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APPLICATION OF GENERAL REGRESSION NEURAL NETWORKS (GRNNS) IN ASSESSING LIQUEFACTION SUSCEPTIBILITY

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ABSTRACT

Liquefaction is considered among the most important hazards associated with earthquakes. The damage resulting from seismic liquefaction may be huge; thus, there always exists needs to mitigate the damage associated with such risks.

One of the main problems challenging geotechnical engineers is how to assess the seismic liquefaction hazard. Statistical and probabilistic approaches for seismic liquefaction are currently available.

In this paper, a general regression neural networks approach (GRNNs) has been used to assess the liquefaction hazard in Egypt. Thus, data from new locations can be analyzed using GRNNs to obtain the liquefaction risk associated with this new site. The computer package "Neuroshell 2®" has been extensively used to build up the GRNNs models. Highly encouraging results have been obtained in the field of seismic liquefaction mitigation.

INTRODUCTION

The evaluation of seismic liquefaction hazard involves considering a large number of variables. Though a broad range of conventional methods tackling the problem of assessing seismic liquefaction exists, most of these means tend to be sophisticated. It has to be noted that liquefaction does not occur randomly but is induced by certain combinations of geologic settings and ground shaking level ([1], [2], [3], [4] and [5]).

The importance of the problem of seismic liquefaction arises from its catastrophic consequences. Fortunately, practical solutions do exist to mitigate such effects. The only dilemma is to precisely predict the site location subjected to liquefaction so as to take active steps towards minimizing the damaging effects of this criterion. Several methods are available for the problem of seismic liquefaction assessment; some are statistical, while others are probabilistic [6] to [15]. In both methods, some important data may be missing, though essential to be incorporated in the analysis. It is extremely difficult to use the conventional techniques to account for such data type. To the contrary, upon the invention of high speed, as well as great capacity personal computers, soft computing techniques started to gain popularity among researchers. These techniques, simply provide a suitable tool for considering as much information as required to precisely assess the problem under study; liquefaction in this case. Recently, Geographic Information Systems (GIS) have also been used to analyse spatial liquefaction data. Luna and Frost [16] have succeeded in developing a GIS that uses both spatial and temporal attributes. Though, practically speaking, access to the digital database of a specific problem in geotechnical engineering applications is still the exception rather than the rule, the ability to work with digital information from a database to analyze, display, and vice versa represents a significant advance for engineering analyses. In all cases, the variables influencing seismic liquefaction can be subdivided into three categories, seismic, geotechnical and site related aspects.

Usually, liquefaction takes place in saturated sandy soils; yet, several cases have been recorded from past earthquakes where saturated sands containing various percentages of silt, have also suffered liquefaction. Amini and Qi [17] experimentally proved that the increase in silt content causes the liquefaction resistance of silty sands to increase for both uniform and layered soil conditions. Although it is possible to identify areas that have the potential for liquefaction, its occurrence cannot be predicted any better than a particular earthquake can be (with a time, place, and degree of reliability assigned to it). Once these areas have been defined in general terms, it is possible to conduct site investigations that provide very detailed information regarding a site's potential for liquefaction.

In many situations in geotechnical engineering, it is possible to encounter some types of problems that are very complex and not well understood. For most mathematical models that attempt to solve such problems, the lack of physical understanding is usually supplemented by either simplifying the problem or incorporating several assumptions into the models. Mathematical models also rely on assuming the structure of the model in advance, which may be sub-optimal. Consequently, many mathematical models fail to simulate the complex behaviour of most geotechnical engineering problems. In contrast, ANNs are based on the data alone in which the model can be trained on input-output data pairs to determine the structure and parameters of the model. In this case, there is no need to neither simplify the problem nor incorporate any assumptions. Moreover, ANNs can always be updated to obtain better results by presenting new training examples as new data become available.

Based on the results of the studies reviewed in this paper, it is evident that one of the widely available soft computing techniques, namely, artificial neural networks, perform better than, or as well as, the conventional methods used as a basis for comparison in many situations, whereas, they fail to perform well in a few. Thus, in this paper, ANNs is used to assess the problem of seismic liquefaction.

