AI-Based Approach for Optimum Soil Stabilization

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Abstract: Results from previous studies confirmed that, adding Ground Granulated Blast-Furnace Slag (GGBS) activated by hydrated lime (L) to a typical Egyptian clayey soil increases strength and decreases swelling. This paper investigates reaching optimum soil stabilization for clayey soil to suit safe and economic road construction. Optimum soil stabilization can be achieved mainly through two stages as proposed in this paper: stage 1: quantify the effect of the soil stabilization parameters represented in the GGBS%, Lime%, and the curing time/condition on the stabilized soil unconfined compressive strength (UCS) and the free swelling percentage (FS%) using Artificial Neural Networks (ANN). Stage 2: determine the optimum set of stabilization parameters by conducting backward optimization on the developed ANN prediction model while meeting practical design preferences, using Genetic Algorithms (GAs). Initially a simple to use ANN add-ins (Neural Tools 5.5) for Excel was used where the UCS was predicted with an acceptable error of 10% for both training and testing sets. A detailed error analysis was performed and showed that the maximum under and over estimate errors were less than 3% and 5.35% for training and testing respectively. However, it is not possible to use neural tool or other ANN software packages in performing backward analysis to determine the optimum set of inputs that may result in a certain output. Accordingly, a more transparent ANN model was developed. After training and testing the developed ANN, it can work as an optimization model where the decision variables are the stabilization parameters with an objective to reach a certain UCS while keeping the swelling percentage within a certain range. The model has been applied on a case study where it was able to come up with the practical ranges of the lime%, GGBS%, and the curing time/condition that would satisfy the required design criteria.

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1. Introduction

The economic development of any country is controlled to a great extent by its highway networks. This is becoming particularly apparent in the developing countries, where tremendous lengths of roads and highways need to be constructed in order to facilitate the development. The type and thickness of the pavement construction represents a large percentage of the cost of any road/highway project. Therefore, the development and use of methods to decrease the cost of pavement construction would result in great cost savings. However before designing the type and the thickness of the pavement, it is essential to take into consideration the conditions of the subgrade soil, as it carries the traffic loads as well as the pavement loads (**Bari, 1995**).

The traditional section for road typically consists of different layers such as: surface course, binding course, base and sub-base courses. These layers are typically made of imported materials that require transportation, environmental and other costs that increase with the distance from the source of the materials to the site where roads being constructed. The reliance on imported material is the main problem, from a sustainability and efficiency point of view, of the traditional road and pavement design and construction. Due to the gradual depletion in the conventional resources, searching for a more rational road construction approach aimed at reducing the dependence on imported material while improving the quality and durability of the roads is necessary (**Marjanovic *et al.*, 2008**).

Many problems associated with foundations on expansive soils, include heaving, cracking and break up of pavements, have been reported. The foundations of light structures supported on the ground (e.g. highways) are more affected by expansive soil problems than heavy or deep buried structures (**Xidakis, 1979**).

Roads constructed on expansive clays may be adversely affected by the behavior of the clay. The volume change of such clays causes upward movement which is difficult to predict (**Mowafy *et al.*, 1990**). Accordingly, roads to be built on these soils require a greater thickness of base layer compared to stronger ones (e.g., sand and gravel), resulting in tremendous increase in its initial and lifecycle costs. Soil stabilization as such represents an important alternative which need to be studied. The soil stabilization process, is neither straight forward nor insignificant for such expansive clays and it needs to be addressed as it is crucial to suppress swelling and increase the strength of the soil. Thus partially decreases the thickness of road pavement layers which are relatively the most expensive layers in the road.

This paper tries to optimally stabilize clayey soils under practical site and design constraints using a mix of artificial intelligence techniques to understand the stabilization behavior then optimize the stabilization process.

