Neural Network Modeling of Shear Wave Velocity of Macau Soils Using SPT and CPT Data

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Abstract. Shear wave velocity of soil is an important parameter for earthquake analysis and civil engineering designs. Correlations between shear wave velocity and SPT-N value based on the simple power-law regression model were provided by previous studies. However, due to the inherent uncertainties of the SPT-N values, estimation of shear wave velocity may be improved by incorporating other site investigation data. In this study, artificial neural network models were used for the correlation analysis between the shear wave velocity with SPT (Standard Penetration Test) and CPT (Cone Penetration Test) data, based on recent field test data obtained from the site investigation program of the Macau major transportation project. The analysis results of this study indicated that incorporating the additional soil parameters in the correlation model would improve the prediction performance. When combined with SPT and CPT to form neural network models, a better prediction would be obtained than that using SPT or CPT alone.

Keywords: SPT-N · CPT · Shear wave velocity · Artificial neural network · Nonlinear regression

1 Introduction

The shear wave velocity (V_s) is a fundamental parameter to determine the dynamic properties of soils. It is also helpful in the evaluation of foundation stiffness, liquefaction potential, earthquake site response, soil stratigraphy, soil density, site classification, and foundation settlements [1].

Standard Penetration Test (SPT) is a basic soil field test that is commonly used to indicate the relative density and compressibility of granular soils. It is also commonly applied to estimate the liquefaction potential of saturated granular soils for earthquake design. In the past half-century, a lot of researchers tend to use regression statistical analysis to establish the relationship between the shear wave velocity and SPT-N value worldwide [2].

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The motivation of this research is because the direct measurement of shear wave velocity needs to deal with the high cost and the lack of qualified operators to perform the field test. Previous researches were mostly on using statistical regression methods to provide correlation equations that can predict shear wave velocity in a specific site condition.

The correlations between shear wave velocity and SPT-N values have considerable dispersions, which may be due to the test error of shear wave velocity and SPT-N values, geotechnical and geological conditions, and the limitation of regression statistical analysis. To reduce the test error and statistical error, other parameters should be added. Excepting the SPT-N value, it is well known that the cone penetration of soil may also have a relationship with shear wave velocity.

In this study, to improve the accuracy of shear wave velocity prediction, the SPT-N and CPT-qc were taken into consideration together to determine the shear wave velocity by BP neural network. The recent field test data obtained from the site investigation program of a major transportation project at Macau was used for this study, and the comparison between different models is depicted in this paper.

2 Back Propagation (BP) Neural Network

The BP neural network as shown in Fig. 1 was adopted in this study. The algorithm is composed of two processes, the forward propagation of the signal and the backward propagation of the error. In the forward propagation, the input samples enter the network from the input layer L_1 and pass through the hidden layer L2 to the output layer L_3. After the forward propagation of signal and the backward propagation of error, the adjustment of weights and thresholds is repeated until the preset number of training times, or the error is reduced to an allowable level. The process of constant adjustment of weights and thresholds is the training process of the network.

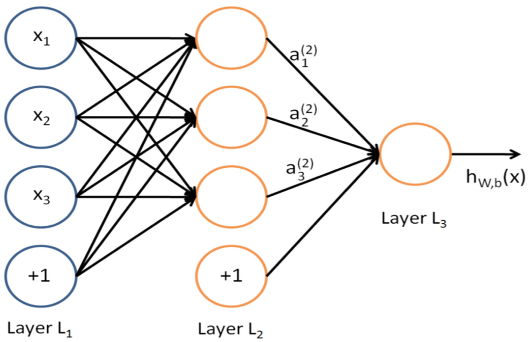

Fig. 1. BP neural network with one hidden layer

3 Case Study

The site investigation data about the shear wave velocity, CPT, and SPT-N values were obtained from a major transportation project at Macau. There are five boreholes contained in this project, the corresponding locations were shown in Fig. 2. The depths of five boreholes are around 18m to 66m. Down-hole seismic test and seismic-cone penetration test (S-CPT) were performed for the measurement of shear wave velocity. A total of 35 pairs of the values of shear wave velocity, SPT-N, and cone resistance values were taken at similar depths from the database of the project.