PROBLEM STATEMENT

Seismic liquefaction constitutes a major challenge to engineers due to the hazards and possible dramatic casualties associated with it. To mitigate such consequences, it is initially vital to predict the sites, regions or locations susceptible to seismic liquefaction. The better judgement for such predictions requires the collection of precise and high quality data. In addition, the quantity of the collected data is directly proportional to the precision of the output results. One of the most appropriate tools to be used in the current application exists within soft computing methods, namely, artificial neural networks. Section 4 of this paper depicts briefly an overview for artificial neural networks, the terminology and mechanism they work with. The type used in this study, general regression neural networks (GRNNs), is also highlighted.

DATA COLLECTION

The quality of the collected data comprises the spinal chord of the analysis of any project. In other words, once a high quality of data exists, rational output is expected. The database used in this study has been collected from a chain of geotechnical reports performed at a group of scattered islands within the middle third of the river Nile of Egypt. To be more specific, data collected from 10 islands existing within the governorates of Assuit, Menia and Beni-Sueif present the main source of data used in the analysis. A single site in Beni-Sueif, 3 sites in Menia and 6 sites in Assuit have been considered. The analysis extends up to 15 m deep, per site. The studied islands have been chosen by the authors as they represent relatively recent geological formations that constitute a fertile field for liquefaction to occur. Detailed geotechnical field and laboratory investigations have been performed at these sites. To be more realistic, geotechnical data has been collected from highly qualified consulting offices in Egypt, ensuring quality data from supervised in-situ works as well as accurate laboratory tests.

The criterion used by [18] in assessing seismic liquefaction occurrence has been adopted in this study. The used method can be summarized as follows:

1. A critical value for the N value obtained from SPT, N_{cri} is computed based on an initial value depending on the earthquake intensity; depth of penetration within the saturated soil; water table depth; and percentage of fines.
2. The N value obtained from SPT is compared with the obtained N_{cri}.
3. If ($N > N_{cri}$), no liquefaction is expected.
4. If ($N \leq N_{cri}$), a liquefaction index, specifying the severity of liquefaction, is computed. The index is based, among other factors, on the number of tests exerted within the top 15m of the soil profile; SPT N value; N_{cri}; and a weight factor depending on the position of the considered depth.
5. According to the value of the liquefaction index, the severity of liquefaction is determined; low, medium or high susceptibility to liquefaction.

The database fields consist of the following geotechnical parameters: the depth under study; soil density; overburden pressure; pore water pressure; effective overburden pressure; a weight, W_i depending on the considered depth; SPT, N value; corrected N value (corrected according to the Egyptian Code of Practice, 2001); relative density; angle of shearing resistance; percentage of fines; and soil classification. In addition, the intensity of the earthquake is accounted for (intensities of 7, 8 or 9 are considered). In addition, the closeness of the site to the source of the earthquake has been included in the analysis. Each of the intensities as well as the closeness to the earthquake source has been considered as a separate output. In other words, five different nets have been built for each case, e.g., the intensity equals 7 and the location is close to the source of the earthquake constitutes an independent net, while similar intensity but for far location has been considered as a different net. Details of the used nets will be described subsequently.

ARTIFICIAL NEURAL NETWORKS (ANNs)

The human beings' brain anatomy, considering the thinking process, has always been one of the extreme mysteries to scientists. Researchers have exerted efforts aiming at mechanically and electronically imitating the reactions of human beings. The invention of computers and the affordability of personal computers with significant processing speeds and huge capacities have encouraged researchers worldwide to tackle problems that have previously been out of the scope of their imagination. ANNs are one of these tools that can be considered as problem-solving programs modelled on the structure of the human brain where the neural network technology mimics the brain’s own problem-solving process. Neural networks can suit pattern recognition problems, while other problems are best solved with conventional methods. Tracing humans’ behaviour, a neural network takes previously solved examples to build a system of neurons that makes new decisions, classifications, and forecasts [19]. ANNs look for patterns in training sets of data, learn these patterns, and develop an ability to correctly classify new patterns, or to make forecasts and predictions. ANNs excel at problem diagnosis, decision making, prediction, and other classifying problems where pattern recognition is important while precise computational answers are not required.

In a supervised network, the network is shown how to make predictions, classifications, or decisions by giving it a large number of correct classifications or predictions from which it can learn. Back propagation networks (BPNs), general regression neural networks (GRNNs), and probabilistic neural networks (PNNs) are examples of supervised network types. On the other hand, unsupervised networks can classify a set of training patterns into a specified number of categories through clustering patterns rather than being shown in advance how to categorize. Kohonen networks are unsupervised ones ([20] as sited in [4]).

