Application of Artificial Intelligence in Geo-Engineering

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Abstract. Geotechnical engineers use various Artificial Intelligence (AI) techniques for solving different problems. This paper will survey the application of different AI techniques {Artificial Neural Network (ANN), Support Vector Machine (SVM), Least Square Support Vector Machine (LSSVM), Genetic Programing (GP), Relevance Vector Machine (RVM), Multivariate Adaptive Regression Spline (MARS), Extreme Learning Machine (ELM), Adaptive Neuro Fuzzy Inference System (ANFIS), Minimax Probability Machine Regression (MPMR), Gaussian Process Regression (GPR), Adaptive Neuro Fuzzy Inference System (ANFIS)} in different fields of geotechnical engineering such as shallow foundation, site characterization, liquefaction, slope stability, reliability, etc. The advantages of different AI techniques will be described.

Keywords: Artificial Neural Network · Support Vector Machine · Relevance Vector Machine · Least Square Support Vector Machine · Geotechnical engineering

1 Introduction

Geotechnical engineers generally use experimental techniques and models for determination of different parameters. Experimental techniques are time consuming and expensive. Therefore, geotechnical engineers prefer models over experimental techniques. AI techniques have been successfully applied in various fields of geotechnical engineering such as pile foundation [1–13]; liquefaction [6, 14–27], shallow foundation ([28–37]; shear strength [38–41], swell pressure [42, 43], permeability [12, 44–47], retaining walls [48, 49], dams [23], blasting [50], mining [51, 52], geo-environmental engineering [53], rock mechanics [54], site characterisation [55–59], tunnels and underground openings [60–66] and slope stability [67–71] & [63]. The main aim of this paper is to discuss the success of various AI techniques for solving different problems in geotechnical engineering.

2 Application of AI in Geo-Engineering

This section will serve the success of different AI techniques for solving different problems ingeo-engineering. Samui [72] showed only two parameters (cone resistance and peck ground acceleration) are sufficient for determination of seismic liquefaction

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potential of soil by using SVM. Probabilistic modeling of seismic liquefaction data was done by using RVM [72]. Various AI techniques {Minimax Probability Machine (MPM), Least Square Support Vector Machine (LSSVM)} have been successfully applied for prediction of seismic liquefaction potential of soil [73–77].

Table 1. Comparison of the different models for determination of seismic liquefaction potential of soil.

Type of in Situ tests	Input variables	ANN [Training performance (%)]	SVM [Training performance (%)]	ANN [Testing performance (%)]	SVM [Testing performance (%)]	ANN [Global data (%)]	SVM [Global data (%)]
SPT	CSR, $(N_1)_{60}$	94	96	88	94	–	–
	PGA, $(N_1)_{60}$	94	98	87	95	70	**77**
CPT	CSR, q_c	97	100	95	100	–	–
	PGA, q_c	96	100	92	100	81	**88**
V_s	CSR, V_s	96	97	87	94	–	–
	PGA, V_s	**83**	**84**	**76**	**82**	**40**	**40**

Table 1 shows the comparison of various models for determination of seismic liquefaction of soil [78]. SVM was developed by Vapnik [79]. Tipping [80] developed the algorithm of RVM. MPM was introduced by Lanckriet et al. [81]. Suykens et al. [82] constructed LSSVM. SVM, RVM, MPM and LSSVM use kernel function for prediction of output.

Goh [83–85] suggested the use of ANN based approach for assessing the liquefaction potential from actual N, qcand Vs data. Juang et al. [86] used ANN to determine the limit state for liquefaction triggering. Kurup and Dudani [87] applied ANN to determine liquefaction potential based on CPT data. Kurup and Garg [88] used ART based networks to evaluate liquefaction potential.

Samui [89] used SVM for prediction of stability status of slope based on slope angle, cohesion, angle of sharing resistance, height of slope, pore water pressure ratio and unit weight. Lee et al. [90] successfully applied back propagation model for determination of stability of slope.

Samui and Kothari [91] used LSSVM model for determination of stability status of slope. The developed LSSVM gave the value of coefficient of correlation is 0.957.

Table 2. Performance of different AI techniques for prediction of stability of slope.

