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STATE-OF-THE-ART REVIEW

Applications of Particle Swarm Optimization in Geotechnical Engineering: A Comprehensive Review

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Abstract Particle swarm optimization (PSO) is an evolutionary computation approach to solve nonlinear global optimization problems. The PSO idea was made based on simulation of a simplified social system, the graceful but unpredictable choreography of birds flock. This system is initialized with a population of random solutions that are updated during iterations. Over the last few years, PSO has been extensively applied in various geotechnical engineering aspects such as slope stability analysis, pile and foundation engineering, rock and soil mechanics, and tunneling and underground space design. A review on the literature shows that PSO has utilized more widely in geotechnical engineering compared with other civil engineering disciplines. This is due to comprehensive uncertainty and complexity of problems in geotechnical engineering which can be solved by using the PSO abilities in solving the complex and multi-dimensional problems. This paper provides a comprehensive review on the applicability, advantages and limitation of PSO in different disciplines of geotechnical engineering to provide an insight to an alternative and superior optimization method compared with the conventional optimization techniques for geotechnical engineers.

Keywords Particle swarm optimization · Geotechnical engineering · Slope stability · Tunneling · Rock and soil mechanics

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1 Introduction

Swarm intelligence (SI) is the collective behaviour of decentralized systems composed of many individuals that coordinate their activities using self-organization (Cui and Gao 2012). SI systems are inspired from biological systems which are usually consisted of a population of simple agents interacting locally with one another and globally with their environment. The ant colonies (Dorigo and Blum 2005), bird flocking (Antoniou et al. 2009, 2013), bee colonies (Karaboga and Basturk 2007, 2008) and fish schooling (Li and Qian 2003; Neshat et al. 2013) are some example of natural SI systems. Based on these systems, several optimization algorithms such as ant colony, artificial bee colony, and PSO have been developed. PSO is a powerful population-based computational method that is able to solve a problem by using a population of candidate solutions. To improve a candidate solution, PSO iteratively relocates the candidates in a search space by employing simple mathematical equations. Compared to other optimization algorithms, PSO has many advantages such as easy realized, fast convergent, promising performance on nonlinear function optimization (Chen et al. 2011).

Ever since the PSO algorithm has been introduced by Kennedy and Eberhart (1995), and Eberhart and Kennedy (1995), it has successfully applied in various fields of civil engineering. This popularity is due to the comprehensible performance of PSO as well as simplicity of its operation. Many scholars applied PSO to solve their problems in the fields of structural (Gholizadeh and Salajegheh 2009; Poitras et al. 2011; Mashhadban et al. 2016), environmental (Wan 2013; Hajihassani et al. 2015; Najafzadeh and Tafarojnoruz 2016), hydrological (Kuok et al. 2010) and geotechnical (Sadoghi Yazdi et al. 2011; Kalatehjari et al. 2014; Armaghani et al. 2014a) engineering. The literature reveals that PSO has been applied frequently in geotechnical engineering, in comparison to the other fields of civil engineering. This is mainly because of the uncertain behavior of rock and soil as the main materials in geotechnical engineering, in contrast with the other civil engineering materials such as concrete and steel. As a powerful optimization technique, PSO has been extensively applied in different geotechnical engineering aspects such as slope stability analysis, pile and foundation engineering, rock and soil mechanics, and tunneling and underground space design.

In addition to the aforementioned applications, PSO is also used as a learning algorithm in artificial neural networks (ANNs) that are widely used in geotechnical engineering (Armaghani et al. 2014a; Hajihassani et al. 2014; Hasanipanah et al. 2016). Backpropagation (BP) is the most well-known learning algorithm which is frequently used as the training algorithm in ANNs. However, BP is a local search learning algorithm and therefore the optimum search process of ANNs might fail and return unsatisfied solution (Liou et al. 2009). On the other hand, PSO as a robust global search algorithm, is a suitable alternative to modify weight and bias of ANNs for getting higher performance prediction. Hence, a combination PSO-ANN algorithm receives advantages of both PSO and ANN to solve/optimize the problems in which PSO searches for global minimum and ANN uses the global minimum to find the best result.

Despite the superiorities of PSO in solving the complex problems, it is occasionally faced with some limitations such as premature and divergence phenomena (Neshat 2013). Consequently, some modifications have been suggested to avoid these limitations and enhance the PSO capabilities [e.g. introducing inertia weight (Shi and Eberhart 1998), constriction factor (Eberhart and Shi 2000), crossover operation (Lovbjerg et al. 2001), self-adaptation (Lü et al. 2006; Zhang et al. 2013a, b), and logistic dynamic weight (Ni and Deng 2013)].The modified PSO techniques were reported to perform with reasonable convergence capability.

2 Overview of Particle Swarm Optimization

Kennedy and Eberhart (1995) developed PSO as a stimulation of birds swarm. Swarm is a group of individuals with defined rules for individual behaviors and communications. The ability of each individual to deal with the previous experiences of the swarm is called swarm intelligence. This capability guides the swarm toward its optimum goal. PSO is a population-based search technique where a population of particles starts their journey in a space with respect to the current best position (Hossain and El-Shafie 2014). Reynolds (1987) described three simple rules for the behavior of individuals inside a swarm which were used as one of the basic concepts of PSO by Kennedy and Eberhart (1995). Although these simple rules model the behavior of individuals, their combination produces a complicated behavior for the swarm:

1. Individuals avoid collision with others
2. Individuals go toward the goal of swarm
3. Individuals go to the center of swarm

The process of decision making related to individuals is other basic concept of PSO. Each individual of the swarm makes decision based on the following two factors:

1. The own experiences of individual that is its best results so far

2. The experiences of other individuals in the swarm that is the best results in the whole swarm

Figure 1 illustrates the standard flowchart of PSO. At the starting step of the original PSO a certain number of individuals, called particles, are distributed in the search space by using a random pattern (Kennedy and Eberhart 1995; Cheng et al. 2007). Each particle is a representative of a feasible solution. Figure 2 shows the schematic structure of a particle in PSO involving three divided parts as its current position, best position, and velocity. The current position, best position, and velocity of particles record respectively the current coordinates, best coordinates, and velocity vectors of a particle in D-dimensional space, where D starts from one (Kalatehjari 2013). Consequently, for a particle in D-dimensional space, a 3D-dimensional particle is desirable.

