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Performance Comparison of Particle Swarm Optimization and Genetic Algorithm for Back-analysis of Soil Layer Geotechnical Parameters

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Abstract

Surface settlement induced by tunneling is one of the most crucial problems in urban environments. Hence, accurate prediction of soil geotechnical properties is an important prerequisite in the minimization of it. In this research work, the amount of surface settlement is predicted using three-dimensional numerical simulation in the finite difference method and Artificial Neural Network (ANN). In order to determine the real geotechnical properties of soil layers around the tunnel; back-analysis is carried out using the optimization algorithm and monitoring data. Among the different optimization methods, genetic algorithm (GA) and particle swarm optimization (PSO) are selected, and their performance is compared. The results obtained show that the artificial neural network has a high ability with the amounts of R=0.99, RMSE=0.0117, and MSE= 0.000138 in predicting the surface settlement obtained from 150 simulations from randomly generated data. Comparing the results of back-analysis using the optimization algorithm, the genetic algorithm shows less error than the particle swarm algorithm in different initial populations. In all cases of analysis, the calculation time for both algorithms lasts about 5 minutes, which indicates the applicability of both algorithms in optimizing the parameters in mechanized tunneling in a short time.

1. Introduction

The most important concern for all the participants of mechanized tunneling is settlement control, especially when the shield machine passes through buildings in urban areas. Since ground movements caused by shield tunneling have attracted the attention of many engineers and researchers, there is a growing demand for settlement control arrangements during mechanized tunneling construction.

Surface settlement can be estimated by using empirical methods [1-3], analytical methods [4-7], and numerical methods [8-12]. Numerical models are a powerful tool in performance-based engineering analysis and design of geotechnical structures compared to the other methods. These models can provide accurate response estimates in terms of displacements, structural support load, failure, and damage to both new structures under construction and existing old ones. However, the main problem in using numerical models is the lack of reliable information about the geology of the site, soil, and rock properties, and in situ stress.

Determining the geotechnical properties of soil and rock in the project environment is very time-consuming and expensive, and is performed with a limited number of on-site and laboratory tests on the samples obtained from boreholes with distances of 50 to 300 m. Therefore, the prediction based on thisdata is made in the design phase that the results can be very different from reality due to the difference between the actual geotechnical properties and the estimated amount [13].

Numerical models of geotechnical problems are characterized by a large number of parameters including the geotechnical characteristics of the ground that in the tunneling projects, these parameters may have significant spatial variability [14].Thus in geotechnical analysis, to decrease the

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model parameter uncertainty, back-analysis based on in situ measurements is often used to calibrate numerical models and determine the parameters of the updated model with more confidence [15].

The back- analysis is the determination of the input parameters according to the reply (e.g. from field measurements).By deviating from the predicted and observed response, the input data is revised iteratively, and this process continues until an error value of at least between the predicted and observed values is reached. Many researchers have conducted back-analysis of geotechnical problems [16-23].

When optimization algorithms such as particle swarm optimization (PSO) or genetic algorithms are used in the back-analysis process, a large number of realizations are often required[15].If large-scale three-dimensional finite difference models are used on a large scale, this is accompanied by a great deal of effort, which is made possible by the use of metamodels for the evolution of objective functions. Meta modelsare a compact representation of the simulation model, and are produced with various methods such as Artificial Neural Networks (ANNs), Proper Orthogonal Decomposition (POD), and Support Vector Machines (SVMs) [24-29].

In many geotechnical problems, neural networks have been used as meta-models that are trained by numerical modeling to predict deformations due to geotechnical [30-34] parameters or to predict tunneling settlement [34-37].

Ninic *et al.* have used a hybrid meta model ANN-PSO based on finite element numerical modeling data to predict surface settlement and real time identification of geotechnical and operational parameters in mechanized tunneling [24].

Wang *et al.* have proposed a meta-model based on numerical simulation-artificial neural network-Bayesian network (NS-ANN-BN) to investigate the factors that affect the ground settlement during the construction of the shield tunnel, taking into account the coupled hydro-mechanical properties [38].

One of the most important issues in the field of mechanized tunneling is determining the amount of surface settlement during operation that this goal will not be possible except with accurate geotechnical parameters of the project environment soil.

Since the number of geotechnical parameters based on the selected behavioral model involved in determining the amount of surface settlement is very high, before performing the back-analysis and predicting these parameters, sensitivity analysis is performed to select important and effective parameters in the amount of surface settlement. The purpose of this work is to reduce the number of parameters and, by nature, to reduce the number of modeling required to build a metamodel to perform back-analysis and save computational time and cost.

Thus in this research work, after performing the global sensitivity analysis by Morris method and selecting 9 parameters, these parameters were used to model and construct a neural network meta model to predict the maximum surface settlement. More details on sensitivity analysis are provided in another article by the authors [32].

Then using a combination of artificial neural network and optimization algorithm, prediction of maximum surface settlement as well as updating of geotechnical parameters of the soil has been carried out by using back-analysis and monitoring data.

The known two algorithms GA and PSO has been selected and used to compare their performance in identifying the geotechnical parameters of soil layers using the amount of error and the time required for the back-analysis process.

2. Methods and Materials

2.1. Case study

Tabriz is one of the major cities of Iran, which is located in the northwest of this country. Therefore, due to the large population, traffic situation, and density of surface structures, creating an underground transport system in the city is essential. The construction of four metro lines is designed in the development plan for the city's transportation system. Line 2 of Tabriz Metro has a total length of about 22 and 20 stations, the map of which is shown in Figureure 1. Considering the old texture and the existence of historical buildings along Metro Line 2 (chainage 4+660 to 4+720, Amirkabir Market), the amount of surface settlement allowed in this part of the tunnel route is 1 cm, so the surface settlement in this part of the project should be carefully checked.