2. Soil Stabilization

Soil stabilization using lime occurs in soils containing a suitable percentage of clay and the proper mineralogy to produce long-term strength; and permanent reduction in shrinking, swelling, and soil plasticity (**National Lime Association, 2012**). The use of waste materials in the road stabilization industry is gradually gaining significance, considering disposal and environmental problems and the gradual depletion of natural resources. A large amount of slag is dumped and left for the most part unused on costly land. The potential use of these materials in road construction was studied initially by evaluating their physical and chemical characteristics. The waste materials were mixed with local soils and their geotechnical characteristics were investigated. The feasibility of using these mixes in the base course of road pavement was investigated by adopting stabilization techniques. It was concluded that a mixture of slag, fly ash, and soil has potential for use in sub-base, base, and wearing courses of road pavement (**Osinubi, 2010**).

Previous work on soil stabilization showed that the type, form, amount and characteristics of the reaction products control the physical, chemical and mechanical properties of the bulk materials after stabilization. Thus, the nature of the long-term cementation in clay stabilization depends on the effect of the curing conditions and time, (**Kinuthia, 1997**). **Mathur, *et al.* (2007)** carried out a study on a sample of clay treated with lime and GGBS. The results of tests showed that properties of the soil improved when treated with lime – GGBS blends. Free swelling percentage (FS%) and linear shrinkage decreased, while the UCS and CBR values increased. Optimum properties of the clay– lime- GGBS mixture were obtained at 8% lime and 7.5% GGBS content based on strength assessments. Accordingly the mixture can be used as sub-base and base courses of lightly trafficked roads

Ouf (2001) investigated the effect of GGBS, activated by lime, on the unconfined compressive strength (UCS) and (FS%) of the tested soil. The tested soil comprised of 80% River Aire soil and 20% calcium montmorillonite similar to a typical Egyptian clay soil (**Ouf, 2001**). He furthermore provided the engineering properties of the Egyptian test clayey soils, the main clay minerals and chemical analysis by X-ray fluorescence. The tested soil showed to have 30% free swelling percentage (**Ouf, 2001**).

Ouf's findings and experiments as such represent a good base for the current research. His results were re-analyzed in this paper to understand the relationship between the stabilization parameters represented by the GGBS%, Lime%, curing temperature and curing time versus both the UCS and the FS% as a percentage, using artificial neural networks. A genetic optimization was applied in a backward fashion to reach an optimal set of stabilization parameters under practical design/site considerations or designer preferences.

3. Available Data

Table 1 shows summary of the information extracted from the tests presented in **Ouf, 2001**. It can be noticed from the table that the maximum and minimum UCS after stabilization were 2931 kN/m^2 and 883 kN/m^2, respectively while the maximum and minimum FS% were 30% and 0% respectively, which have a lot of variation based on stabilizing parameters.

The main conclusions according to **Ouf (2001)**, were as follows:

The UCS of the test soil increased dramatically with the increase in the total binder content, the lime/GGBS ratio and the curing period and temperature.

About 4 % binder with 20% GGBS replacement by lime, cured at CC2 after 28 days could satisfy the maximum recommended strength values for bas course for low cost roads.

The FS% of the tested soil decreased dramatically with the increase in total binder content, the lime/GGBS ratio, and the curing period and the temperature.

4. Research Methodology

Although the findings of Ouf in 2001, targeting a certain UCS after stabilization under practical site constraints need further research, the methodology adapted in this research to reach an optimum design for soil stabilization under practical constraints goes through two stages as shown in Fig.1. The two-stage process depends primarily upon the results obtained from **Ouf, 2001**.

