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SOFT GROUND SUBSIDENCE PREDICTION OF HIGHWAY BASED ON THE BP NEURAL NETWORK

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ABSTRACT: - Soft clay ground subsidence data of highway embankment Ipoh project in Malaysia use to build Back-Propagation artificial neural network model. The forecasts of soft ground subsidence final settlement find then comparing results of soft ground subsidence final settlement, then comparing the predict results with curve fitting hyperbola method, the curve method, three-point method forecast results. It turns out that neural network can avoid the human factors of interference from traditional methods, gaining high precision.
KEYWORDS: Improvement soft ground soil; Settlement prediction; Back-Propagation neural network.

1- INTRODUCTION

The foundation in soft clay soil under Embankment have big problem in control of foundation settlement (1). In order to control of the behavior deformation during construction must establish dynamic observation and soft soil dynamic prediction system. On one hand, ensuring safety and stability in the construction process; On the other hand, the potential post-construction settlement of soft soil ground of highway will cause considerable damage, so getting correctly predicted post-construction settlement is necessary, thus making sure that post-construction settlement is in permissible range. There are many factors which can influence soft ground foundation subsidence (2), and the factors are constantly changing over time, and the properties of soft soil, whose parameters is difficult to determine, it is very complex, so obtaining the accurate calculation and predicting soft ground foundation subsidence is the technical difficulties of soft ground construction control.

This paper takes BP artificial neural network, and use soft ground foundation data of Ipoh highway to build neural network model, and give predicted settlement of soft ground soil, then compare the predicted results with field test.

2- PREDICTION MODEL OF SETTLEMENT GROUND SOIL

i. Data study and normalized

The training and testing sample data are getting from Ipoh project Malaysia as shown in Figure 1. In this project, vibro-replacement is used with stone columns adopted as ground treatment. To enable network training more effective, sample data can be normalized before practice ,and make input and output data map in the range of [0, 1], after training, simulation output is reflected back to the range of databases. The training sample data can directly call normalization and reverse normalization function, which is provided by Matlab neural network toolbox (3).

ii. Architecture ANN Model

Because only one hidden layer of the BP neural network has nonlinear mapping, which is strong, this paper adopts neural network of only one hidden layer. The number of input neurons is three, hidden layer neurons is 15 and the output layer is 1; The transfer function of hidden layer neurons is Tansig, and the transfer function of output layer is Purelin; Training function selects Traingdx; Learning function selects Learngdm; Performance function selects MSE.

3- DEVELOPMENT OF ANN MODELS

The BP artificial network model used in this work was developed by[4] and was implemented using code in Matlab [3]. The model inputs were friction angle, length ratio, high of embankment and time settlement.

The measured settlement (S_m) was the single output. The available data were randomly divided into training, testing and validation sets [5]. The training data divided into 70% for the training set and 30% for the testing set. Input and output parameters were scaled between 0.0 and 1.0 to eliminate their dimension and to ensure that all variables receive equal attention during training. The optimal model geometry was determined utilising a trial-and-error approach in which MLP models were trained using one hidden layer with rang from 1 to fifteen hidden layer nodes, respectively. It should be noted that one hidden layer can approximate any continuous function, provided that sufficient connection weights are used (Hornik et al. 1989). It should also be noted that 11 is the upper limit for the number of hidden layer nodes needed to map any continuous function for a network with 5 inputs. The optimal network parameters were obtained by training the MLP model with different combinations of learning rates and momentum terms. A model with 2 hidden layer nodes, a learning rate of 0.2, a momentum term of 0.8, tanh transfer function for the hidden layer nodes and sigmoidal transfer function for the output layer node was found to perform best[4,6].

The performance of the BP model obtained is summarised. The sets of training data were applied to train the networks, and the training is achieved after 4 epochs as shown in Figure 3, which depicts the numbers of training epochs against the training errors. It is worth mentioning that for the traditional BP networks, the improved BP network is much more efficient compared with the traditional ones [7].

4- PREDICT THE SETTLEMENT AND COMPERED RESULTS

The training network is completed, after that the network can use test sample to test network predict effect, and its inspection methods is the same with network training, only need to change input vector into the data of the testing samples. Comparing network forecast results with the practical results of testing samples, the training quality is easily inspected. There are 10 network prediction test sample results in Table 1. It shows that the prediction results of BP network is closer to the measured value, and the forecasting accuracy is precise, having certain extension, unknown engineering can be reasonable forecast.