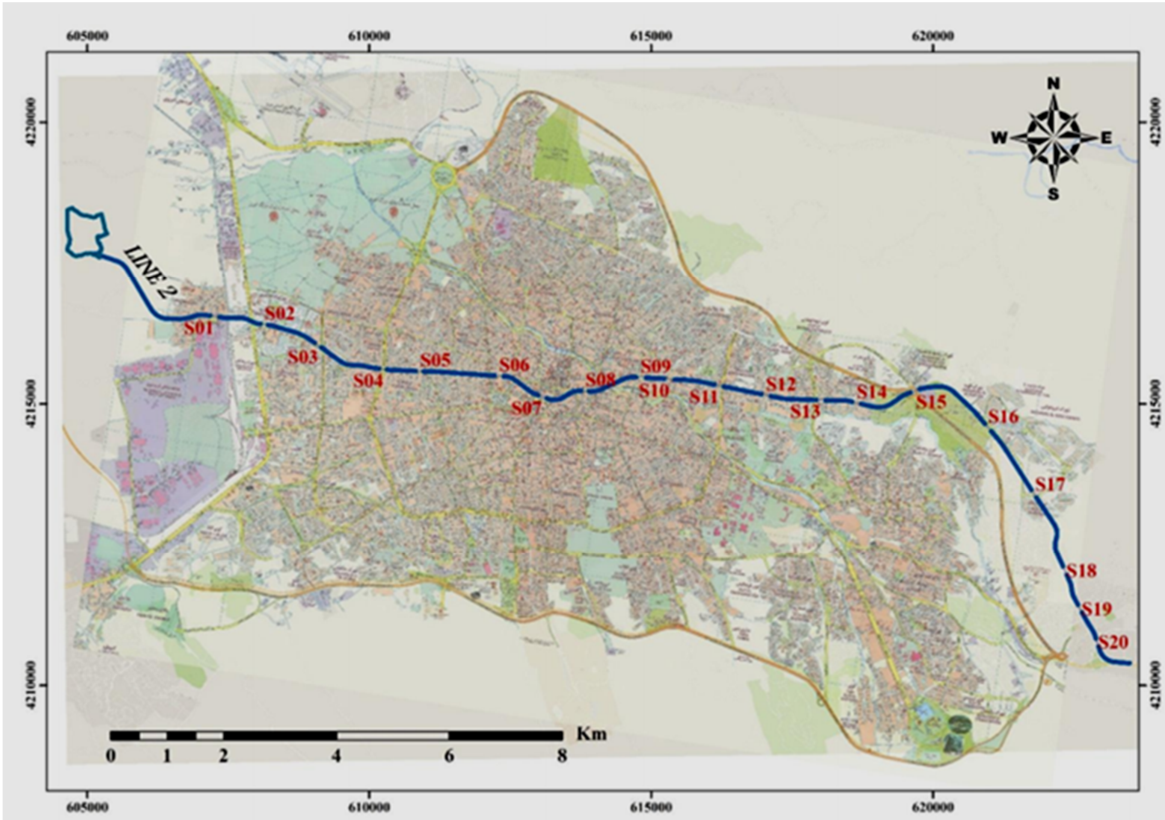

Figure 1. Tabriz metro line 2.

Geotechnical studies of Line 2, which include drilling 53 boreholes and 17 wells along the route, showed that this part of Tabriz at the investigated depth (about 30 m) is mainly composed of fine-grained soils. Groundwater depth in this area varies from 5 to 18 m.

Based on the geotechnical investigations, the ground of the study area is composed of alluvial layers, mostly fine-grained, between layers of sand. Studies of groundwater conditions during and after the drilling of boreholes showed that the groundwater level is about 13.1 m below the surface.

Pins are applied to measure surface ground settlements. The pins are mounted just above the axis of the tunnel to recognize the surface settlement during the project operation. Figure 2 shows the position of the pins in the projects.

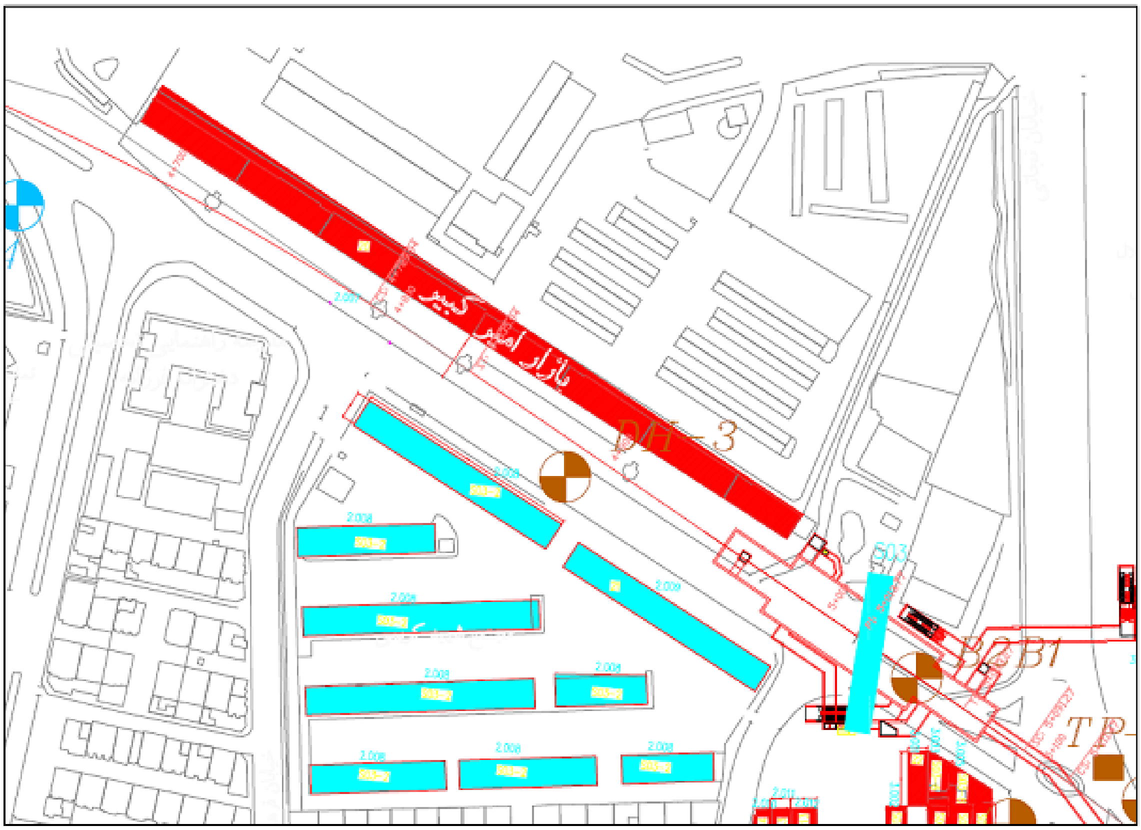

Figure 2. Installed pins map.

