Article

Spatial Interpolation of SPT with Artificial Neural Network

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Abstract. In large infrastructure projects, initial geotechnical investigation is conducted at large spacing (~ 100m to 250m), in which SPT is the common test performed while dynamic tests are limited in number. The preliminary planning and design of the buildings are performed based on this information. Hence, estimate of dynamic properties of soil (say, shear wave velocity) at building locations becomes necessary. This can be performed by estimation of SPT at building locations, by interpolation from borehole locations, and thereafter using correlation expressions for estimating shear wave velocity at building location. Interpolation of SPT has been handled earlier in literature with statistical and geospatial techniques. In this article, an artificial intelligence technique, namely, artificial neural network (ANN) is explored for addressing this problem. ANN allows multiple degrees of freedom to data and optimizes weights and biases of the network to yield the best possible estimates of the desired output, in this case, the SPT at intermediate locations. ANN is known to be robust in handling data with noise and thus would be suitable for this application. Five neighbouring points were found suitable for efficient and accurate spatial interpolation of SPT using ANN with two to three neurons in one hidden layer. The performance was very good (correlation higher than 0.9 and errors lower than 2) and better than the geo-statistical approaches reported in literature (correlation lower than 0.9 and errors higher than 6). Within the limits of the study, the number of degrees of freedom (varying from 9 to 37) of the ANN did not affect its generalization capability.

Keywords: Spatial interpolation, artificial neural network, SPT, shear wave velocity.

1. Introduction

For preliminary site layout, planning and design of important infrastructure facilities, the geotechnical parameters assume particular significance. The initial soil explorations are carried out at locations of the bore-holes based on the conceptual layout of the buildings at that stage. The preliminary geotechnical investigations are primarily meant for arriving at an estimation of soil properties from which the static and dynamic foundation parameters might be ascertained. Thus, a grid pattern with inter bore-hole distance of 100 m to 250 m is adopted, considering time and cost involved. Hence, suitable and efficient techniques are needed for estimation of soil properties at intermediate locations because in most cases, the particular building might not be located at the preliminary test grid locations. The preliminary estimation of soil parameters at building location assumes importance as the behaviour of structure can vary depending upon the variation in the response of soil in the founding strata, particularly in seismic conditions. Accurate and robust preliminary estimates of soil properties from data at wider grids would help in analysis and design of the structures and detailed confirmatory soil investigations at the execution stage in parallel mode, thereby reducing the overall project time and cost.

The preliminary soil explorations are usually carried out up to a desired depth and field tests are conducted, which are later followed by laboratory tests. Standard penetration test (SPT) is one of the most common in-situ tests in geotechnical engineering, which can be used in estimation of soil properties and foundation parameters. This test is versatile and can be applied for various soil conditions. Static soil property such as bearing capacity as well as dynamic soil properties such as shear wave velocity can be estimated using expressions from national standards or literature, once the SPT values are available for any particular site. Thus accurate estimation of SPT could be useful in evaluation of preliminary dynamic soil properties.

Spatial interpolation of different soil properties have been attempted using various statistical and geo-statistical tools and have been reported in literature [1] – [9]. Liquefaction potential was estimated by using geostatistical interpolation technique by Dawson and Baise [10]. Otherwise, there have been studies wherein geospatial interpolation was employed for estimation of chemical properties of soil [11] – [13]. Earlier, for the same site, the estimation of SPT at finer grid spacing was reported using geo-statistical techniques [8] – [9]. The site exhibited large variability in the values of SPT with different locations, and thus it was deemed necessary to explore further the possibility of improving the accuracy of estimation employing other tools. Soft computing technique can come very handy in such applications, as has been earlier reported (artificial neural network: ANN) in literature for spatial interpolation of ocean currents [14].

The ANN has been favoured over the conventional modelling techniques in geotechnical engineering by many researchers for the flexibility in model structure and the reduction of the a-priori assumptions in development of ANN models. The ANN is tolerant to noise in data and is adaptable to updating with new data as well. Koelewijn and Maccabiani [15] discussed application of ANN in estimation of settlement model parameters, safety classification of dykes from poor field data, and slope stability analysis. Kordnaeij et al. [16] discussed evaluation of soil property such as recompression index with ANN. Ghorbani and Hasanzadehshooiili [17] predicted unconfined compressive strength (UCS) and California bearing ratio (CBR) of microsilica-lime stabilized sulfate silty sand with ANN and evolutionary polynomial regression with good results. The authors [17] concluded that this approach could be very useful in selecting the optimized percentage of stabilizers or for controlling purposes in the QC/QA phases of deep soil mixing projects. Ranasinghe et al. [18] applied ANN for successfully predicting the rolling dynamic compaction using dynamic cone penetrometer test results. Thus ANN has found application in optimisation and monitoring of engineered ground improvement for foundations of structures.