Fig. 2. The corresponding locations of five boreholes for the project

4 Analysis Results

In the field of machine learning, overfitting is a frequently encountered problem. In the BP algorithm, when more hidden layers are added, the network becomes more complex and can make the fitting error between observation and prediction data smaller. However, when the model encounters new data, the prediction results may be very terrible. In this study, to avoid the overfitting problem, the data is divided into two parts, including training data and test data. The training data is to train the model. The test data is mainly to evaluate whether the model can fit the observation when encountering new data. In this study, three different models are analyzed. To evaluate the model, the coefficient of determination (R^2) is adopted. The R^2 mainly reflects the degree of fit between prediction and observation data. If the R^2 is larger, the predicted data fits the observed data better. Finally, by comparing the R^2 among the three models, the best model will be chosen.

4.1 The Model with SPT and Vs

Firstly, the correlation model between SPT and Vs is built, and the SPT-N value is used as the only input to predict the Vs. By changing the number of neurons in the hidden layer and the hidden layers, the error in training data and test data. By comparing the error, the best structure of the BP model is got and shown in Fig. 3.

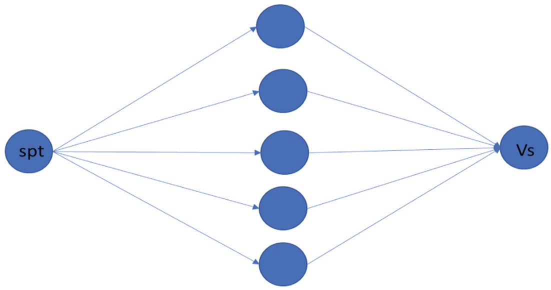

Fig. 3. The best structure of the BP model between SPT and Vs

When this model was trained in the learning process, the training loss became smaller and smaller. Simultaneously, validation loss also became smaller and smaller. The results of these two loss-reducing curves are shown in Fig. 4.

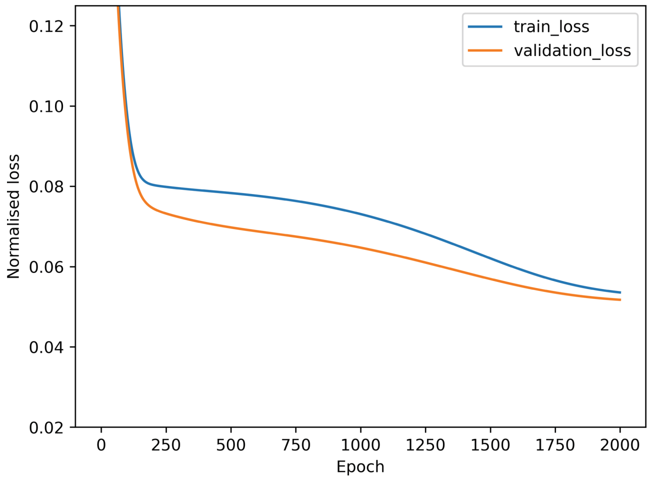

Fig. 4. The loss reducing curve versus the training epoch for SPT and Vs model

From the above figure, both the training and testing losses decrease very quickly and then become stable. Finally, these two lines are very close, which means this model can get a balance between underfitting and overfitting. The prediction by this model and observation results are also shown in Fig. 5. The coefficient of determination (R^2) is 0.352.

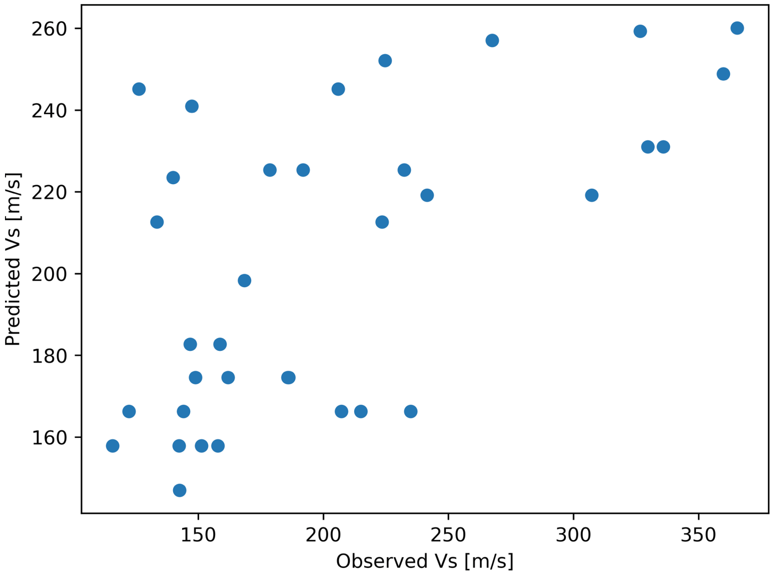

Fig. 5. The fitting results between observation and prediction by SPT

4.2 The Model Between CPT and Vs

Secondly, the model for Vs is obtained using the CPT-cone resistance as the only input. Using the same previous procedure, the same best structure of the BP model was got and shown in Fig. 6.

