ARTIFICIAL NEURAL NETWORK (ANN) MODEL IN PREDICTING MULTI - LAYERED GROUND SETTLEMENTS OF METRO TUNNEL

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Abstract: *Artificial neural networks (ANNs) have been successfully applied to many engineering problems. In this paper, an ANN model is developed in predicting multi-layered ground settlements over time of metro tunnel. The criterions to evaluate the accuracy of the models are the coefficient of correlation, r, and the lowest root mean square error, RMSE. Comparing the predictions data with the measured data, the result indicate that ANN might be used for predicting multi-layered ground settlements over time at once. It's hard to carry out if using the traditional methods.*

Keywords: *Prediction, artificial neural network (ANN), ground settlements, metro tunnel.*

Tóm tắt: *Mạng nơ-ron nhân tạo (artificial neural network - ANN) đã được áp dụng thành công trong nhiều vấn đề của khoa học kỹ thuật. Bài báo này sẽ phát triển một mạng nơ-ron nhân tạo (ANN) để dự đoán độ lún của nhiều lớp đất theo thời gian của đường hầm metro. Độ chính xác của mô hình sẽ được đánh giá qua hai chỉ số: Hệ số tương quan (r) và căn bậc hai của độ lệch bình phương trung bình (RMSE). So sánh kết quả dự đoán và kết quả đo cho thấy: mạng nơ-ron nhân tạo (ANN) hoàn toàn có thể sử dụng để dự báo một lúc đồng thời độ lún của nhiều lớp đất theo thời gian – một điều khó khi sử dụng các phương pháp truyền thống.*

Từ khóa: *Dự đoán, mạng nơ ron nhân tạo (ANN), lún mặt đất, hầm metro.*

1. Introduction

In the last few decades, artificial neural network (ANN) has been successfully applied to virtually many engineering problems. In foundation design, ANNs have been applied in predicting the axial - lateral load capacity of pile foundations, drilled shafts, ground anchors [2]; the bearing capacity and the settlement of shallow foundations [12]. ANNs have also been used for site characterization [9], mining [10], dams [6], slope stability [3], earth retaining structures [7] and geoenvironmental engineering [14]. Within the tunneling and underground technology, [16] applied the artificial neural networks for predicting the maximum surface settlement caused by EPB shield tunneling, [4] also developed a hybrid particle swarm optimization (PSO) algorithm-based ANN to predict the maximum surface settlement and inflection points in transverse and longitudinal directions. Interestingly, no studies have been performed on predicting multi-layered ground settlements over time of metro tunnel using ANNs.

Recently, ANN has also been attaching special importance to applications in different areas in Viet Nam. However, within building – construction area, application of ANN just all start and has not been studied deeply. The reason might be the lack of big data, or good data set, which can come and handy for model training, or deep learning.

In this paper, an ANN model is developed in predicting multi-layered ground settlements over time of metro tunnel. The criterions to evaluate the accuracy of the models are the coefficient of correlation, r, and the lowest root mean square error, RMSE. The measured data is referenced from [15]. The relative conclusions would be drawn by comparing the predictions data with the measured data.

2. Overview of artificial neural networks

Artificial neural networks (ANNs) are numerical modeling techniques inspired by the functioning of the human brain and nervous system [13]. The purpose of ANNs is similar to conventional statistical models, which is to determine the relationship between the model inputs and corresponding outputs. However, ANNs only use the data and do not require predefined mathematical equations of the relationship between the inputs data and outputs data. This allows ANN to get pass the limitations of the conventional models.

A Multi-layer feed-forward with the back-propagation algorithm training [11] is used in this study. The multi-layer feed-forward neural network is composed of several processing elements (called nodes or neurons). The processing elements are fully or partially connected via connection weights, and they are often classified into layers: an input layer; an output layer; and hidden layers (layers in between).

Many authors already described the structure and operation of ANNs. Figure 1 shows the structure and operation of an ANN depicted by M. A. Shahin [13]. At each processing element, the input from the processing element of the previous layer (x_i) is multiplied by an adjustable connection weight (w_{ji}), and weighted inputs are summed and a bias (θ_j) is added or subtracted. The combined input (I_j) is then passed through a non-linear transfer function (f(.)) (e.g. sigmoidal function or tanh function) to produce the output of the processing element (y_j).

The training of the multi-layer feed-forward neural network starts at the input layer, after that, a learning rule is used to obtain the network output (Figure 1). The weights and the bias are adjusted in order to get the smallest possible error between the desired output and the output which is obtained from the preview step. As soon as the training phase is accomplished, the trained model would be validated by an independent testing set. Several of steps used to development an ANN are discussed by Maier & Dandy [8].