Over the last few decades, applications of ANN in the broad field of geotechnical engineering has increased manifold, and these include: site characterization [19], settlement prediction [20], soil swelling [21], tunnelling [22] – [23], mathematical constitutive modelling [24], retaining structures such as wharves [25], mapping of soil layers [26], underground openings [27], classification of soils [28], liquefaction [29], slope stability [30] – [31]; bearing capacity of pile [32] – [33]; and geo-material properties [34]. A systematic review of these and many other articles on application of ANN in various geotechnical engineering problems was presented by Moayedi et al. [35].

ANN has been employed for another geotechnical application important for site excavation and tunnelling, namely, blasting studies [36] – [43]. The progress of machine learning in geosciences was discussed [44]. Another recent review of application of artificial intelligence in geotechnical engineering was presented by Yin et al. [45]. With this brief literature review, the suitability of ANN for solving geotechnical problems of diverse nature can be easily appreciated. The complex non-linear relationships between the different variables in geotechnical problems can be well handled with ANN when sufficient data is available for training the networks.

Recent advances of evolutionary algorithm have prompted enhanced ANN models and comparisons, such as Gene Expression Programming – ANN [46] -, Group Method of Data Handling – ANN [47] – [48], Artificial Bee Colony Algorithm-ANN [49]. However, the authors favoured attempting the problem with conventional ANN as a starting point, and the results have been reported in this article.

Till date, there has not been any report of application of ANN for interpolation of engineering properties of soil. It has been earlier experienced by the authors that the interpolation of SPT for the site under consideration using the conventional geostatistical tools gave good results [8] – [9], but there was scope for further improvement. Therefore, the objective of the present study was identified as the improvement of the spatial interpolation of SPT for the site using ANN as the tool and comparison of its performance with the traditional methods reported elsewhere [8] – [9] for the same site and dataset.

2. Data and Methods

2.1. Data

Data is obtained from field geotechnical investigations carried out at site located in northern Karnataka, approximately 200 km from Bangalore. The total area of the site is approximately 5.5 km². The layout of the site along with the locations for which the SPT data is available for the strata 1.5 m below ground level is shown in Fig. 1.
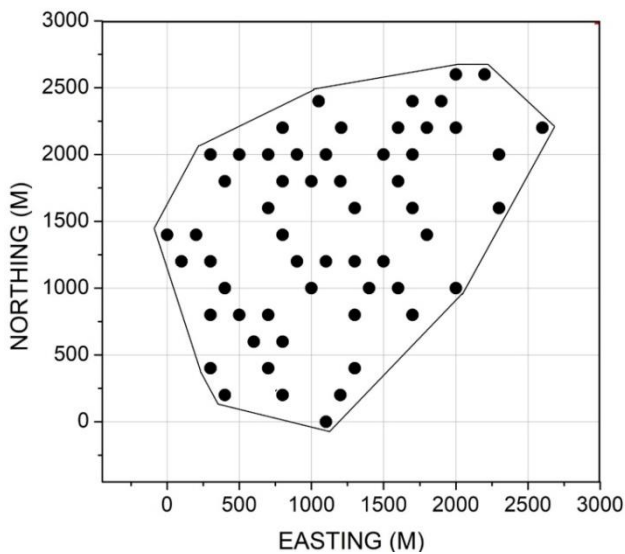

Fig. 1. Location of boreholes at the site with SPT data.

