Load-Settlement Response of Friction Piles Socketed in Weak Rock ANN Prediction - RQD Based Approach

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Abstract - *Major civil engineering structures like multi-storey buildings, bridges etc. require stable foundations to ensure safe working conditions with minimal maintenance. In majority of cases, the surface soils are not of adequate strength to provide stable foundations and instead the large loads imposed by these structures must be carried to stronger rock at depth. Large diameter bored piles socketed in rock are widely used as a common engineering solution to transfer heavy structural loads through weak overburden soil to underlying rock. It is commonly accepted that pile load testing is the best way to predict accurate pile capacity. In current design practice, empirical relations derived from load tests are often used to predict the ultimate side resistance and the end bearing resistance. However, there is large variation of the values obtained from empirical relations. Because of the limitations discussed above, there is need to search for alternative solutions for prediction of pile capacity/settlement/load-deformation response of piles. Artificial Neural Networks (ANNs) is one of the alternative techniques, to predict pile capacity/settlement/load-settlement response of piles. Artificial neural networks (ANNs) are computer models that mimic the knowledge acquisition and organizational skills of human brain. In the present study, feed-forward back propagation neural network models based on RQD based approach have been developed and implemented successfully to predict the load-settlement response for skin friction piles socketed in mudstone. The prediction of load-settlement response of piles using neural networks has been found to be close to the field pile load test results. The developed neural network model may be used by the pile designers for analysis and design of bored piles socketed in rock.*

Keywords – Artificial Neural Networks, Friction Piles, Load-Settlement Response, Neural Networks and RQD.

I. INTRODUCTION

Piles are used for various civil engineering structures like multistory buildings, bridges, elevated freeways, offshore oil and gas platforms, jetties, wharves etc. It is recognized worldwide that the techniques dealing with auger and bored piles can help to solve many foundation problems (Van Impe, 1988). Bored cast-in-situ piles socketed in rock are widely used to transfer the heavy structural loads through weak overburden soil to underlying rock. Bored piles when formed in rock, the portion of the pile into rock is referred to as a socket. The rock socket derives its load from two components: *shearing resistance* at the shaft-rock interface around the vertical cylindrical shaft surface of the socket, and *end bearing resistance* at the base of the pile. The development of empirical design rules for pile shafts in rock commenced in the 1970's (Haberfield and Seidel, 1996). The shaft resistance and end bearing resistance have been related to the unconfined compressive strength of the rock (McVay, 1992; Zhang, 1997). The roughness of the interface between concrete and the rock mass plays an important role in the behavior of rock socketed piles (Pells et al., 1980; Williams and Pells, 1981; Horvath, 1983; Hassan and O'Neill, 1997).

It is believed and commonly accepted that pile load testing is the best way to determine the pile capacity and load-settlement behavior of piles. However, field load tests are very expensive and very often in case of bored piles in rock, tests have to be terminated well before the anticipated values. Therefore there is a need for research to develop alternative methods to determine the pile capacity/settlement and load-settlement behavior of piles socketed in weak/weathered or hard rock. Neural Networks (NNs) is one of the alternative techniques, to predict pile capacity/settlement/load-settlement response of piles. An attempt has been made in the present study to predict the load-settlement behavior of skin-friction piles socketed in weathered rock (mudstone) using neural networks. The in-situ pile load test data of thirteen skin-friction piles collected from the literature (Williams, 1980) have been used for training and testing of the neural network. In the present study feed-forward-back propagation algorithm is used to develop the NN model.

II. NN MODEL DEVELOPMENT

In the development of NN model for skin-friction piles in mudstone, an approach based on Rock Quality Designation (RQD) has been adopted. The following 11 input parameters are considered, which affects the settlement of pile at given side resistance: average side resistance (f_s), ratio (D/B) of embedment depth (D) to diameter of pile (B), ratio (L/B) of socket length (L) to diameter of pile (B), mean asperity height for socket portion (h_{av}), standard deviation for asperity height (S_h), mean asperity angle for socket portion (i_{av}), standard deviation for asperity angle (S_i), normal stress acting at the bottom of socket (σ_n), unconfined compressive strength of intact rock for socket portion($\sigma_{i(s)}$), rock quality designation for socket portion (RQD$_s$) and the factor β reflecting the ratio of actual maximum unit skin friction (f_{max}) and maximum unit skin friction (f_a). During search for a better solution with neural network, it has been observed that results are improved when the maximum-minimum range of various parameters is increased for normalization procedure (Patil and Shankariah, 1999). Therefore, the parameters for increased range of values are considered for normalization procedure.