Three basic entities specify ANNs' models: namely, models of the neurons themselves; models of the synaptic interconnections and structures; and the training or learning rules for updating the connecting weights. A group of neurons is called a slab. Neurons are also grouped into layers according to their connection to the outside world. Thus, a neuron receiving data from outside the network is in the input layer while that containing the network's prediction is in the output layer. Neurons in between the input and output layers are in the hidden layer(s). A layer may contain one or more slabs of neurons.

Neural network "learns" by adjusting the interconnection weights between layers. Iterations take place until reaching an acceptable tolerance between the output results obtained by the network and the actual, correct output initially fed to the system. Eventually, if the problem can be learned, a stable set of weights adaptively evolves that will produce good answers for all sample decisions or predictions. The real power of ANNs is evident when the trained network is able to produce good results for data that the network has never seen before. Unlike statistical methods, ANNs "discover" relationships in the input data sets through the iterative presentation of the data and the intrinsic mapping characteristics of neural topologies "learning" [19].

Two main phases operate ANNs. First, the training or learning phase which is very time consuming since the data is repeatedly presented to the network, while weights are updated to obtain a desired response. The second phase is the recall or the retrieval phase, where the trained network with frozen weights is applied to data that it has never seen before. To the contrary of the training phase, the retrieval phase can be very fast.

It is worth mentioning that a professional experience is the time to stop training. In other words, training may be insufficient and consequently the network will not learn the patterns, while the training may also be excessive which results in the network learning the noise or memorizing the training patterns rather than generalizing well with new patterns. A practical guide to overcome such problems is to randomly extract about 20% of the patterns in the training set to be used for cross validation. The error should then be monitored in the training and validation sets. When the error in the validation set increases, this is a signal to stop training where the point of best generalization has then been reached. Cross validation is amongst the most powerful methods to stop the training.

Generally, neural networks offer viable solutions when there are large volumes of data available for training. Moreover, ANNs are considered appropriate solutions when field or experimental data is available and a problem is difficult, or impossible, to formulate analytically.

In this paper, General Regression Neural Network (GRNN) has been used as a tool for the analysis. Specht [21] gave a comprehensive introduction to the GRNNs. The following subsections give brief explanations for the terminology used hereinafter.

<u>GRNN Architecture</u>

General Regression Neural Networks (GRNN) are types of supervised networks known for their ability to train quickly on sparse data sets. In general, GRNN responds much better than back -propagation to many types of problems (but not all). GRNN can have multidimensional input, and it will fit multidimensional surfaces through data [22].

GRNN is a three-layer network where there must be one hidden neuron for each training pattern. There exists a smoothing factor, described subsequently, that is applied after the network is trained. A GRNN network requires a comparison between the new pattern and each of the training patterns.

Slabs: The number of neurons in the hidden layer is usually chosen identical, greater than or equal to, the number of patterns in the training set. The number of neurons in the input layer (Slab 1) is the number of inputs in the problem, while the number of neurons in the output layer (Slab 3) corresponds to the number of outputs. Upon the completion of the slabs, a scaling function for the input layer is selected.

Links: A smoothing factor for each link should be determined. The same smoothing factor applies to all links. Adequate smoothing factor results after several experimental runs to discover which works best for the considered problem. The trained network is then applied to the pre-prepared training set, and perhaps a test set, using different smoothing factors to find out which one gives the best answers.

GRNN Learning: GRNN is essentially trained after one pass of the training patterns, and it is capable of functioning after only a few training patterns have been entered. Obviously, GRNNs training improves as more patterns are added.

Smoothing Factor: Higher smoothing factors cause more relaxed surface fits through the data. For GRNNs, the smoothing factor must be greater than 0 and can usually range from 0.01 to 1 with good results. Trials are required to determine which smoothing factor is most appropriate for the available data. Fortunately, no retraining is required to change smoothing factors, because the value is specified when the network is applied.

Training Patterns: GRNN training patterns are only presented to the network once.

Test Patterns: The number of test patterns propagated through the network.