The soil profile at site can be generalized as sandy gravel with thickness varying from 500 mm to 3 m on top followed by completely weathered rock of thickness 3 m to 5 m, highly weathered rock of thickness 5 m to 10 m, moderately weathered rock of thickness 3 m to 7 m, slightly weathered rock with thickness of 2 m to 5 m and fresh rock of thickness 1 m to 4 m along the depth of soil. Thus, the layer for which the SPT values are taken would be consisting of sandy gravel or highly weathered rock. The data set comprised of SPT values at 57 locations, the descriptive statistics of which are listed in Table 1, and the histogram is presented in Fig. 2. The mean (33.63) is higher than the median (32), along with a positive skewness – indicatingthat the data has a long

right-hand tail, as can also be observed in Fig. 2. A coefficient of variation of around 3 indicates high variability in the data which ranges from a low value of 12 to a high value of 65. The peakedness of the dataset is less than that of a Normal distribution, with a kurtosis of 0.46 (< 3). It can be observed that among the 57 available SPT values, a majority (38 nos.) of the data falls between 20 and 40 with few (6 nos.) below 20 and some above 40 (13 nos.).

Table 1. Descriptive statistics of the SPT data from site.

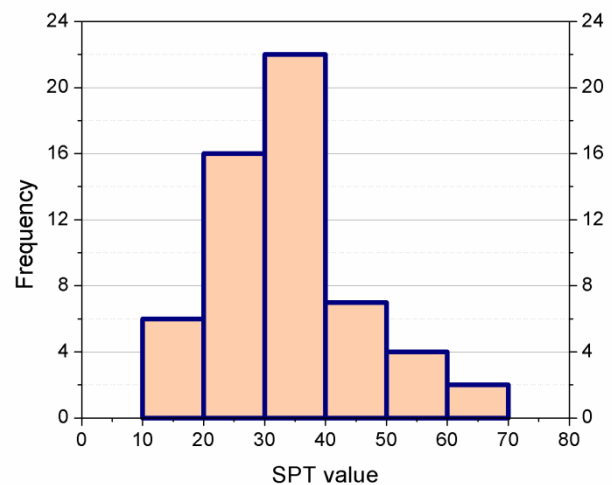| Statistics	Value
Mean	33.63
Median	32
Standard Deviation	11.72
Coefficient of variation	2.87
Skewness	0.62
Kurtosis	0.46
Maximum	65
Minimum	12

Fig. 2. Histogram of the SPT data used for the study.

2.2. Methodology

ANN is a soft computing tool that maps a set of inputs to a set of outputs, without any a-priori assumption of the relationship between the input and output sets. The ANN essentially consists of three or more layers of artificial neurons: one input layer, one output layer, and one or more hidden layers in between. The artificial neurons are functions, which take a weighted sum of inputs, add a bias term to it and then pass the result through a transfer function to obtain the output of the neuron. This output of the neuron is passed to the neurons of the subsequent layer. The multi-layered perceptron (MLP) structure is generally favoured for implementing ANN. The number of layers and the number of hidden neurons in the hidden layer are controlled by the user, and then with the training dataset, the parameters of ANN (the weights and biases of

different neurons) are optimised based on some performance function, such as mean square error, or absolute error. The errors in the output set of the training dataset are propagated back through the ANN for optimisation of the weights and biases. The basic artificial neuron and the MLP are depicted in Fig. 3 and Fig. 4 respectively.
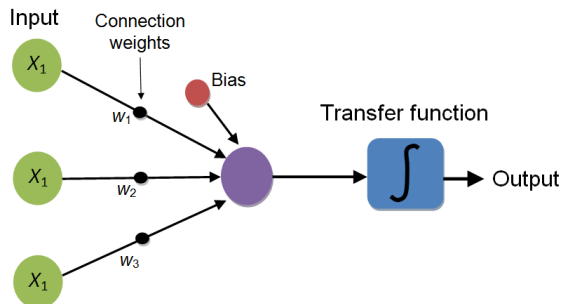

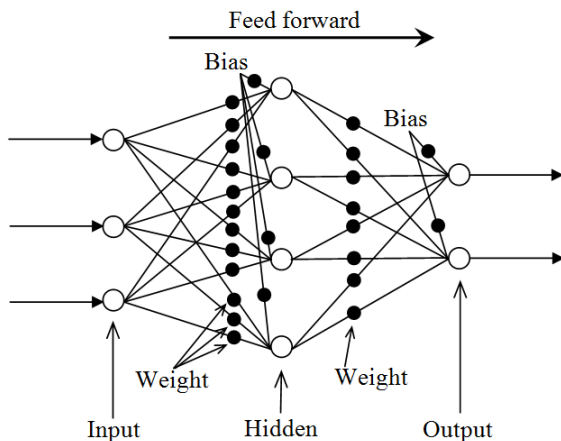Fig. 3. Basic structure of artificial neuron.