When the network testing is finished and testing effect is good, it can undertake subsidence prediction, using this design neural network to predict final settlement of soft ground foundation. Suppose that embankment design service life is 3.5 years, predicting samples and predicted result is 0.590 mm.

Specification recommends several subsidence prediction methods: Peribe method, the Equilibrium method and three points to predict embankment settlement and the final settlement, and compare the calculation results with BP network. For example, in monitoring section of L100 + 680, the final predict settlement of this section is in Table 2 and shown in Figure 4.

5- CONCLUSION

Back-propagation neural network are used to demonstrate the feasibility of ANNs to predict the settlement of foundations on soft clay soils. More than Actual field measurements for settlement of stone column under soft soils were used for model development and verification. The predicted settlements obtained by using ANN and three other conventional methods were compared with the measured settlements. The results indicate that back-propagation neural networks have the capability of predicting the settlement of stone column under soft clay soil with a high degree of accuracy. The results also demonstrate that the ANN method outperforms the conventional methods for an independent validation set. The ANN method has another advantage over the conventional methods in that once the model is trained; the model can be used as an accurate and quick tool for estimating the settlement of shallow foundations. In contrast with the conventional methods, the ANN method does not need any manual work such as using tables or charts to calculate the settlement.

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Table 1 Measured and predict settlement of test sample

Phi	s/D	L/D	H	T	S_{total} (Field)	S_{total} (ANN)	Residual
27.5	3.33	13.33	10.5	1000	0.7042	0.7573	0.0531
30	2.5	2.5	1	4	0.0388	0.0407	0.0019
30	3.33	13.33	4	54	0.2233	0.2342	0.0109
30	2	2	1	4	0.0358	0.0376	0.0018
35	2	2	1	4	0.0356	0.0376	0.0020
35	2	2	10.5	1000	0.6212	0.6752	0.0539
35	2	4	7	56.5	0.3091	0.0336	-0.2756
40	3.33	3.33	4	11	0.1901	0.2024	0.0123
40	1.67	3.33	1	4	0.0283	0.0302	0.0019
42	2.5	5	1	4	0.0313	0.0340	0.0026

Table 2 Total settlement results with compared various method

Forecast Period	Peribe Method	Equilibrium Method	FEM Method	BP Artificial Network
Total settlement(m)	0.568	0.545	0.570	0.590
Actual settlement(m)	0.840	0.883	0.810	0.920