Table 1: Effect of GGBS and lime on the UCS and FS% of the test soil (**Ouf, 2001**)

Experiment ID	GGBS %	Lime %	Curing Temp. °C	Curing Time (days)	UCS	FS%
1	2	0	20	7	887	30
2	2	0	20	28	890	30
3	2	0	35	7	940	30
4	2	0	35	28	955	30
5	1.8	0.2	20	7	895	30
6	1.8	0.2	20	28	931	25
7	1.8	0.2	35	7	952	30
8	1.8	0.2	35	28	1126	25
9	1.6	0.4	20	7	915	15
10	1.6	0.4	20	28	1054	10
11	1.6	0.4	35	7	969	15
12	1.6	0.4	35	28	1239	10
13	1.4	0.6	20	7	933	15
14	1.4	0.6	20	28	1121	10
15	1.4	0.6	35	7	973	10
16	1.4	0.6	35	28	1280	5
17	4	0	20	7	899	25
18	4	0	20	28	948	20
19	4	0	35	7	1100	25
20	4	0	35	28	1185	20
21	3.6	0.4	20	7	1150	25
22	3.6	0.4	20	28	1398	20
23	3.6	0.4	35	7	1249	25
24	3.6	0.4	35	28	1482	20
25	3.2	0.8	20	7	1652	15
26	3.2	0.8	20	28	2202	10
27	3.2	0.8	35	7	1852	15
28	3.2	0.8	35	28	2350	10
29	2.8	1.2	20	7	2041	12
30	2.8	1.2	20	28	2561	10
31	2.8	1.2	35	7	2152	10
32	2.8	1.2	35	28	2753	5
33	6	0	20	7	883	20
34	6	0	20	28	941	18
35	6	0	35	7	978	20
36	6	0	35	28	1275	15
37	5.4	0.6	20	7	1150	25
38	5.4	0.6	20	28	1429	20
39	5.4	0.6	35	7	1201	20
40	5.4	0.6	35	28	1549	20
41	4.8	1.2	20	7	1871	15
42	4.8	1.2	20	28	2381	10
43	4.8	1.2	35	7	1952	15
44	4.8	1.2	35	28	2449	5
45	4.2	1.8	20	7	2251	10
46	4.2	1.8	20	28	2750	5
47	4.2	1.8	35	7	2245	10
48	4.2	1.8	35	28	2931	5