Model	Performance (%)
SVM [90]	85.71
LSSVM [91]	92.85
ANN [90]	75.1
MPM [74]	100

Kaveh [92] adopted various AI techniques for determination of stability of slope. He concluded that Patient Rule-Induction Method (PRIM) and M5 algorithm are most effective. Table 2 shows a comparative study of various AI techniques for slope stability analysis.

Muduli et al. [93] compared various AI techniques for determination of uplift capacity of suction caisson in clay. Table 3 shows the values of R value of the various models.

Table 3. Comparison of various of AI techniques for prediction of uplift capacity of suction caisson in clay.

Models	R
ELM [93]	0.998
GP [94]	0.997
FEM [95]	0.995
ANN [95]	0.986
ANN(BRNN) [93]	0.991
SVM [93]	0.989
RVM [93]	0.992
GPR [96]	0.967
MPMR [97]	0.997
FNN [98]	0.997
GMDH-HS [99]	0.998
MARS [100]	0.997

It is clear from Table 3 that the developed AI techniques give reasonable performance for prediction of for prediction of uplift capacity of suction caisson in clay. ELM is the modified version of single-hidden-layer feed forward neural network [101]. GP is developed based on Genetic Algorithm [102]. MARS was developed byFriedman [103]. It uses basis functions for prediction of output. GMDH is self-organizing type submodel of neural networks [104]. FNN is modified version of neural network [105]. Kordjazi et al. [106] applied SVM for determination load carrying capacity of pile foundation.

Table 4. Performance of various AI models for prediction of lateral load of pile.

Model	R
RVM [107]	0.998
LSSVM [108]	0.994
MARS [108]	0.995
SVM [89]	0.998
FNN [109]	0.990
ANN [109]	0.967

Table 4 shows the performance of various AI techniques for prediction of lateral load of pile. The performance of all models is reasonably well.

Table 5. Performance of various AI techniques for prediction of ultimate capacity of pile.

Model	R
MARS [110]	0.984
RVM [110]	0.981
GRNN [1]	0.954

The performance of various models for prediction of ultimate capacity of pile has been shown in Table 5. It is clear from Table 5 that the developed models have ability for prediction of ultimate capacity of pile.

Table 6. Performance of various AI techniques for prediction of pullout capacity of small ground anchors.

Model	R
ANN [111]	0.858
LSSVM [112]	0.942
MOFS1 [113]	0.849
MOFS2 [113]	0.851
FNN [113]	0.846
RVM [114]	0.944
EPR [115]	0.808
NHW [116]	0.98
DANFIS [116]	0.999

Researcher applied various AI techniques for determination of pullout capacity of small ground anchor. Equivalent anchor diameter, anchor embedment depth, average cone tip resistance, average cone sleeve friction, and installation technique have been considered as inputs of AI models. Table 6 shows the performance of various models for prediction of pullout capacity of small ground anchor. The best performance was given by DANFIS [116].

AI has been also used for solving different problems in rock engineering. Table 7 shows the performance of various models for determination of elastic modulus of jointed rock mass. Joint frequency, joint inclination parameter, joint roughness parameter, confining pressure and elastic modulus of intact rock have been as adopted as inputs of the AI models.

Table 7. Performance of various AI techniques for determination elastic modulus of jointed rock mass.

Model	R
GPR [117]	0.996
MARS [118]	0.989
ELM [119]	0.900
MPMR [119]	0.968
GRNN [119]	0.969

Table 8. Performance of various AI techniques for Travertine sample.

Model	R
GPR [120]	0.984
RVM [120]	0.992
MPMR [120]	0.914

Table 9. Performance of different AI models for determination of tensile strength of rock.

Model	R^2
FFNN [121]	0.516
SVM [121]	0.607
LSSVM [121]	0.655

Table 10. Performance of various models for analysis of rock slope.

Model	Performance (%)
SVM [117]	100
LSSVM [117]	100
RVM [117]	100
MPM [122]	100

The performance of various AI techniques for solving various problems has been shown in Tables 8, 9 and 10. For travertine sample, point load index, porosity, P-wave velocity, and Schmidt hammer rebound number have been considered as inputs of the AI models. For determination of tensile strength of rock, the developed AI models used total porosity, sonic velocity, slake durability index and aggregate impact value as inputs. The developed AI techniques did not produce good performance for prediction of tensile strength of rock.