Background for the used Statistical Indicator: This subsection is concerned with introducing the main statistical indicator used in this paper; namely, R^2, coefficient of multiple determinations. R^2 is a statistical indicator usually applied to multiple regression analysis. It compares the accuracy of the model to the accuracy of a trivial benchmark model wherein the prediction is just the mean of all of the samples. A perfect fit would result in an R^2 of 1, a very good fit near 1, and a very poor fit near 0. If the neural model predictions are worse than could be predicted by just using the mean of the sample case outputs, the R^2 value will be 0.

Use of ANNs in Liquefaction Assessment

ANNs have been used by many researchers in the field of civil engineering (e.g., [4], [23] to [34]) yet, the applications in the field of geotechnical engineering are still scarce. Nevertheless, the Artificial Neural Networks technique has been utilized earlier in assessing liquefaction potential. Back propagation neural network (BPN) was used in the previously performed applications. Tung et al., [1] used BPN method to assess liquefaction by making use of 4 parameters applied to a Chinese data set. The 4 parameters used were: ground shaking intensity (MMI), ground water level, depth of liquefiable soil deposit, and SPT blow counts. Afterwards, another attempt took place where Goh [30] utilized 7 parameters to assess liquefaction susceptibility, based on CPT seismic liquefaction data, through a back propagation neural network algorithm. The 7 parameters used were: magnitude of the earthquake, effective overburden pressure (σ'_0), total overburden pressure (σ_0), q_c from the cone penetration test, normalized peak horizontal ground acceleration at the grounds surface, cyclic stress ratio (τ/σ'_0) and D_{50} of the soil. The latter study indicated that neural networks could successfully model the complex relationship between seismic parameters, soil parameters, and liquefaction potential. The model is simpler, yet as reliable as the conventional methods of evaluating liquefaction potential.

In the current study, several neural networks have been developed using the neural network development program *Neuroshell 2*®. This program implements different neural network algorithms, including BPN, PNN, and GRNN. To use the program, a set of inputs and outputs must be defined, and a suitable training set has to be developed. The developed network in this paper consists of 12 input parameters and 5 different output parameters, each one depending on the earthquake intensity and the distance, whether close of far, from the source of the earthquake.

ANALYSIS

Thirteen GRNN models have been built for each of the five expected outputs. In other words, the output, including the result of whether, or not, the considered site is susceptible to liquefaction, according to the intensity of the earthquake and the closeness of this site to the source of the earthquake, presents a single output for each of the 13 built models. Thus, a total of 65 GRNNs has been developed. Each net is composed of three slabs; an input slab, a single hidden layer and an output layer. Table 1 presents the topology of the built network.

$$W_i = 10 \qquad d_s < 5m$$
$$W_i = 15 - d_s \qquad d_s \geq 5m$$
$$\text{Where } d_s \text{ is in meters} \qquad (1)$$

In the subsequent analyses, the production set has been included within all runs. Each of the runs has been repeated five times, twice for the earthquake intensity 7, close and far, denoted by NET7C, NET7F, respectively, twice for the intensity 8, close and far, NET8C, NET8F, respectively, and once for the earthquake intensity 9, NET9C, close to the earthquake epicenter.

The original net, in each of the above five cases, has been designed using all the 12 input variables. The collected data records, consists of 98 tested sites, 19 of which were set aside to be used as a test set, 9 for the production set, whereas the 70 remaining records have been used for the training of the net. The net has been trained to acquire the minimum possible error. Twenty generations has been set as an auto termination criterion, i.e., the program terminates automatically and the attained net is saved to be subsequently used if no significant improvement takes place after 20 generations. In addition, the genetic breeding pool size has been chosen to be 200. This number has been detected after several initial trials to attain the optimum net results in accordance to the number of the available data, to which the genetic breeding pool size is proportional.

The R^2 value for the whole pattern file, including all data, detected from the Table 1: Topology of the used GRNN original nets, have been 0.6254, 0.7527, 0.805, 1.000, 1.000 for NET7C, NET7F, NET8C, NET8F and NET9C, respectively.