The aim of PSO is to meet the termination criteria which are defined as the criteria for terminating the iterative search process. To select an appropriate termination criterion, it should be noted that the termination condition does not cause a prematurely converge and it should protect against oversampling of the fitness (Engelbrecht 2007). The following termination criteria are frequently used in PSO:

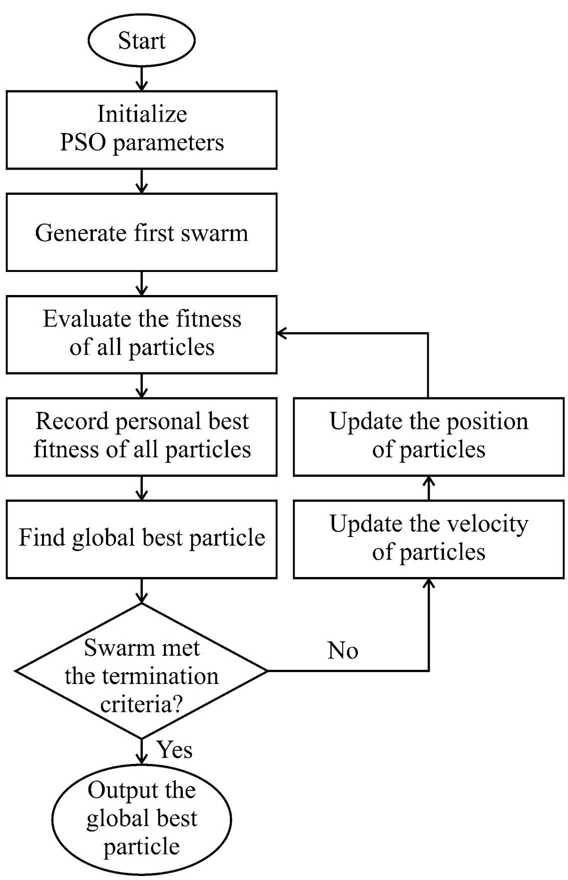

Fig. 1 Stard flowchart of PSO (Kalatehjari 2013)

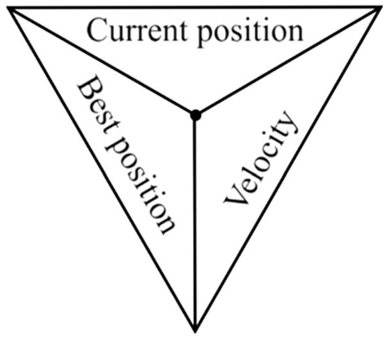

Fig. 2 Schematic structure of a particle in PSO (Kalatehjari 2013)

1. Termination when the maximum number of iterations is exceeded
2. Termination when an satisfactory solution is found based on the condition of each problem
3. Termination when no improvement is achieved over a certain number of iterations

These criteria are applied to ensure that PSO is able to converge on a feasible solution. In fact, PSO tries to make the objective function as minimum or maximum depend to the problem to be solved. To lead the swarm toward this aim, the fitness value of each particle is determined by evaluating its current position by the objective function. After evaluation the fitness of all particles, Eq. 1 (velocity equation) is used to calculate the velocity of particles based on their best position and the position of the best particle in the swarm. Using Eq. 2, particle positions can be updated according to their current positions and velocities. This iterative process continues until reaching the termination criteria. Equations 1 and 2 are as follow (Kennedy and Eberhart 1995):

$$v_{n(i)} = v_{n(i-1)} + u(0,\vartheta_1)\left(bp_{n(i)} - x_{n(i)}\right) + u(0,\vartheta_2)\left(bg_{n(i)} - x_{n(i)}\right) \tag{1}$$

$$x_{n(i+1)} = x_{n(i)} + v_{n(i)} \tag{2}$$

where, $v_{n(i-1)}$ is the velocity of nth particle in past iteration and $v_{n(i)}$ is the velocity of *n*th particle in current iteration. The vectors of random numbers of *n*th particle are presented by $u(0,\vartheta_1)$ and $u(0,\vartheta_2)$, $bp_{n(i)}$ is the best position of nth particle so far, $bg_{n(i)}$ is the position of the best particle of the swarm so far, and $x_{n(i-1)}$ and $x_{n(i)}$ are the position of nth particle respectively in the current and the next iterations.

Three components of velocity equation are respectively the initial, cognitive, and social parts. Two specifications of searching, explorations and exploitation, depend on the velocity of particles that is controlled by the values of ϑ_1 and ϑ_2. Consequently, these values control the searching behaviour of PSO. It is usual to set $\vartheta_1 = \vartheta_2 = 2$ in early search. A greater value of ϑ_1 provides faster convergence, while increase in ϑ_2 helps to discover new solutions in the search space. Since the velocity of particles may increase surprisingly by changing the mentioned coefficients, a limiting bound of velocity as $[-v_{max}, v_{max}]$ was attached to the original PSO. The value of v_{max} is called constriction coefficient. Poli et al. (2007) advised to select the constriction coefficient carefully, since it influenced the balance of exploration and exploitation. By introducing ω as the inertia weight of particles, the original formula of velocity was edited by Shi and Eberhart (1998) to minimize/reduce the role of constriction coefficient as presented in Eq. 3. However, Clerc and Kennedy (2002) showed that using the inertia weights of greater than one interrupts the converge process of PSO. They proposed Eq. 4 by introducing ξ as the constant multiplier to prevent the explosion of the swarm, guarantee its convergence, and eliminate the necessity of constriction coefficient.

$$v_{n(i)} = \omega v_{n(i-1)} + u(0,\vartheta_1)\left(bp_{n(i)} - x_{n(i)}\right) + u(0,\vartheta_2)\left(bg_{n(i)} - x_{n(i)}\right) \tag{3}$$

$$v_{n(i)} = \xi\left[v_{n(i-1)} + u(0,\vartheta_1)\left(bp_{n(i)} - x_{n(i)}\right) + u(0,\vartheta_2)\left(bg_{n(i)} - x_{n(i)}\right)\right] \tag{4}$$

$$\xi = \frac{2}{(\vartheta_1 + \vartheta_1) - 2 + \sqrt{(\vartheta_1 + \vartheta_1)^2 - 4(\vartheta_1 + \vartheta_1)}}, \quad (\vartheta_1 + \vartheta_1) > 4 \tag{5}$$

In PSO, all members of the population stay alive and move along the process of optimization. Therefore, it can guarantee to save all feasible solutions (Kennedy and Eberhart 1995). Moreover, PSO works with real variables, operates simple, and needs slight tune-up studies to make convergence and searching in balance (Clerc and Kennedy 2002). These features have equipped PSO with simple implementation and fast convergence to the optimal solution which are the main reasons of its popularity (Windisch et al. 2007).