Geotechnical engineers used different AI models for solving different problems in shallow foundation. Table 11 depicts the performance of various AI models for prediction of settlement of shallow foundation oncohesionlesssoil. Load, width of foundation, length of foundation, depth of foundation, and SPT value have been used as inputs of AI models for prediction of settlement of shallow foundation.

Table 11. Performance of AI models for determination of settlement of shallow foundation on cohesionless soil.

Model	R
ANN [29]	0.902
SVM [89]	0.932
LSSVM [123]	0.928
EPR [124]	0.969
GP [124]	0.972
GEP [124]	0.954
RVM [125]	0.945

Table 12. Performance of AI models for determination of bearing capacity of shallow foundation on cohesionless soil.

Model	R
ANN [127]	0.995
FIS [127]	0.990
ANFIS [127]	0.998
SVM [128]	0.993
RVM [128]	0.996

The performance of various AI models for determination of bearing capacity of shallow foundation has been shown in Table 12. Width of footing, depth of footing, footing geometry, unit weight of sand and angle of shearing resistance have been taken as inputs of the AI models. It is clear from Tables 11 and 12 that the developed AI techniques have ability for modeling different problems in shallow foundation.

Table 13. Comparison between different AI models for determination of Compression Index.

Model	R
ANN [129]	0.975
LSSVM [91]	0.749
RVM [126]	0.960
MPMR [130]	0.980
ELM [130]	0.930

Table 14. Performance of various models for permeability prediction.

Model	R^2
EPR [131]	0.920
ANN [131]	0.900
ANFIS [132]	0.973

It is seen from Tables 13 and 14 that the developed AI models have ability for prediction of permeability and compression index.

Table 15. Performance of various AI models for determination of effective stress parameter.

Model	R
ANN [133]	0.960
GPR [134]	0.973
GP [135]	0.987
MARS [135]	0.983

Table 16. Performance of various AI models for determination of OCR.

Model	R
SVM [89]	0.894
RVM [126]	0.956
MARS [136]	0.904
LSSVM [136]	0.934

It is confirmed from Tables 15 and 16 that the developed AI modelsproves his capability for determination of OCR and effective stress parameter of soil. For prediction of OCR, the developed AI models use cone resistance, vertical total stress, hydrostatic pore pressure, pore pressure at the cone tip, and the pore pressure just above the cone base as input variables. Net confining pressure, saturated volumetric water content, residual water content, bubbling pressure, suction and fitting parameter have been adopted as inputs of the AI model for prediction of effective stress parameter.

Table 17. Performance of various AI models for site characterization.

Model	R
BP [78]	0.945
GRNN [78]	0.503
SVM [78]	0.986
RVM [137]	0.982
LSSVM [137]	0.952

It is observed from Table 17 that only the developed GRNN model did not give good performance. In Table 17, the developed AI models have been adopted for prediction of N values at any point in Bangalore(India). For developing site characterization model, latitude, longitude and depth have been used as inputs of the AI model.

Table 18. Performance various AI models for retaining wall.

Model	R
ANN [49]	0.974
EBBP [138]	0.997
ABC-ANN [139]	0.992

Table 18 confirms that the developed AI models have ability for solving different problems of retaining wall.

Samui et al. [93] investigated the performance of Adaptive Neuro Fuzzy Inference (ANFIS) and MARS for determination of spatial variability of rock depth. Kumar et al. [140] applied different AI techniques for reliability analysis of infinite slope. Chan and Low [141] successfully applied ANN for reliability analysis of pile foundation. Kang and Li [142] investigated the capability of SVM for reliability analysis of slope. LSSVM has been also used successfully for reliability analysis of slope by Kang et al. [143]. MPMR has control over future prediction. However, ANN, SVM, RVM, MARS, GP and LSSVM have no control over future prediction. ANN uses many tuning parameters compared to MPMR, SVM, RVM, LSSVM, MARS, ELM, and GP. ANN can give local minima. However, SVM always gives global minima.

3 Conclusion

This article has presented the application of different AI techniques in various fields of geo-engineering. The developed AI models can give better prediction for new dataset. A comparative study has been carried out between the different AI techniques. The developed AI techniques can be used as quick tools for determination of different parameters. It provides a convenient and often highly accurate solution to various problems of geo-engineering. In summary, it can be concluded that various AI techniques can be used for solving different problems in geo-engineering.

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