PREDICTION OF SETTLEMENT OVER TIME FOR ROAD CONSTRUCTION IN BAC NINH AND HAI DUONG PROVINCE OF VIETNAM USING ANNS MODELS

DỰ BÁO LÚN THEO THỜI GIAN CHO XÂY DỰNG ĐƯỜNG Ở BẮC NINH VÀ HẢI DƯƠNG BẰNG MẠNG NƠ RON NHÂN TẠO

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Abstract: *Artificial neural networks (ANNs) have been applied successfully to virtually every problem in the predictions of the settlement. However, there is not much research on predicting the settlement over time. In this paper, an ANN model is developed and compared with two traditional methods (Asaoka method and the method of Asaoka combined with Polynomial) in predicting the settlement of two cases of road construction. The criterions to evaluate the accuracy of the models are the R squared (R) and the mean square error (MSE). Comparing the criterions of these models, and the predictions data of these models with the monitoring data, the result indicates that ANNs should be used for predicting settlement over time without knowing parameters related to the surcharge and soil.*

Keywords: *Prediction, artificial neural network (ANN), ground settlements, road construction.*

Tóm tắt: *Mạng nơ-ron nhân tạo (artificial neural network - ANN) đã được áp dụng trong các vấn đề dự báo độ lún. Tuy nhiên chưa có nhiều nghiên cứu về dự báo độ lún theo thời gian. Trong bài báo này một mô hình mạng nơ-ron nhân tạo sẽ được phát triển để dự báo độ lún của hai công trình xây dựng đường khác nhau. Kết quả dự báo sẽ được so sánh với hai phương pháp truyền thống (phương pháp Asaoka và phương pháp Asaoka kết hợp đa thức). Độ chính xác của mô hình sẽ được đánh giá qua hai chỉ số: Hệ số tương quan bội (R^2) và sai số toàn phương trung bình (MSE). So sánh kết quả dự đoán của các mô hình với kết quả thực tế có thể thấy: nên sử dụng mạng nơ-ron nhân tạo (ANN) để dự báo lún theo thời gian trong quá trình thi công đường.*

Từ khóa: *Dự đoán, mạng nơ ron nhân tạo (ANN), lún mặt đất, xây dựng đường.*

1. Introduction

Artificial neural network is a branch of the 'artificial intelligence', which also includes case-based reasoning, expert systems, and genetic algorithms [19]. The efficient manipulation of large amounts of data and the ability to generalize results are the main advantages of neural networks [23]. Thus, the applications of the artificial neural network have been found in innumerable fields [2, 4, 10-15, 18, 21, 22].

In the last few decades, artificial neural networks (ANNs) have been successfully applied to virtually every problem in the predictions of the settlement problems. Alkroosh and Nikraz [10] simulated the load-settlement behavior of pile foundations embedded in sand and mixed soils (subjected to axial loads) by artificial neural networks (ANNs). The results indicated that the ANN model performed very well after comparing predictions from the ANN with predictions of number of currently adopted load-transfer methods. Ismail and Jeng [13] developed a high-order neural network (HON) for simulating the pile load–settlement curve using properties of the pile and SPT data along the depth of pile embedment as inputs. The HON model presented better predictions than the predictions of elastic and hyperbolic models. Shahin, Jaksa [8] presented a new hand-calculation design formula for settlement prediction of shallow foundations on granular soils based on a more accurate settlement prediction from an artificial neural network model. The model had five inputs (the footing width, net applied footing load, average blow count, obtained using a standard penetration test (SPT) over the depth of influence of the foundation as a measure of soil compressibility, footing geometry, and footing embedment ratio), and one output (foundation settlement). Shahin, Jaksa [20] developed a set of charts incorporating the uncertainty associated with the ANN method, which enable the designer to make informed decisions about the level of risk correlated with predicted settlements.

It can be seen that there is not much research on predicting the settlement over time. In this paper, an ANN model is developed and compared with two traditional methods (Asaoka method and the method of Asaoka combined with Polynomial) in predicting the settlement of two cases of road construction. The parameters of two traditional methods are referenced from Tran, Nguyen [9]. The criterions to evaluate the accuracy of the models are the R squared (R^2) and the mean square error (MSE). The relative conclusions would be drawn by comparing the criterions of these models, and the predictions data of these models with the monitoring 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 [7].

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 past the limitations of the conventional models.