A. *Implementation of Neural Network Model*

The neural network model for prediction of load-settlement response of skin-friction piles socketed in weathered or weak rock was implemented in three phases as per the procedure reported by Goh (1996):

- Data collection
- Data normalization and
- Execution and validation

Data Collection: For the development of NN models, the pile load test data is collected from Ph.D. Thesis of A. F. Williams (1980), Monash University, Melbourne, Australia. The database considered for the study includes 13 case studies of in-situ pile load tests consisting of 13 skin friction piles in mudstone. The collected data include bore log details, rock test data and load-settlement relations for bored piles in rock. The measurement of pile displacement avoids elastic settlement interaction effects. Young's modulus of concrete (E_c) is 35 GPa and Poisson's ratio (ν) is 0.2. For the rock mass, the Poisson's ratio is 0.25. In the present study the effect of these parameters is less because they are constant for all the piles.

Data Normalization: The data used for training and testing set are normalized between 0 - 1 before presenting the patterns to the neural network. The following procedure is used for normalization (Masters, 1993 reported by Goh, 1996):

$$A = (V - V_{min}) / (V_{max} - V_{min}) \quad \text{---------} \quad (1)$$

where,

A = Normalised value of parameter
V_{max} = Maximum value of the parameter
V = Value of each parameter
V_{min} = Minimum value of the parameter

Execution and Validation: In a present study feed-forward backpropagation algorithm with supervised learning have been used. The execution and the validation of the neural network model have been carried out using 'MATLAB - Neural Network Toolbox' package. The training and the testing of the network is performed based on the overall results. Practical way is to check the absolute relative error (ARE) between the predicated output and actual output in the validation or testing set. The error in training and testing set should be monitored. When the error in the validation set increases, the training should be stopped because the point of best generalization has been reached. This crossed validation is one of the most powerful methods to stop training of net. The result of predicted output for all the patterns used for both training and testing should be higher or up to decided satisfaction based on the problem and the data. The absolute relative error (ARE) for individual pattern is calculated using the following expression:

$$ARE = Abs\,[(V_{pred} - V_{actual}) / V_{actual}] \times 100 \quad \text{----} \quad (2)$$

where,

ARE = Absolute relative error in percentage
V_{pred} = Predicted value of the output by neural network
V_{actual} = Actual or measured value of the output

Then mean absolute relative error (MARE) for all the patterns (training and testing patterns) is calculated. The correlation coefficient (CORR COEF) between actual (measured) load and predicted load is determined for all the patterns in the MATLAB. The weights and biases are then saved. The relative importance of each of the input parameters in each NN model is determined by the procedure of 'partitioning of weights' proposed by Garson (1991) which is also reported by Goh (1994). Then mean absolute relative error (MARE) for all the patterns (training and testing patterns) is calculated. The correlation coefficient (CORR COEF) between actual (measured) load and predicted load is determined for all the patterns in the MATLAB.

III. RESULTS AND DISCUSSIONS

The load-settlement behavior of skin friction piles socketed in rock using NN model has been predicted as described. The results obtained during training and testing phases of developed NN model (NN1B) are presented and discussed.

Neural network model was developed with 9 training patterns and 4 testing patterns. The summary of results of developed model with one set having 11 input parameters is given in Table 1. The comparison of predicted and measured load-deformation behavior for 5 cases from training set and 4 cases from testing set is shown in Fig.1. The results achieved by Seidel (ROCKET Program 1993) are also shown in the same figures itself to have comparison with developed NN model (NN1B).

Table I
Summary of Results: NN Model (NN1B) - RQD Based Approach-Prediction of Load-Settlement Behavior

Details	Successful Cases	Unsuccessful Cases	Total Cases	Percentage of Success
Training Data	9	0	9	100
Testing Data	3	1	4	75
Total	12	1	13	92

Input Parameters: f_s, D/B, L/B, h_{av}, S_h, i_{av}, S_i, σ_n, $\sigma_{i(s)}$, $RQD_{(s)}$, β (11 Nos.)
Network Structure: 11-5-1; Initff. = 5, 5; Cycles = 4*5000 = 20,000
SSE = 0.180862; Correlation Coeff. = 0.7510 (average)

It is observed that the overall results achieved are 92 % with correlation coefficient of 0.7510 between measured and predicted load. When comparison is made between predicted load and measured load at given settlement, the absolute relative error is observed as 29.16 %. It is observed that the load-settlement response is highly influenced by β, RQD_s, f_s and least influenced by i_{av}, $\sigma_{i(s)}$, S_i. Moreover, it is observed that the NN predictions are far better compared to Seidel predictions.