2.2. Numerical model

EPB TBM excavation was modeled by theFLAC3D code based on the finite difference method. The soil around the tunnel was considered as a homogeneous and isotropic environment with linear elastic perfectlyplastic behavior of Mohr-Coulomb criterion. This criterion is extensively applied in tunnel modeling due to the simplicity and obtains ability of the necessary geotechnical parameters.

This criterion is widely applied in tunnel modeling due to the simplicity and availability of the necessary geotechnical parameters [39].Also segmental lining and backfill grouting materials were considered with elastic behavior in the model. The excavation diameter is 9.5 m, of which 0.35 m is for segmental lining and 0.15 m is for the grouting area. The geotechnical properties of the soil layers used in the metamodel are accessible in Table 1.

Table1. Geotechnical parameters of soil layers.

Layer	Soil type	Thickness (*m*)	Density (*Kg/m*^{3})	Elasticity modulus (*MPa*)	Poisson ratio	Cohesion (*KPa*)	Fraction angel($^\circ$)
1	Filling material	1	1610	30	0.35	0	32
2	CL-ML1	3	**1300-1700**	**10-40**	0.41	**0-12**	**15-30**
3	ML	7.3	**1500-1700**	**10-50**	0.38	**5-30**	**20-35**
4	SM1	1.8	**1800-2200**	**30-160**	0.35	**5-30**	**20-35**
5	CL-ML2	7.9	**1800-2300**	**20-70**	0.37	**8-40**	**20-35**
6	SM2	29	2030	**60-110**	0.33	9	34

The dimensions of the model are X = 124.8 m, more than 2H and 4D (H is the height of the overburden, and D is tunnel diameter), Y = 60 m, about 7D and Z = 55 m, more than H and 4D. Figure 3 shows the dimensions of the model and the soil layer position in it.

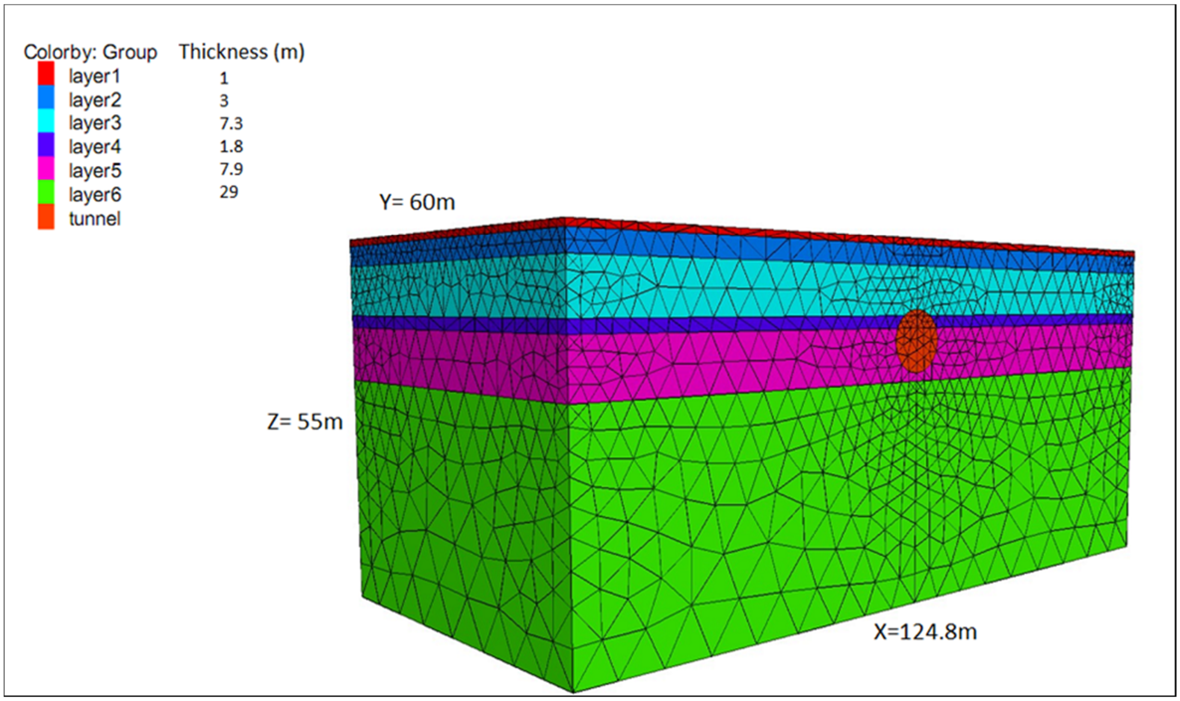

Figure 3. Dimensions of 3D model and location of soil layers.

The surface loads of buildings and the traffic load were selected as 30 kPa and 20 kPa, respectively. The ratio of horizontal to vertical stress for each layer was calculated by the formula K = 1– sinφ, and applied in the model. Groundwater was considered as the pore pressure. The monitoring point was considered in the center line of the tunnel and the position of Y = 30 m.

As the mechanical boundary conditions, the upper bound of the model was assigned free, and the lower bound for the vertical motion was fixed; the other boundaries were fixed in the X and Y directions to avoid any movement.

