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Application of an immune algorithm to settlement prediction*

Jia GUO, Jun-jie ZHENG‡, Yong LIU

(*Institute of Geotechnical and Underground Engineering, Huazhong University of Science and Technology, Wuhan 430074, China*)

E-mail: daisy1118@163.com; zhengjj@hust.edu.cn; yonliu@yahoo.com.cn

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Abstract: The settlement curve of the foundation endured the ramp load is an S-type curve, which is usually simulated via Poisson curve. Aimed at the difficulty of preferences in Poisson curve, an immune algorithm (IA) is used. IA is able to obtain a multiple quasi-optimum solution while maintaining the population diversity. In this paper, IA is used in an attempt to obtain accurate settlement prediction. The predicted settlements obtained by IA are compared with those predicted by the least squares fitting method (LSM), the Asaoka method and the genetic algorithm (GA). The results show that IA is a useful technique for predicting the settlement of foundations with an acceptable degree of accuracy and has much better performance than GA and the Asaoka methods.

Key words: Settlement, Prediction, Foundation, Immune algorithm (IA)
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INTRODUCTION

The two major criteria that control the design of shallow foundations are the bearing capacity and settlement of the foundation. Settlement prediction is crucial in the design of foundations on soft soil since settlement, rather than bearing capacity, generally controls the design process. Although there are several empirical and semi-empirical formulae available for predicting settlement, most of them cannot make accurate prediction of the settlement. Duncan (1993) and Olson (1998) analyzed the uncertainties causing shortcomings in settlement prediction. The estimation of the foundation settlement in soft soil is very complex and has not yet been explicitly explained. This can be attributed to the uncertainties associated with the factors that affect the magnitude of this settlement. These factors are the distribution of the applied load, the stress and strain histories of the soil and soil compressibility. Consistent and accurate prediction of the settlement of foundations on soft soil has always been achieved by the use of a variety of methods, ranging from the purely empirical to complex non-linear finite elements (Poulos, 1999).

A genetic algorithm (GA) has been used as a method for solving optimization problems for a long time. A GA is the application of the genetic and evolutionary mechanisms of life to engineering models. In a GA-based approach, the population diversity is frequently lost before the search for a solution is fully completed. Such a phenomenon is generally referred to as a premature convergence. In this phenomenon, when a superior solution is generated in the initial searching stages, the solution remains in the population in large numbers, making the mating with individuals of the same gene type easier, and causing a quick loss in the diversity of the population. In order to overcome these drawbacks, several researchers (Bersini and Varela, 1991; Mori *et al.*, 1993) have studied new optimization methods based on the immune system. Farmer *et al.*(1986) introduced the concept of an immune algorithm (IA), and the research into IA and its application has blossomed since its introduction. An IA, which shares something in common with a GA, maintains the diversity of solutions, and can provide multiple suboptimal solutions.

An IA has successful applications in some civil

‡ Corresponding author

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engineering problems. Some scholars (Miyamoto *et al*., 2004) applied IA to the optimum structural design problem, in order to obtain a multiple quasi-optimum solution while maintaining diversity. An IA was used in the multi-objective optimal design of a truss structure (Luh and Chueh, 2004a) and multi-modal topological optimization of a structure (Luh and Chueh, 2004b). Rajasekaran and Lavanya (2007) hybridized GA with an immune system mechanism by avoiding the implementation of penalty constants. The interwoven algorithm is applied to obtain optimal sectional areas for the minimum weight of space trusses subjected to static loading. Based on an IA and geometric implication of the reliability index, Zheng and Guo (2007) proposed a global optimization method to calculate the reliability index. IA may thus be considered as a relatively new tool in the field of prediction and forecasting.

This paper deals with the prediction of the foundation settlement on soft soil using IA, and consists of two parts: One is to investigate the feasibility of the IA technique for predicting the settlement of foundations on soft soils and to provide a numerical objective function for routine use in practice; The other is to compare the performance of IA with GA, using the least squares fitting method (LSM) and the Asaoka method.

CONVENTIONAL SETTLEMENT PREDICTION MODEL

Asaoka (1978) proposed an "observational procedure" in which early settlement data can be used to predict the ultimate primary settlement and in-situ coefficient of consolidation for 1D consolidation. The method is becoming increasingly popular because of its simplicity and few requirements for detailed sampling and laboratory testing to determine soil properties or for the monitoring of field pore pressure behavior.