With the aim of improving the PSO performance, many attempts have been made to incorporate obtained knowledge from other evolutionary computation approaches through adapting PSO parameters. By employing the Gaussian noise, Mira and Fonseca (2002) proposed self-adapting PSO. In this technique, the variance of distributions is evolved using selection. Lovbjerg et al. (2001) utilized a sort of breeding to recombine solutions. In their technique, by performing weighted averaged of PSO parameters, the position and velocity of the selected pairs of particles were recalculated. PSO and GA algorithms were combined by Robinson et al. (2002) through switching one of them to another one after several iterations. The best results were obtained by switching of the PSO to GA. Ciuprina et al. (2002) proposed intelligence PSO based on the combination of PSO with Tabu search method. The successful performance was obtained for solving the difficult multimodal problems.

PSO has been greatly effective to solve/approximate a huge range of problematic optimization problems in the civil engineering arena such as construction litigation, design optimization of water/wastewater distribution networks, traffic control, structural design, parameter calibration of hydrological models, river stage prediction, transportation network design, geotechnical model calibration, slope stability analysis, and pavement engineering. Consequently, the application of PSO has increased surprisingly in recent years. Table 1 presents a comparison between PSO and three other well-known metaheuristic methods.

3 PSO Applications in Geotechnical Engineering

Complexity of analysis of geotechnical behavior is due to multivariable dependencies of soil and rock responses. Most of the materials that geotechnical engineers deals with show uncertain behavior in

Table 1 Comparison of metaheuristic methods (Kitagawa et al. 2004)

Methods	GA[a]	SA[b]	TS[c]	PSO
Advent	1970	1983	1989	1995
Target problem	Combinatorial optimization problem	Combinatorial optimization problem	Combinatorial optimization problem	Continues optimization problem, Mixed-integer nonlinear optimization
State variable	Discrete variable	Discrete variable	Discrete variable	Discrete variable, Continuous variable
Search points	Multi-point	Single point	Single point	Multi-point
Run time	Medium	Long	Short	Short
Features	In recent years, application efficacy for multi-objective optimization problems has been under review	A good quality solution can be obtained, but it will require a long amount of time	Good quality solution can be obtained for combinational problems in a shorter amount of time than GA and SA	Good quality solutions can be obtained within a short amount of time for mixed-integer nonlinear optimization problems, for solutions difficult to obtain with conventional methods

[a] Genetic algorithm

[b] Simulated annealing

[c] Tabu search

consequence of the complex formation of these materials. Therefore, in some geotechnical engineering problems, the objective function is non-convex and discontinuous. Consequently, simple optimization techniques may have difficulties in finding the global optimum solution due to get trapped in local solutions. To overcome this limitation, using a powerful optimization method to obtain the global optimum solution is of interest. In recent years, soft computing techniques have been widely used to predict geotechnical parameters (Sharma et al. 2017a, b, c; Singh et al. 2017; Sharma and Singh 2017). Accordingly, as a powerful optimization technique, PSO has entered in the field of geotechnical engineering to solve its problems. In the following sections, a review of the PSO applications in geotechnical engineering is presented.

3.1 Slope Stability Analysis

Slope instability is one of the main concerns in geotechnical engineering. It has been identified as one of the most frequent natural disaster in mountainous regions that can lead to serious economic loss, property damage, and communication passage interruption (Singh et al. 2016; Sharma et al. 2017a). More importantly, it is an incessant cause of suffering because it puts human life in danger (Sharma et al. 2017b). A single factor or more likely a combination of different factor including slope geometry, properties of slope forming material, groundwater condition, structural discontinuity, development of weak zones, disruption in geological formation, and heavy rainfall can initiate slope failure (Umrao et al. 2017).

The application of PSO in slope stability analysis is mainly within the framework of limit equilibrium method for soil slopes (Kalatehjari and Ali 2013). This context involves two major steps as calculating the factor of safety of possible slip surfaces and determining the critical slip surface with the minimum factor of safety. PSO is mainly used to the second step, since the shape and location of the critical slip surface is generally unknown in soil slopes (Bolton et al. 2003).

PSO can be applied to two-dimensional (2D) or three-dimensional (3D) slope stability problems (Kalatehjari 2013). In 2D analyzes, a search engine can be applied to the problem to determine the shape of the critical slip surface in a pre-defined section of the slope. The common shapes of the slip surface in 2D analyzes are circular, ellipse, spiral, and polygonal or arbitrary (Chen et al. 2006; Kalatehjari et al. 2014). In contrast, 3D analyzes assume space shapes of slip surfaces such as spherical, ellipsoidal, and Non-

Uniform Rational B-Splines (Li et al. 2008; Kalatehjari et al. 2012; Taha et al. 2012).

Figure 3 shows the general flowchart of PSO to determine the critical slip surface in slope stability analysis. The initial PSO parameters were set in order to start optimization procedure. After that, a number of particles equal to swarm size are generated by using a random pattern over the search space. The personal best particles for the first swarm are identical to particles themselves; because no other swarm exists yet to make a comparison. The velocity of all particles at the starting point is set to zero, because the particles