The excavation phase was modeled in a stepwise manner, and all soil layers were activated to achieve equilibrium in the initial stage. The advancement of TBM was done with a sequence of 1.5 m soil excavations and in a total of 40 steps. The excavation steps were modeled as follows:

- Tunnel excavating corresponding to segment length (1.5 m)
- Putting on face pressure in the tunnel face
- Creating a TBM shield as a fictive boundary
- Converging Over excavation in each excavating step until the drilling wall reaches the shield diameter.
- Solve the model
- Eliminating the face pressure on the tunnel face and repeating the above steps
- Putting on grouting pressure (grouting pressure was assumed to be a uniformly distributed load acting on the soil elements),generation of segments and grout material after 9 m advancement (equal to shield length)
- Solving the model
- Repeating the above steps until excavation reached the end

Interaction of lining and surrounding soils were modeled using interface elements. The normal stiffness of interface is 8e9(N/m/m), shear stiffness is 7.7e6 (N/m/m),and friction angel was 20 degree. Face pressure and grouting pressure were considered in the range of 110-150 kPa and 120-200 kPa, respectively, according to the project operational report.

With continuous injection of grout behind the lining, sealing of segments and the presence of appropriate face pressure, water entry into the tunnel was not considered during the tunnel construction stage. Thus the water level and the soil layer geotechnical characteristics during the construction operation were assumed to be constant.

In order to validate the model, the data of the first parts of Metro Tabriz line 2(Chainage 0+750m) were used and the difference of about 10% between the maximum surface settlement obtained from numerical modeling and on-site monitoring, confirmed the validity of the constructed model. The maximum amount of monitoring settlement that was recorded in this section was11.2 cm, and the settlement gained from numerical modeling was in the range of 11-12.5 cm. Figure 4 shows the model of this section and vertical displacement by TBM advancement.

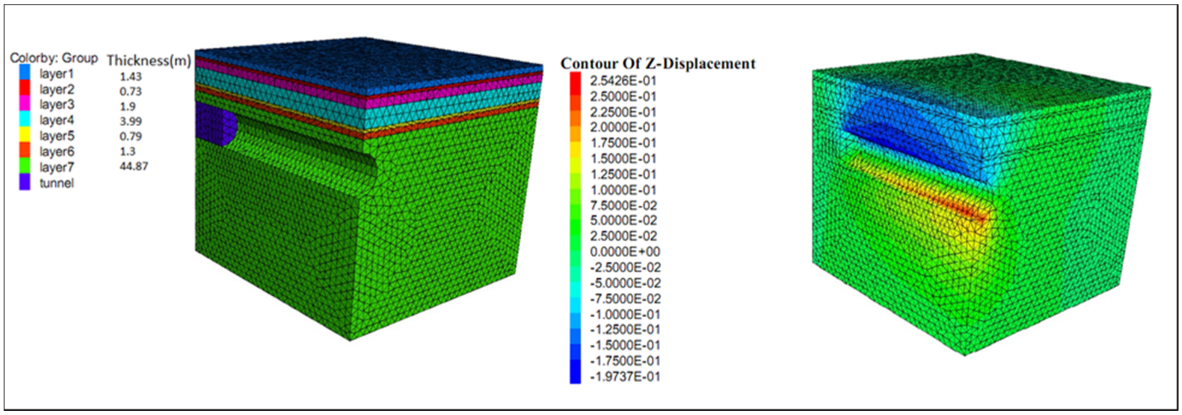

Figure 4. 3D finite difference model of Chainage 0+750m and contour of vertical displacement.

2.3. ANN model

The artificial neuron network (ANN) is generated for data processing, and is based on the function of the human brain. An ANN consists of three main parts, the input, output, and hidden layers. Data is transmitted between layers through connecting elements. The weight generated by the system controls this transfer to strengthen or weaken the processes. The output of each neuron in the layer must be calculated from an activation function (such as the sigmoid type). The number of neurons in hidden layers is obtained by applying a complicated approach or trail-and-error process. One of the most common training algorithms used in the field of engineering is the back-propagation (BP) training algorithm. This algorithm runs to adjust the network weight according to minimize the error value. For this purpose, the comparison of the desired output values with the values reached in each step is carried out. The process continues until the output values are obtained and the system error is reduced [36].

2.4. Genetic algorithm (GA)

GA was first introduced by Holland (1975) . Genetic algorithms are mainly used to solve optimization problems and in a wide variety of scientific fields such as bioinformatics, computational science, engineering, manufacturing, and phylo-genetics. [40]. Figure 5 shows the flowchart of this algorithm.

Genetic algorithm applies different biological techniques such as inheritance, selection, cross-over, mutation, and reproduction in the different stages such as random production of the initial population, calculating the amount of fitness function for each member of the population [41, 42].In this algorithm, a set of particles called chromosomes is defined as a population. These chromosomes are then evaluated using the fitness function, which is the objective function of the problem. In the reproduction stage, the next generation is formed from the current generation. The process used to exchange genetic material between chromosomes is called cross-over. The mutation process is used to make changes to a single chromosome, which avoids the algorithm from getting stuck at a special point, and the last step in the genetic algorithm is the stop criteria, which can be to stop the iteration by reaching a desired solution or to continue the iteration up to the maximum number of cycles [43-45].

2.5. Particle swarm optimization (PSO)

PSO was first proposed by Eberhart and Kennedy [46]. The performance of this algorithm is based on the collective behavior of animals, especially birds. PSO is used to solve optimization in various sciences. In general, the function of this complex set can be simulated with the following three aspects: following the person closest to the object, moving toward the object, and moving toward the center of the group [47, 48].

The algorithm starts by generating a random population, and then searches for the optimal value by updating the next generations. Persons of society called particles follow the current optimal persons and move in the space of the problem. Each particle in this algorithm has two properties: velocity (V) and position (X),and moves in the problem space to finally find the best solution (object function) and the best particle value (XB).The best position of each particle compared to all particles in the swarm is called G, and belongs to the desired amount of fitness function. In the modified version of the algorithm, the weight of inertia (W) was introduced as the updated constitution to reduce the particle velocity when searching large areas [49].The particle velocity and position are updated in each iteration by the following equations:

$$V_{i,j+1} = W_{ij} + CLz_1\left(X_{ij}^B - P_{ij}\right) + SLz_2\left(X_{ij}^G - X_{ij}\right) \quad (1)$$

$$X_{i,j+1} = X_{ij} + V_{i,j+1} \quad (2)$$

where z_1 and z_2 refer to random numbers generated uniformly in the range of [0, 1]. CL and SL also introduce cognitive learning factors and social learning factors, respectively. Figure 6 shows the flowchart of this algorithm.