Fig. 4. Basic structure of artificial neural network.

The spatial variability of soil is well recognised. The variation of the soil properties at a site with location and depth depends on various factors such as the type of soil, geological process of formation, the stress history, overburden pressure, moisture content, and activities of biological agents, among others. It is for this reason that the task of estimation of any soil property from coarse grid data is challenging, and being pursued as an active topic of research. The engineer is assigned the task of arriving at the best estimates from the available data and therefore has to select the best suited one among the available tools to achieve acceptable results for practical application. Higher the variability of the soil property at a given site, higher would be the errors involved in estimates of the particular property at intermediate locations when obtained from coarse grid data.

In this study, the ANN was used as an extension of distance based interpolation scheme, wherein the SPT value at one point was assumed to be a function of the SPT at a certain number of neighbouring points and their corresponding distances. Here the assumption is that the SPT at a point would be correlated with SPT at the closer points more than the SPT at the points far away. This assumption follows from the natural geological process of formation and weathering of soil. The number of points from which SPT values would be used for estimation of SPT at the point of interest would be selected based on the performance metrics, which would be explained subsequently. From the past experience of the authors in case of application of the geo-statistical tools for interpolation of SPT for the same site [8] – [9], the number of neighbouring point for interpolation was varied from three to five.

The input to the ANN were the SPT values and the corresponding distances from the point under consideration. Thus for each point considered in the input layer of ANN, there were two input values: the SPT and the distance of that point from the point of interest. Therefore, for three nearest neighbouring points, the number of inputs to ANN was six; for four points, the number was eight; and for five neighbouring points, the input layer had ten neurons in this study. The output from the ANN was the SPT value at the point under consideration. One hidden layer was used, with the number of neurons in hidden layer being varied from one to three. The typical values were chosen keeping in mind the limitation of the number of data available for the site, such that the ANN could achieve good generalisation capability. The details of statistical and geo-spatial techniques for spatial interpolation may be found in textbook [50] and for the further theory and concepts of the artificial neural network (ANN), readers are referred to textbooks [51] – [52].

Feed-forward back-propagation ANN was adopted for the spatial interpolation of SPT. Compared to the other training algorithms available for ANN such as gradient descent, conjugate gradient, resilient propagation, etc. in back-propagation training options, the Levenberg-Marquardtalgorithm was favoured owing to the speed of convergence. The transfer functions used were tan-sigmoidal and linear in the hidden and the output layers respectively. Mean square error was used as the performance function while training the network.

For the current study, entire data set (SPT at 57 locations) was divided randomly into modelling and testing data sets in three ratios: 90:10, 80:20, 70:30. The modelling data set was used to formulate the model and estimate the model parameters. Using the thus developed model, the SPT or N-values were estimated at testing data locations. Subsequently, these estimated results were compared with testing data set to evaluate the suitability of the model using various performance measures discussed subsequently. Here it is noted that the data division for model formulation and testing could result in a certain of bias, and could affect the proper evaluation of the developed model. An elegant method of eliminating this possible bias could be ten-fold cross-validation approach [53] – [54]. The authors however had found that developing multiple models with various

random data divisions for a problem could provide similar insight into the possible bias arising out of division of the data into modelling (training) and evaluation (testing) sets [55] – [58]. This second approach has been adopted in this study.

The performance metrics employed in this study included correlation (R), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), the expressions for evaluation are provided in Eq. (1), Eq. (2), Eq. (3) and Eq. (4) respectively. The correlation coefficient indicates the linear dependency of the two variables, and values closer to unity are better. RMSE is an error measure which penalises the models with higher values of errors, and the MAE indicated the error on the absolute scale. MAPE, being normalised error term, becomes useful to judge the proportionate errors in the estimates of a given model. The formulations for the aforementioned performance metrics are enumerated below:

$$R = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2(P_i - \bar{P})^2}} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - P_i| \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - P_i}{O_i}\right| \times 100 \quad (4)$$

Lower values of all these error measures (RMSE, MAE and MAPE) would indicate a better model. When considered in conjunction, these four performance metrics would help to evaluate the developed model from different aspects and thus facilitate a comprehensive examination of the goodness-of-fit. Scatter plots are presented for the best models for visual appreciation of the accuracy levels.