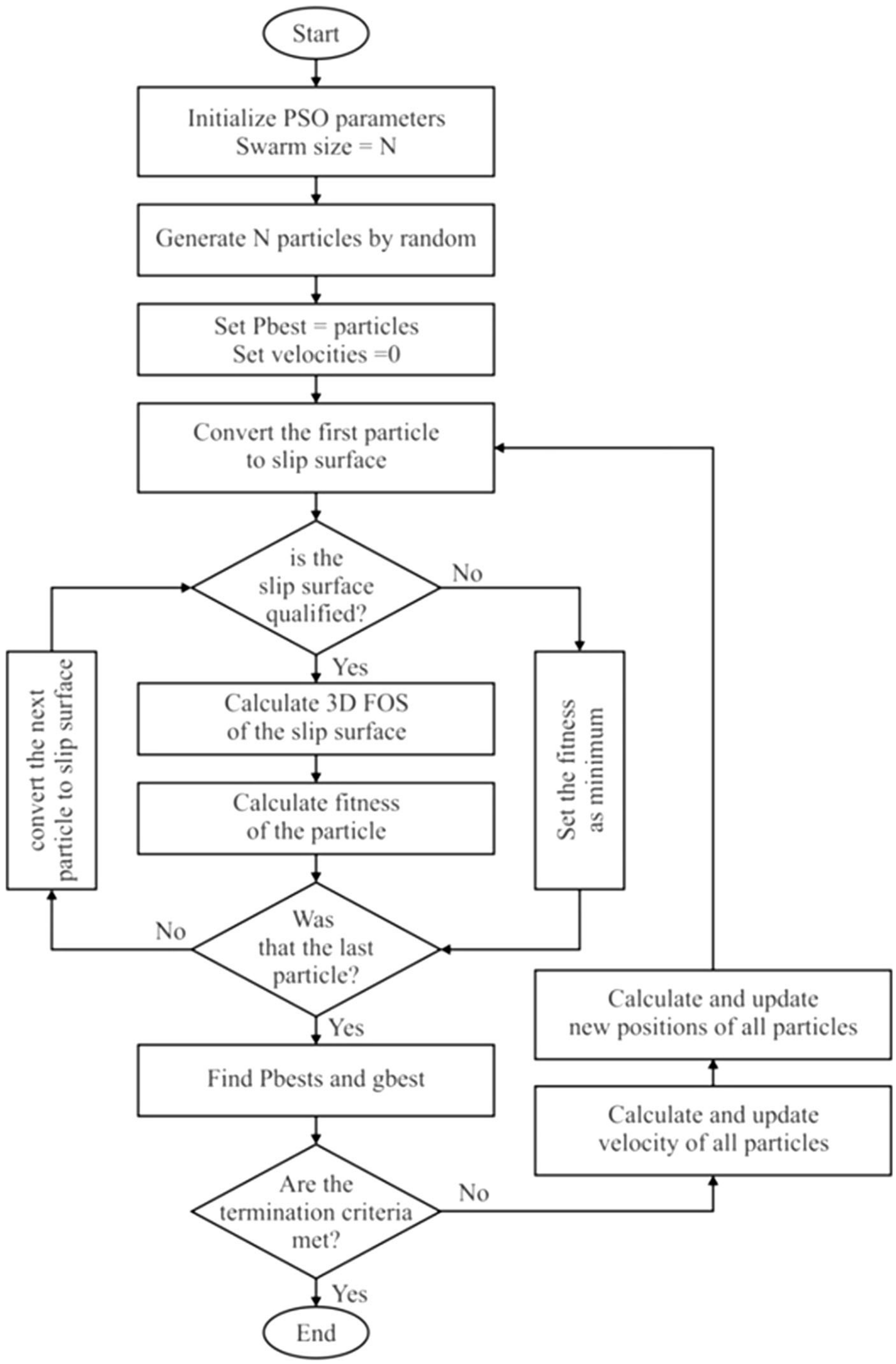

Fig. 3 Flowchart of PSO to determine the critical slip surface in slope stability analysis (Kalatehjari 2013)

are just created without any movement. After setting up the initial values, the first particle is converted to a slip surface. If this slip surface has an acceptable intersection with the slope, it is qualified. Otherwise, the slip surface is disqualified. A pre-defined value of fitness is given to disqualify slip surfaces as the minimum fitness. This value is obtained by setting the maximum allowed value of FOS. In parallel, the value of FOS together with the unique direction of sliding are calculated for qualified slip surfaces. Then, the corresponding fitness values of particles are calculated by fitness function of PSO. This process is repeated for all particles of the swarm (Kalatehjari 2013).

The global best particle is defined as the one with the greatest fitness value in a swarm. The current position of particles that improved their fitness value is recorded as their new personal best positions, while the previous best position is retained for other particles. Through an iterative process, subsequent swarms are generated by updating the velocity and position of particles. The optimization process is finished when the particles of a swarm satisfy the termination criteria. Eventually, the position of the last global best particle represents the critical slip surface of the slope.

Kalatehjari et al. (2012, 2014), Taha et al. (2012), and Wang et al. (2013) used PSO in 2D analysis to determine the location of critical slip surface with circular shape. They proved the ability of PSO in determining the critical slip surface by re analysing three numerical examples from the literature and actual slope stability problem. Moreover, Zhou et al. (2012) proposed an arbitrary shape of 2D slip surface defined by seven control points with arbitrary horizontal spacing to determine the general shape and location of the critical slip surface. They benefited the global feature of PSO to avoid local minima and verified their approach by evaluating two examples for simple slope and complex slope.

Li et al. (2005) applied a modified PSO to determine the critical slip surface of slope. Their proposed method, discontinuous flying PSO, was created by relating the position and velocity update of particle to their fitness value. They found an average improvement of 6% and faster convergence in the results of their method compared with the original PSO. Li et al. (2010) introduced a mutation PSO to solve the search of critical slip surface in complex soil slopes. They concluded that their proposed method can locate the true critical slip surface.

Chen et al. (2006) adopted PSO to determine the 2D non-circular critical slip surface of slope. They listed the benefits of PSO as providing a good balance between global search and local refinement, solving the local minima problem, great efficiency, and easily incorporating with both limit equilibriums and finite element methods. Zhao et al. (2008) applied an updated PSO method to determine the 2D non-circular critical slip surface of non-homogeneous slope. They found that faster convergence rate and better precession are the superior abilities of PSO.

Kang et al. (2006) and Wen-Tao (2009) respectively developed the combined method of PSO by adding support method machines and least square vector machines methods to evaluate the 2D stability of rock slopes. They concluded that fast speed of problem solving, more accurately estimation of slope stability, and global optimization are the advantages of this technique.

Li et al. (2008, 2009), Wang et al. (2010), Li and Chu (2011), and Cheng et al. (2011) applied a coupled optimization method of PSO/harmony search to solve the nonlinear function of factor of safety in slope stability problem. The feasibility and applicability of this technique was supported by evaluating practical engineering problems and re-evaluating bench mark problems from literature. In addition, Khajehzadeh et al. (2010, 2011) used a same combined optimization method of PSO/harmony search to analyse the reliability of earth slope in 2D. They obtained lower values of reliability and factor of safety in comparison with the standard PSO and other methods by employing their new method in previous studies. Xu et al. (2011) developed an optimization method based on the Projection Pursuit (PP), PSO, and the Logistic Curve Function (LCF) to evaluate the 2D problem of slope stability. PSO was used to optimize the PP function and the parameters of LCF. They verified the feasibility and affectivity of their proposed model in practice by evaluating a case study.

Li et al. (2012) proposed a modified PSO in cooperation with finite element limit equilibrium method (FELEM) to determine the location and shape of non-circular critical slip surface in 2D geotechnical problems. Based on the slope geometry and stress distribution, they established the stress compatibility constraints together with the geometrical and kinematical compatibility constraints. These extra features were used to guarantee the realistic shape of the critical slip surface. They went through several numerical examples to prove the affectivity and efficiency of their approach in routine geotechnical practices.

Gandomi et al. applied PSO in a comparison study of 2D slope stability analysis with the presence of a weak layer. They compared the performance of three recent swarm intelligence algorithms, firefly algorithm (Yang 2008), Cuckoo search (Yang and Deb 2009) and levy flight krill herd algorithm (Gandomi and Alavi 2012) in solving three cases of slope stability analysis. All cases were also resolved by PSO algorithm as the benchmark. Their results showed that none of the new algorithms can provide the best solution for all the problems. However, promising performance were observed from Cuckoo search and levy flight krill herd algorithms.

