied to half of these children, thus forming the new child population.
- The second phase of the algorithm takes as a starting point the child individuals from the first phase that have not been modified by the mutation. Each child individual will serve as a basis for local improvement through an exploration of the various neighborhoods of the child individual until reaching new child individuals of better quality. Once this phase is completed, all the child individuals are stored in a tabu list (T) which keeps track of the last solutions recently examined. The next generation is then

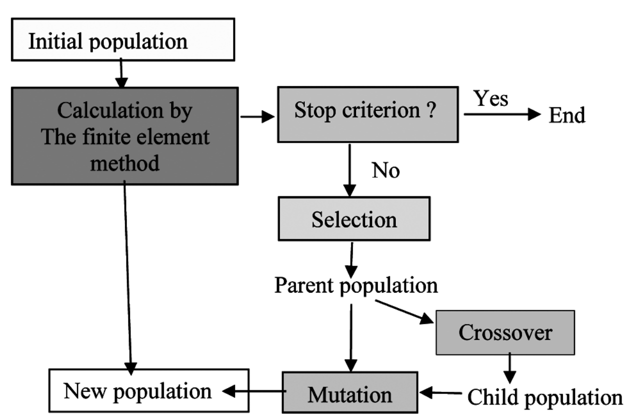

Fig. 3 — Research process chart of the genetic algorithm.

composed by combining all the obtained child individuals. This evaluation and reproduction loop is repeated until the algorithm reaches the best possible solution. The research process chart of the hybrid genetic algorithm is shown in Fig. 4.

2.2 Presentation of the study area

The study area (Fig. 5 (c)) is the city of 140 housing units in the Boulakroud site of Skikda (Fig. 5 (b)) in Algeria (Fig. 5 (a)). This site suffered a landslide. The landslide occurred in a slope formed by

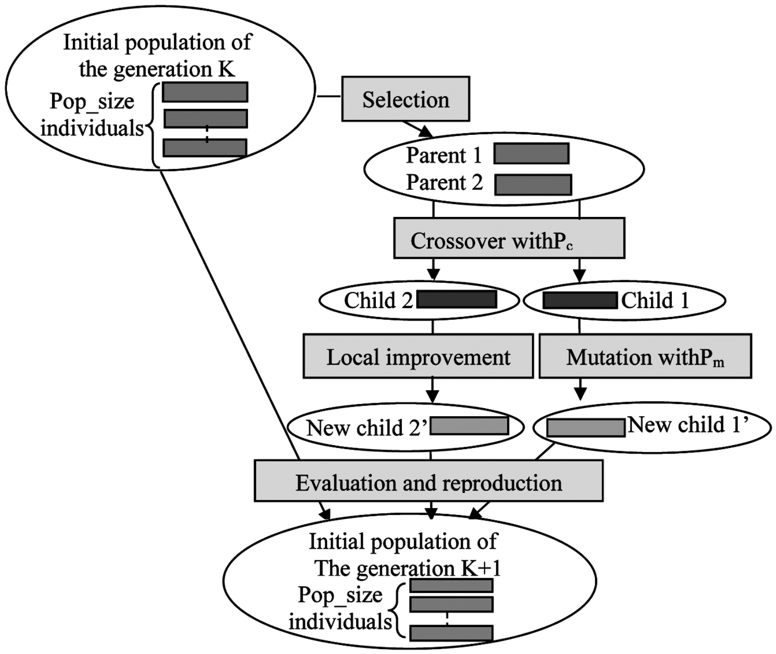

Fig. 4 — The overall process of a hybrid genetic algorithm.