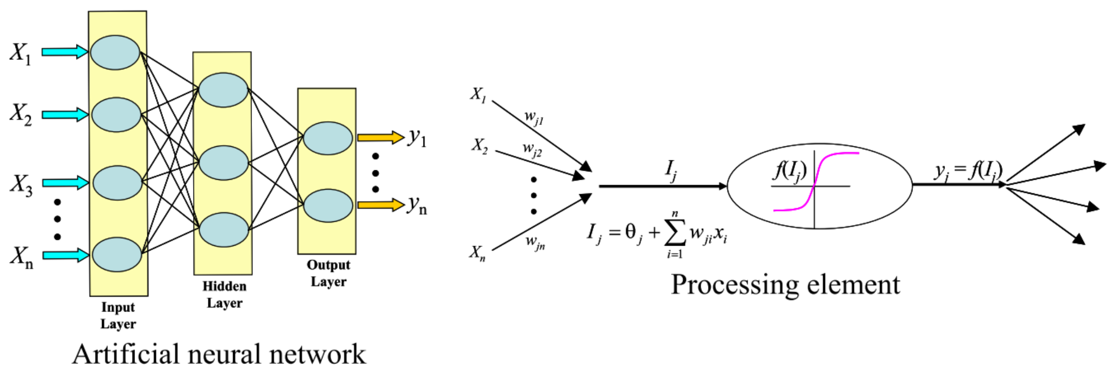

Figure 1. *Structure and operation of an ANN [13]*

3. Development of the ANN model

An artificial neural network (ANN) model has been developed for the estimation of layered ground settlements over time of metro tunnel with the aid of the software package PYTHON Version 3.6, using a database from [15] (Figure 5).

3.1 Data division and preprocessing

Good data set is an urgent need for training ANN. The bigger data (not including error data), the more accuracy of ANN. However, if the input variables are too much and some of them do not affect the output variables, the ANN would become vague. The output variables would be scattered over the place.

In this paper, monitoring data includes time and layered ground settlements, thus, the time is chosen as an input variable and two layered settlements (1m - 309.2m and 28.2m - 309.2m) are chosen as output variables.

The data have been divided into two subsets, training set for model calibration and validation set for model verification. As the rules, the purpose of prediction of the settlement over time is estimating the settlement at the next step. Thus, the data from the beginning to 2725 days are allocated for the training data. The last four monitoring data are used for model verification.

In order to minimize the dimension of the variables and to make sure that all variables get equal attention during the training process, the preprocessing is conducted by scaling the input and output variables between 0.0 and 1.0. The scaled value of each variable x, x_n, is calculated as follows:

$$x_n = x / x_{max} \quad [1]$$

Where: x_{max} is maximum values of each variable x.