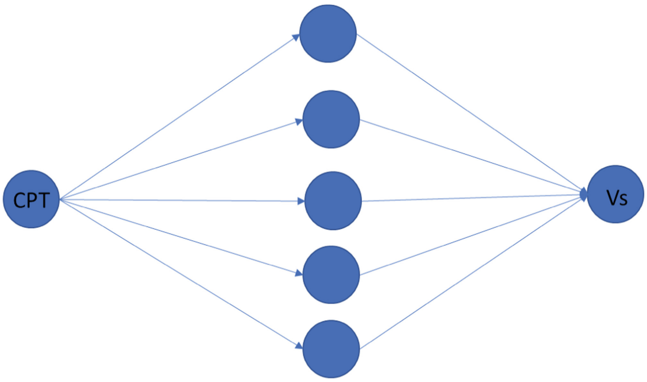

Fig. 6. The best structure of the BP model between CPT and Vs

When the best model was trained in the learning process, similar phenomena are happening with the previous model. The results of these two loss-reducing curves are shown in Fig. 7.

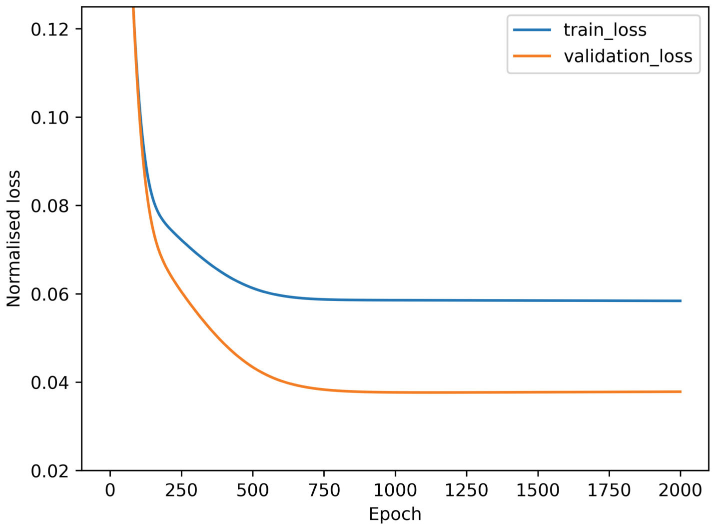

Fig. 7. The loss reducing curve versus the training epoch for CPT and Vs model

From the previous figure, both the training and validation losses decrease and become stable very quickly, but the testing error is smaller than the training error, which means this model has little underfitting problems. The prediction by this model and observation data are also shown in Fig. 8. The coefficient of determination (R^2) is 0.339.

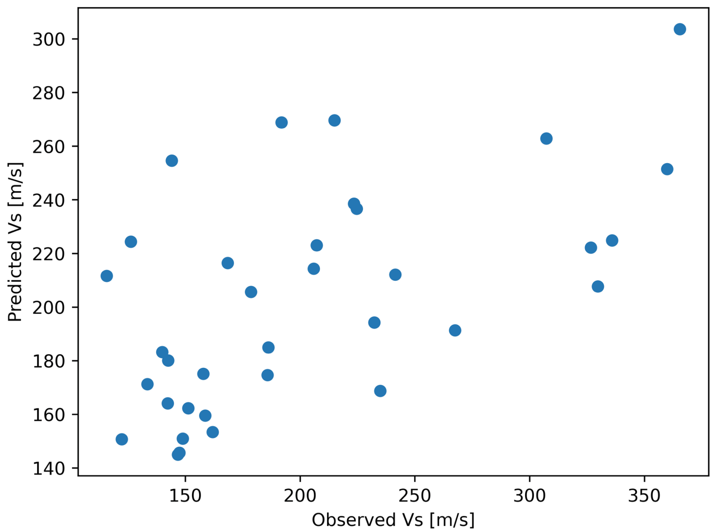

Fig. 8. The fitting results between observation and prediction with CPT and Vs

4.3 The Model Combining SPT, CPT, and Vs

Finally, the model which combines the SPT-N and the CPT-cone resistance to predict the Vs is built and both the SPT-N and the CPT-cone resistance are used as the input. By changing the structure of the neural network, the best structure of the BP model is got and shown in Fig. 9.