A Multi-layer feed-forward with the back-propagation algorithm training is used in this study [6]. 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 have already described the structure and operation of ANNs. Figure 1 shows the structure and operation of an ANN depicted by Shahin [7]. 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 the steps used to develop an ANN are discussed by Maier and Dandy [5].

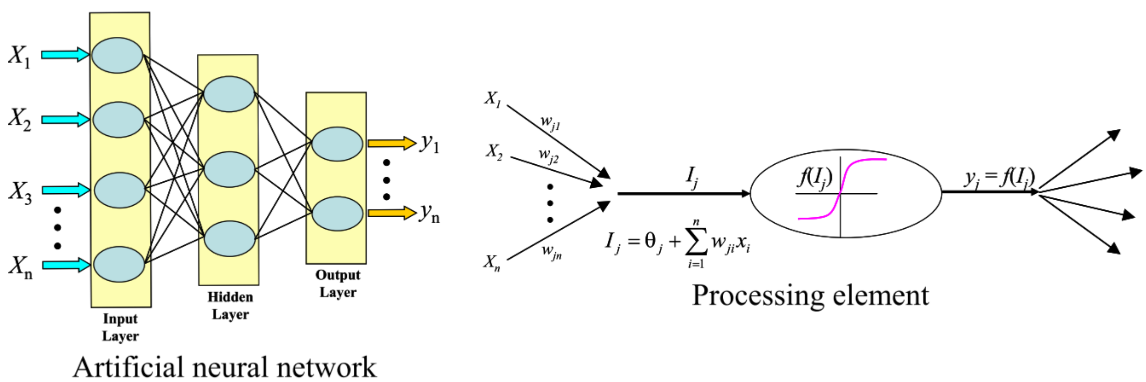

Figure 1. *Structure and operation of an ANN [7]*

3. Development of the ANN model

The ANN model is created with the aid of the software package PYTHON Version 3.6. The constructed sites of two roads were located in Bac Ninh and Hai Duong province with different soil types and geotechnical conditions. The data used to calibrate and validate the ANN model are shown in Table 1 and Table 2.

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Table 1. *Road surface settlement over time in the first case [9]*

No	Time (day)	Field data (mm)	No	Time (day)	Field data (mm)	No	Time (day)	Field data (mm)
1	1	-2	14	63	-60	27	115	-290
2	6	-6	15	68	-65	28	118	-295
3	10	-9	16	71	-70	29	125	-310
4	14	-13	17	75	-94	30	131	-325
5	20	-19	18	78	-112	31	138	-340
6	24	-29	19	82	-125	32	145	-360
7	27	-32	20	86	-141	33	152	-381
8	31	-35	21	92	-155	34	159	-395
9	35	-37	22	96	-172	35	166	-411
10	39	-42	23	100	-189	36	173	-425
11	46	-49	24	104	-214	37	179	-439
12	52	-54	25	108	-242			
13	57	-56	26	110	-262			

Table 2. *Road surface settlement over time in the second case [9]*

No	Time (day)	Field data (mm)	No	Time (day)	Field data (mm)	No	Time (day)	Field data (mm)
1	4	-1	17	280	-52	33	515	-92
2	23	-3	18	298	-53	34	522	-95
3	43	-4	19	319	-54	35	531	-99
4	61	-6	20	333	-55	36	547	-103
5	90	-7	21	350	-57	37	566	-108
6	111	-8	22	363	-58	38	578	-112
7	140	-10	23	375	-60	39	587	-115
8	158	-13	24	384	-61	40	599	-117
9	165	-19	25	398	-65	41	613	-118
10	172	-25	26	403	-68	42	636	-118
11	181	-28	27	417	-74	43	662	-121
12	197	-35	28	438	-78	44	683	-123
13	209	-38	29	459	-81	45	704	-125
14	226	-45	30	474	-82	46	726	-126
15	237	-47	31	494	-86	47	782	-127
16	254	-50	32	502	-89			

3.1 Data division and preprocessing

Monitoring data includes time and settlement, thus, the time was chosen as an input variable and settlement was chosen as an output variable.

The data have been divided into two subsets, training set for model calibration and validation set for model verification. All the methods in this paper are developed for the purpose of predicting the settlement at the next step. Thus, the data from the beginning to 159 days and the data from the beginning to 683 days are allocated for the training data in the first and the second case, respectively. The last three monitoring data are used for model verification.