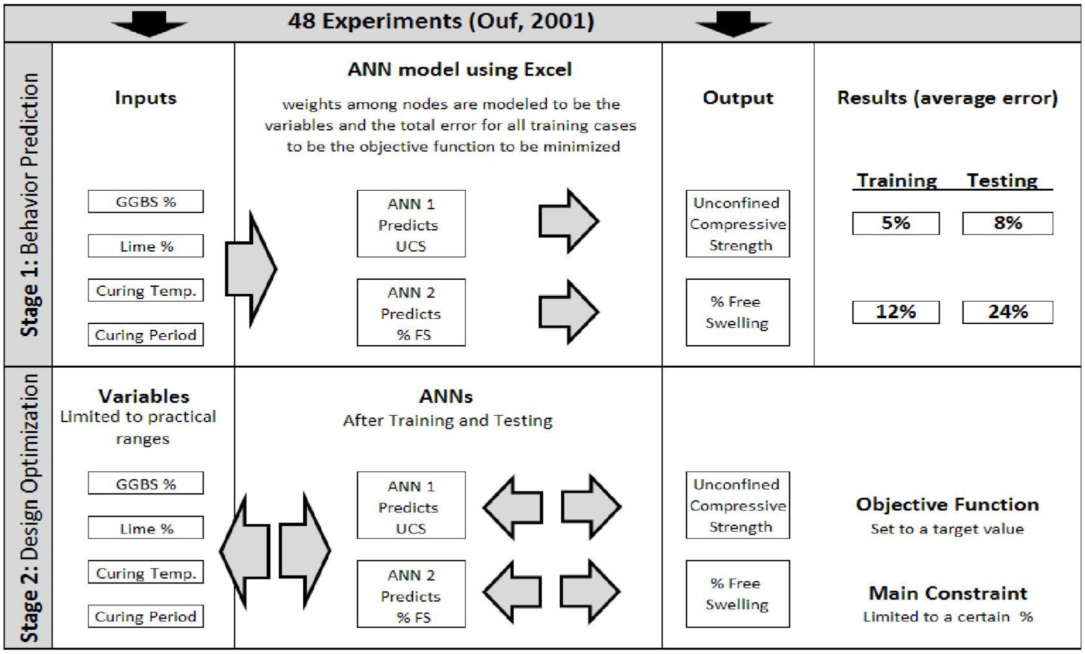


Figure 1: Research methodology for optimum soil stabilization

4.1Behavior Prediction

The first stage is to identify the behavior of clayey soil in terms of UCS and FS% under any combination of stabilization parameters (i.e., GGBS %, Lime %, curing conditions and period). In this research ANN was proposed to be used for this prediction. First, an investigation for the suitability of using ANN in prediction was carried out, and then a spreadsheet ANN model was developed which suit the current study. To start the investigation, simple to use ANN add-ins (Neural Tools 5.5) for Excel was used and the UCS was predicted with the following preferences (Figure 2):

- Training and testing sets are 80% and 20% of the cases, respectively; and
- The acceptable error was set to be 10% for both training and testing.

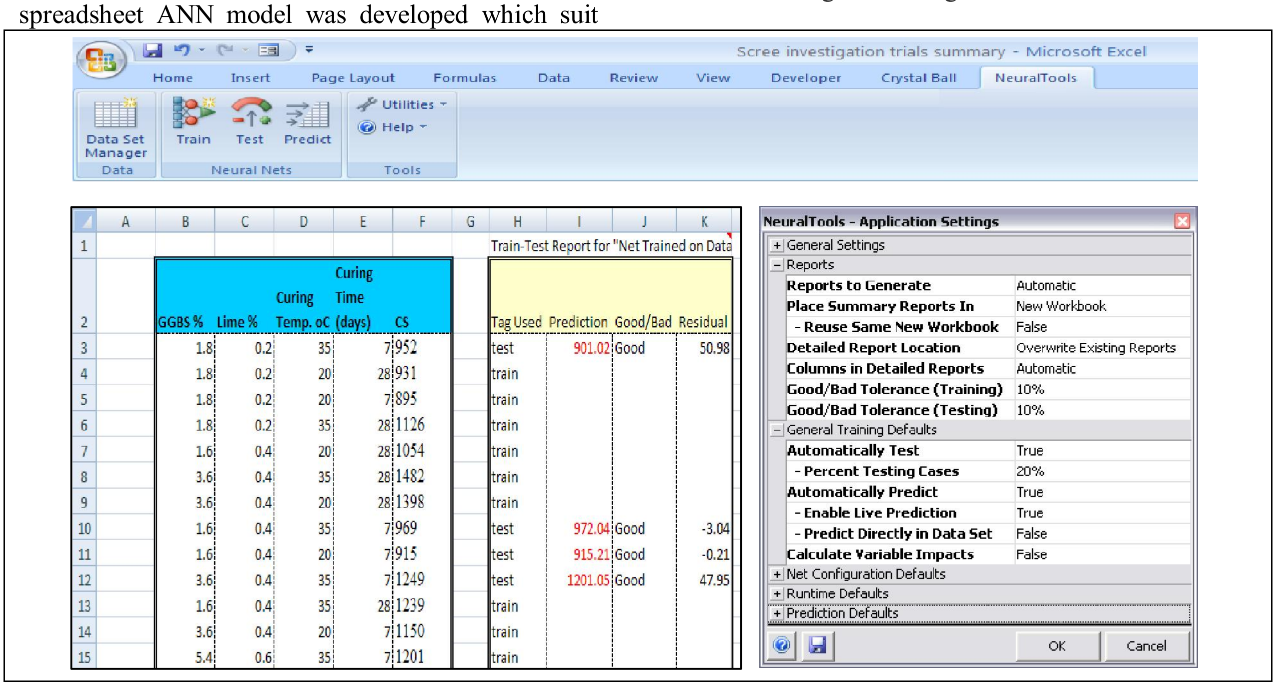
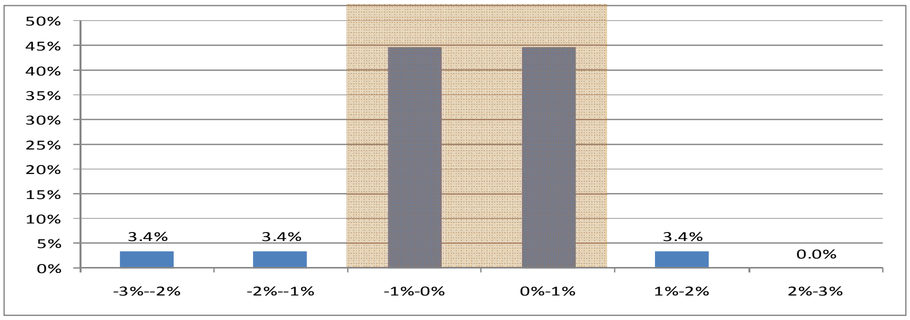