With the 1D consolidation theory, Mikasa's equation is

$$\frac{\partial \varepsilon(t,z)}{\partial t} = C_V \frac{\partial^2 \varepsilon(t,z)}{\partial z^2}, \tag{1}$$

where $\varepsilon(t, z)$ is vertical strain, z is depth from the top of clay stratum, C_V is coefficient of consolidation.

The Asaoka method is based on the fact that Eq.(1) is adopted as a governing equation of the settlement-time relationship,

$$S + a_1 \frac{\mathrm{d}S}{\mathrm{d}t} + a_2 \frac{\mathrm{d}^2 S}{\mathrm{d}t^2} + \cdots + a_n \frac{\mathrm{d}^n S}{\mathrm{d}t^n} = b, \tag{2}$$

where S represents the ultimate settlement, a_1, a_2, …, a_n and b are regarded as unknown constants.

The Asaoka method assumes that 1D consolidation settlements are S_0, S_1, S_2, … at times 0, Δt, $2\Delta t$, …, respectively. Eq.(2) can be reduced to

$$S_j = \beta_0 + \sum_{i=1}^{n} \beta_i S_{j-i}, \tag{3}$$

where S_j denotes $S(t_j)$, the settlement at the time $t=t_j$, and the coefficients β_0 and β_i (i=1, 2, …, n) are unknown parameters.

For the sake of convenience in succeeding discussions, the first order approximation equation

$$S + a_1 \frac{\mathrm{d}S}{\mathrm{d}t} = b \tag{4}$$

is examined here. Let the initial condition be

$$S(t=0) = S_0, \tag{5}$$

Eq.(4) can be easily solved:

$$S(t) = S_\infty - (S_\infty - S_0)\exp(-t/a_1), \tag{6}$$

where $a_1=5h^2/(12C_V)$. The final order difference equation is expressed as

$$S_j = \beta_0 + \beta_1 S_{j-1}. \tag{7}$$

Substituting the stable state

$$S_j = S_{j-1} = S_\infty \tag{8}$$

into Eq.(7), we obtain

$$S_\infty = \beta_0/(1-\beta_1). \tag{9}$$

From Eq.(6) we obtain

$$S(t_{j-1}) = S_\infty - (S_\infty - S_0)\exp(-t_{j-1}/a_1), \tag{10}$$

therefore

$$S_\infty - S(t_{j-1}) = (S_\infty - S_0)\exp(-t_{j-1}/a_1), \tag{11}$$

$$\begin{aligned} S(t_j) &= S_\infty - (S_\infty - S_0)\exp\left(-\frac{t_{j-1}+\Delta t}{a_1}\right) \\ &= S_\infty - (S_\infty - S_0)\exp\left(-\frac{t_{j-1}}{a_1}\right)\exp\left(-\frac{\Delta t}{a_1}\right). \end{aligned} \tag{12}$$

Substituting Eq.(11) into Eq.(12) yields

$$\begin{aligned} S(t_j) &= S_\infty - [S_\infty - S(t_{j-1})]\exp\left(-\frac{\Delta t}{a_1}\right) \\ &= S_\infty\left[1-\exp\left(-\frac{\Delta t}{a_1}\right)\right] + S(t_{j-1})\exp\left(-\frac{\Delta t}{a_1}\right). \end{aligned} \tag{13}$$

Comparing with Eq.(7), we obtain

$$\begin{cases} \beta_0 = S_\infty\left[1-\exp\left(-\Delta t/a_1\right)\right], \\ \beta_1 = \exp(-\Delta t/a_1). \end{cases} \tag{14}$$

However, it should be noted that the values of β_0 and β_1 are Δt dependent, which means that different time intervals may result in different values of β_0 and β_1. Therefore, the ultimate settlement predicted by the Asaoka method is partly dependent on the practitioners' in-situ records and especially the duration of time intervals.

IMMUNE SYSTEM

The immune system, which performs complex tasks, possesses several properties, such as self/non-self discrimination immunological memory, positive/negative selection, an immunological network, clonal selection and learning.

Immune algorithm based on clonal selection theory

Clonal selection theory (Burnet, 1959) has been developed to explain how an immune response is mounted when a non-self antigenic pattern is recognized by a B cell.