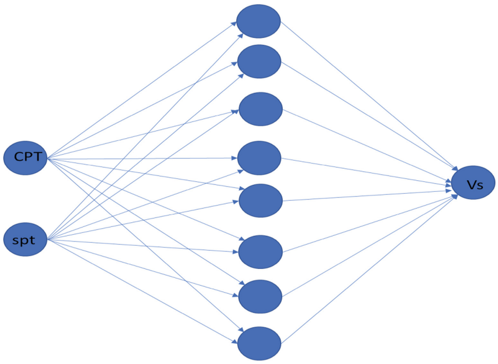

Fig. 9. The best structure of the BP model combining SPT, CPT, and Vs

The results of the two loss-reducing curves for this model are shown in Fig. 10. From this figure, both the training and validation losses decrease very quickly at the early epoch and then become stable, but the testing error is smaller than the training error, which means this model has little underfitting problems. Finally, these two lines are very close, which means this model can get a balance between underfitting and overfitting.

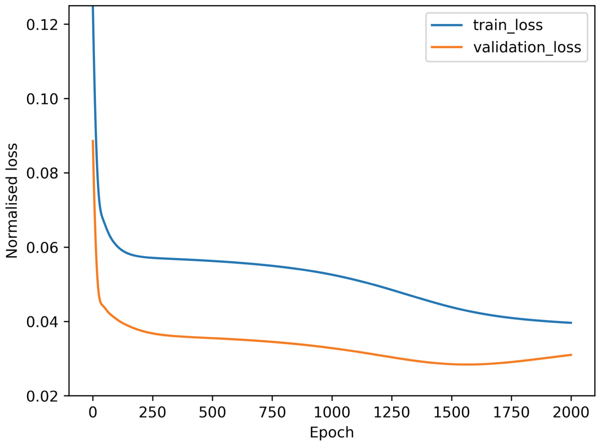

Fig. 10. The loss reducing curve versus the training epoch for combining model

The prediction using this model and observation data are also shown in Fig. 11. The coefficient of determination (R^2) is 0.538.

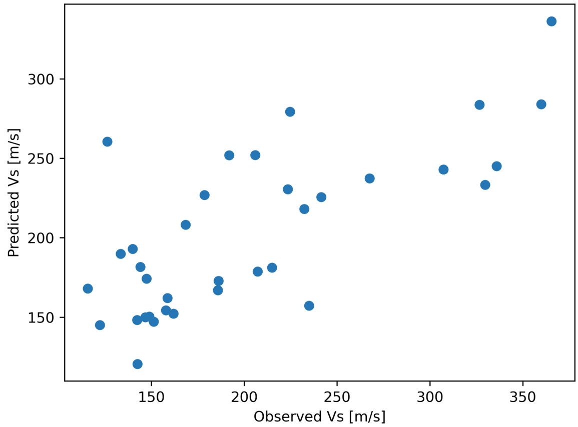

Fig. 11. The fitting results between observation and prediction for the combining model

5 Conclusion

In this study, the BP algorithm is chosen to analyze the database of a major transportation project in Macau. Using this method, the correlation models between SPT-N, CPT, and shear wave velocity are established. By comparison of three models, the model combining the CPT and SPT-N can fit the observed data best.

According to the results, it can be found that the BP method is a powerful method to do nonlinear regression. In traditional statistical analysis, the relationship between SPT-N and Vs are considered. However, according to the above analysis, the CPT also has a relationship with Vs. When combining SPT-N and CPT, the prediction can improve a lot.

References

1. Richart, F.E., Hall, J.R., Woods, R.D.: Vibrations of Soils and Foundations, p. 414. Prentice-Hall, Englewood Cliffs (1970)
2. Marto, A., Soon, T.C., Kasim, F.: A correlation of shear wave velocity and standard penetration resistance. Electron. J. Geotech. Eng. **13**, 463–471 (2013)
3. NG, K.F.: Correlation analysis of shear wave velocity of macau soils using nonlinear curve fitting and genetic programming. Final Year Project Report, University of Macau (2015)