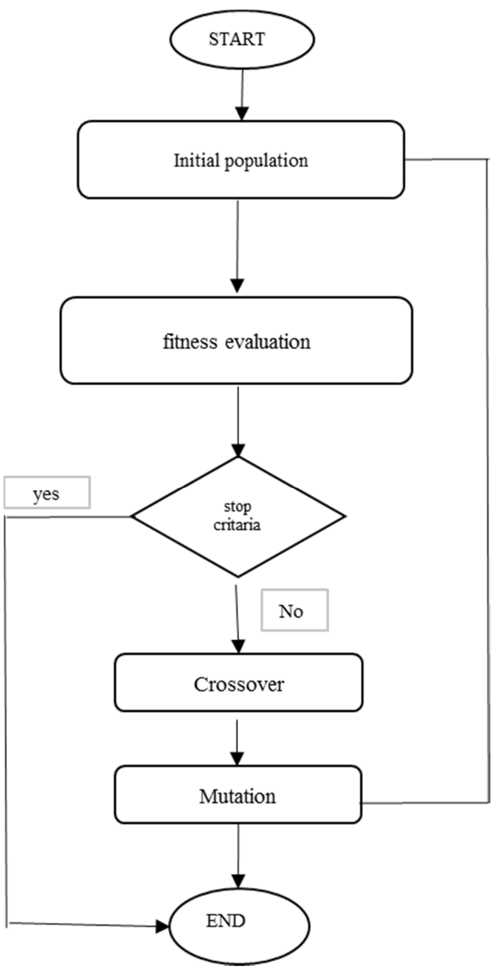

Figure 5. Genetic algorithm flowchart.

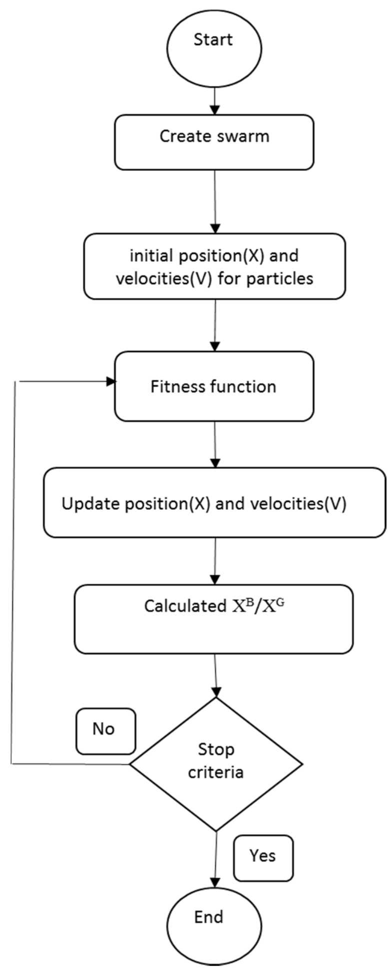

Figure 6. Flowchart of PSO algorithm.

3. Model Development

After performing sensitivity analysis and selecting 9 geotechnical and operational parameters including Gama5, E3, E4, E5, E6, C5, Phi5, face pressure, and grout pressure, 150 simulations were performed in the range of these parameters to predict surface settlement. Input data production for these simulations was done randomly using the Latin Hypercube Sampling (LHS) technique. Thus from these samples, 1650 input data was generated to produce the ANN network. The research process is shown in Figure 7.

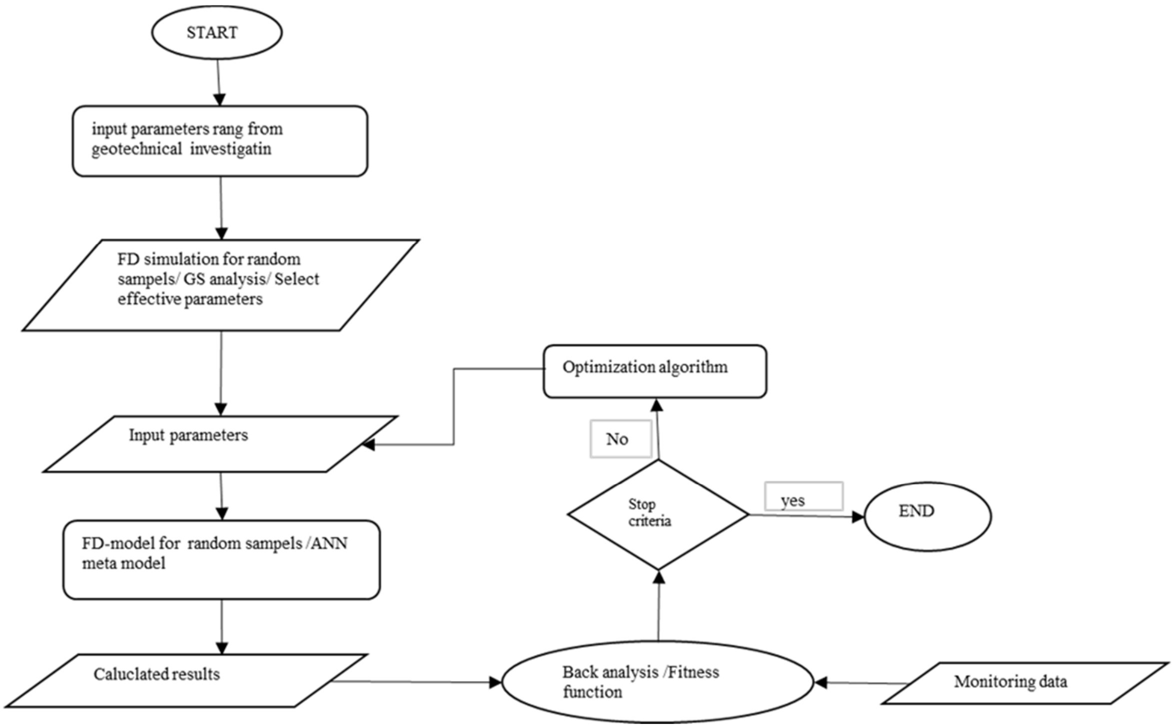

Figure 7. Algorithm of research steps.