In order to minimize the dimension and to make sure all variables get equal attention during training, 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

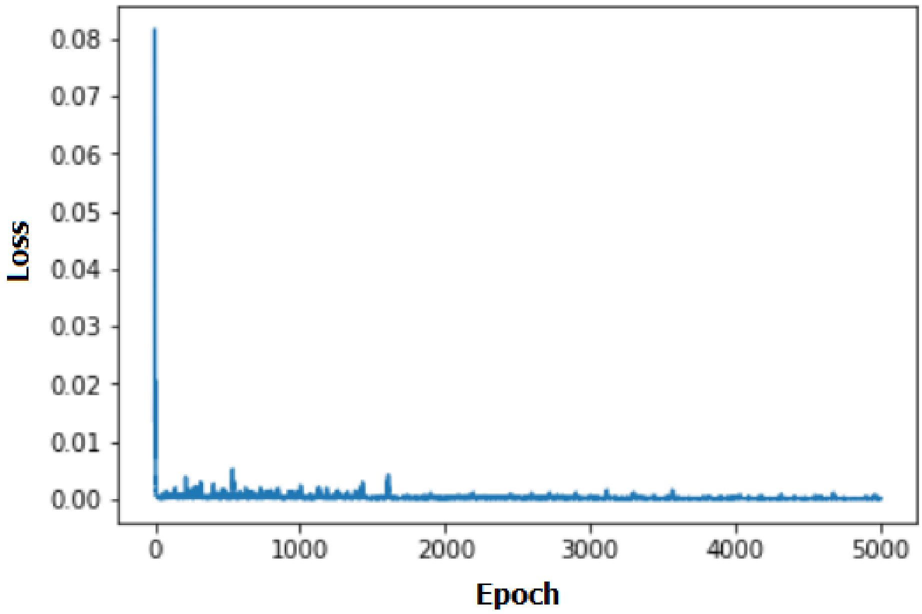

Figure 2. *Variation of loss against epoch*

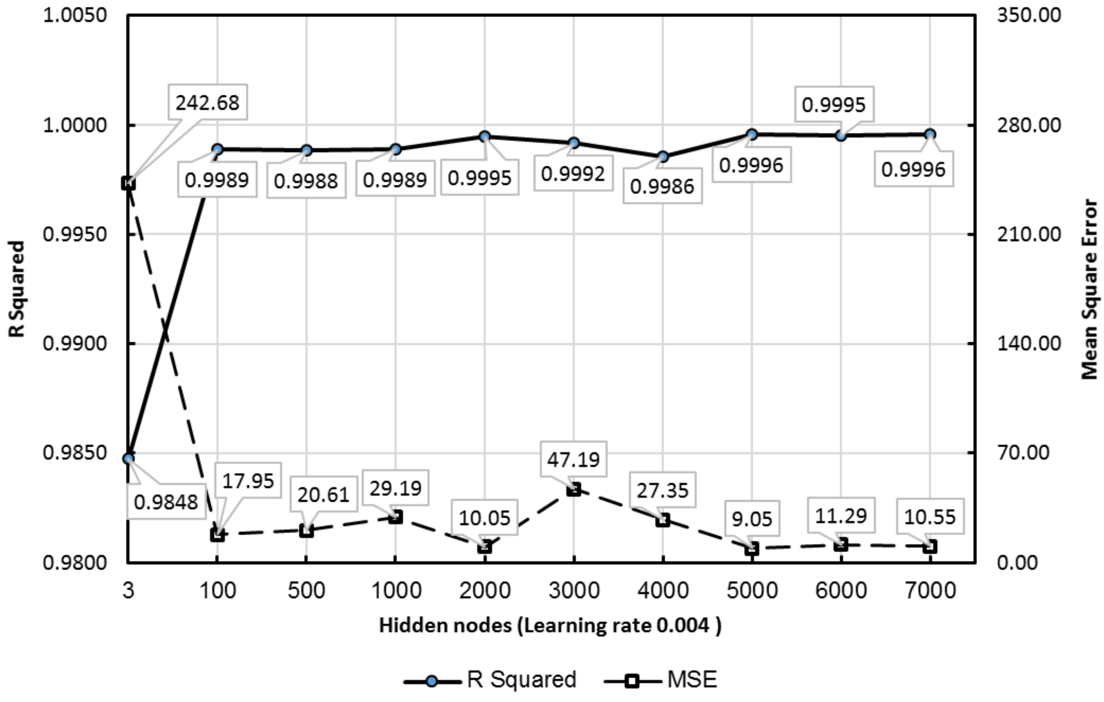

Figure 3. *Effect of number of hidden layer nodes on performance of ANN model*

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, Stinchcombe [3] 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 (*ReLU* and *tanh* are activation functions, which outputs a small value for small inputs, and a larger value if its inputs exceed a threshold; ReLu: f(x) = max(0,x); Tanh: $f(x) = (e^x - e^{-x})/(e^x + e^{-x})$). The 5000 training cycles (epochs) is used to terminate the training process, which is the same as the training cycles previously published by Shahin [7]. This number basically satisfies the requirement that there is no increase in the error. The training loss at the end of the training process does not fluctuate and does not increase (see Figure 2).

Caudill [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 value of the R squared and the lowest value of the mean square error). 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 Caudill [1] before.