3.2 Model architecture, weight optimization and stopping criterion

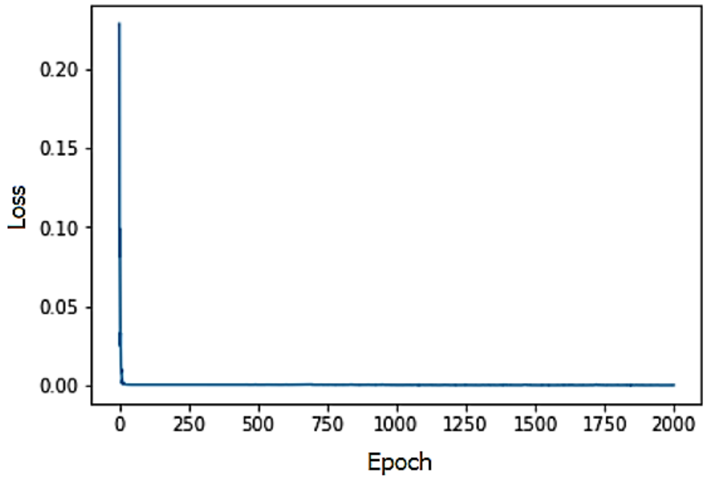

Figure 2. *Variation of loss against epoch*

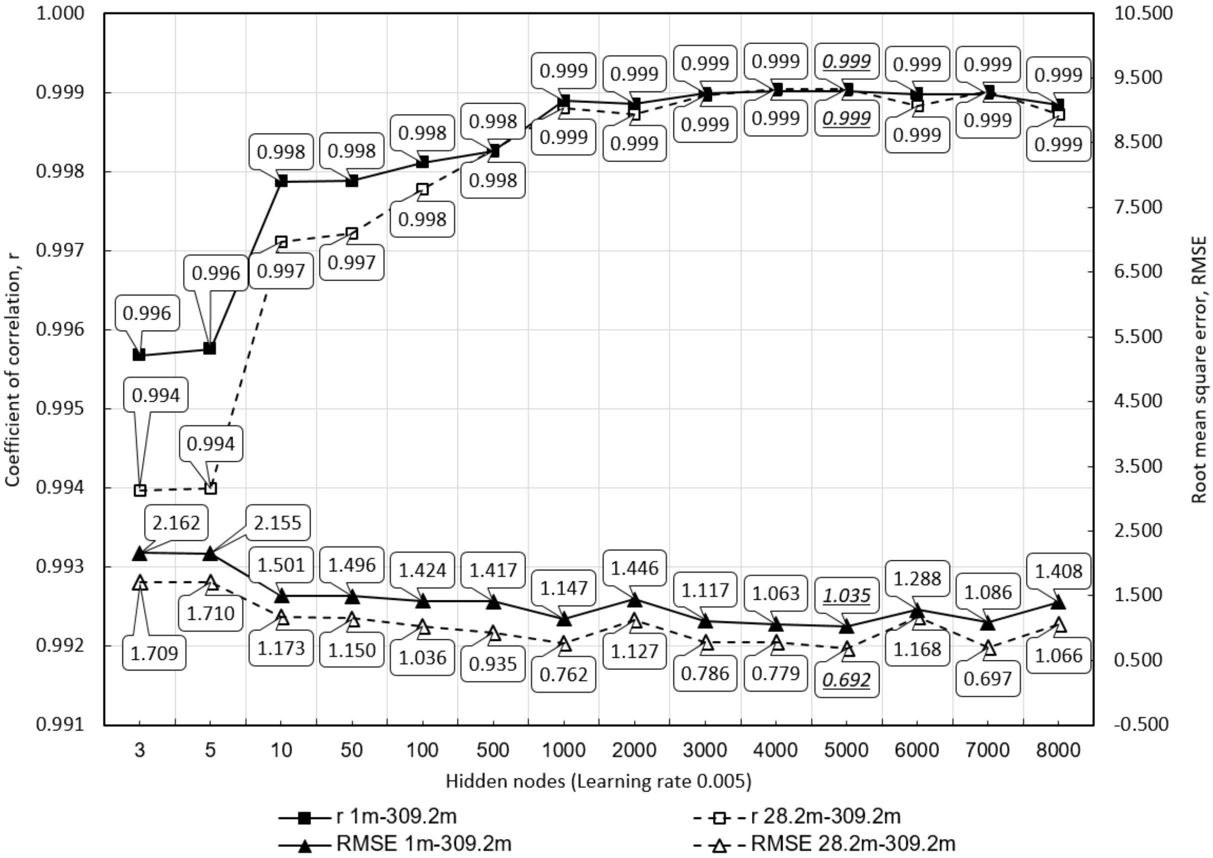

Figure 3. *Effect of number of hidden layer nodes on performance of ANN model*

The model geometry (i.e. the number of hidden layers, the number of hidden nodes in each layer) and weight optimization (i.e. learning rate and momentum term) play a major role in the development of the ANN models.

Hornik, 1989 [5] noted that a network with one hidden layer can approximate any continuous function provided that sufficient connection weights are used. Thus, one hidden layer is used in this ANN model.

ReLU and *tanh* are selected as transfer functions in the hidden and output layers. The 2000 training cycles (epochs) is used to terminate the training process. This number basically satisfies the requirement that there is no significant improvement in the error occurs. The training loss at the end of the training process does not fluctuate and does not increase (Figure 2).

Caudill, 1988 [1] noted that 2I+1 hidden layer nodes are the upper limit needed to map any continuous function for a network with I number of inputs. However, based on the effect of the number of hidden nodes on the performance of ANN model

(Figure 3), the ANN model with 5000 hidden nodes has the lowest prediction error (the highest coefficient of correlation, r, and the lowest root mean square error, RMSE). The number of hidden nodes using for ANN model in this paper is much more than the number of hidden nodes recommended and used by authors [1] before.

The effect of learning rate on the performance of ANN models is shown in Figure 4. It can be seen that the ANN model with the learning rate 0.005 has the lowest prediction error. The gradient descent optimization algorithm is Adam. It already incorporates something like momentum, thus, the momentum term is not examined.