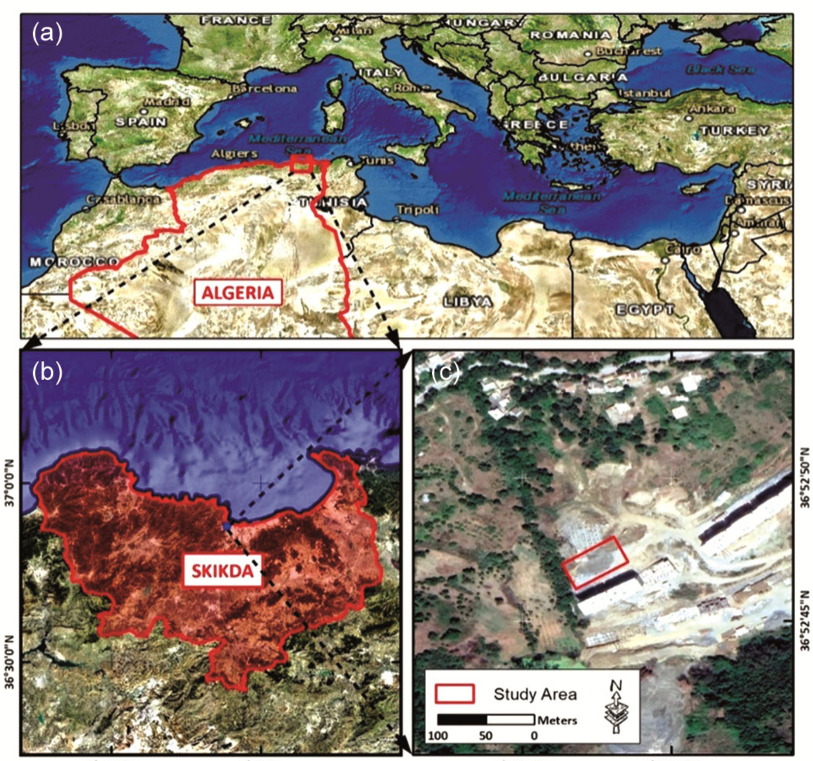

Fig. 5 — (a) Map of Algeria,(b) Skikda region and (c) Study area.

backfills resulting from the construction of a series of buildings upstream. To construct other buildings downstream of the slope, earthworks were carried out. It is likely that during these earthworks part of the foot of the slope is removed. It can thus be accepted as an initial hypothesis that the landslide will result from the removal of the abutment at the foot of the slope [16]. Our visual observations in the field revealed several indications of ground instability(Fig. 6):

- Appearance of vertical and parallel cracks progressive over time(Fig. 6 (a)).
- Massive landslide from top to bottom(Fig. 6 (b)).

2.2.1 Landslide causes

This instability can have several causes. Based on a study of the site and the various phases of activity, several possible causes of this landslide can be identified:

- Absence of a retaining structure.
- The geological formation of the schistose site, topped by backfills.
- It is clear that one of the most important factors in ground disturbance and instability is the presence of water (Fig. 7).

2.2.2 Geotechnical reconnaissance

Geotechnical reconnaissance is necessary for a correct description of the grounds and the estimation of their physical and mechanical properties which will be used in the calculations [17]. The national laboratory of habitat and construction of Skikda in Algeria carried out the recognition program includes the realization of:

- Two core surveys (SC) with collection of intact or reworked samples.
- One presiometric survey (SP) with tests every 2.00m.
- One inclinometer at the foot of the slope to monitor landslides.

The lithological sections established during the execution of the core drillings, show that the ground consists essentially of:

- At the level of the core surveys SC 02 (Fig. 8):

(a) 0.00-5.00: Backfill formed by clays, shale debris and construction debris (Fig. 8 (a)).
(b) 5.00-20.00: Altered to grayish friable shale with passages of clay shale (Fig. 8 (b)).

So the geotechnical properties of the study site according to the geological map of Philippe city N°14 on a scale of 1/50000 (Fig. 9), and the geotechnical investigations executed on site by the national laboratory of habitat and construction of skikda in Algeria indicate that the geological context of the site is characterized by micaceous shales, shales and phyllades, essentially consisting of a layer of weathered to grayish friable shale with passages of clayey shale surmounted by a recent backfill formed from a mixture of shale, clays and clay construction debris[18].

Fig. 6 — Morphology of landslide (a) Visible cracks in the ground and (b) Ground collapse.

Fig. 7 — Presence of a river at the bottom of the study area.

Fig. 8 — Display of boxes from core surveys SC02(a)The coring campaign at a depth between 0.00m and 5.00m, and (b)The coring campaign at a depth between 5.00m and 20.00m.