The learning rate is a tuning parameter in an optimization algorithm that determines the step size at each iteration while moving toward a minimum of a loss function [17]. 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 of 0.01 has the lowest prediction error. The prediction errors tend to increase at the larger learning rate. The gradient descent optimization algorithm is Adam optimizer. It already incorporates something like momentum, thus, the momentum term is not examined.

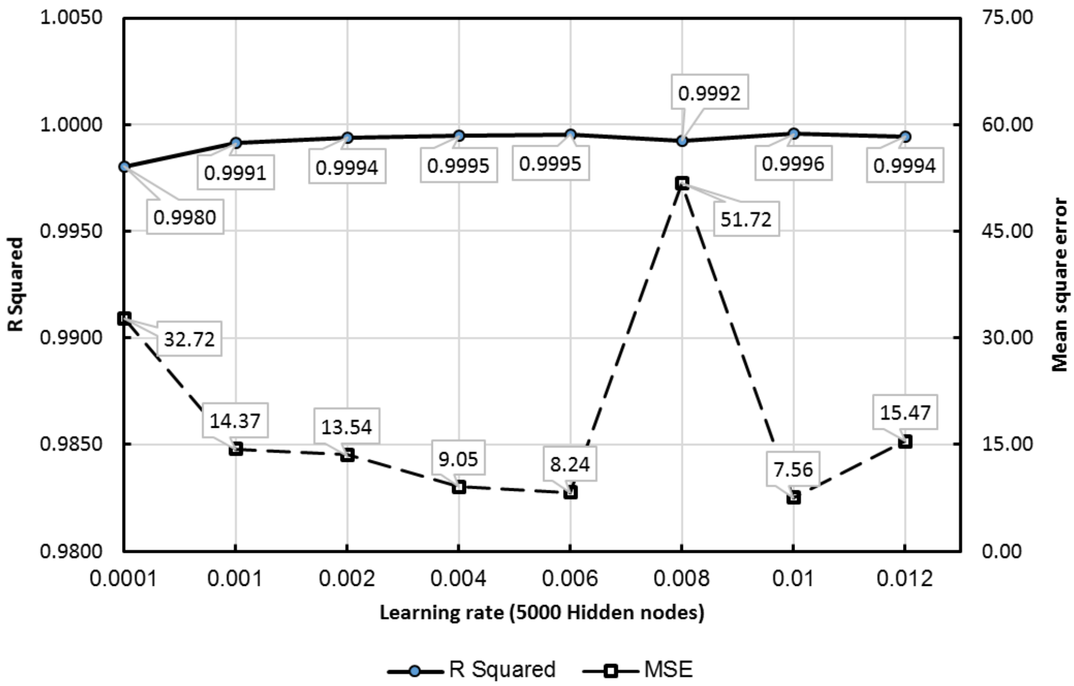

Figure 4. *Effect of learning rate on performance of ANN model*

4. Comparison of ANN model with difference methods

The performance of the ANN models and two traditional methods for the first case is summarized in Table 3. It may be seen that the ANN 1 model performs well; as it has the highest value of R squared (0.9996), and lowest value of mean squared errors (7.6) for the training data set. However, the next three predicted data (validation set) of the ANN 1 model does not even draw a line of best fit between predicted data and field data (Figure 4 and Figure 5). It also validates that, like all empirical models, ANNs perform best in interpolation rather than extrapolation [16].