Table 1: Topology of the used GRNN

Input	Hidden Layer	Output
1. The depth under study; 2. Soil density; 3. Overburden pressure; 4. Pore water pressure; 5. Effective overburden pressure; 6. Weight,W_i, according to Equation (1); 7. SPT, N value ; 8. Corrected N value; 9. Relative density; 10. Angle of shearing resistance; 11. Percentageof fines; 12. Soil classification	Includes 98 neurons representing the collected data	A single output among the following: 1.No liquefaction; 2. Low susceptibility; 3.Medium susceptibility; and 4.High susceptibility to liquefaction

<u>Proposed Procedure</u>

A sensitivity study has been carried out. The aim of this study is to find out the relative importance of each of the 12 input parameters. The first step is to set a reference case in which all variables are considered, termed original net. Other steps follow in order to attain the required goal, namely, the influence of each of the considered variables. To do so, each of the variables is removed once and the influence factors of the remaining variables are studied. This step is repeated according to the number of the studied variables. The influence factors are sorted in a descending order, i.e., the most important variable is listed first, followed by the less important one, and so on. A global table is developed in which the frequency of repetition of the considered variable in a specific position is traced. Weights are given to each position so that a weighted average can then be computed.

In this paper, an inverse weight criterion has been used in such computation. In other words, only eleven positions have been available upon the deletion of the variable under study. Thus, 11 ratings are expected. The weight is considered to be "*12-n*", in which *n* is the rank considered. After this preliminary step, the weighted average is computed as the product of the frequency of repetition by the assigned weight. The highest resulting number presents the most important variable influencing the problem under study. This is followed in a descending order by another slightly less important factor, and so forth.

The weighted average procedure, adopted to sort the variables according to their importance can be summarized in the following steps.

- Find out the frequency of occurrence of each of the variables in a specific rank, i.e., the first, or the most important position …etc.
- Repeat the above step for all subsequent ranks up to the 11^{th} position.
- Assign weights for each of the obtained ranks. In this paper, the weight is chosen to be (12-n), where n is the rank, e.g., the weight of the 3^{rd} rank is 9.
- Compute the weighted average for each of the variables.
- Sort the resulting numbers in a descending order; thus, the highest obtained number presents the most important variable, and vice versa.

Following this procedure, the 12 used variables have been sorted according to their influence in the considered problem. The variables may be further divided into three categories, most important, intermediately important, and least important.

The utilized criterion accounts for all possible variations resulting in a better representation of the selected variable rather than that given by the Neuroshell 2® package. The latter takes the influence of the variable within the considered run only whereas the proposed criterion takes an integral measure to the variable's importance among other ones.

Table 2 shows the ranks of the used variables, where the most important variable ranks the first, and so forth

Variable		Rank				
		NET7C	NET7F	NET8C	NET8F	NET9C
1.	The depth under study;	7	7	4	7	7
2.	Soil density;	11	11	6	11	11
3.	Overburden pressure;	12	12	1	12	12
4.	Pore water pressure;	5	5	9	6	6
5.	Effective overburden pressure;	6	6	8	5	5
6.	Weight, W_i;	9	9	11	9	9
7.	SPT, N value;	8	8	5	8	8
8.	Corrected N value;	3	4	10	4	4
9.	Relative density;	4	3	7	3	3
10.	Angle of shearing resistance;	10	10	3	10	10
11.	Percentage of fines;	1	1	12	1	1
12.	Soil classification	2	2	2	2	2

Examining Table 2, the following can be noted:

- All nets, except NET8C, are almost identical in the ranks of the variables.
- The expected reason for the different trend encountered by NET8C is that it is located half ways between NET7C, NET7F from one side and NET8F, NET9C from the other side. To be clearer, for the same data at a specific site, no liquefaction may be encountered within the first two nets, while liquefaction may be detected within the last two nets. The intermediate net, NET8C may be either way. Thus, the net is trained differently with some hesitation, at most of the sites.
- The percentage of fines usually comes first implying that it is the most important variable in the study. This is directly followed by the soil classification. Both variables can be considered from the same origin, i.e., the percentage of fines plays an important role in classifying soils.
- The following most important group of variables is the relative density and the corrected N value from the SPT test. This finding is logical since the relative density, directly correlated to the corrected N value, constitute one of the crucial variables in the problem of seismic liquefaction to the extent that in some cases, e.g., [9], the liquefaction susceptibility can be detected via the relative density and the peak horizontal ground acceleration, compensated for in the current analysis by the intensity of the earthquake.
- The next important two variables are the pore water pressure and the effective overburden pressure. In the authors' opinion, these ranks are reasonable among others and again interchangeable. In other words, the pore water pressure is a direct need in computing the effective overburden pressure.
- The studied depth appears in the seventh position and is adequately located among other variables.
- The N value form the SPT follows in the rank. It should be noted that the original, uncorrected value lags the corrected one by 5 ranks, since the corrected value is that which is utilized in the analysis.
- The weight, W_i, which is a direct computation from the considered depth, follows. This lags the depth by 2 ranks.