The number of parameters in a model might affect the result and the corresponding performance metrics. In case of ANN models, the number of parameters broadly refers to the degrees of freedom assigned to the ANN model, which in turn are reflected by the number of weight and bias values which get optimized during the training process of the ANN. So, for the simplest architecture employed in this study of 6-1-1, the number of parameters would be 9; for the most complex one of 10-3-1, the number of parameters would be 37. To examine whether number of parameters affected the results in the present study, the various performance metrics are plotted against the number of parameters of the developed ANN models and evaluated.

3. Results and Discussions

The results of the spatial interpolation of SPT using ANN are presented in this section.

3.1. Best ANN Performance for Different Data Divisions

For each data division, as noted in Section 2.2, the performance was tabulated for the various combinations of number of neighbouring points used for interpolation and the number of hidden neurons. As mentioned earlier, the division of data for each proportion (70:30 / 80:20 / 90:10) was performed multiple times, and ANN models were generated for each selected set of number of nearest neighbouring points (3, 4, and 5) and number of neurons in hidden layer (1, 2, and 3). This would help to identify any bias in the ANN models arising out of the data division carried out earlier. The performances of the ANN developed from these multiple data division for each proportion and each set of number of points and hidden neurons were found to vary within five percent. This indicated that the random data division into training and testing sets did not result in any bias in the results. However, for brevity, the best performance from each such data division and corresponding set of neighbouring points and hidden neurons have been reported in this article.

From this table (ex. Table 2 for the data division 90:10), the most efficient ANN architecture was selected by considering the four performance measures together. Though the best performance in this case indicated that the performance of the developed ANN models could further improve with more input data or more hidden neurons, such exercise could not be carried out due to limitation of data. However, the potential of ANN for carrying out such modelling and estimates is definitely established. The best performances obtained for the three data divisions along with their architectures are presented in Table 3.

Table 2. Performance of spatial interpolation with ANN for data division 90:10.

Number of neurons in hidden layer	R	RMSE	MAE	MAPE
Number of neighboring points: 3				
1	0.87	8.6	6.7	21.32
2	0.80	9.4	8.0	34.37
3	0.52	9.7	8.3	22.59
Number of neighboring points: 4				
1	0.85	7.1	5.2	21.71
2	0.98	3.2	2.6	17.86
3	0.65	8.6	7.8	19.44
Number of neighboring points: 5				
1	0.72	9.0	6.9	21.39
2	0.89	7.2	5.8	18.33
3	0.97	2.0	1.8	6.03

Table 3. Best performance obtained for various data divisions and ANN architecture in spatial interpolation of SPT with ANN.

Data Division	R	RMSE	MAE	MAPE	ANN Architecture
90:10	0.97	2.0	1.8	6.03	10-3-1
80:20	0.91	13.1	7.9	21.76	10-2-1
70:30	0.58	11.4	8.1	27.74	10-3-1

For these ANN-s developed, the scatter plots show the accuracy of estimation for the training as well as the testing data respectively in Fig. 5 to Fig. 7, for the three cases. The interesting point to note here is that the deviations in the testing data for all three data divisions conducted in this study are less than equal to the deviations in the training data. The fact that the errors in the testing data are less than the training data indicates that the training of the ANN has achieved good generalisation in all three cases.
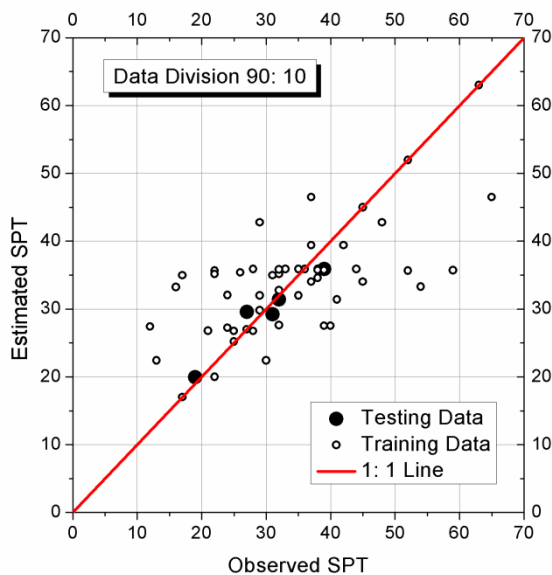

Fig. 5. Scatter plot for data division 90:10 – depicting the interpolation accuracy of training as well as testing data for the ANN architecture 10-3-1 (5 neighboring points).