Table 3. *Performance of the models for first case*

Name of Method	Equation (or Model architecture)	R squared (traning data)	MSE
Asaoka	$S_{ti} = -6.0372 + 1.0423 * S_{ti-1}$	0.9976	37.4
Asaoka + Polynomial	$S_{ti} = -9.838 + 0.4776 * t_i - 0.0117 * t_i^2 + 4.474 * t_i^3 + 0.9096 * S_{ti-1}$	0.9985	24.0
ANN 1	5000 Hidden nodes; lr 0.01; epochs 5000	0.9996	7.6
ANN 2	5000 Hidden nodes; lr 0.008; epochs 5000	0.9992	51.7

Table 4. *Field data and Prediction data for first case*

Time (day)	Measurement (mm)	Prediction (Diviation) (mm)					
		Asaoka		Asaoka + Polynomial		ANN 1	
166	-411	-418	(-7)	-407	(4)	-406	(5)
173	-425	-434	(-9)	-419	(6)	-414	(11)
179	-439	-449	(-10)	-429	(10)	-418	(21)

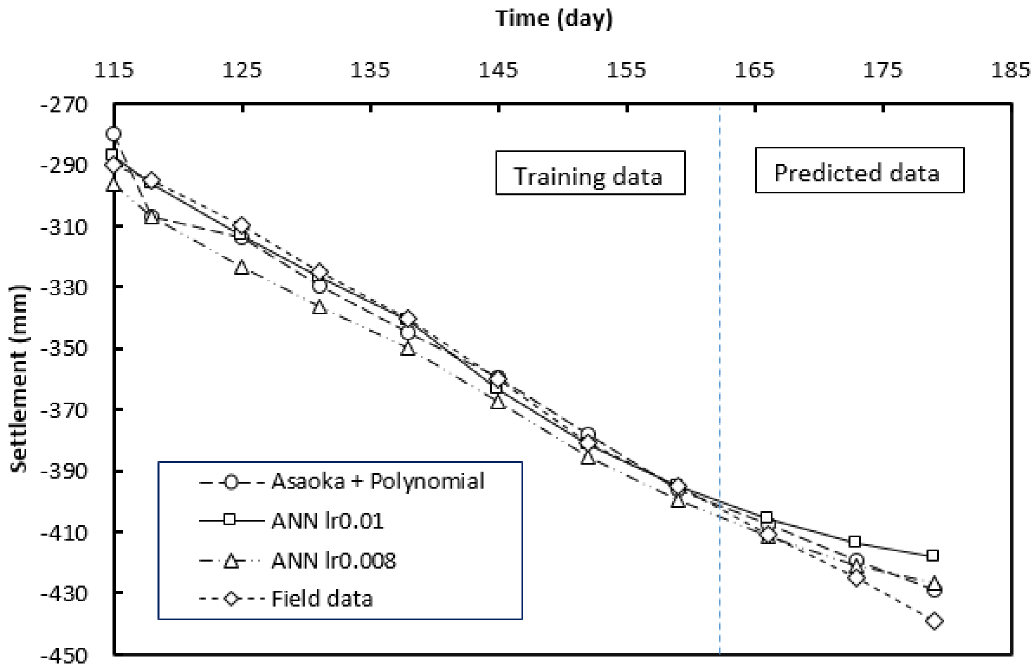

Figure 5. *Settlement for first case*

The method and the model performs well in predicting the next three data (validation set) is the Asaoka combined with Polynomial (AP) and ANN 2 (with 5000 Hidden nodes, learning rate 0.008 and epochs 5000). Though their criterions to evaluate the accuracy of the models in the training data set are not the best (the values of R squared are not the highest and the values of mean squared errors are not the lowest). This may due to the training data is not enough in this case.

Table 5 shows the performance of the ANN 1 model and two traditional methods for the second case. The ANN 1 model also performs well for the training data, as it has the highest value of R squared (0.9993), and lowest value of mean squared errors (1.2). However, in this case, the next three predicted data of ANN 1 model have a very small deviation from the field data (Table 6). It may be because the road has moved to the stage of the commissioning work. All the data given by the ANN 1 model creates the best fit line between predicted data and field data (Figure 6). Thus, when the training data is enough, the ANN method provides a more accurate prediction than traditional methods.