As popularity of PSO increased in solving 2D slope stability problems. Researchers started to integrate PSO into other effective solutions to increase their accuracy while maintaining or enhancing their computational time. Chen et al. (2015a, b) use the standard landslide analysis program (STABL) and turned it into a computation engine for PSO. Their work continued by Shen and Chen (2017) by modification of the previous PSO scripts and adding two strength parameters of the soil, cohesion intercept and frictional angle, to the analysis. Their research showed very promising results achieved from contribution of PSO into the results of STABL on a standard soil slope, as the algorithm converged to the best solution ever in the literature. Gordan et al. (2016) successfully applied PSO in training stage phase of artificial neural network (ANN) to predict seismic slope stability.

Recently, a hybrid system including least squares support vector machine (LSSVM) and particle swarm optimization (PSO) was applied in prediction of the slope stability by Xue (2017). Similar to what Gordan et al. (2016) did for the ANN, Xue applied a modified PSO algorithm as a tool in determining the optimal values of the LSSVM parameters with the aim of improving the accuracy of the prediction. The PSO contribution to the hybrid model was recognised to be beneficial in providing a feasible, efficient, and accurate predicting tool for slope stability.

Although PSO has successfully contributed in determining the 2D critical slip surface, it is absent in 3D slope stability analysis. In fact, only a few researchers published their results in determining the critical slip surface in 3D slope stability problems and none of them applied PSO. Yamagami and Jiang (1997) applied Dynamic Programming with Random Number Generator, Jiang et al. (2003), Mowen (2004), and Mowen et al. (2011) used Monte Carlo method, Cheng et al. (2005) utilized Simulated Annealing, and Toufigh et al. (2006) applied Gradient methods to determine the critical slip surface in 3D slopes stability problems. The shortage of studies in this area is caused by the potential difficulties in performing a successful search within a complicated 3D slope stability problem. The problem of determining the 3D critical slip surface needs a fast and precise global optimization technique to work integrated with the complicated 3D equations of FOS and slip surface respectively as its objective function and particle generator (Kalatehjari 2013). Based in the successful performance of PSO in 2D slope stability analysis as well as other problems of geotechnical engineering, it is believed that PSO can be a competent candidate in the study of 3D critical slip surface.

3.2 Pile and Foundation Design

In General, the application of PSO in pile and foundation design is mainly in predicting the behavior of axially loaded piles and ultimate bearing capacity of foundations. In addition, PSO has been used to estimate the secant pile construction time.

A hybrid PSO-BP model was developed by Ismail and Jeng (2012) to predict the relationship of load/settlement in a single pile. They considered pile settlement as a non-linear function of related parameters as follow:

$$\mathrm{S} = f\left(\mathrm{P},\ \mathrm{k_s},\ \mathrm{E_p},\ \mathrm{D},\ \mathrm{L}\right) \tag{6}$$

in which, S, P, ks, E_p, D and L are pile settlement, pile load, soil stiffness, pile modulus, pile diameter and pile length, respectively. A database of 92 static pile loading tests on concrete piles was used to conduct the modeling. The results of their study show high values of correlation coefficient between predicted settlements obtained by PSO-ANN model and measured settlements obtained by static load tests.

In the field of geotechnical engineering, construction time is a critical factor for control the cost and planning in construction projects. Regarding this, Chen et al. (2009) compared the construction time of a secant pile wall using two optimization methods including self-organizing map based optimization (SOMO) and PSO. A database consists of 207 primary and secondary bored piles for a secant pile wall was used in this study. The results of the study revealed that the total saved time for the SOMO and PSO was 27.21 and 23.79 h respectively. They concluded that the SOMO method yields better construction compared to the PSO method.

A research on the load-deformation behaviour of axially loaded piles was conducted by Ismail et al. (2013). They utilized a hybrid PSO-BP model for predicting behavior of single piles embedded in soil medium and subjected to an axial load. The data of full scale static load tests of 115 piles were considered to train and validate the network. Subsequently, the PSO-BP algorithm was used to solve the soil-structure interaction problem, including a difficult mechanism of load transfer from the pile to the supporting geologic medium. Pile load, soil stiffness, pile modulus, pile diameter, and pile length were used as inputs whereas pile load-deformation was considered as output. For evaluation purpose, they compared the results the proposed model with BP and PSO models as well as the PSO-BP model developed by Zhang et al. (2007). Finally, they found that the proposed PSO-BP hybrid technique simulates the load-deformation curve of axially loaded piles more accurately compared to other models.

Zhao and Yin (2010) utilized a Chaotic PSO (CPSO) and support vector machine (SVM) method for ultimate bearing capacity prediction of shallow foundation. CPSO is a more superior algorithm in comparison to simple PSO in terms of searching quality, efficiency and robustness on initial conditions. Figure 4 shows the algorithm of CPSO-SVM proposed by Zhao and Yin (2010) to determine the ultimate bearing capacity of shallow foundations. They utilized footing width (B), footing depth (D), footing geometry (L/B), unit weight of sand (γ_d) and angle of shearing resistance (θ) as input parameters, whereas the ultimate bearing capacity (q_u) was used as the single output variable. The results revealed that the CPSO-SVM model predicts the ultimate bearing capacity of shallow foundation with high degree of accuracy.

Evaluation of pile capacity and control of pile driving are significant issues in pile installation process. In this way, Cheng et al. (2012) developed a modified model based on hybrid of harmony search (HS) and PSO for selection of parameters related to the maximum axial load. The purpose of selecting parameters was to minimize difference between the calculated axial load values obtained from formula and the measured axial load values obtained from the pile driving analyzer (PDA) tests. From the conclusion part of this study it can be found that the proposed coupling model is effective over a wide range of problems and also this model can be applied in different fields of engineering. In another study, a hybrid PSO–ANN model was proposed by Armaghani et al. (2017a) to estimate the ultimate bearing capacity of rock-socketed piles. They worked on 132 piles socketed in various rock types in Malaysia. PSO was used as an optimization algorithm to adjust weight and bias of ANN predictive moel. They mentioned that the developed model would be most useful in the preliminary stages of pile design and should be used with caution.

3.3 Rock Mechanics

The application of PSO in rock mechanics included but not limited to determining the roughness profiles of rocks, back analysis of geomechanical parameters, analysis of uniaxial compressive strength (UCS), identifying the structure of rocks, and recognizing the structure of altered rocks.