As expected, the less number of points available for training the ANN resulted in comparatively poor performance when compared to higher number of training data. This is reflected in lower R, higher RMSE, MAE & MAPE (Table 3) and the larger scatter in the Fig. 6 & Fig. 7 when compared to Fig. 5. Generally, five neighbouring points are found to be efficient in spatial interpolation of SPT using ANN in this study. The optimized network parameters are included in the Appendix, for interested readers. However, it is highlighted here that this ANN model, as was developed for spatial interpolation of SPT values in this study, is site specific in nature and can provide estimates of SPT only

for this location with the stated error margins. The approach of use of ANN for spatial interpolation of engineering properties of soil, however, would be useful for any other location and can be employed after requisite calibration of the network.

3.2. Comparison of Performance of ANN Models (This Study) with Geostatistical Models in Literature [9]

The best performances obtained in spatial interpolation using different geostatistical techniques [9] from the same SPT data are compared with the comparable data division (80:20) using ANN in Table 4. It can be noted that the ANN yields model with comparable correlation coefficient, and lower errors (RMSE / MAE). Thus, application of ANN has helped to improve the spatial interpolation model of SPT for the site over the methods of K-nearest neighbour, inverse distance weighted interpolation and trend surface analysis [9].
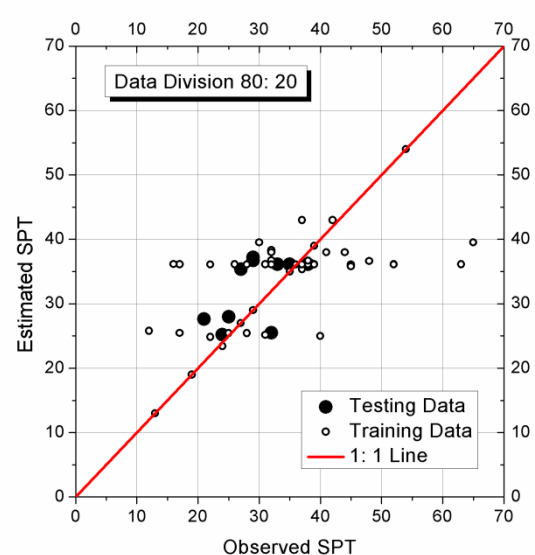

Fig. 6. Scatter plot for data division 80:20 – depicting the interpolation accuracy of training as well as testing data for the ANN architecture 10-2-1 (5 neighboring points).

The possible reason for this improvement using ANN could be that whereas the geostatistical tools [9] assume a dependency relationship between the variables and attempts to find the parameters for the relationship from the site investigation data, the flexibility of the ANN model allows it to determine the model as well as estimate the parameters from the data only, without any a-priori assumption. This feature makes ANN better suited for modelling complex processes, where the data dependencies are non-linear. It may be mentioned here that the best performance of the ANN obtained in this study was for the data division of 90:10 (more data for training) and for that case, the performance metrics were

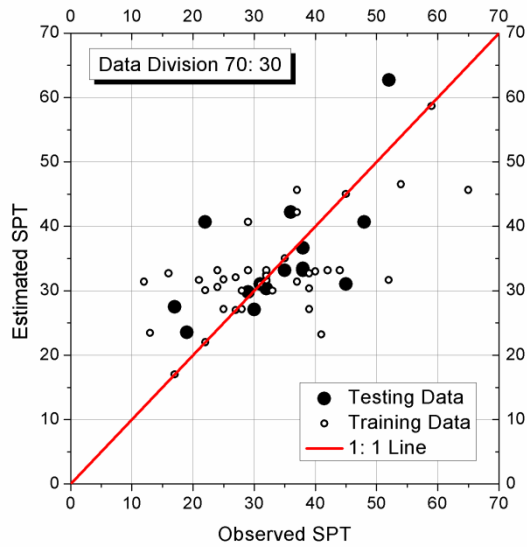much better than that of the 80:20 data division listed in Table 4.

