International Journal of Performability Engineering, Vol. 10, No. 3, May 2014, pp.325-328.

Printed in India

Use of Minimax Probability Machine Regression for Modelling of Settlement of Shallow Foundations on Cohesionless Soil

PIJUSH SAMUI
Centre for Disaster Mitigation and Management, VIT University, Vellore-632014, INDIA.

(Received on August 8, 2013; revised on November 8, 2013)

Abstract: This article examines the performance of Minimax Probability Machine Regression (MPMR) for prediction of settlement(s) of shallow foundation on cohesionless soil. MPMR maximizes the minimum probability that future predicted outputs of the regression model will be within some bound of the true regression function. Width of footing (B), net applied pressure (q), average Standard Penetration Test (SPT) blow count (N), length (L), and embedment depth (D_f) have been adopted as inputs of the MPMR. A sensitivity analysis has been carried out to determine the effect of each input. The results of MPMR have been compared with the Artificial Neural Network (ANN).

Keywords: *Minimax probability machine regression, artificial neural network, sensitivity analysis, settlement, shallow foundation.*

1. Introduction

The determination of settlement(s) of shallow foundation on cohesionless soil is an important task for designing shallow foundation. It is a complicated task due to uncertainty Shahin *et al.* [1]. Geotechnical engineers use different methods for determination of s of shallow foundation on cohesionless soil [2-7]. The available methods have some limitations Shahin *et al.* [1]. Shahin *et al.* [1] successfully applied Artificial Neural Network (ANN) for determination of s of shallow foundation on cohesionless soil. ANN has been successfully applied for solving different problems in engineering [8-10]. However, ANN has few drawbacks such as low generalization capability, black box approach, arriving at local minima, overtraining problem, *etc* [11, 12].

This study employs Minimax Probability Machine Regression (MPMR) for prediction of s of shallow foundation on cohesionless soil. MPMR is developed based on Minimax Probability Machine Classification Lanckriet *et al*. [13]. It maximizes the minimum probability that future predicted outputs of the regression model will be within some bound of the true regression function. There are lots of applications of MPMR in the literatures [14-16]. MPMR has been developed based on the database collected from the work of Shahin *et al*. [1]. The database contains information about width of footing (B), net applied pressure (q), average Standard Penetration Test (SPT) blow count (N), length (L), embedment depth (D_f) and s. The results of MPMR have been compared with the ANN. A sensitive analysis has been also carried out to determine the effect of each input on *s*.

2. Details of MPMR

This section will present MPMR for prediction of s of shallow foundation on cohesionless soil. For regression problem, MPMR takes the following form:

*Corresponding author's email: *pijush.phd@gmail.com*

$$y = \sum_{i=1}^{N} \beta_i K(x_{i,} x) + b \tag{1}$$

where y is output, x is input, N is number of datasets, $K(x_i,x)$ is kernel function, βi and b are output of the MPMR algorithm. This article uses B,q, N, L and D_f as inputs of MPMR. The output of MPMR is s. So, $x = \lfloor B, q, N, L, D_f \rfloor$ and $y = [s]$.

MPMR is developed by constructing a dichotomy classifier Strohmann and Grudic [17]. One data set is obtained by shifting all of the regression data $+\varepsilon$ along the output variable. The other dataset is obtained by shifting all of the regression data $-\varepsilon$ along the output variable. The classification boundary between these two classes is defined as a regression surface. To construct the MPMR for prediction of *s* of shallow foundation on cohesionless soil, the available datasets have been divided into the following two groups: 1) Training Dataset: This is used to develop the MPMR. This article uses 122 datasets out of 174 have been adopted as training dataset. 2) Testing Dataset: This is used to verify the developed MPMR. The remaining 52 datasets have been taken as testing dataset.

Radial basis function ($K(x_i, x) = \exp\left[-\frac{(x_i - x)(x_i - x)^T}{2\sigma^2} \right]$, where *s* is width of radial basis function) has been adopted as kernel function. The datasets are normalized against their maximum values Sincero [18]. The program of MPMR has been developed by MATLAB.

3. Results and Discussion

The success of MPMR depends on the choice of proper value of ε and σ. The design values of ε and σ have been determined by trail and error approach. The developed MPMR produces best performance at ε=0.001 and σ=0.4.