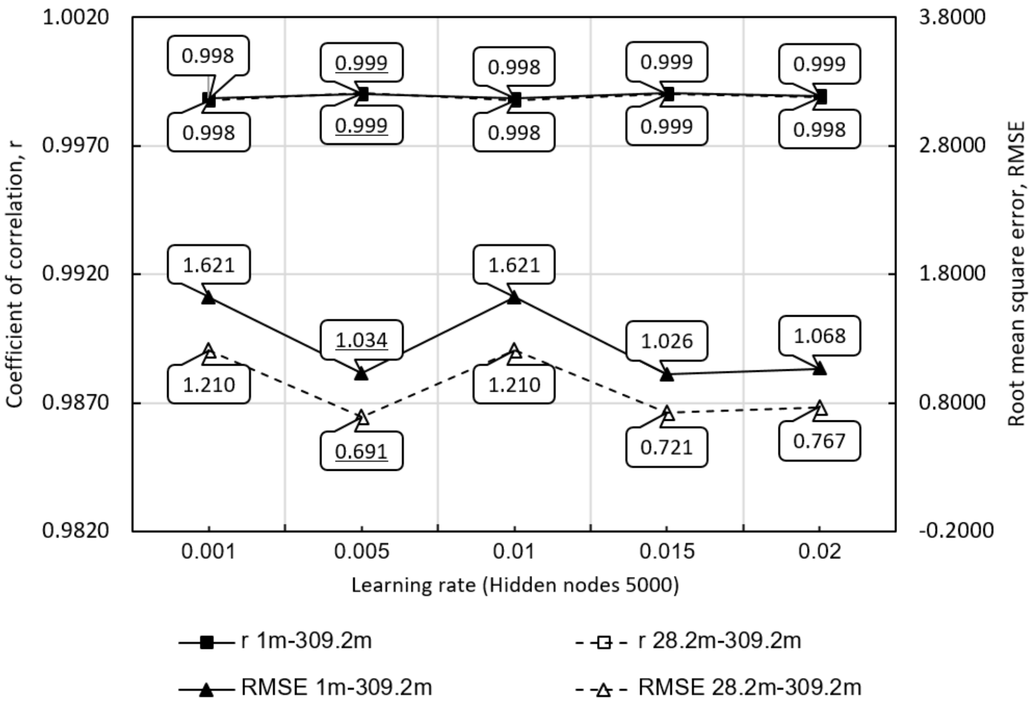

Figure 4. *Effect of learning rate on performance of ANN model*

4. Model validation

Figure 5 shows the predicted data and the measured data. The predicted data show acceptable agreement with the measured data. The performance of the ANN model in the training and validation sets (Figure 6 and Figure 7) also validates that. The ANN model has minimum scatter around the line of equality between the measured and predicted data (almost is in range of less than 10%).

The models have high coefficients of correlation, r (0.999), in the training test. However, some predicted value of the ANN model is beyond and above the accuracy line 10% (see Figure 5, Figure 6 and Figure 7). It can be seen that the accuracy of ANN model tends to decrease each time the ground settlements change suddenly or quickly. The decrement of accuracy also happen if the next predicted data is far from the last data in training set (Table 1). Thus, in order to guaranty the best performance of the ANN model, the elapsed time between each measured data should to be shorter. The more constantly measured data the best performance of ANN model. That’s why the ANN or AI (artificial intelligent) would not be better off without big data.