Fig. 7. Scatter plot for data division 70:30 – depicting the interpolation accuracy of training as well as testing data for the ANN architecture 10-3-1 (5 neighboring points).

Table 4. Comparison of best performance for various geostatistical tools [9] and ANN in spatial interpolation of SPT.

Tool	Particulars	R	RMSE	MAE
KNN	No. of points: 4	0.87	8.6	6.7
IDW	No. of points: 4; Exponent: 3	0.80	9.4	8.0
TSA	Degree: 1	0.52	9.7	8.3
ANN	No. of points: 4; 10-2-1;	0.85	7.1	5.2

3.3. Range of Performance with Varying Parameters in ANN

One factor which assumes importance in ANN modelling is that whether the additional parameters in more complex networks are resulting in less generalising capabilities of the network. In such cases, the performance measures for the testing data get worse with the increasing number of parameters of ANN. In order to check this aspect, in this section the performance metrics obtained for the various cases are examined vis-à-vis the number of parameters in the ANN model in the Fig. 8 to Fig. 11. In these figures, the maximum and

minimum values of correlation R, RMSE, MAE and MAPE are plotted against the number of parameters. In general, the best correlation is between 0.7 and 0.9; the best RMSE is between 6 and 10; the best MAE is between 5 and 8; and the range of MAPE is within 30%, with the variation in the number of parameters from 9 to 37.
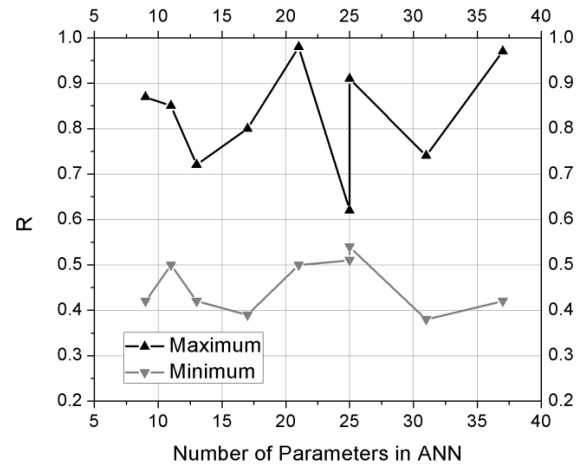

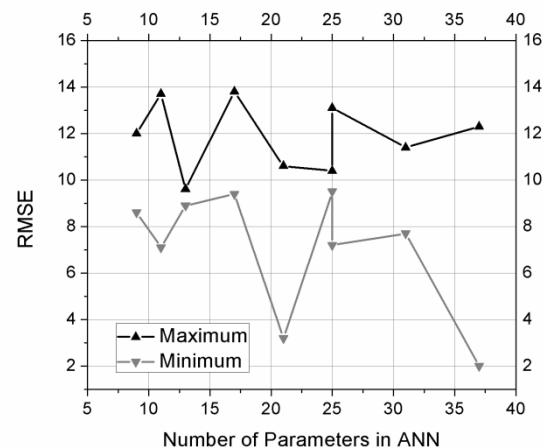Fig. 8. Variation of R vis-à-vis number of parameters in ANN.

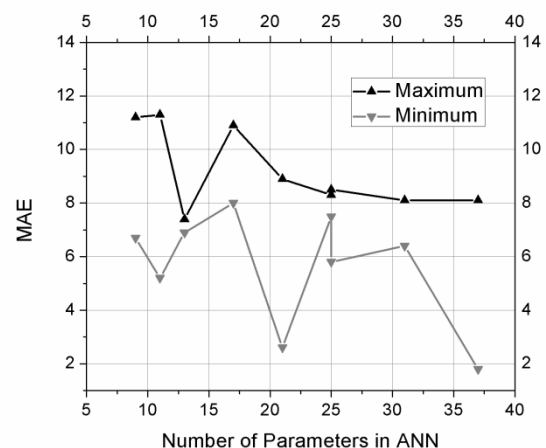Fig. 9. Variation of RMSE vis-à-vis number of parameters in ANN.