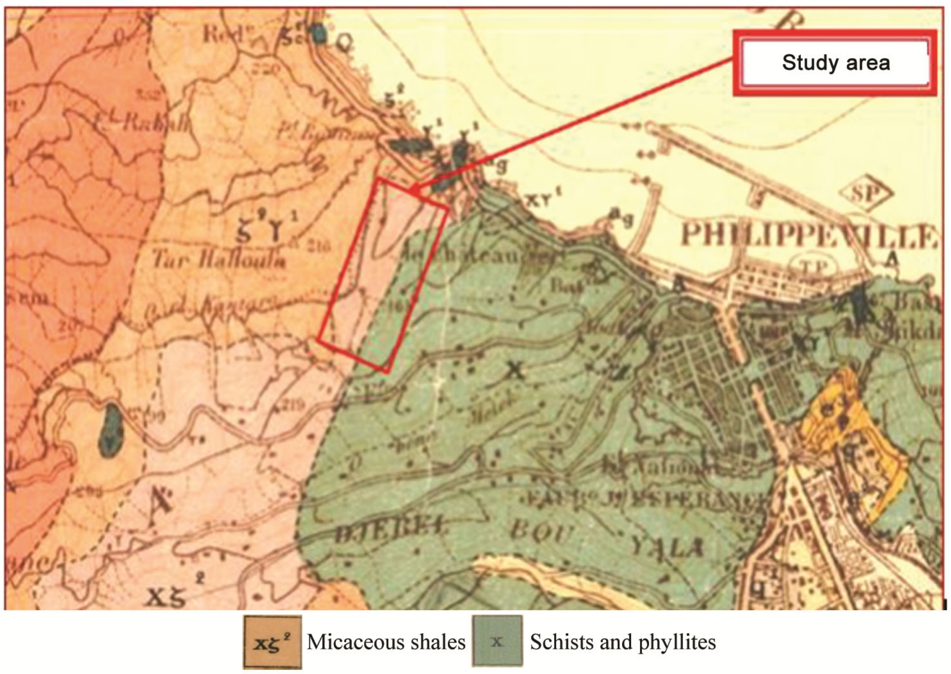

Fig. 9 — Extract from the geological map of philippe city N°14 -Scale 1/50000-.

Figure 10 illustrates the experimental curve obtained from the horizontal displacements measured by an inclinometer installed at the base of the slope. The physical and mechanical characteristics of the soil are detailed in Table 3.

2.2.3 Numerical simulation of the study area

In this study, we have implemented a numerical modeling approach to simulate the slope using Plaxis 2D software. The geometric model adopted for the numerical modeling of the slope, it has a width of 41 m, and a height of 20 m, formed of weathered shale to grayish friable with passages of clay shale topped on a backfill. An 80 kPa load system was used to simulate the buildings (Fig. 11). The behavior model used in the calculations is the Mohr-Coulomb model. The mesh configuration of this model is presented in the Fig. 12. The location of the landslide is shown in Fig. 13.

3 Results and Discussion

3.1 Parameters identification with the genetic algorithm program

The success of the genetic algorithm program, in terms of solution quality and calculation time, is based on the definition of several fundamental parameters. These parameters are detailed below:

- Individuals size (N= 30)
- Maximum number of generations (K =100)
- Number of bits coding a parameter (l =18 bits)
- Crossover probability (P_c = 0.6)
- Mutation probability (P_m = 0.08)
- In order to accurately identify the adequate values of the cohesion (c) and the friction angle (φ), we

begin by defining an exhaustive search space. Subsequently, we implement the hybrid genetic algorithm program that begins its optimization process with an initial population of 30 individuals, randomly selected within this space, and subjects them to a simulated evolution over 100 generations, integrating selection, crossover, and mutation mechanisms. From Fig. 14, we observe a significant decrease in the value of the error function during the first five generations, indicating a rapid exploration of the search space. Then, the algorithm gradually refines its search in a more gradual manner between the fifth and tenth generations before converging to the minimum of the error function at the eleventh generation, where the optimization process ends, with the identification of the following optimal parameter combination: c = 14 kPa; $\varphi = 16°$

The analysis of the results presented in Fig. 15 reveals a significant proximity between the displacement values calculated numerically using the optimal parameters from the genetic algorithm and those measured by the inclinometer. This observation suggests that the optimum identified for the problem is generally close to the exact solution.