The main goal of the immune system is to protect the human body from the attack of foreign (harmful) organisms called antigens. The molecules called antibodies play a main role in the immune system response. The immune response is specific to a certain foreign organism (antigen). When an antigen is detected, those antibodies that best recognize the antigen will proliferate by cloning. This process is called clonal selection theory.

The main features of clonal selection theory are explained as follows (Burnet, 1978): (1) Generation of new random genetic changes which are subsequently expressed as diverse antibody patterns by a form of accelerated somatic mutation; (2) Phenotypic restriction and retention of one pattern to one differentiated cell (clone); (3) Proliferation and differentiation on contact of cells with antigens.

An IA was developed on the basis of clonal selection theory of the immune system. It has been proved that it can solve optimization design tasks. In all runs of the algorithm, the stopping criterion is predefined as the maximum number of generations.

The terminology of an IA is outlined in Table 1.

An IA can be described as follows (de Castro and von Zuben, 2000).

IA is basically composed of two repertoires (populations) of strings: a set of antigens *Ag* and a set of antibodies *Ab*. The set *Ab* can be decomposed into a memory cell subset and a remaining cell subset.

Step 1: to define the problem. In an optimization

Table 1 Terminology of immune algorithm

Terminology	Meaning
Antigen	Objective function and constraint conditions in an optimization problem
Antibody	The system made to recognize the antigen to calculate evaluations (fitness value) of antibodies, corresponding to actual solution
Affinity between antigen and antibody	Corresponding to fitness (evaluation of solution)
Memory cell	Storage area which stores candidates of solution

problem, *Ag* refers to an objective function and constraint conditions, and *Ab* refers to the feasible solutions.

Step 2: to generate an initial set of antibodies Ab_1. Randomly generate N antibodies in accordance with the objective function and the constraint conditions.

Step 3: to calculate the affinity between antigen and antibody. The affinity refers to the value of the objection function.

Step 4: to select the n highest affinity antibodies from Ab_1.

Step 5: to clone the n selected antibodies to compose a new set of antibodies Ab_2. The remaining antibodies of Ab_1 with low antigenic affinity die out.

Step 6: to submit the set of antibodies Ab_2 to an affinity maturation process inversely proportional to the antigenic affinity, and generate a population Ab_3 of matured clones. The higher the affinity is, the smaller the mutation rate will be.

Step 7: to determine the antigenic affinity of the population Ab_3, and from this set of mature clones Ab_3, to reselect antibodies with the highest affinity to enter the set of memory antibodies. If their antigenic affinity is larger than that of the memory antibodies, those antibodies with the highest affinity will replace the same number of memory antibodies.

Step 8: to replace the d lowest affinity antibodies by novel ones (diversity introduction). The lower affinity cells have a higher probability of being replaced.

Repeat Steps 4~8 until the predetermined number of generations is reached.

Verification of immune algorithm

To verify the excellence of an IA, we adopted a numerical objective function to compare the performance of a GA and an IA.

IA and GA are applied respectively to calculate the minimum of the Shubert function Eq.(15):

$$\min f(x_1, x_2) = \sum_{i=1}^{5} i\cos\left[(i+1)\cdot x_1 + i\right] \cdot \sum_{i=1}^{5} i\cos\left[(i+1)\cdot x_2 + i\right], \tag{15}$$

where $[x_{1\min}, x_{1\max}]=[-10, 10]$, $[x_{2\min}, x_{2\max}]=[-10, 10]$, and $f(x_1, x_2)$ is multimodal.

Fig.1 shows the function graphing.

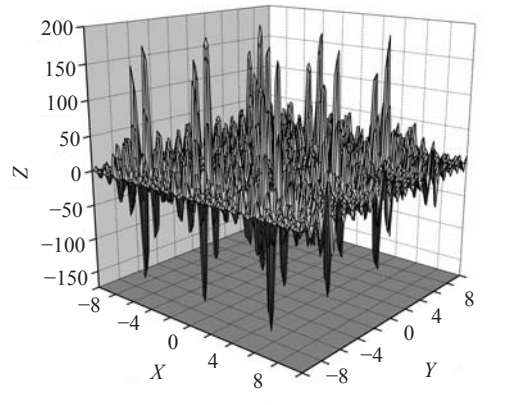

Fig.1 Shubert function graphing

As for the simulation of the function $f(x_1, x_2)$, the genotype of an individual and an antibody is 25 bits, the number of individuals and antibodies is 50, the mutation rate is 0.7, and the number of generations is set as 50. The capacity of a memory cell (candidate for solution) is set as 2 antibodies. The simulation results for the function are shown in Fig.2.