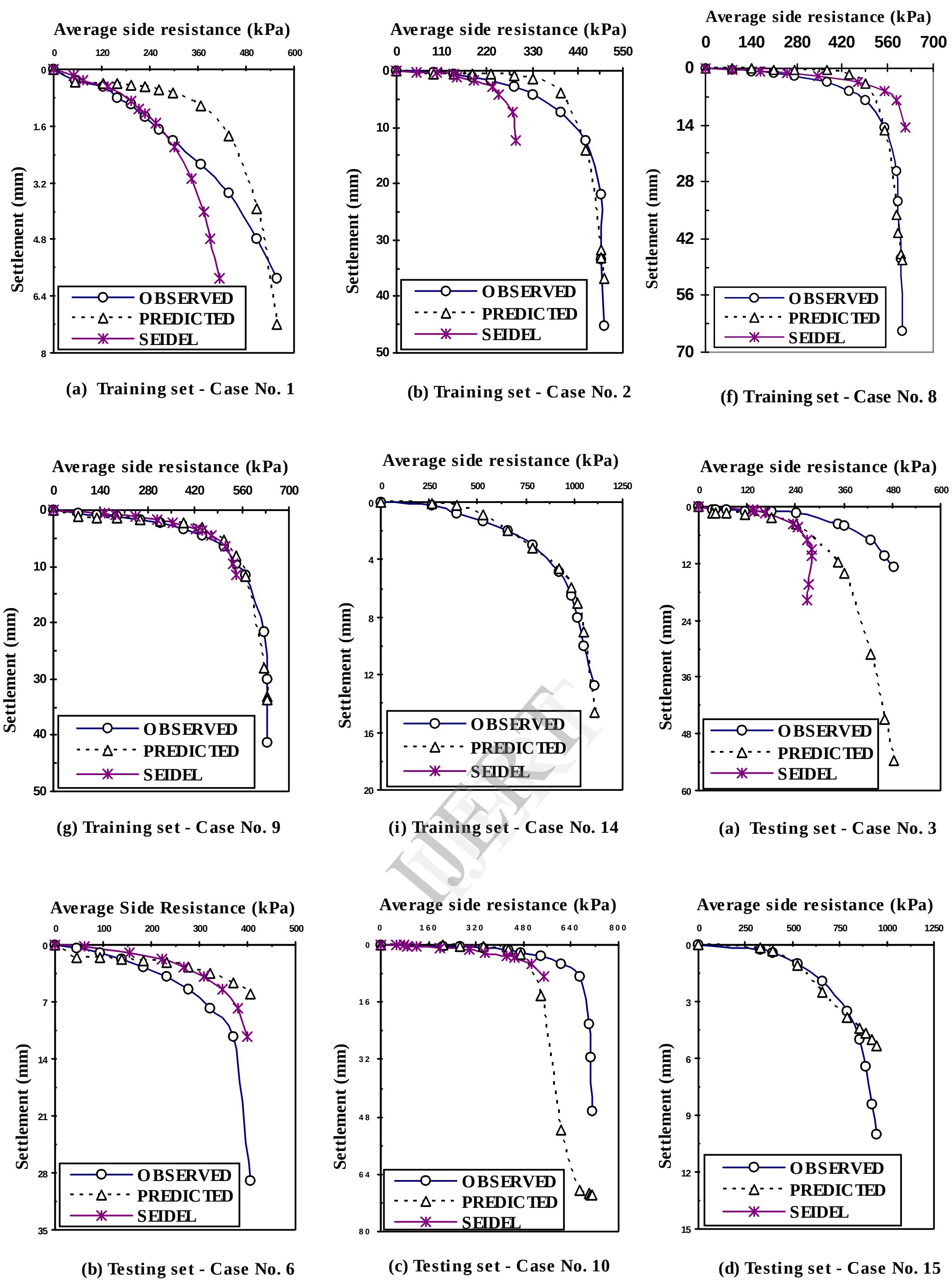

Fig. 1 Comparison between Predicted (NN1B) and Observed Load-Settlement Response for Skin Friction Piles in Mudstone (Cases from Australia)

Network Structure: 11-5-1; Initff. = 5, 5; Cycles = 4*5000 = 20,000
Sum-squared Error (SSE) = 0.180862; Correlation coefficient = 0.7510 (average)
Mean absolute Relative Error = 29.16 %

IV. CONCLUSIONS

In the study reported in this paper, feed-forward backpropagation neural network models have been developed and successfully implemented to predict the load-settlement response for skin friction piles socketed in mudstone. On the basis of the present investigations, the following conclusions are drawn:

- The correlation between the interpretation of the neural network output and observed load-settlement response of skin-friction piles in weak rock comes out to be very good.

- As quoted by Williams (1980), it is observed through the results of neural network models that the standard deviation of both asperity height and asperity angle has least effect on the skin friction resistance of the piles socketed into rock.

- The results of prediction of the load-settlement response for skin friction piles socketed in mudstone using neural network showed that neural networks are used to obtain necessary mapping from other multivariate mappings with complex and non-linear behaviour.

The overall results indicated the feasibility and applicability of neural network model for prediction of load-settlement response for skin friction piles socketed in weathered rock.

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