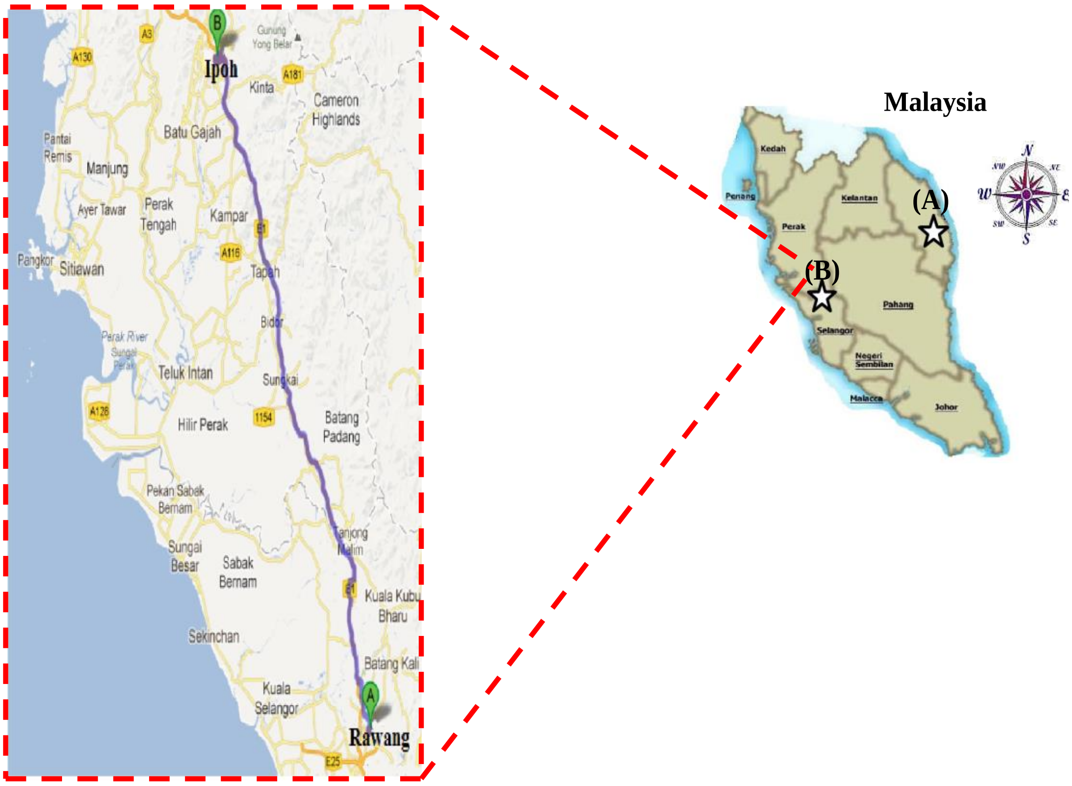

Figure 1 Location of study sites in Malaysia

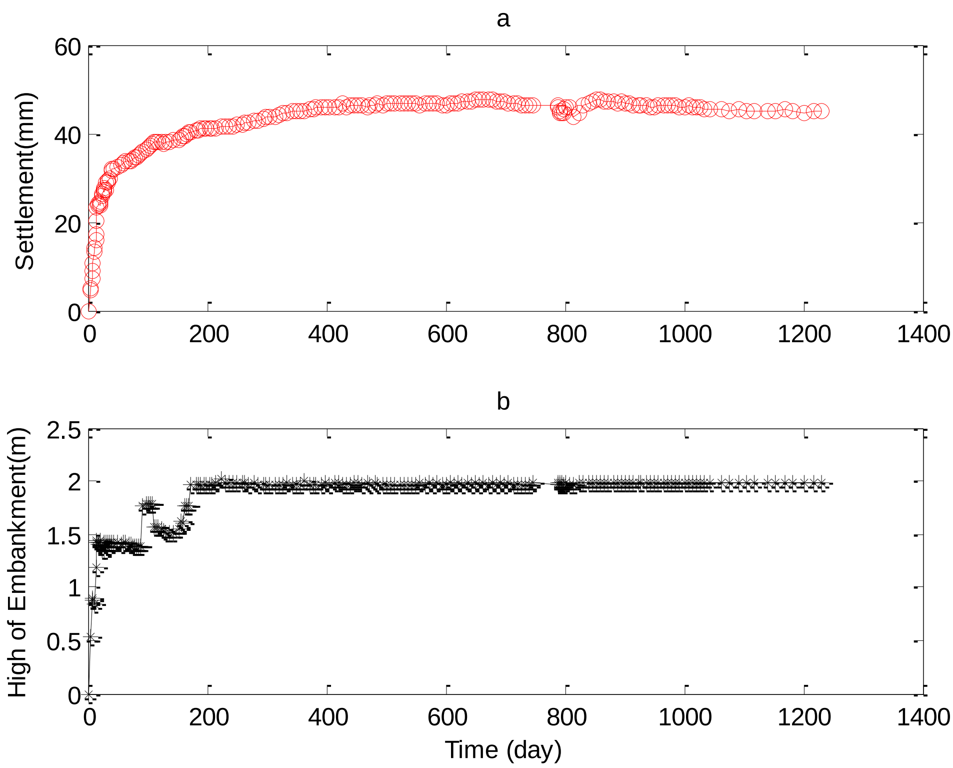

Figure 2 Stone columns behaviour under embankment: (a) settlement vs. time, (b) Relationship between

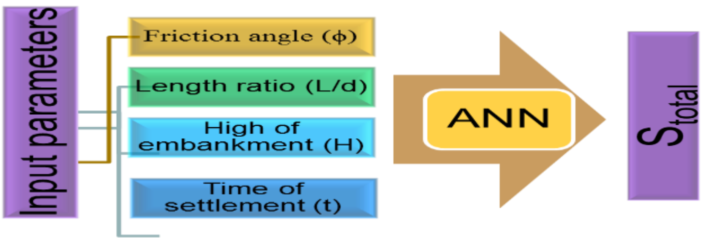

Figure 2 Input parameters, settlement of stone column parameter (output), artificial intelligent methods