The structure of ANN for 10 inputs is shown in Figure 8. The 10th input (n) is the tunnel excavation step. In designing the neural network structure in order to find a suitable solution, it is recommended that the numerical values of the input and output be normalized[37]. Therefore, the data sources are normalized according to the following formula:

$$A_{Norm} = \frac{A - A_{min}}{A_{max} - A_{min}}(0.9 - 0.1) + 0.1 \qquad (3)$$

where A_{Norm} is the normalized value of the variable A, and A_{min} and A_{max} are the minimum and maximum values of this variable. Using Equation (3), the data was normalized in the range of 0.1-0.9.

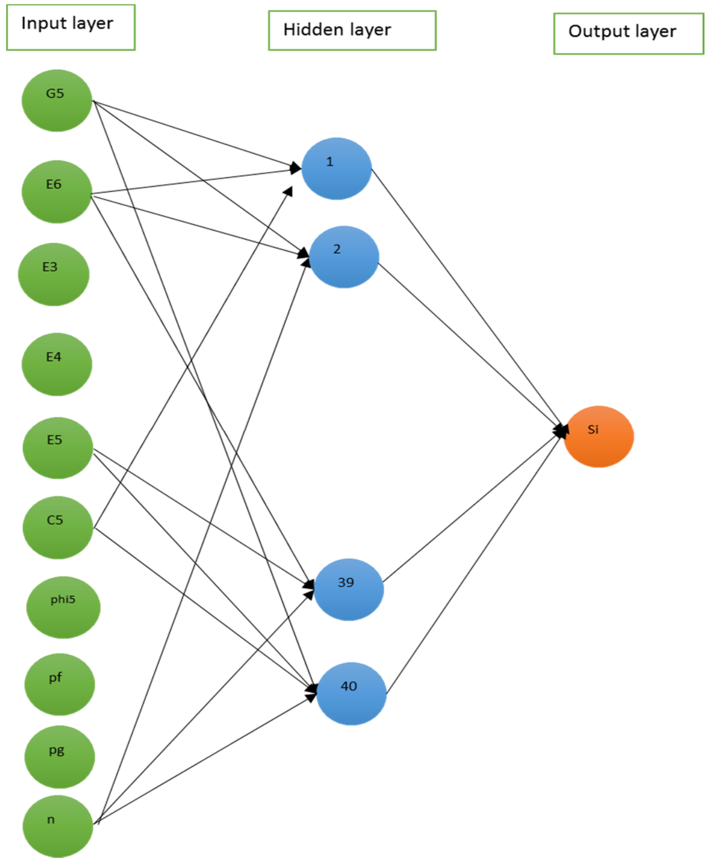

Figure 8. ANN structure.

Next, the prepared database should be broken down into training, testing, and validation datasets. Therefore, the 70%-15%-15% ratios were selected for training, testing, and validation. In using ANN, choosing the ANN training algorithm is a difficult task. The efficiency of the Levenberg-Marquardt (LM)algorithm compared to other algorithms in solving engineering problems has been confirmed by many researchers[50-52]. Thus this algorithm was selected and used in the ANN training. Another parameter that must be determined in the design of neural network architecture is the number of neurons in the hidden layer. Using the method of error and trial and examining the different numbers of neurons, 40 neurons were selected for the hidden layer. There are different criteria for examining the neural network model[53].In this work, the three criteria R^2, root mean square error (RMSE), and mean absolute error (MSE) have been used, which are calculated according to the following equations:

$$R^2 = \frac{[\sum_{i=1}^{n}(s - s_{mean})^2] - [\sum_{i=1}^{n}(s - s')^2]}{[\sum_{i=1}^{n}(s - s_{mean})^2]} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n}(s - s')^2} \quad (5)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|s - s'| \quad (6)$$

where is the measured surface settlement value, s' is the predicted value, s mean is mean of the measured value, and n is the number of datasets. The results of the neural network model are shown in Figure 9. According to the results shown in the Figure, there is a very good agreement between the input data and the target data, and the values of the parameters R, RMSE, and MSE were estimated 0.99, 0.0117, and 0.000138, respectively.

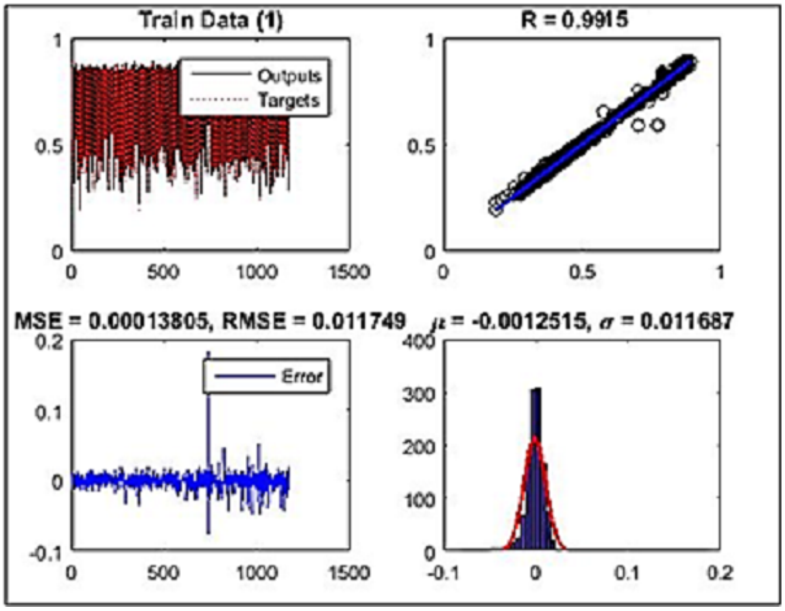

Figure 9. ANN results.