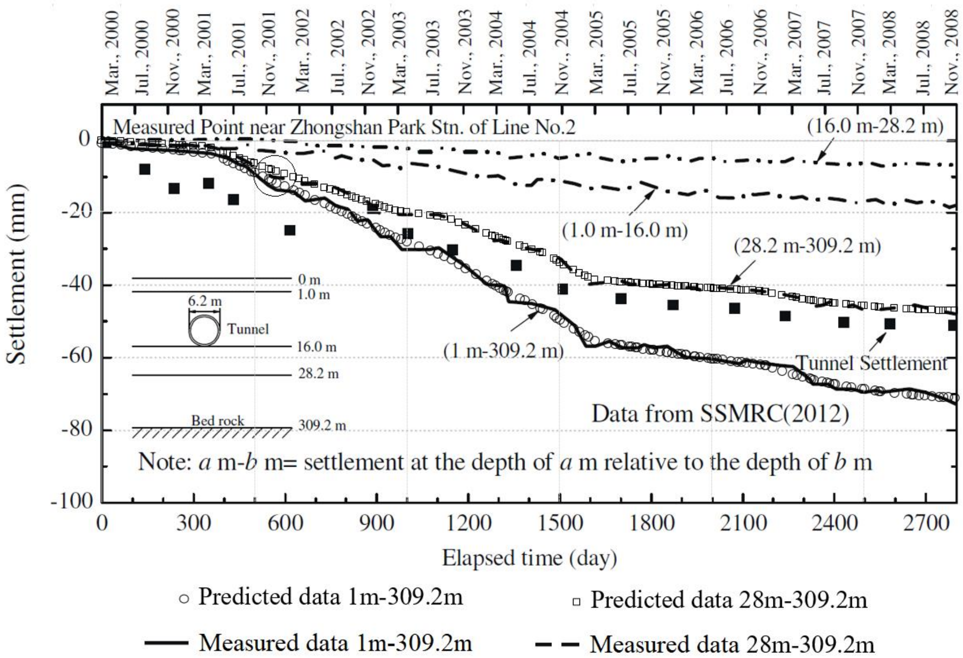

Figure 5. *Predicted data (this study) and measured data [15]*

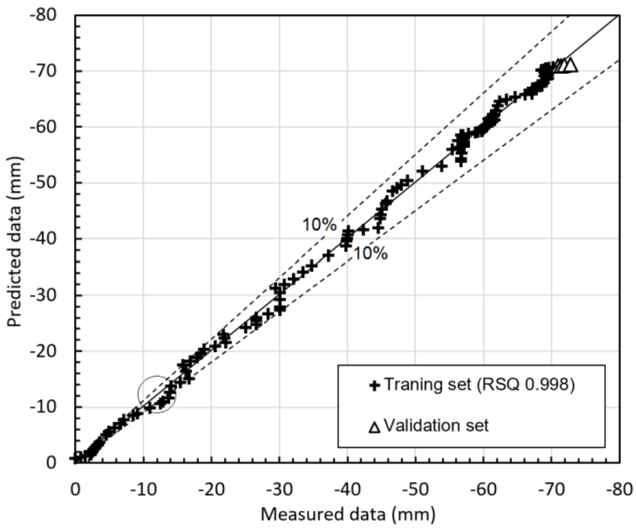

Figure 6. *Scatterplots of predicted versus measured data for settlement (1m-309.2m)*

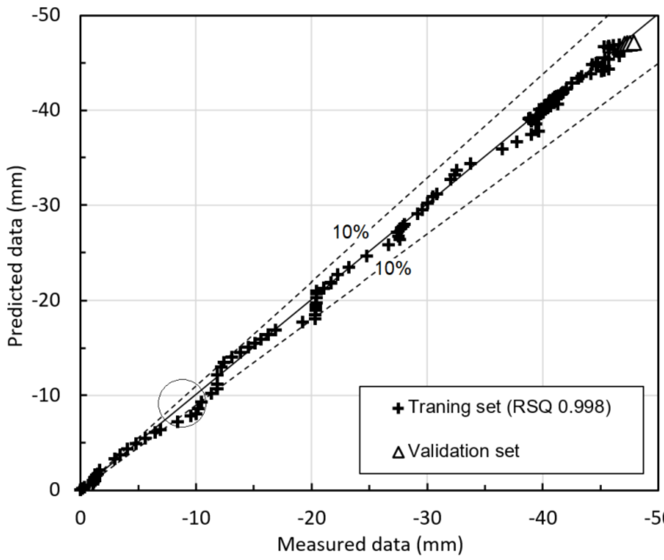

Figure 7. *Scatterplots of predicted versus measured data for settlement (28m-309.2m)*

Table 1. *Accuracy of ANN model (validation set)*

No	Elapsed time (day)	Settlement (1m-309.2m) (mm)			Settlement (28m-309.2m) (mm)		
		Measured value	Predicted value	Accuracy (%)	Measured value	Predicted value	Accuracy (%)
1	2748	-70.93	-70.88	-0.06	-47.04	-46.99	-0.12
2	2762	-71.42	-70.97	-0.63	-47.33	-47.03	-0.62
3	2777	-71.91	-71.05	-1.19	-47.54	-47.07	-0.99
4	2800	-72.82	-71.17	-2.27	-47.88	-47.13	-1.55

5. Conclusion

After comparing the predicted data with the measured data, the following conclusions can be drawn:

- ANN might be used for predicting multi-layered ground settlements over time of metro tunnel with hight acucracy at once. It’s hard to carry out by using the traditional methods;

- The ANN model with 5000 hidden nodes has the lowest prediction error in predicting multi-layered ground settlements over time of metro tunnel. The number of hidden nodes is much more than the hidden nodes discussed by [1];

- The models also have high coefficients of correlation, r, in the training test. However, the accuracy of ANN model tends to decrease each time the ground settlements change suddenly or quickly. It also happens if the next predicted data is far from the last data in training set. Thus, the constantly measured data is vital in order to guaranty the best performance of the ANN model.

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