Figure 2: UCS prediction using ANN (NeuroTool 5.5 screenshot)

The first round of the investigation showed high percentages of "BAD" predictions for both training and testing. Reviewing the bad cases, revealed that they all include zero lime percent. This reflects that using of GGBS only in soil stabilization makes the results difficult to be predicted. Accordingly, all cases with zero lime were eliminated from the training and testing sets. Results showed that, it is possible to reach errors less than 10% for both training and testing. ANN as such, can be used in predicting the UCS of the stabilized soil with good accuracy.

A detailed error analysis was performed, where Figure 3 shows the error distribution for the training cases. As shown in this figure, almost 90% of the training cases had less than 1% estimated error. Figure 3 also shows the range of error distribution. It was also found that the maximum under estimated error is 2.09% (less than 3%) and the maximum over estimated error is 1.41%.

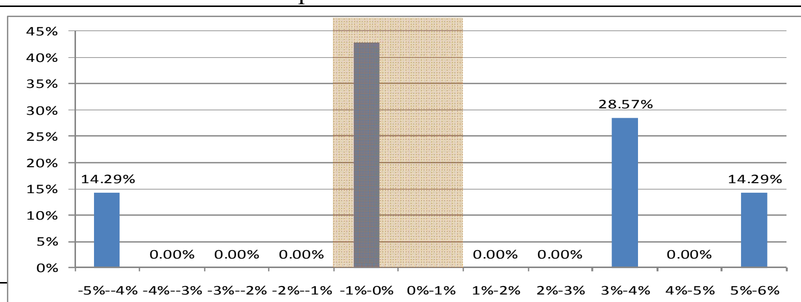


Error Range	Percentage of training cases	Error value
+/- 3 %	100.00 %	Less than 3 %
+/- 2 %	96.55 %	Less than 2 %
+/- 1 %	89.66 %	Less than 1 %

Figure 3: Error distribution and range of error/value – Training Set

Figure 4 shows the analysis for the testing set. It can be noticed that the error ranges from 5.35% to -4.38%. It is important to note that, the figure might be misleading if compared to figure 3, however the maximum error is less than 6%, showing good accuracy.