In order to obtain the optimal values for the parameters, the back-analysis is used to establish a good agreement between the predicted values of the surface settlement and the measured values. Thus ANN was combined with optimization algorithm by applying of objective function. This function is the learning error of the ANN and describes as follows:

$$\text{Error function} = 1/2(\sum_{s=1}^{n}(o_s - t_s)^2) \qquad (7)$$

$$\text{Objective function} = \sum_{0}^{Pn} \text{Error function} \qquad (8)$$

Where Os is the output of the nodes (s=1… n), and t_s is the target value in the ANN model. The parameters used in the algorithms GA and PSO are given in Tables 2 and 3, respectively.

Table 2.GA parameters.

GA Parameter	Value
Cross-over rate (%)	70
Mutation rate (%)	30
Number of iterations	100

Table 3.PSO parameters.

PSO parameters	Value
CL	1
SL	1.8
W	0.9
Number of iterations	100

4. Results and Discussion

In the two algorithms discussed above, the fundamental difference is the generation procedure of new population from the old population. In GA, the solutions are graded by the fitness values parents are selected based on their likelihood of better fitness. The cross-over operation generates child with parts taken from the parents; therefore, the solutions are presumably to be like to the parents.According to this operation, GA tends to produce solutions that are more probably to cluster around several "good "solutions in population. The diversification appearance of GA is done through the mutation operation that perfuses some "difference" into the solutions sometimes. The time required to solve problems with GA also increases non-linearly as the population size increases due to the sorting required.

In the PSO algorithm, new particle is produced by the velocity and position update equations.Thus all new particles can be very different from the old particles. This process is according to the floating point arithmetic; it could build any potential values within the solution space, i.e. The solutions in this algorithm can be very close to each other and compact in solution space compared to the genetic algorithm. Also the best particle in the swarm applies its one-way efficacy in the whole remained solutions [54].

Therefore, in this section, the performance of these algorithms was compared in terms of the number of initial population, taking into account the error rate and calculation time. All algorithms have been written in the MATLAB software.

Six back-analyses with different initial populations were performed for both algorithms including PSO and GA. In these analyses, nine parameters were optimized base on the measured surface settlement in the controlling point. Table 4 shows the results of back-analyses in the different initial population values of PSO and GA.

Table 4. Result of back-analyses in PSO and GA.

Number of initial populations	Error value (%)		Time(s)	
	PSO	GA	PSO	GA
20	8.99	8.82	123.54	141.53
30	8.02	7.96	133.13	163.76
40	7.09	6.84	143.57	209.02
50	6.97	5.65	153.54	217.35
60	5.96	5.73	164.12	223.12
70	6.54	5.85	174.63	248.1

According to the values shown in Table 4, GA shows less error in all the initial populations. On the other hand, the time required for calculations for the algorithm PSO is always less than the algorithm GA but this time in total for each algorithm is 5 minutes, and in the mechanism of back-analysis in mechanized tunneling is not considered a long time. Generally, comparison of these two algorithms, the best result for the genetic algorithm was obtained in terms of error rate in the initial population of 50 and error 0.0165 and the amount of the parameters are Gama5=2235 kg/m^3, E3= 15MPa, E4=110 MPa, E5=63 MPa, E6=66 MPa, C5=36 kPa, Phi5=22, face pressure=85 kPa, and grout pressure=160 kPa after back-analysis. Figure 10 shows the best result obtained in the 33rd iteration.

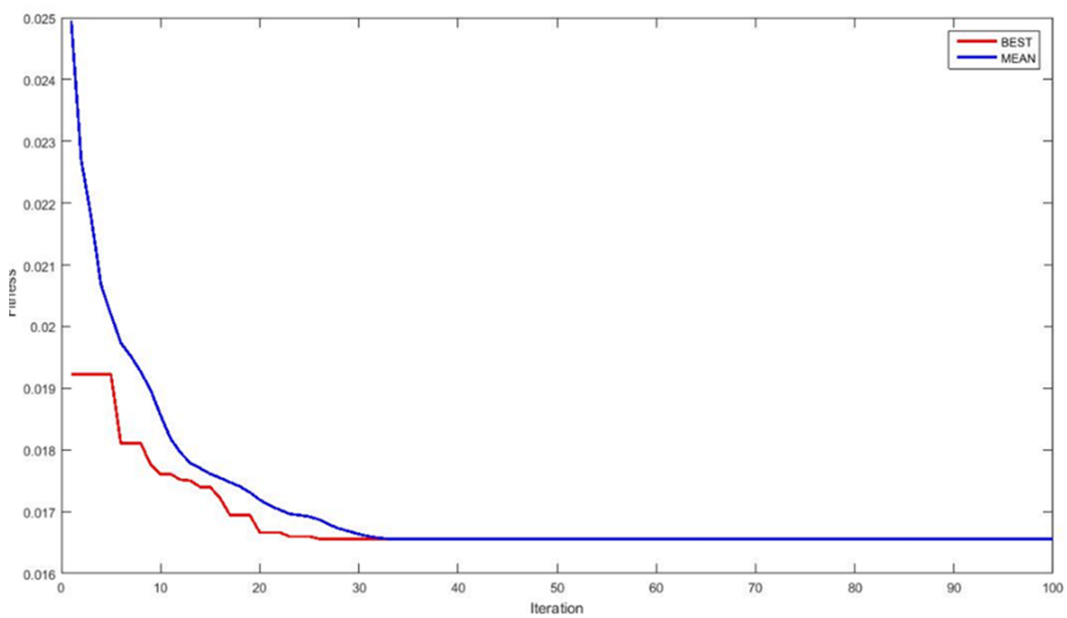

Figure 10. Fitness diagram versus number of iterations in a genetic algorithm with an initial population of 50.

Table 5 shows the identified parameters values with these two methods. Using this result obtained in each algorithm, the amount of surface settlement at the control point against the TBM advancement steps was investigated, which is shown in the Figure 11. As it was observed, the genetic algorithm has a smaller error than the algorithm PSO.

Table 5. Identified parameters values.