In comparison with experimental estimations of soil mechanical parameters, the work of Levasseur (2007)[19] explored the application of pressuremeter testing, combined with genetic algorithm optimization, to characterize the properties of sands whose behavior is governed by the Mohr-Coulomb model. The findings of this study revealed that this approach allows the

Table 3 — Physico-mechanical characteristics of the soil.

Soil	Backfill	Shale weathered to grayish crumbly with shale passages
γ_d (KN/m^3)	17,20	18,50
γ_{sat}(KN/ m^3)	19,40	20,90
C' (KN/ m^2)	12	40
φ'(°)	15	17
G(Kpa)	376	1154
ψ(°)	0	0
E(Kpa)	1500	10000
ν (-)	0.33	0.30

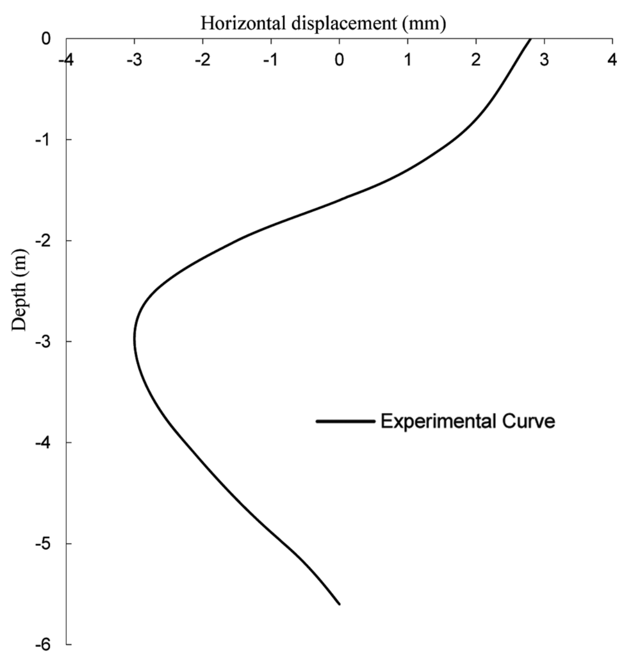

Fig. 10 — Horizontal displacement measured by the inclinometer at different depths.

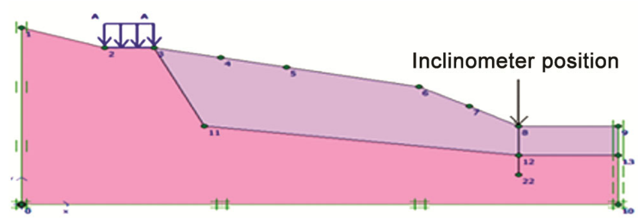

Fig. 11 — Geometric model.

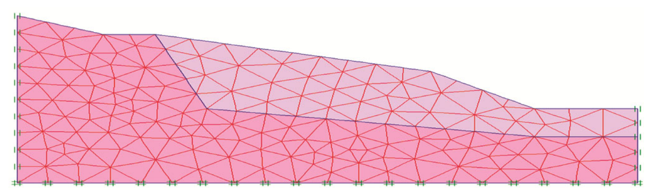

Fig. 12 — Mesh configuration.

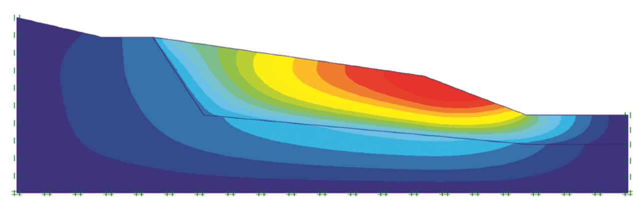

Fig. 13 — Landslide location in the red zone.

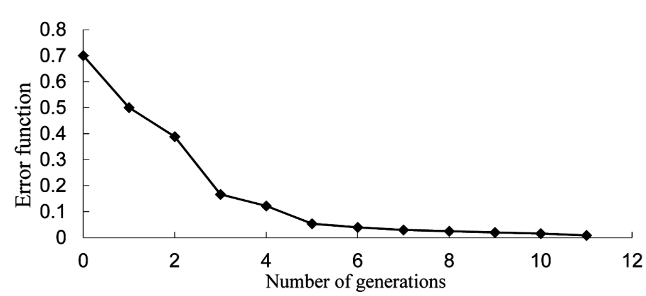

Fig. 14 — Variation of the error function with the number of the genetic algorithm generations.