Although there is a variety of friendly and easy to use ANN software either stand alone programs or add-ins for other programs (e.g., Excel spreadsheets), they are black boxes with no clear or transparent link between inputs and outputs. This makes it very difficult to perform backward analysis to determine the optimum set of inputs that may result in certain output. Accordingly, a more transparent model for neural network was developed. The developed model imitates the architecture and the process flow of an ANN with one hidden layer using spreadsheet modeling similar to **Hegazy and Ayed (1998), Hosny (2005) and Hosny *et al.*, (2011).**



Error Range		
+/- 5 %	85.71 %	Less than 5 %
+/- 4 %	71.43 %	Less than 4 %
+/- 3 %	42.86 %	Less than 3 %
+/- 2 %	42.86 %	Less than 2 %
+/- 1 %	42.86 %	Less than 1 %

Figure 4: Error distribution and range of error/value – Testing Set

The learning process was done through optimization where the errors between ANN predictions and actual results for the training set were minimized. The variables are the weights between ANN layers. As such, the core of the model is an optimization formulation using a spreadsheet. Once the weights are determined, the model can be tested using the other set of data then used to predict the outputs for any set of inputs. The reader can refer to **Hegazy** and **Ayed (1998)** for more details. Figure 5 shows the developed spreadsheet ANN model. To train the ANN, 36 randomly selected cases were considered while the remaining 12 cases were used for testing. It is worth to mention that, many trials were conducted in order to determine the best configuration (number of hidden nodes and the activation functions) for the ANN. These trials revealed that developing two ANNs to detect the behavior of UCS and FS % separately would give better results compared to the case of considering only one ANN with two outputs for both UCS and FS%. A summary of results for used ANNs is shown in figure 1 (Stage 1) with accepted average errors for training and testing cases.

4.2 Design Optimization

As the developed ANN model links the stabilization parameters in the input layer with the design criteria in the output layer, the model can function as an optimization model in a reverse order in which the UCS (predicted) represents the objective function and the stabilization parameters (in the input layer) represent the decision variables to be determined (Fig. 1- Stage 2).