As shown in Figs.2a and 2b, it is obvious that the minimum value can be obtained by both IA and GA. However, the mean of populations calculated by IA is closer to the minimum value of the function than that by GA.

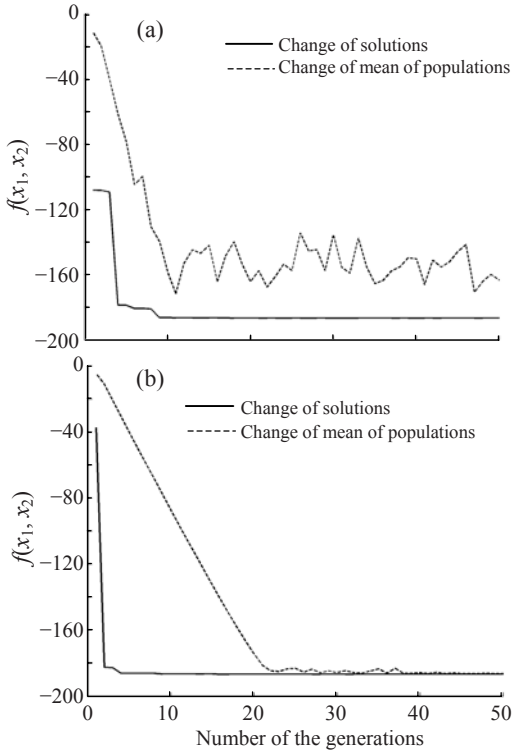

Fig.2 (a) GA and (b) IA applied to the shubert function

ESTABLISHING MODEL FOR IMMUNE ALGORITHM

Based on the stress-strain relationship of soil, it is proved that the settlement-time curve is a Sigmoid function when the load increases linearly, which is usually simulated via a logistic curve (Mei *et al*., 2005). This method provides estimation of the ultimate settlement from early records of time/settlement vs time relationships. The equation of a settlement-time curve is expressed as

$$S_t = \frac{S_\infty}{1 + a\mathrm{e}^{-bt}}, \tag{16}$$

where S_t is the settlement at time t; S_∞ is ultimate settlement; a, b are the estimated parameters. Eq.(16) has three estimated parameters: a, b and S_∞.

In conventional methods of logistic curve fitting, S_∞ must be estimated first and then a, b can be obtained by line fitting. However, the parameter of the ultimate settlement cannot be determined easily. Previous studies have presented some methods (Zai and Mei, 2000; Yin, 2002), both theoretically and experimentally, to predict the ultimate settlement of foundations. However, sometimes it is difficult to estimate the ultimate settlement.

APPLICATION TO SETTLEMENT PREDICTION

As an application of an IA to settlement prediction, two cases of settlement prediction of soft soil foundations are described.

Case one

The Ning-Hang expressway was built on soft soil. In order to control the settlement, some ground improvement techniques, including surcharge preloading, jet grouting and geogrids were applied. The roadbed settlements in Liyang were observed by the researchers at the Transportation School, Southeast University, and the data are shown in Table 2 (Tu *et al.*, 2005). The subgrade treatment in this zone is a preloading method. The settlement prediction is usually based on the parameter estimation. In order to apply an IA, a logistic curve is used in the model of settlement prediction.

A general discrete IA for settlement prediction is proposed as

$$\min F = \sum_{i=1}^{n}\left(S_t - \frac{S_\infty}{1 + a\mathrm{e}^{-bt}}\right)^2, \tag{17}$$

where F is the objective function (minimizing the summed square of residuals), and n is the number of measured settlement data.