Figure 1 shows the performance of training and testing dataset. The performance of MPMR has been assessed in terms of coefficient of determination (R^2). For a good model, the value of R^2 should be close to one. It is observed from figure 1 that the value of R^2 is close to one for training as well as testing dataset. Therefore, the developed MPMR predicts s reasonably well. The developed MPMR has been compared with the other models [1-4]. Comparison has been done in terms of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

Figure 2 shows the bar chart of RMSE and MAE of the different models. It is clear from Figure 2 that the developed MPMR outperforms the other models. ANN has no control over future prediction. However, the developed MPMR has control over future prediction.

A sensitivity analysis has been carried out to determine the effect of each input variables (B,q, N, L and D_f) on s. The procedure of sensitivity analysis has been taken from the work of Liong *et al*. [19]. According to [19], the sensitivity(S) of each input parameter has been calculated by the following equation

$$\mathrm{S}(\%) = \frac{1}{122} \sum_{j=1}^{122} \left(\frac{\%\ \text{change in ouput}}{\%\ \text{change in input}} \right)_j \times 100 \tag{2}$$

The analysis has been carried out on the trained model by varying each of input parameter, one at a time, at a constant rate of 30%. The results of sensitivity analysis have been plotted in Figure 3. It is clear from Figure 3 that N has maximum effect on the predicted *s*.

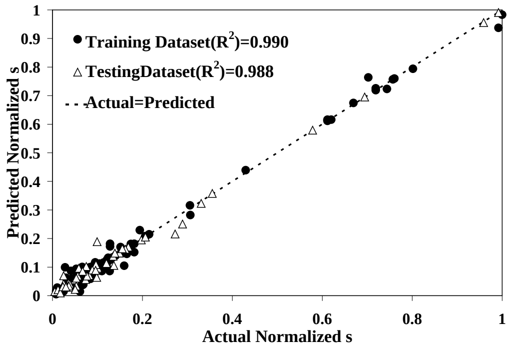

Figure 1: Performance of the developed MPMR.

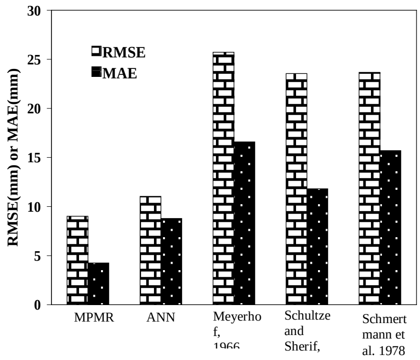

Figure 2: Bar chart of RMSE and MAE values.

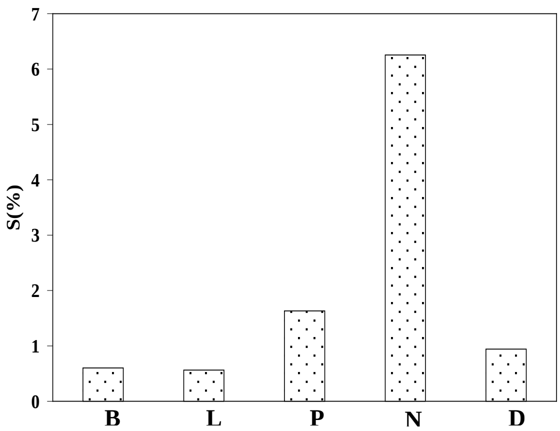

Figure 3: Bar Chart of Effect of Different Input Variables.

4. Conclusion

This article describes MPMR for prediction settlement of shallow foundation on cohesionless soil. 174 datasets have been adopted to construct the MPMR model. The developed MPMR gives excellent performance (RMSE=9.014mm, MAE=4.253mm and R^2=0.988). The performance of MPMR is better than the other models. Sensitivity analysis indicates that N has maximum impact on settlement of shallow foundation on cohesionless soil. This article shows that the developed MPMR can be used to model different problem in engineering.

Acknowledgment: Author would like to thank M. A. Shahin and M. B. Jaksa for providing the data and referees for comments.

References

[1] Shahin, M. A., H. R. Maier, and M. B. Jaksa. *Predicting Settlement of Shallow Foundations using Neural Networks*. Journal of Geotechnical and Geoenviromental Engineering, ASCE 2002; 128(9): 785-793.

[2] Meyerhof, G. G. *Shallow Foundations*. Journal of Soil Mech. Found. Div., Am. Soc. Civ. Engineering 1965; 91(SM2): 21-31.

[3] Schultze, E., and G. Sherif. *Prediction of Settlements from Evaluated Settlement Observations for Sand.* Proc., 8th Int. Conf. Soil Mechanics and Foundation Engineering 1973; 1(3): 225-230.