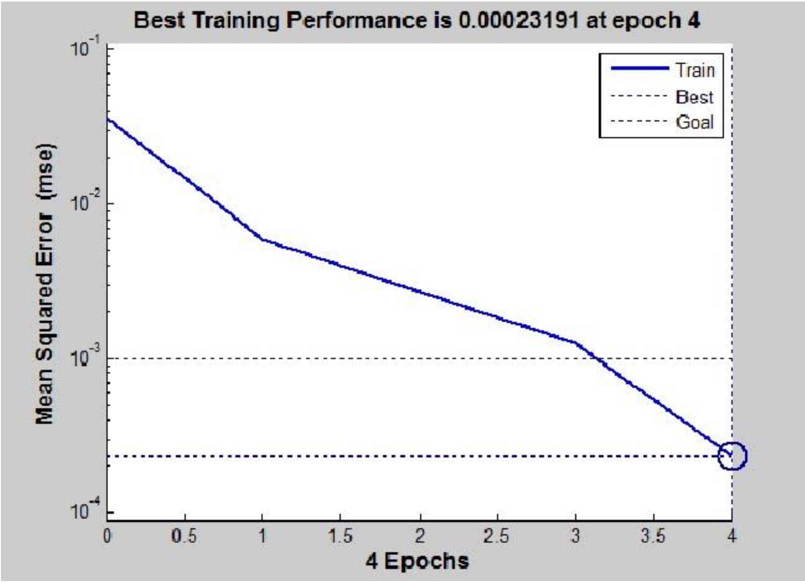

Figure 3 Plot of errors versus training epochs.

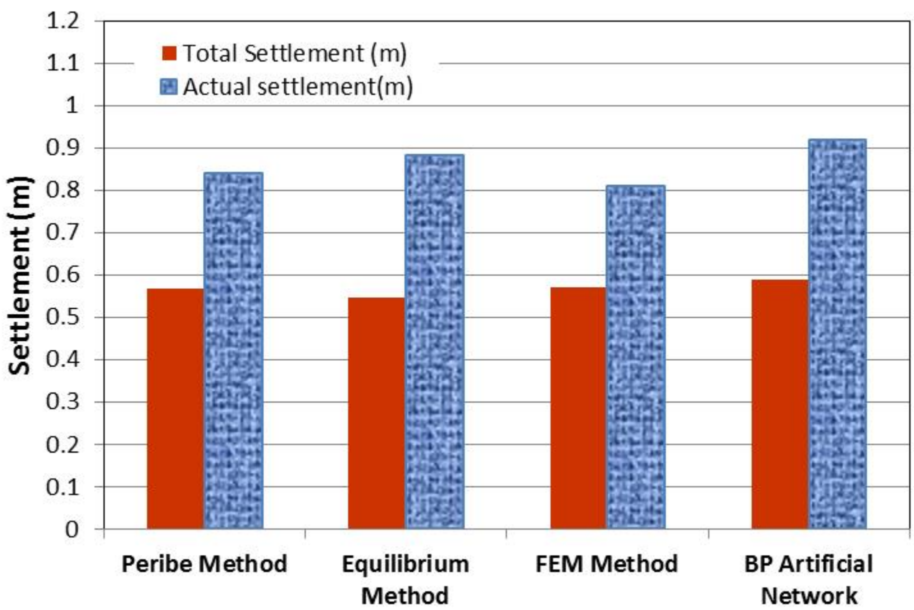

Figure 4. Compare various settlement methods of stone columns under embankment

الخلاصة:

ان بيانات هبوط التربة الطينية الضعيفة تحت حمل السدة الترابية للطرق السريعة لاحدى مشاريع في ماليزيا تم استخدامها لبناء موديل ذكي بطريقة الذكاء الاصطناعي.حيث تم تنبؤ الهبوط النهائي ومن ثم مقارنة النتائج مع الطرق التقليدية الحقلية وتبين ان تصرف منحني الهبوط للعمود الحجري تحت حمل الطريق السريع باستخدام موديل الذكاء الاصطناعي والذي يعطي نتائج اكثر دقة من الطرق التقليدية الشائعة الاستخدام وتجنب الاخطاء في القياس.