Table 2 Measured settlements for k95+520 m of Ning-Hang expressway

Time (d)	Measured (cm)	Time (d)	Measured (cm)	Time (d)	Measured (cm)
5	0.51	35	6.56	62	9.010
10	1.44	40	7.48	65	9.180
20	2.71	45	7.82	70	9.810
21	3.21	48	8.05	75	10.04
25	3.57	50	8.38	76	10.06
30	5.35	55	8.59	80	10.11
34	5.88	60	8.84		

The method used by an IA for settlement prediction in this paper is based on clonal selection theory. The stepwise procedure is as follows:

Step 1: Eq.(17) is the objective function.

Step 2: Code. In this paper, the real code is used since it does not need to be transformed to binary code and is appropriate to geotechnical engineering problems.

Step 3: Population. A population of 500 B cells (antibodies) can be randomly generated. The number of generations is 50.

Step 4: Compute antibody-antigen affinity. In this paper, the objective function value is the affinity which is served as a measure of degree of satisfaction of the feasible solution.

Step 5: Select the 50% highest affinity B cells from antibodies to be cloned to form a new population.

Step 6: Submit a new population of B cells to an affinity maturation process inversely proportional to the antigenic affinity and generate a maturation set, compute the maturation set of antibody-antigen affinity. The average hypermutation rate is 0.5. If the affinity of an antibody is greater than the average affinity of the population, the mutation rate of antibody is 0.45; otherwise is 0.55. From this maturation set, re-select 5% antibodies with the highest affinity to enter the set of memory antibodies. These memory antibodies replace the lowest affinity B cells in the initial population.

Step 7: The process is over; otherwise skip to Step 4.

The non-linear LSM is employed to validate IA. Then a comparison among IA, GA and the Asaoka method is conducted. The values calculated by IA, GA and LSM are listed in Table 3. It shows great similarity among the values obtained by the three methods. Table 4 presents the measured settlements and predicted settlements by IA and LSM. It can be seen from Fig.3 that the predicted ultimate settlements using IA are very close to the measured values and that the values of IA are validated by LSM. The predicted ultimate settlements using the Asaoka method are 13.30, 12.70, 12.63 cm for time intervals of 5, 8, 10 d, which vary with different time intervals. Furthermore, the predicted values have a comparatively great difference from the measured values.

Table 3 Parameters estimated by IA, GA and LSM

Algorithm	S_∞ (cm)	a	b
Immune algorithm	10.0757	13.1424	0.0862
Genetic algorithm	9.8913	14.9640	0.0911
Least squares fitting method	9.8410	14.9120	0.0914

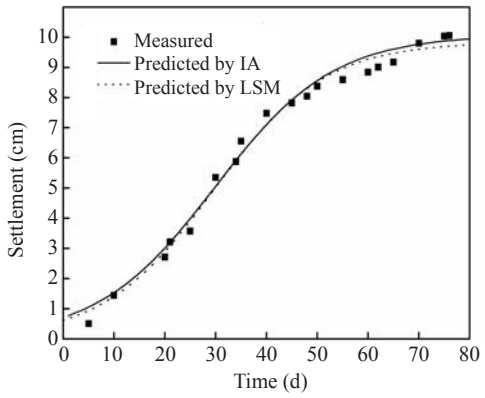

Fig.3 Comparison of IA and LSM in predicting the settlements

Case two

A high-rise building on Beiyuan Road in the Chaoyang District of Beijing is selected in Case 2, which has 24 stories above the ground and two stories underground, and is supported by a cement fly-ash gravel (CFG) pile composite ground and raft foundation and constructed with a cast-in-situ shear wall structure. The design value of the bearing capacity of the foundation is 505 kPa, while the standard value of the bearing capacity of natural ground is only 150 kPa. In CFG pile composite foundation, the CFG piles are arranged in a square pattern, and the diameter, average effective length and spacing of the piles is 410 mm, 14.5 m, and 1.4 m, respectively (Zhang *et al.*, 2006).

The building was under observation from May 2002 to January 2004. The data observed at four points are presented in Table 5.

The predictive performance of IA, GA and LSM is summarized in Table 6, which shows clearly that ultimate settlements obtained by IA are much closer to the measured values than those obtained by GA. The predicted ultimate settlements using the Asaoka method are listed in Table 7, which depend partly on the practitioners' in-situ records, especially the duration of time intervals.

CONCLUSION

In this paper, the feasibility of predicting the settlement of soft ground by IA is validated. Two cases of field measurements on the settlement of soft ground were used for model development and verification. The comparison is carried out between the predicted and measured values.