A new method based on hybrid PSO algorithm and multi-layer perceptron (MLP) neural network was developed by Babanouri et al. (2013) to estimate fractal dimension of roughness profiles (D) and standard deviation (σ) of rock. It is worth noting that determination of D is still a problem in geotechnical engineering due to attributed different values of the fractal dimension. There are two kinds of errors for prediction of fractal dimension; stochastic and systematic. Modelling of these errors is difficult because of the complexity relationship between the fractal dimension and the measurable variables. A huge number of fractional Brownian including 39900 profiles was generated and their statistical features were extracted. They examined this model for 10 standard profiles of roughness and concluded that the proposed estimator gives an error 15 times smaller

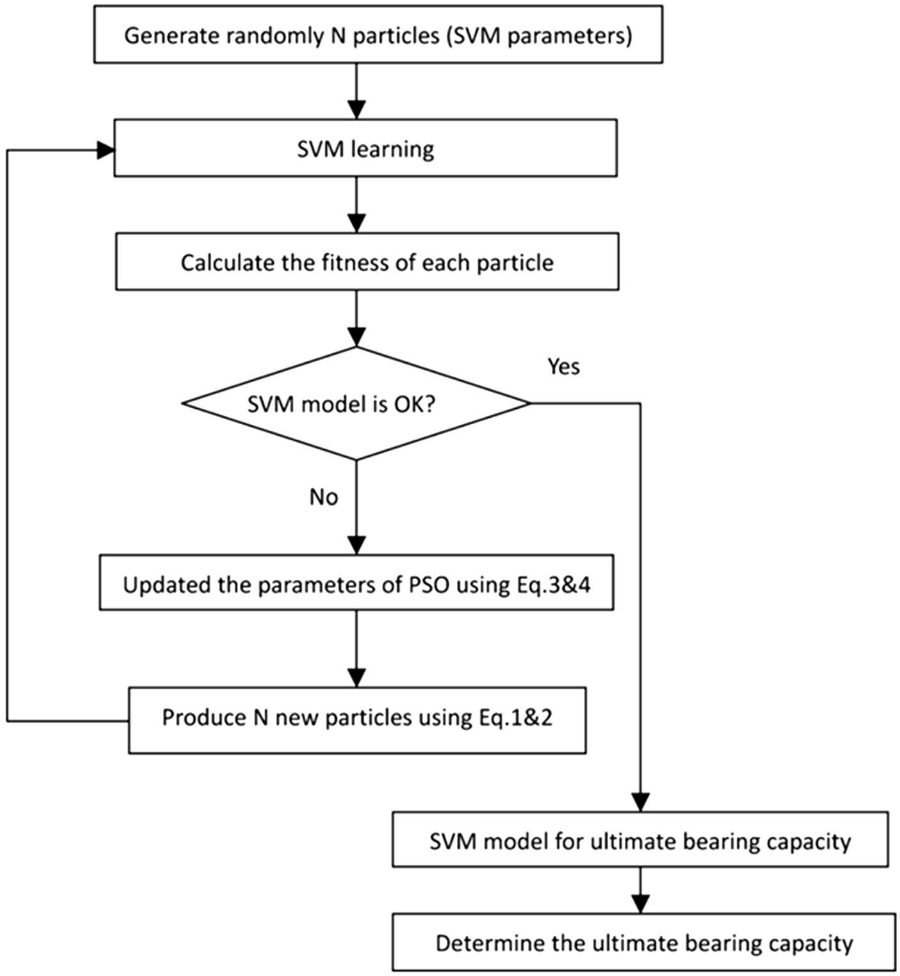

Fig. 4 The flowchart of CPSO-SVM to determine the ultimate bearing capacity (Zhao and Yin 2010)

than the roughness-length method. The results show that the fractal dimension does not necessarily increase with increasing roughness.

Zhao and Yin (2009) proposed a new intelligent displacement back analysis method based on the combination of support vector machine, PSO, and numerical analysis. A non-linear relationship between displacement and geomechanical parameters of rock mass was described by SVM. They used PSO to increase the generalization performance of searching process in the SVM model. A series of numerical analyses (using FLAC2D) was conducted to produce the required datasets for training and testing steps. Figure 5 shows the process of recognizing the rock mass parameters using the back analysis based on the proposed method. The results revealed that the proposed technique increases the efficiency and precision of back analysis of geomechanical parameters.

A hybrid genetic programming with modified PSO algorithm was proposed by Feng et al. (2006) to identify the structure of visco-elastic models of rocks. In this study, genetic programming was utilized to explore the structure of the model and the modified PSO was used to investigate coefficients in the provisional model. They concluded that if the evolving factors and number of generation are appropriately set, the fitness method can be found with a global optimum solution.

Mohamad et al. (2015, 2016), and Momeni et al. (2015) highlighted a successful application of PSO in optimizing ANN weigh and bias in order to estimate UCS of the rock material. Since direct determination of UCS is difficult, they used rock index tests (e.g., point load test, p-wave velocity, Schmidt hammer rebound number and rock density) as inputs for predicting UCS of different types of rock. A high