- The angle of shearing resistance and the soil density rank tenth and eleventh. These are actually hindered ranks in the authors' opinion. They should have been in higher ranks, yet, both variables correlates well with other variables of better ranks, e.g., N value from SPT.
- Finally, the overburden pressure ranks last. The expected reason is that this value is not directly used in the liquefaction susceptibility problem, but its successor, e.g., the effective overburden pressure is used implicitly in the analysis.

Sensitivity Analysis

An approach has been adopted to test the efficiency of the formed nets. In this approach, a production set has been adopted in addition to the pattern, training and test sets. This gives more realistic results since a considerable portion of the data is "veiled" from the net, which sees this group for the first time, once in operation.
The R^2 errors in the original nets, including all variables are shown in Table 3.

Table 3: R^2 values for the original nets

R^2 Error	PAT	PRO	TRN	TST
NET7C	0.6254	0.3092	1.0000	0.7361
NET7F	0.7527	0.3418	1.0000	1.0000
NET8C	0.8050	0.4864	1.0000	1.0000
NET8F	1.0000	1.0000	1.0000	1.0000
NET9C	1.0000	1.0000	1.0000	1.0000

It has to be clarified that the low values encountered within the pattern and production sets for NET7C, NET7F & NET8C in addition to that of the test set, only at NET7C, do not mean that the net has not been well trained. Actually, this only means that there is a scarce in one or more of the outputs presented to the net; e.g., there might be only a single record that suffered medium susceptibility to liquefaction, whereas all other data fluctuates between no liquefaction and low susceptibility. Thus, the net is not amply trained to precisely determine such data. Upon the computation of the value of R^2 error, the single odd value diverts the result to be apparently very poor. The solution for such limitation in the future is to add several data points having the same trend, which would result in better assessment. Another valuable outcome is that shown in both NET8F and NET9C, where all types of sets result in a value of R^2 equals unity. This is attributed to the fact that both nets are exposed to almost the very same results, which, in turn, have a variety of output results. Thus, each of the nets is exposed to a larger domain, and can consequently be better trained.

Table 4 depicts the values of the smoothing factors in the original nets, including all variables.

Table 4: Smoothing factors for the original nets

moothing Factor	PAT	PRO	TRN	TST
NET7C	0.035	0.490	0.030	0.035
NET7F	0.033	0.510	0.031	0.033
NET8C	0.029	0.460	0.029	0.029
NET8F	0.099	0.099	0.099	0.099
NET9C	0.041	0.041	0.041	0.041

DISCUSSION AND CONCLUSIONS

According to the previous studies, it is evident that ANNs perform better than, or as well as, conventional methods used as a basis for comparison in many situations, whereas, they fail to perform well in a few.

- The main objective of this paper has been to develop reliable GRNNs that can be used to assess liquefaction susceptibility. The developed nets can be used as a standalone, simple, yet reliable, technique for statistical liquefaction risk assessment.
- Due to its excel in classification problems, such as that of liquefaction, GRNN has been selected rather than other supervised networks as an application to the current study. Several GRNNs have been developed that make use of a variety of input data for their training and testing.
- According to the earthquake intensity and the site's location apart from the earthquake's source distance, five main GRNNs including production set and similar number excluding the production set have been developed. In each of the formed nets, 12 input parameters covering a variety of factors with different relative importance have been used. On the other hand, a single output exists specifying the occurrence, or non occurrence of liquefaction. In case of liquefaction, its severity has also been specified, whether low, medium or highly susceptible to liquefaction. The output is dependent on the earthquake intensity and the site location with respect to the source of the earthquake.
- The proposed study proved that using GRNNs in the problem of assessing liquefaction susceptibility produces excellent results via a cheap, accurate, yet simple tool.
- More rational networks results when using production sets.
- As further field case records become available, the performance of the neural networks can be improved. With larger number of data, a more precise analysis can be attained for soil and seismic parameters. Moreover, data filtering, i.e., removal of odd results, would enhance the results to a great extent.
- Further development for the ANNs is required so as to account for uncertainties associated with geotechnical engineering problems so as to result in more realistic solutions. Fuzzy reasoning plays an important role in such development.

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