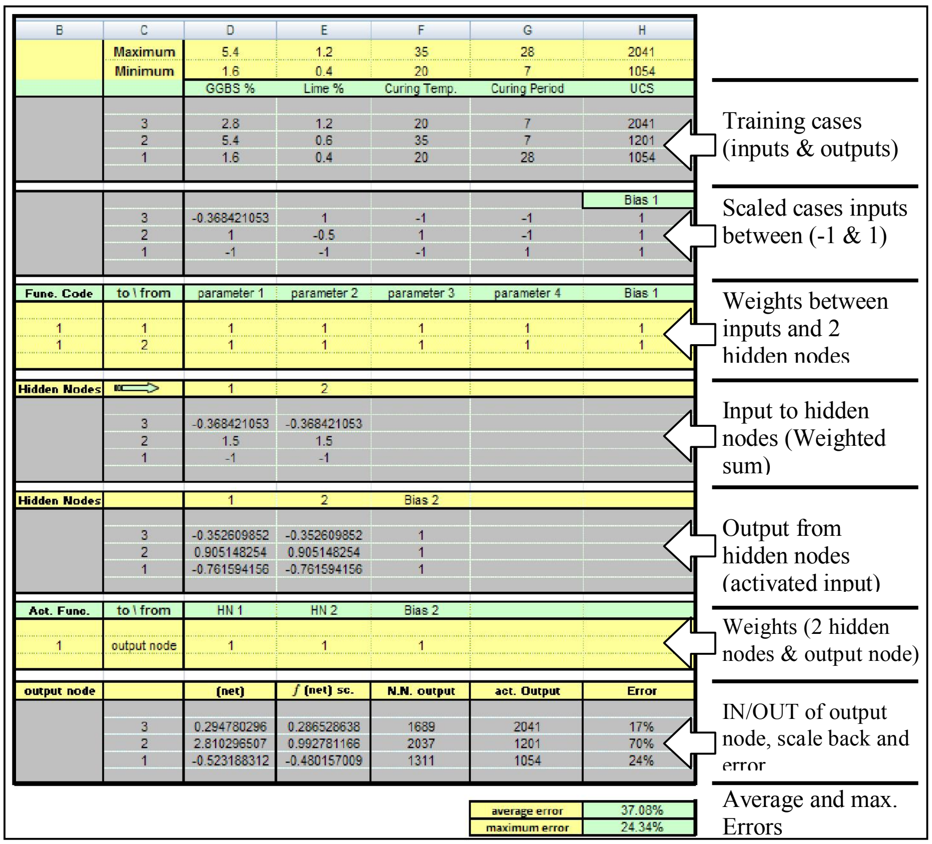


Figure 5: Developed ANN spreadsheet model

A backward optimization as such is proposed using the same ANN model after training and testing. The variables in the proposed optimization problem are the stabilization parameters that can be varied to be determined under practical site and design constraints with an objective to reach a certain UCS keeping the swelling percentage within a certain range.

Implementation and Testing

To implement the proposed approach, an Excel application was developed in three sheets. The first and the second sheets are the ANNs models for the USC and FS%, respectively (similar to Fig. 5). After training and testing, these two sheets represent the UCS and FS % predictors. The third sheet however represents the friendly-user interface (Fig. 6) to optimize the UCS for any set of stabilization parameters. The user can set any stabilization parameters preferences (Fig. 6- Index 3) which are linked automatically with the two ANNs sheets to reflect the expected UCS and FS% (Fig.6 - Indices 1 and 2 respectively). With the automatic link between the stabilization parameters, UCS and FS%, this interface can function as an optimization model. Upon activating EVOLVER (GAs based optimization solver for Excel), it can be used so that the user can get the optimum set of stabilization parameters.

To test the developed model practical ranges for the UCS were obtained from **Odier *et al.*** (1971) who proposed guiding values between 345 KN/m^2 and 1700 KN/m^2 for base construction in low cost roads. The design parameters should be decided both on cost and performance, including the total GGBS and lime content to achieve an acceptable UCS value. Figure 6 shows practical ranges in terms of minimum and maximum values for the UCS, FS %, the GGBS %, Lime %, curing temperature, and period. For example, the minimum and maximum UCS is set to be 1000 KN/m^2 and 1800 KN/m^2, respectively.