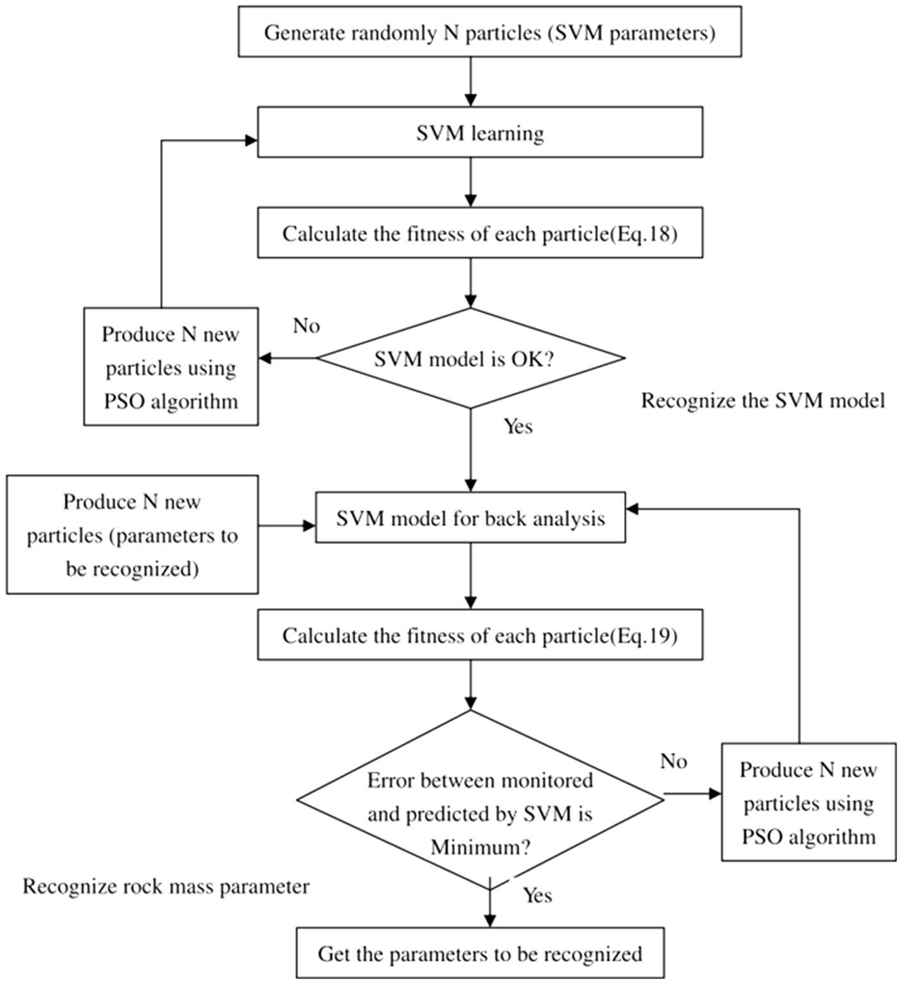

Fig. 5 Intelligent displacement back analysis based on PSO SVM (Zhao and Yin 2009)

level of accuracy was reported by these researchers by developing PSO-ANN model. They showed ability of PSO-ANN model by comparing its results with a pre-developed ANN model in predicting UCS.

Zhan and Wu (2009) recognized the hyper-spectral altered rock using an improved algorithm based on PSO and neural network. The point was mentioned in their paper that PSO can be improved into two parts; reinforcing the particles diversity and avoiding the prematurity of particle swarm. Field survey of altered rock spectral data was used to investigate samples of illite, chlorite, gypsum and kaolinite for using in the network. To show the ability of the improved PSO-BP model, the network was also modelled using BP algorithm. The results indicated that the BP algorithm easily falls into the local minima whereas the proposed PSO-BP method can be effectively applied to identify the altered rocks.

3.4 Soil Mechanics

PSO have successfully encountered with some problems in soil mechanics such as determination of soil erosion characteristics, behavior of unsaturated soil, soil-structure interaction, and soil parameters.

Yunkai et al. (2010) predicted soil erosion characteristics in small watersheds using a combination of SVM and PSO. In fact, they introduced the application of PSO for automatic selection of SVM parameters and presented a model by linking PSO and SVM for small sample data analysis. The predicting model in this study was based on the monitoring data of sand production. According to the results, the proposed model can simulate successfully the erosion characteristics in small watersheds with low degree of average error (3.85%).

Zhang et al. (2009, 2013a, b) utilized a hybrid moving boundary PSO (HMPSO) method to minimize the difference between measured (field data) and computed values on the cavity pressure-cavity strain curve in unsaturated soil. They used the HMPSO algorithm to select parameter values in the Barcelona Basic Model (BBM) which is one of the best known constitutive models for unsaturated soils. Field data were obtained from Suction Monitored Pressuremeter tests, which employ tensiometers to measure suction. The computed cavity pressure-cavity strain curve was obtained using finite element model of an unsaturated soil. In their study, an HMPSO algorithm was used to identify model parameters of field Pressuremeter tests. The combination of field Pressuremeter tests, finite element results and the HMPSO algorithm introduces a practical technique to determine parameter values for geotechnical modelling in unsaturated soils.

Fontan et al. (2011) used PSO algorithm and finite element (FE) method to develop an inverse identification process. The objective here was to recognize the equivalent structure stiffness that mimics soil-structure interaction problem. For this purpose, experimental tests and FE analysis were conducted to validate methodology and to show the role of the input data (displacement) on the identification quality. In this study, a general frame based on different combination tools (inverse analysis, FE and PSO techniques) was developed to solve the problem. PSO was utilized for treatment of the mechanical properties recognition. They concluded that the combination of aforementioned methods is able to investigate the parameters related to inverse problem.

Sadoghi Yazdi et al. (2011) calibrated the soil parameters using the linear elastic-hardening plastic constitutive model and the Drucker–Prager yield criterion by the combination of the neuro-fuzzy (ANFIS) and PSO model. For providing nonlinear relationship between the deviatoric stress and axial strain ($\sigma_d - \varepsilon$) resulted from a consolidated drained triaxial test on sand samples, an ANFIS model was used in this study. According to Fig. 6, PSO was utilized to determine soil model parameters. For verification of the accuracy and applicability of the proposed technique, a series of data obtained from different confining pressures was modelled using the proposed model. The outcome showed a close match with the same order of accuracy.

3.5 Tunneling and Underground Space Technology

Since tunneling deals with many uncertainties, the conventional empirical and analytical methods face with some difficulties in tunnel designing. Based on the applicability of PSO in funding the optimum solution, its applications have been developed in different aspects of tunnel design such as prediction of tunneling-induced ground movements and building damage, determining the rock displacements around a tunnel, finding the optimized supporting system parameters, and obtaining the optimized performance of tunnel boring machines (TBM).

Hajihassani (2013) developed hybrid PSO-based ANN model to predict three dimensional ground movements induced by tunneling. For that reason, an extensive database consisting of measured settlements, geotechnical parameters and tunneling parameters were collected From Karaj Tunnel in Iran. In order to assess the ability and accuracy of the proposed model, the predicted ground movements using proposed model were compared with the measured settlements. In addition, for a particular point, ground movements were obtained using FE analysis and the results were compared with the proposed model. He indicated that the proposed model is able to eliminate the limitations of the current methods and is an applicable tool to predict three-dimensional tunneling-induced ground movements with high degree of accuracy.