Parameters	Min value	Mean value	Max value	GE	PSO
Gama 5	1800	2300	2050	2235	1980
E3	10	30	50	15	14
E4	30	95	160	110	105
E5	20	45	70	63	62
E6	60	85	110	66	64
C5	8	24	40	36	35
Phi5	20	27.5	35	22	22

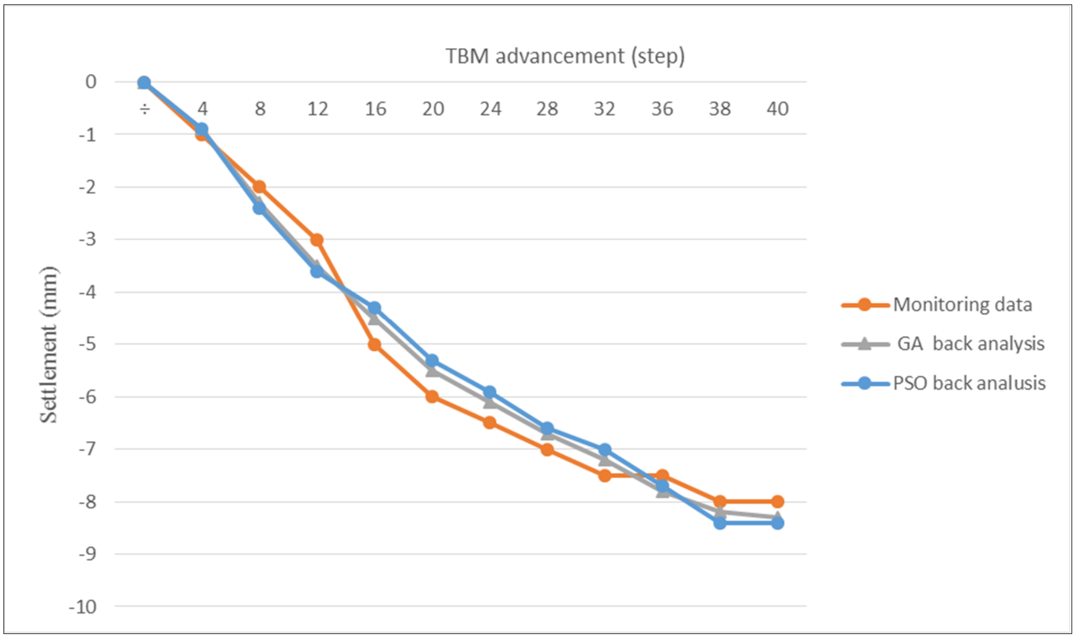

Figure 11. Comparison of settlement *vs.* TBM advancement for monitoring data and after parameter identification by GA and PSO.

5. Conclusions

This research work investigated the performance of the two algorithms GA and PSO in the back-analysis of soil geotechnical data in mechanized tunneling. For this purpose, three-dimensional numerical simulation of all mechanized tunneling steps was performed using three-dimensional FLAC software. By performance of the sensitivity analysis, 9 parameters were selected as the most effective ones in the amount of surface settlement due to tunneling, then150 random samples were generated and used in simulation. The results of these simulations were applied in predicting settlement by artificial neural network. Finally, to perform back-analysis using monitoring data, the results of the two algorithms GA and PSO were compared. In general, the following results were obtained:

Artificial neural network has a very good ability to predict the surface settlement using simulated data so that the values of parameters R, RMSE, and MSE were obtained 0.99, 0.0117, and 0.000138, respectively.

One of the most important differences in the algorithms GA and PSO is how the new population is produced from the old population. Therefore, in this work, the performance of the two algorithms in different initial population numbers was investigated.

In order to compare the results of the back-analysis, the amount of error and the time required for the calculation were used, and the genetic algorithm showed a lower error rate in all the initial populations.

The amount of time required to calculate in the PSO algorithm was in all cases less than the GA algorithm but due to the small time (about 5 minutes) compared to the time required to advance the tunnel in each step (about 2-3 hours), this difference can be ignored. In general, both two algorithms can be used in back-analysis of parameters in mechanized tunneling.

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مقایسه عملکرد الگوریتم بهینه سازی تراکم ذرات و الگوریتم ژنتیک در آنالیز برگشتی پارامترهای ژئوتکنیکی لایه خاک

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چکیده:

یکی از مهمترین مشکلات ناشی از تونلسازی در محیط شهری، نشست سطحی می باشد. از این رو، پیش‌بینی دقیق ویژگی‌های ژئوتکنیکی خاک، پیش‌نیاز مهمی در به حداقل رساندن آن است. در این تحقیق، میزان نشست سطحی با استفاده از شبیه‌سازی عددی سه بعدی به روش تفاضل محدود و شبکه عصبی مصنوعی (ANN) پیش‌بینی شده است. به منظور تعیین ویژگی های ژئوتکنیکی واقعی لایه‌های خاک اطراف تونل؛ تجزیه و تحلیل برگشتی با استفاده از الگوریتم بهینه سازی و نظارت بر داده ها انجام شده است. از میان روش‌های مختلف بهینه‌سازی، الگوریتم ژنتیک (GA) و تراکم ذرات (PSO) انتخاب شده و عملکرد آنها با هم مقایسه شده است. نتایج به‌دست‌آمده نشان می‌دهد که شبکه عصبی مصنوعی با مقادیر $R=0.99$، $RMSE=0.0117$ و $MSE=0.000138$ توانایی بالایی در پیش‌بینی نشست سطحی به‌دست‌آمده از ۱۵۰ شبیه‌سازی از داده‌های تولید شده به‌طور تصادفی دارد. با مقایسه نتایج تحلیل برگشتی با استفاده از الگوریتم بهینه‌سازی، الگوریتم ژنتیک خطای کمتری نسبت به الگوریتم تراکم ذرات در جمعیت‌های اولیه مختلف نشان می‌دهد. در تمامی موارد تحلیل، زمان محاسبه برای هر دو الگوریتم کمتر از ۵ دقیقه به طول می‌انجامد که نشان دهنده کاربردی بودن هر دو الگوریتم در بهینه سازی پارامترها در تونل زنی مکانیزه در زمان کوتاه است.

کلمات کلیدی: آنالیز برگشتی، $FLAC^{3D}$، شبکه عصبی مصنوعی، الگوریتم ژنتیک، الگوریتم تراکم ذرات، تونلسازی مکانیزه