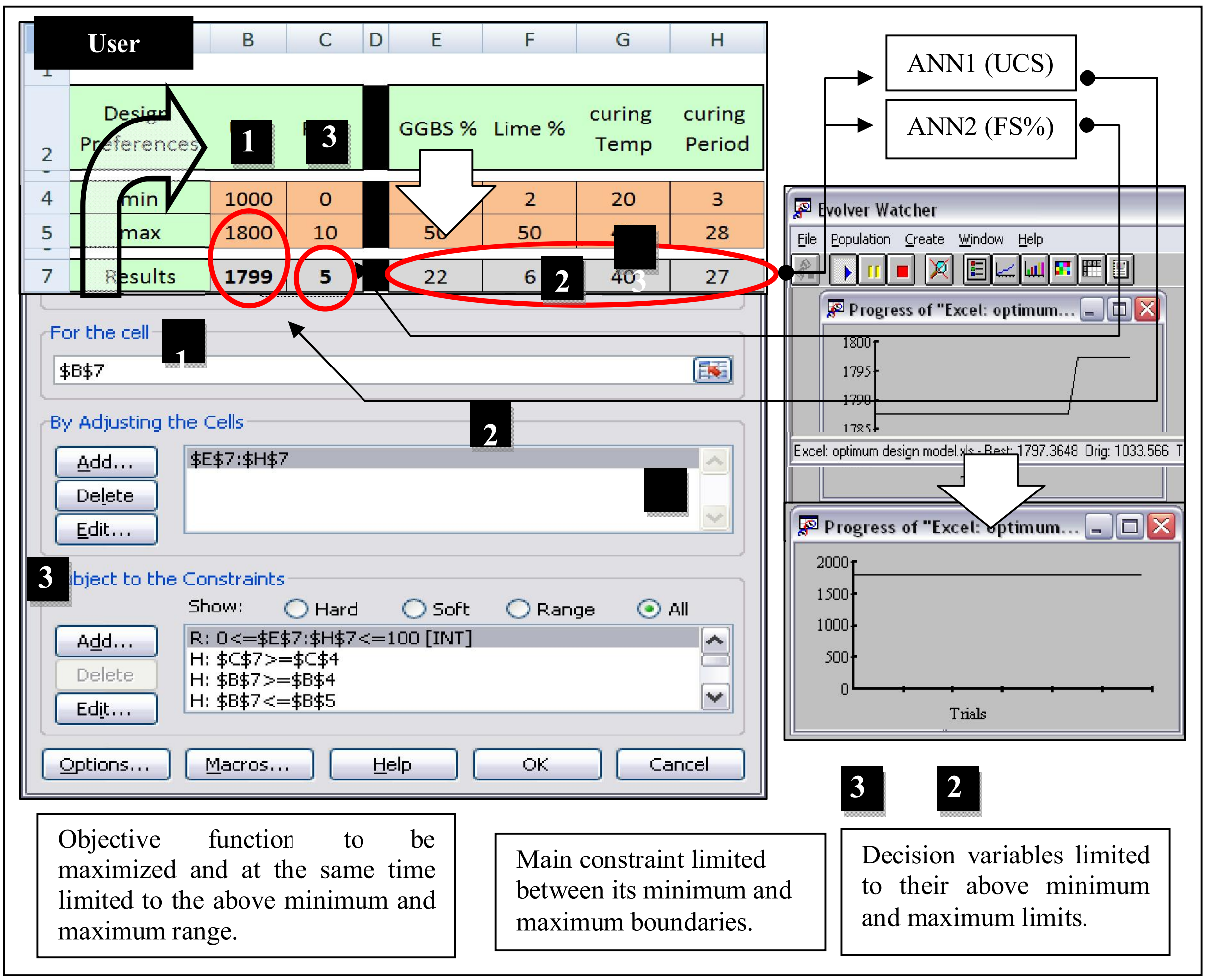


Figure 6: Optimum soil stabilization Model

Evolver is then used to maximize the UCS within the given range of minimum and maximum. All other stabilization parameters in addition to the FS% are also constrained within their specified ranges. Figure 6 shows the Evolver settings and two screenshots during the optimization process. Optimization results show that it is possible to reach a UCS of 1799 KN/m^2 with a 5% FS by considering a 22% of GGBS and a 6% of lime at 40^{o}C curing temperature for 27 days. With the fact that the temperature is fixed at a certain location during certain months around the year, it can be fixed in the model based on location and month. If the temperature is 37°C during the soil stabilization process then the optimum set of results would be reaching a 1792 KN/m^2 with a 5% FS by considering a 6.3% of GGBS and a 0.7% of lime for 27 curing days.

Conclusions

A novel approach for optimum stabilization of clayey soil in Egypt is introduced. The approach depends mainly on developing many models and using various tools such as experimental testing, neural network prediction, and GAs optimization. The process through these different models and tools is structured and illustrated. The paper showed the ability to integrate among these models and tools to achieve the research/paper objectives paving the road for further more complicated applications. Two significant researches were presented, as follows: (1) The ANN investigation and model development showed the ability to predict UCS and the FS% for stabilized soil using different GGBS activated by different lime percentages and cured at various time and temperature with accuracy more than 97% (error less than 3%). This shows strong potential to use ANN with GAs as a tool to get near optimum designs in timely manner. The paper also introduced the spreadsheet ANN model which is more transparent and provides accurate results as the commercial software. With the need for real cases for the ANN learning process, a set of experimental results are proposed and conducted to provide input-output patterns for that purpose; (2) The soil stabilization design model is presented which links the stabilization parameters represented by the curing time and temperature, the percentage of lime and GGBS versus both the UCS and the FS%. The model can also be used as an optimization model to reach an optimum soil stabilization configuration corresponding to a targeted UCS and FS%.

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