This paper shows that IA is able to predict the settlement of soft ground with an acceptable degree of accuracy and has much better performance than GA

Table 4 Measured settlements and predicted settlements by IA and LSM

Time (d)	Measured (cm)	IA prediction (cm)	LSM prediction (cm)	Time (d)	Measured (cm)	IA prediction (cm)	LSM prediction (cm)	Time (d)	Measured (cm)	IA prediction (cm)	LSM prediction (cm)
5	0.51	1.06	0.94	35	6.56	6.13	6.12	62	9.01	9.48	9.36
10	1.44	1.54	1.41	40	7.48	7.10	7.10	65	9.18	9.61	9.47
20	2.71	3.01	2.90	45	7.82	7.92	7.91	70	9.81	9.76	9.60
21	3.21	3.20	3.09	48	8.05	8.32	8.30	75	10.04	9.87	9.69
25	3.57	3.99	3.91	50	8.38	8.56	8.52	76	10.06	9.89	9.71
30	5.35	5.06	5.01	55	8.59	9.03	8.96	80	10.11	9.94	9.74
34	5.88	5.92	5.90	60	8.84	9.37	9.27				

Table 5 Measured data of CFG piles composite foundation

Date of observation	No.	Time (d)	Settlements of observation point (mm)				Remark
			C27	C28	C31	C34	
05-28-2002	1	0	–	–	–	–	
06-15-2002	2	18	0.5	0.5	0.7	0.9	4 floors
06-25-2002	3	28	1.1	0.9	1.3	1.6	6 floors
07-05-2002	4	38	2.0	1.4	1.9	2.4	8 floors
07-29-2002	5	62	5.9	5.9	5.9	7.0	10 floors
08-24-2002	6	88	9.8	9.3	8.1	10.6	12 floors
09-05-2002	7	100	13.3	13.1	10.6	13.5	14 floors
09-13-2002	8	108	18.0	16.4	13.0	15.8	16 floors
09-21-2002	9	116	21.1	18.8	15.4	18.7	18 floors
09-30-2002	10	125	22.9	20.9	17.2	21.8	20 floors
10-13-2002	11	138	25.7	22.4	18.4	23.5	22 floors
11-14-2002	12	170	27.5	23.8	20.0	24.9	24 floors
11-27-2002	13	183	28.7	24.1	20.3	25.9	Fitment
01-02-2003	14	219	28.6	24.2	20.5	26.3	Fitment
02-12-2003	15	260	28.8	24.4	20.7	26.4	Fitment
03-18-2003	16	294	29.0	24.5	20.9	26.2	Fitment
04-12-2003	17	319	28.9	24.7	21.0	26.0	Fitment
07-16-2003	18	414	28.8	24.9	21.1	25.7	Completed
10-15-2003	19	505	28.7	25.1	21.4	25.8	Completed
01-13-2004	20	595	28.9	25.3	21.5	26.0	Completed

Table 6 Parameters estimation of points by IA, GA and LSM

Observation point	S_∞ (mm)			a			b		
	IA	GA	LSM	IA	GA	LSM	IA	GA	LSM
C27	28.96	31.45	29.04	48.9250	43.9187	54.1261	0.0413	0.0364	0.0410
C28	25.06	29.96	24.93	48.2930	40.3649	51.5302	0.0411	0.0334	0.0421
C31	21.64	23.31	21.15	54.2978	31.4008	33.2655	0.0401	0.0122	0.0372
C34	26.07	31.60	26.30	48.2930	53.7315	37.1183	0.0411	0.0403	0.0385

Table 7 Comparison of different ultimate settlements by the Asaoka method

Δt (d)	Predicted settlement (mm)			
	C27	C28	C31	C34
45	29.5748	25.4665	21.6929	26.5764
60	29.0627	24.9447	21.2631	26.1764
75	28.8226	24.8239	21.1260	25.9876

and the Asaoka methods. Once the model is established, IA is featured as an accurate and fast tool with no need for any use of tables or charts. The values estimated by IA are closer to the measured ones than that by GA. The main shortcoming of IA is the lack of theory to help in its development. However, despite the foregoing limitations , this study indicates that IA has a number of significant benefits which make it a powerful and practical tool for settlement prediction of soft ground.

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