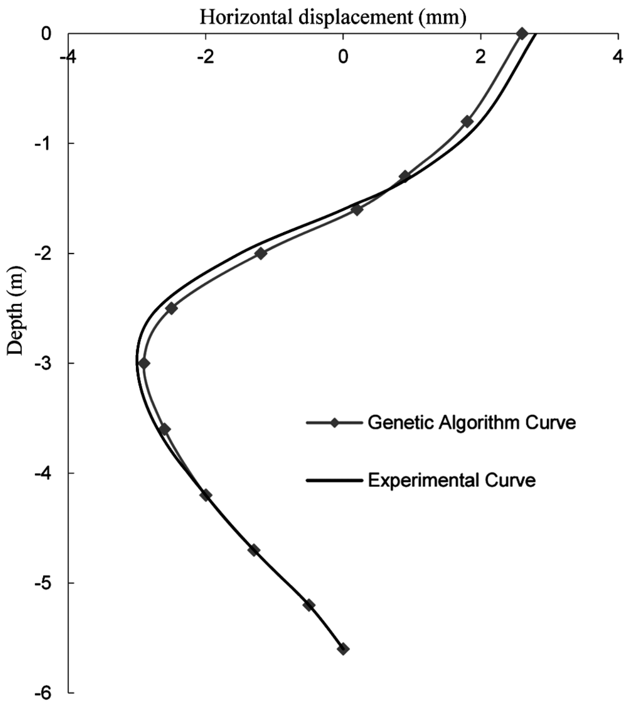

Fig. 15 — Horizontal displacement measured by the inclinometer at different depths, (-): Experimental measurements used for optimization; (♦): Modeling of measurements after optimization by the genetic algorithm.

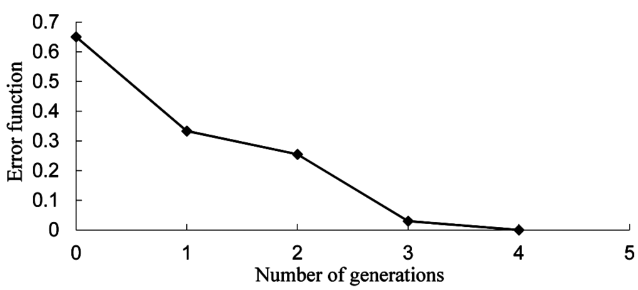

Fig. 16 — Variation of the error function with the number of the hybrid genetic algorithm generations.

identification of a very satisfactory optimum, which is not only close to the exact optimal value but also guarantees a very faithful reproduction of the experimental data. The genetic algorithm optimization process proved capable of finding a solution to the problem and sampling other solutions with good accuracy and a competitive computational cost compared to exhaustive exploration. It should be noted, however, that the reliability of the results is linked to the values of the intrinsic parameters chosen within the genetic algorithm. It is crucial to employ a sufficiently large population size so that the sample of solutions is truly representative. Unfortunately, a larger population implies more expensive finite element calculations. Additionally, research by Iacono *et al.* (2006)[20] has shown that using a genetic algorithm to identify soil mechanical parameters from a pressuremeter test allows a greater number of parameters to be determined, including those that are correlated or insensitive, which is an advantage over gradient methods that encounter difficulties in these situations.

According to Castro et *al.* (2004)[21], the way a genetic algorithm evolves to reach its optimum can be exploited to obtain qualitative information on the sensitivity of a model's parameters. By following the evolution of the error function and the dispersion of the parameters across generations, it is observed that convergence is not uniform for all parameters. However, the order of convergence is constant and directly linked to the influence of each variable on the model under study: the most influential parameters stabilize first, while those with the least influence stabilize last. Furthermore, a post-convergence analysis of the "best" individuals identified during optimization provides qualitative indications on the correlations between parameters. In summary, Castro et *al.* (2004)[21] emphasize that genetic algorithms do not simply identify parameters; their evolutionary dynamics provide a set of very relevant information that deserves to be explored.