A research has been conducted by Xing et al. (2010) to study the adaptive control of tunnel excavation in rock. Focusing on the uncertainty of underground engineering, they introduced PSO application to recognize rock mechanical parameters and obtaining the optimum supporting parameters. Using the in situ monitoring displacements, they obtained rock mechanics parameters and subsequently optimized anchor parameters using these parameters. Furthermore, they investigated the process of combining PSO with 3D fast Lagrange numerical method and applied this method to Dalian Gezhenpu tunnel in China. They resulted that the PSO arithmetic can be easily realized and the proposed method provides a new way to inform construction design. Annan and Zhiwu (2011) also used an improved PSO to optimize the anchor and spay layer parameters in rock tunneling. They applied the presented method in metro tunnel of Dalian City in

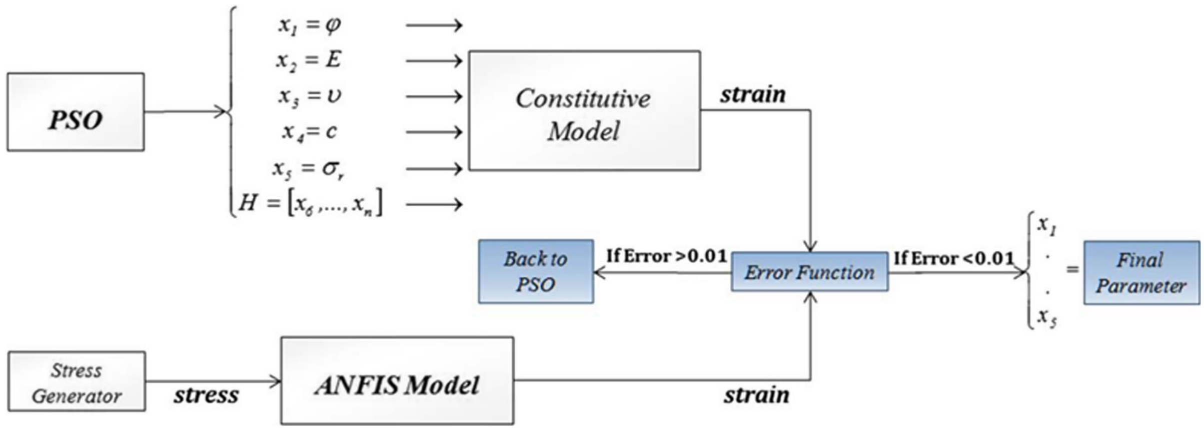

Fig. 6 Combination of PSO ANFIS techniques for calibration of soil model parameters (Sadoghi Yazdi et al. 2011)

China with satisfied results. A similar study on the rock displacements around a tunnel was conducted by Jiang et al. (2011). They employed a combination of PSO and SVM to identify the nonlinear relationship between tunnel parameters and displacements around a tunnel. For this purpose, they used numerical analysis to produce training and testing samples. Afterwards, they utilized SVM to determine the nonlinear relationship between parameters and displacements. The parameters of SVM were determined using PSO algorithm and the results were validated with a case study.

Performance prediction of hard rock TBM is a complex and essential task in mechanized excavation which may reduce the risks related to high capital costs. Yagiz and Karahan (2011) employed PSO algorithm to predict the performance of TBM using a database consisting of intact rock parameters, rock mass properties and field machine performance data. They generated seven different PSO models employing the variety of datasets with various percentages of rock type and concluded that the PSO is applicable to predict TBM penetration rate (PR) precisely. Moreover, Armaghani et al. (2017b) developed a PSO-ANN model in order to predict PR of TBM in a tunnel excavated in Malaysia. They highlighted a sucsessful implementation of this model in predicting TBM PR.

In addition to abovementioned application, PSO algorithm was employed to increase the ANN applicability in modeling the trench layer location around a pipeline. In this respect, Choobbasti et al. (2014) utilized an integrated PSO-ANN model to determine the optimum locations of a trench layer around a pipeline. The local radial basis function differential quadrature (LRBF-DQ) method was used in their study to obtain the pore pressure and the obtained data were utilized to train the ANN. Finally, PSO was used to determine the best location of trench later. The results demonstrated the minimum liquefaction is happened when the trench layer is placed beneath the pipeline.

3.6 Other Applications

In addition to aforementioned applications, PSO algorithm has been employed in optimization problems of varies geotechnical engineering fields. Hajihassani et al. (2014, 2015), and Armaghani et al. (2014b) employed PSO as the training algorithm of ANN to predict environmental impacts of blasting operation such as air-overpressure, flyrock and ground vibration. The PSO was used in their study as optimization algorithm to achieve the best weights and biases for applying in ANN. Collected datasets from blasting operations including the most influential parameters on environmental impacts of blasting were considered in their researches. The proposed models presented satisfactory results to predict environmental impacts of blasting operation with a high degree of precision. In addition, Hasanipanah et al. (2017) applied a hybrid model of PSO and support vector regression (SVR) for air-overpressure prediction and concluded that PSO can be used as a reliable algorithm to train the SVR model.

To minimize maintenance-related, Xu and Zeng (2010) utilized PSO algorithm to solve a dynamic equipment allocation problem (DEAP) through the operation of a concrete-faced rock-fill dam. As an important maximization factor in construction throughput, the uncertainties associated with equipment failures were considered in a mathematical model. Their model was confined by initial and constraint conditions. Afterwards, PSO algorithm was implemented to find the optimum solution of the DEAP. The Shuibuya Hydropower Project was utilized to investigate the applicability and efficiency of the propose method. The results demonstrated that the proposed optimization model is applicable and efficient in solving the DEAP with uncertainties.

Based on PSO algorithm, a decision support system was proposed by Wang et al. (2011) to reduce the disequilibrium degree of filling intensity in rock-fill dams. They analyzed the main affecting parameters on substage-zoning filling design and proposed an optimization model based on analyses. Based upon this, a decision support system for the substage-zoning filling design of rock-fill dams was developed. They employed the proposed model in a hydropower project and demonstrated the applicability of the proposed model in various types of rock-fill dams.

4 Conclusions

Complex and not well-understood problems are the common obstacles in geotechnical engineering. In this regard, finding the optimum solution is difficult and even impossible in some cases. Consequently, based on available literature, PSO has been extensively used in geotechnical engineering as a powerful optimization technique to find the optimum solution. Simplicity of the operations and reasonability of the results have paved the way to use PSO in various fields of geotechnical engineering such as slope stability analysis, pile and foundation engineering, rock and soil mechanics, and tunneling and underground space design.

In PSO algorithm, each individual learns not only from its own experience, but also from the others, especially from the best particle. Therefore, PSO presents some advantages over conventional optimization techniques by using simultaneous combination of particles cooperation and competition. Despite the advantages of PSO in solving the complex engineering problems, it should be applied with caution in consequence of the fact that divergence phenomenon happens occasionally in its optimization process. In addition, local solutions may trap PSO by setting inappropriate initial parameters in which depend on the condition of each problem.

In this study, applications of PSO in many geotechnical studies were carefully reviewed and its capability in solving geotechnical problems was highlighted. In the reviewed cases, PSO plays a significant role as an optimization algorithm to predict/optimize geotechnical outputs. It can be concluded that the application of PSO should be always utilized with caution. Additionally, sensitivity analysis on initial parameters should be conducted in order to avoid returning disappointing results.

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