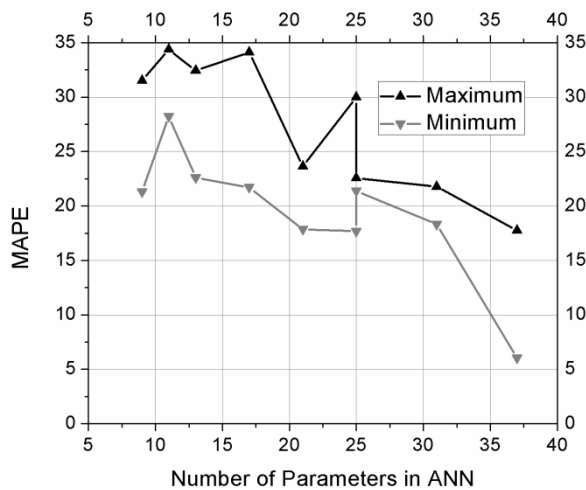Fig. 10. Variation of MAE vis-à-vis number of parameters in ANN.

Fig. 11. Variation of MAPE vis-à-vis number of parameters in ANN.

Though there is no marked change in the performance measures for increasing number of parameters of ANN, it is noted that with increasing number of parameters, the range of R, RMSE and MAE increases slightly. Exception is seen for 25 parameters where the range of RMSE, MAE and MAPE – all appear to narrow. However, it can be generally concluded that the higher number of parameters of the network does not result in fall of the performance and hence, from this consideration also, it is indicated that the generalization capabilities achieved by the ANN models in this study was good.

4. Summary

The present article dealt with the application of ANN for spatial interpolation of geo-technical parameter for a site, namely, SPT. From the results discussed here, the following conclusions may be drawn:

- ANN can be efficient in interpolation of engineering properties of soil from preliminary investigations, and thus may be useful in estimation of dynamic soil parameters from preliminary geotechnical investigations results as well.
- In this study, the distance based interpolation using ANN was quite successful, and comparatively better than the geostatistical interpolation reported for the same data in literature [9].
- The number of neighbouring points used for ANN based interpolation was found to be five, with two to three neurons in hidden layer being the efficient architecture.
- In general, higher number of training data resulted in better accuracy of estimation.

- In the limits of the study, the variation of number of parameters from 9 to 37 did not depict any marked change in range of performance. However, with more parameters to be trained from less data, the performance was affected slightly.
- The training errors were more than or equal to the testing errors and further the performance did not get affected much by the increasing number of parameters of ANN. From these observations, it is concluded that the ANN models developed in this study for spatial interpolation of SPT achieved good generalisation capabilities, without any drawbacks such as overfitting.
- This study establishes the potential of ANN for interpolation of engineering properties of soil.

Further studies are indicated for exploring the application of advanced or hybrid versions of ANN for spatial interpolation of geotechnical properties such as SPT in a more efficient and accurate manner. Other soft computing tools may also be explored for such applications and interpolation of other soil properties would also be useful.

Acknowledgement

Appendix

For interested readers, the optimized network parameters are listed in the appendix. However, readers may please note that the network thus finalized is site specific and applicable with the stated error limits only for the site under study.

Number of layers: 3 (input, hidden, output);

Network architecture: 10-3-1 (10 neurons in input layer, 3 neurons in hidden layer and one neuron in output layer);

Inputs: total 10 nos–SPTat five nearest neighboring points (5 nos.) and the corresponding distances from point of interest (5 nos.);

Output: 1 no. – SPT at the point of interest;

Training algorithm: Levenberg-Marquardt;

Transfer function: tan-sigmoidal (hidden layer) and linear (output layer);

Performance function: mean squared error;

Weights for Neuron 1 (hidden layer): [-33.02   -37.42   -33.06   -37.56   32.90   -48.32   -32.90   -37.24   -30.41   -38.56];

Bias for Neuron 1 (hidden layer): [135.11];

Weights for Neuron 2 (hidden layer): [19.99   -1.91
    20.12   -0.41   18.84   -1.04   17.84   -0.66
    17.59   -1.00];
Bias for Neuron 2 (hidden layer): [-22.52];
Weights for Neuron 2 (hidden layer): [4.95   15.07
    5.04   17.24   -9.51   -36.80   4.04   17.13
    6.27   -11.35];
Bias for Neuron 3 (hidden layer): [-3.82];
Weights for Neuron 1 (output layer): [0.18   -0.26
    0.52];
Bias for Neuron 1 (output layer): [0.34];

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