Table 5. *Performance of the models for the second case*

Name of Method	Equation (or Model architecture)	R squared (traning data)	MSE
Asaoka	$S_{ti} = -2.9164 + 0.9987 * S_{ti-1}$	0.9980	2.9
Asaoka + Polynomial	$S_{ti} = -1.159 - 0.0207 * t_i - 3*10^{-5} * t_i^2 - 2.2*10^{-8} * t_i^3 + 0.9598 * S_{ti-1}$	0.9981	2.8
ANN 1	5000 Hidden nodes; lr 0.01; epochs 5000	0.9993	1.2

Table 6. *Field data and Prediction data for the second case*

Time (day)	Measurement (mm)	Prediction (Diviation) (mm)					
		Asaoka		Asaoka + Polynomial		ANN 1	
704	-125	-126	(-1)	-127	(-2)	-125	(0)
726	-126	-128	(-2)	-129	(-3)	-126	(0)
782	-127	-129	(-2)	-130	(-3)	-127	(0)

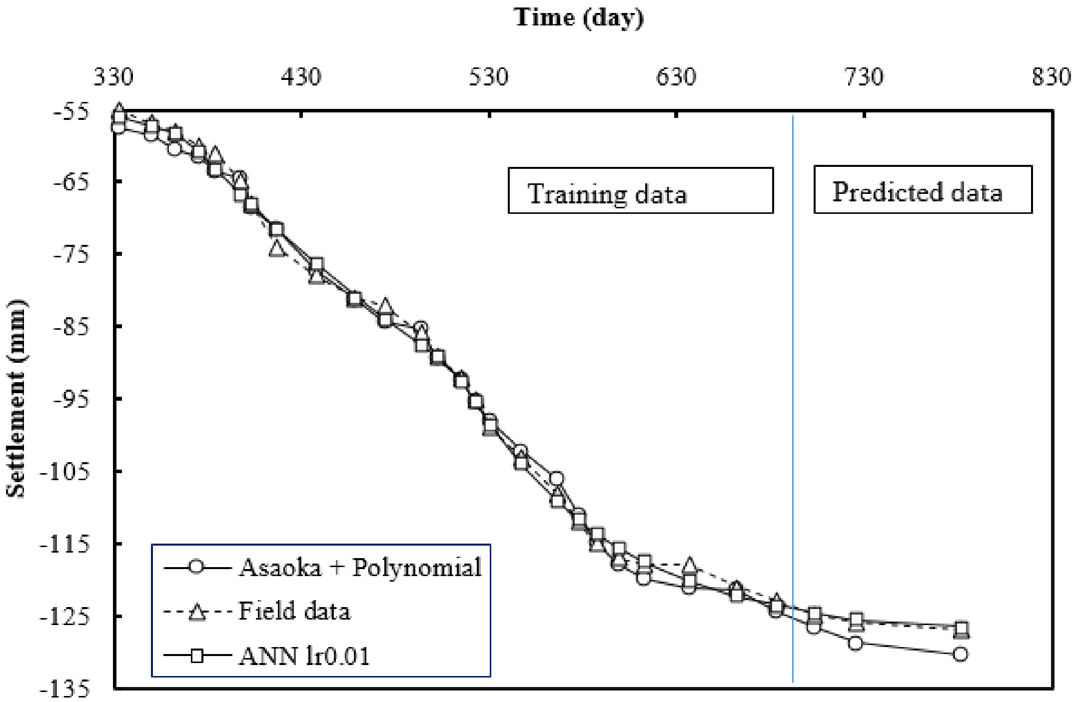

Figure 6. *Settlement for the second case*

5. Conclusion

After comparing the accuracy of ANN method with the accuracy of traditional methods (Asaoka method and the method of Asaoka combined with Polynomial) for predicting the settlement of two case histories, the following conclusions can be drawn.

- The ANN model with 5000 hidden nodes has the lowest prediction error in predicting settlement over time (time is input variable and settlement is output variable). The number of hidden nodes is much more than the hidden nodes discussed by Caudill [1];

- The criterions to evaluate the accuracy of the ANN model are much better than other models, however, the accuracy of the next three predicted data of the ANN models (validation set) is not good if it does not have enough training data (i.e. 34 data in the first case history);

- If the training data is enough (i.e. 44 data in the second case history) the accuracy the ANN model for the next three predicted data (validation set) is extremely high, and ANN model should be used for predicting settlement over time without knowing parameters related to the surcharge and soil.

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