[4] Schmertmann, J. H., J. P. Hartman, and P. B. Brown. *Improved Strain Influence Factor Diagrams.* Journal of Geotechnical and Geoenviron. Engineering 1978; 104(8): 1131–1135.

[5] Jeyapalan, J. K. and R. Boehm. *Procedures for Predicting Settlements in Sands.* Proc., Settlement of Shallow Foundations on Cohesionless Soils: Design and Performance, Geotechnical Special Publication No. 5, ASCE, Seattle, Wash 1986; 1–22.

[6] Tan, C. K. and J. M. Duncan. *Settlement of Footings on sands:Accuracy and Reliability*. Proc., Geotechnical Engineering Congress, Boulde, Colo., 1991; 446-455.

[7] Wahls, H. E. *Settlement analysis for shallow foundations on sand.* Proc., 3rd Int. Geotechnical Engineering Conf., Cairo, Egypt 1997; 7-28.

[8] Ardi, A., H. Minowa, and K. Suzuki. *Detection of Runaway Reaction in a Polyvinyl Chloride Batch Process Using Artificial Neural Networks.* International Journal of Performability Engineering 2009; 5(4): 367-376.

[9] Hariprasad, B. P., Bhattacharjee, and A. Venugopal. *Prediction of Vehicle Reliability using ANN.* International Journal of Performability Engineering, 2012; 8(3): 321-329.

[10] Fuqing, Y., U. Kumar, and D. Galar. *A Comparative Study of Artificial Neural Networks and Support Vector Machine for Fault Diagnosis.* International Journal of Performability Engineering, 2013; 9(1): 49-60.

[11] Park, D., and L. R. Rilett. *Forecasting Freeway Link Ravel Times with a Multi-layer Feed Forward Neural Network.* Computer Aided Civil and Infastructure Engineering 1999; 14: 358-367.

[12] Kecman, V. *Learning and Soft Computing:Support Vector Machines,* Neural Networks, Fuzzy Logic Models. (Cambridge, Massachusetts.London, England. The MIT press, 2001.

[13] Lanckriet, G. R. G., L. E. Ghaoui, C. Bhattacharyya, and M. I. Jordan. *Minimax Probability Machine.* In T. G. Dietterich, S. Becker, and Z. Ghahramani, (editors), Advances in Neural Information Processing Systems 14, Cambridge, MA, MIT Press, 2002.

[14] Wang, J., S. T. Wang, Z. H. Deng, and Y. S. Qi. *Image Thresholding based on Minimax Probability Criterion.* Pattern Recognition and Artificial Intelligence 2010; 23(6): 880-884.

[15] Yang, L., L. Wang, Y. Y. Sun, and R. Zhang. *Simultaneous Feature Selection and Classification via Minimax Probability Machine.* International Journal of Computational Intelligence Systems 2010; 3(6): 754-760.

[16] Zhou, Z., Z. Wang, and X. Sun. *Face Recognition based on Optimal Kernel Minimax Probability Machine.* Journal of Theoretical and Applied Information Technology 2013; 48(3): 1645-1651.

[17] Strohmann, T. R. and G. Z. Grudic. *A Formulation for Minimax Probability Machine Regression.* In Advances in Neural Information Processing Systems (NIPS) 14, Dietterich, T. G., Becker, S. and Ghahramani Z. editors, Cambridge, MA: MIT Press, 2002.

[18] Sincero, A. P. *Predicting Mixing Power using Artificial Neural Network.* EWRI World Water and Environmental. 2003.

[19] Liong, S. Y., W. H. Lim, and G. N. Paudyal. *River stage forecasting in Bangladesh: Neural Network Approach.* Journal of Comput Civil Engineering 2000; 14(1): 1–8.

Pijush Samui is a professor at Centre for Disaster Mitigation and Management in VIT University, Vellore, India. He obtained his B.E. from Bengal Engineering and Science University; M.Sc. and Ph.D. from Indian Institute of Science, Bangalore, India. He worked as a postdoctoral fellow at University of Pittsburgh (USA) and Tampere University of Technology (Finland). He is the recipient of CIMO fellowship from Finland. Dr. Samui worked as a guest editor in “Disaster Advances” journal. He also serves as an editorial board member in several international journals. Dr. Samui is editor of International Journal of Geomatics and Geosciences. He is the reviewer of several journal papers. Dr. Samui is a Fellow of the International Congress of Disaster Management and Earth Science India. He is the recipient of Shamsher Prakash Research Award for the year of 2011.