3.2 Parameters identification with the hybrid genetic algorithm

The ability of the hybrid genetic algorithm program to find excellent solutions depends on the configuration of several key parameters. These parameters are described below:

- Individuals size (N= 30)
- Maximum number of generations (K= 100)
- Number of bits coding a parameter (l = 18 bits)
- Crossover probability (P_c= 0.6)
- Mutation probability (P_m= 0.04)
- Tabu list size (T= 3)

The identification of the cohesion (c) and the friction angle (φ) of the Mohr-Coulomb model by our hybrid genetic algorithm program revolves around the minimization of the error function in the search space. The evolution of this function over the generations, illustrated in Fig. 16, reveals that the solutions explored by the hybrid genetic algorithm get closer to the optimal solution as the generations progress, as indicated by the decrease in the average error function from the first generation. The algorithm continues to refine its search and very quickly moves towards the area where the error function is zero. After only four generations. The optimal parameter combination identified is as follows:

c= 17 kPa; φ = 19° … (1)

The optimization carried out using the hybrid genetic algorithm program validated the obtained solution as the exact optimum. This validation is clearly demonstrated by a remarkable fit between the experimental curve and the numerical response generated from the parameters identified by this algorithm, as illustrated in Fig. 17.

Hybrid methods are recognized for their ability to quickly achieve satisfactory optima. Tsai *et al*. (2003)[22] confirmed this by combining a genetic algorithm and a Quasi-Newton method for the identification of hydrological parameters. Their work highlights that the genetic algorithm offers good initial exploration but is slow, while Quasi-Newton is fast but potentially less reliable. The synergy of the two allows the genetic algorithm to roughly estimate the parameters, which are then refined by the hybrid system, resulting in better estimates and making these methods flexible, robust, and fast. Similarly, Cui and Sheng (2005)[23] developed a hybrid algorithm integrating a neural network and a genetic algorithm for inverse groundwater modeling. Their study showed rapid convergence to an acceptable solution despite the complexity of the problem. In essence, hybrid methods are very effective optimization tools because they combine the global exploration power of genetic algorithms with the accelerated convergence of other stochastic techniques. This results in more efficient search, reduced computation time compared to the genetic algorithm alone, and above all, greater assurance of reaching the global minimum, making them particularly competitive.

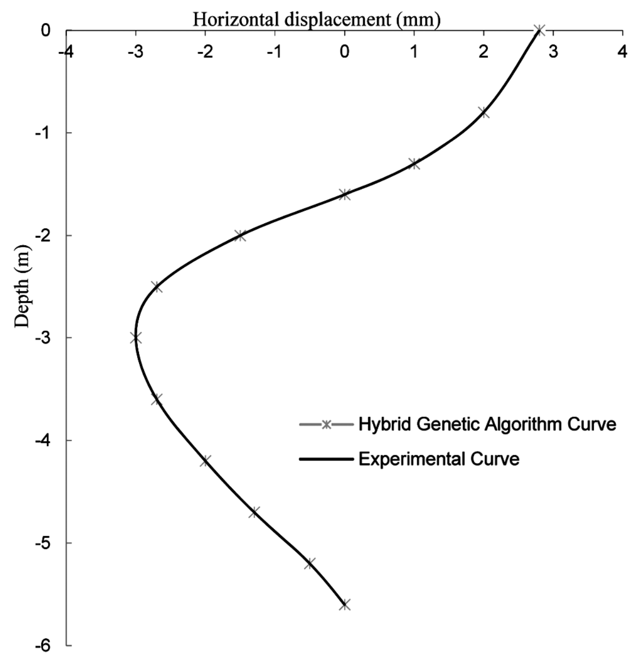

Fig. 17 — Horizontal displacement measured by the inclinometer at different depths (-): Experimental measurements used for optimization; (⁎): Modeling of measurements after optimization by the hybrid genetic algorithm.

3.3 Comparison of different optimization algorithms

A comparative analysis was carried out to evaluate the performance of two optimization algorithms in order to identify the optimal parameter sets of the cohesion (c) and the friction angle (φ) that minimize the deviation between the model and the experimental data. This comparison focused on the horizontal displacements generated by the different curves of the optimization algorithms, namely the genetic algorithm and the hybrid genetic algorithm, and those obtained experimentally by inclinometric measurements. The evaluation was carried out through the calculation of the error function and its convergence speed for each algorithm.

Fig. 18 illustrates a minimal deviation between the optimization curve obtained by the genetic algorithm

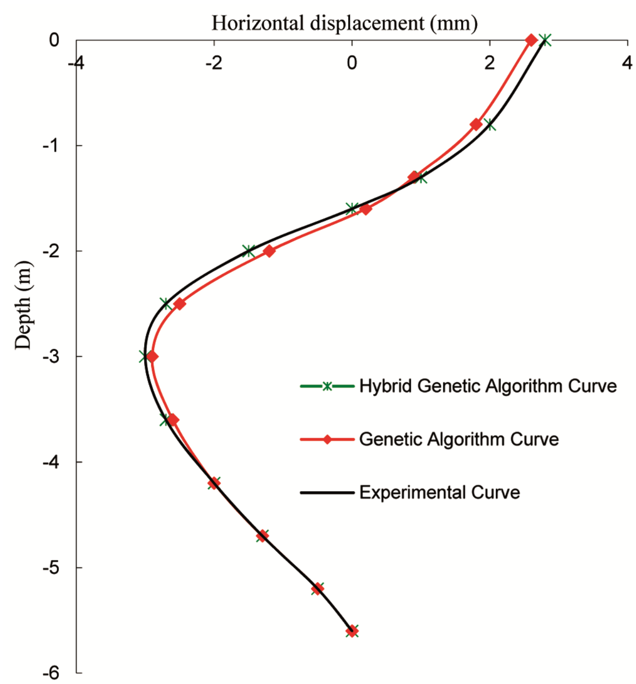

Fig. 18 — Horizontal displacement measured by the inclinometer at different depths (-): Experimental measurements used for optimization; (◆): Modeling of measurements after optimization by the genetic algorithm; (⁎): Modeling of measurements after optimization by hybrid genetic algorithm.

and the experimental curve, thus demonstrating that this method manages to determine a pair of parameters close to the exact optimum of the problem. In addition, an excellent agreement was observed between the optimization curve of the hybrid genetic algorithm and the experimental curve, which results in a deviation, measured by the error function, equal to zero. This indicates that the identification of the two soil parameters reaches the exact optimum of the problem.

Regarding the convergence speed of the error function of both algorithms to the global optimum, it was found that the hybrid genetic algorithm exhibits faster convergence than the genetic algorithm. Indeed, the hybrid genetic algorithm converges as early as the fourth generation, while the genetic algorithm requires up to the eleventh generation to reach the same level of convergence. Therefore, we can conclude that the best parameter sets (c and φ) that minimize the gap between the model and the experiment are found by the hybrid genetic algorithm, with a very short convergence time.

4 Conclusion

The study presented in this paper aims to identify two key parameters of the Mohr-Coulomb model: cohesion (c) and friction angle (φ) which are considered unknown. To do this, an inverse analysis approach was implemented using two programs developed under Matlab 07. These programs exploit two optimization algorithms: a standard genetic algorithm and a hybrid version integrating tabu search. The effectiveness of these tools was validated on the concrete case of a landslide that occurred on the Boulakroud site in Skikda, Algeria, with the aim of finding the optimal values of these parameters in order to obtain a better agreement between the experimental curves and the numerical simulations carried out with the Plaxis 2D software.

The results obtained validate the effectiveness of these algorithms for determining the studied parameters. The genetic algorithm has shown its ability to evaluate solutions close to the optimum, but its convergence towards a single solution requires a large number of generations. In contrast, the hybrid genetic algorithm has proven to be faster and more efficient in locating the exact optimum. Our results indicate that the determination of both parameters is feasible, even if the combined use of the genetic algorithm and the tabu search for the direct identification of soil parameters from in situ measurements had not been explored before.

The major interest of the hybrid genetic algorithm therefore lies in its ability to solve more complex problems where the genetic algorithm alone struggles to be efficient. Therefore, adequate estimation of the parameters of soil constitutive models is a complex task that requires a thorough understanding of the direct problem, the choice of an appropriate optimization technique, and precise tuning of its parameters, which generally requires the know-how and experience of the user.

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