Implementation of Artificial Neural Network for Prediction of Pavement Structure Strains at Critical Locations

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Abstract

Falling Weight Deflectometer (FWD) test is commonly used to evaluate the conditions of a pavement structure. The surface deflections measured by a FWD test are normally used in back-calculation analysis to determine the elastic Young's modulus of the pavement structure materials, which later on is inputted into a forward calculation, usually by a Linear Elastic Analysis (LEA), to determine the strains mobilised at the critical locations ($\varepsilon_{t,ac}$ and $\varepsilon_{c,sg}$) in the pavement structure for evaluation of the remaining life. It is of interest to develop a tool for predicting the values of $\varepsilon_{t,ac}$ and $\varepsilon_{c,sg}$ directly from the FWD deflections while bypassing the above-mentioned back- and forward calculations, which are highly time-consuming. In this research, artificial neural network (ANN), which is a function built-in MATLAB2020 program, was used as the tool for such a prediction. There are three types of pavement structures investigated, which are: i) cement-modified crushed rock base pavement structure; ii) combined-surface pavement structure; and iii) thin-surface pavement structure. A database consisting of the strains at the critical locations and the FWD deflections for each pavement structure type, which were obtained by data generating with LEA in the previous research, were used. The FWD deflections were transformed to various deflection basin parameters (DBPs), and then used to train ANN to correlate with the strains at the critical locations. By comparing the strains predicted by ANN with the ones from LEA as the input, it is found that, in general, the maximum error is around only 3%. In addition, the results predicted by ANN in the present study are substantially more accurate than the ones predicted by a non-linear regression method with statistical equations of the previous study. Hence, the developed ANN can be used to analyse the FWD deflections to determine the critical location's strains for evaluating the conditions of a pavement structure.

Keywords: Artificial Neural Network, Deflectometer, Deflection Basin Parameter, Falling Weight, Pavement Strains

1. Introduction

Artificial neural network (ANN) is a system that adapts from learning of neuron in human brain. It can learn from data by training to recognize patterns. Falling Weight Reflectometer (FWD) is a nondestructive test device used for evaluating pavement structure responses and assessing the structural performance of a pavement structure. After performing a FWD test, the surface deflections are known and inputted into a back-calculation analysis to determine the elastic moduli of pavement structure layers. The serviceability of a pavement structure is then estimated and the required overlay thickness of asphalt layer for rehabilitation is determined by using a back-calculation method (e.g., ELMOD 4.0). To establish the strains mobilized in a pavement structure, the forward calculation method with a software (EVERSTRESS 5.0) is required. Therefore, it becomes necessary to use ANN for predicting the pavement structure strains as shown in Fig. 1.

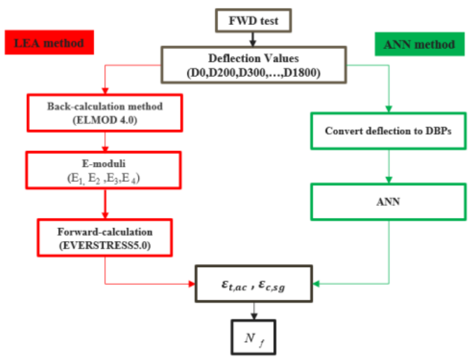


Fig. 1 Application of ANN to determine pavement strains

From the above, it can be seen that the determination of the pavement structure strains from a FWD test requires an expert to calculate, and it takes a long time to calculate due to there are many processes. The study of Wantanagun [1] showed that DBPs can be used to determine pavement structure strains. However, the predicting accuracy proposed by Wantanagun [1] was not accurate enough to predict pavement structure strains precisely. Thus, this study attempts on application of ANN to improve such a predicting accuracy.

In view of the above, this study was performed with the objectives as follows. To develop an ANN from analyzing results of linear elastic analysis (LEA) from the previous research for predicting strains of a pavement structure. To determine the most influence set of DBPs for each type of pavement structure. And to use the developed ANN and the most influence set of DBPs for prediction and comparison of pavement structure strains from Wantanagun [1].

There are scope and limitation of the present study as listed below. Analyses were performed with three pavement structure type which are: i) cement modified crushed rock base pavement, ii) combined surface pavement structure, and iii) thin surface pavement structure. The Pearson's correlation coefficient (r) was used to weight DBPs from seven DBPs to three DBPs. Comparisons were performed between the results developed by ANN and results from Wantanagun [1] only. The ANN used in this study was developed by MATLAB2020. The LEA results were from Wantanagun [1]. The influence of temperature was not studied in this study. And, in case of weighting DBPs by the same Pearson's correlation coefficient (r), the mean square error (MSE) was used to weight DBPs instead.

2. Background of the Study

2.1 Typical Pavement in Thailand

In Thailand, the flexible pavement is the most favorite one due to the economic capital cost. Flexible pavement consists of a thin asphalt layer, which is supported by the underlying base, subbase materials and subgrade as shown in Fig. 2.

2.2 Pavement Distress

The horizontal tensile strain at the bottom of the asphalt layer and the compressive strain at the top of subgrade layer are used to predict fatigue cracking and rutting failure, respectively [2].

2.2.1 Fatigue Cracking

Fatigue cracking is a cracking from the horizontal tensile strain at bottom of asphalt concrete layer as shown in Fig. 3. This strain can be used to predict the lifetime of a pavement by allowable number of load repetition (N_f) as shown in Eq. (1).

$$N_f = k_1(\varepsilon_{1,\alpha})^{-k_2}(E_1)^{-k_2} \tag{1}$$

2.2.2 Rutting

Rutting is a failure from vertical compressive strain at the top of base layer or subgrade layer as shown in Fig. 4. This strain can be used to predict lifetime of a pavement by allowable number of load repetition (N_f) as shown in Eq. (2).

$$N_f = k_4(\varepsilon_c)^{-k_5} \tag{2}$$

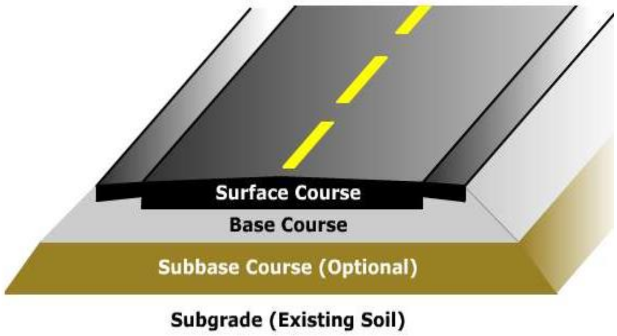


Fig. 2 A typical flexible pavement

2.3 Falling Weight Deflectometer (FWD)

FWD is a nondestructive test device that is generally used for evaluating pavement layer moduli and assesses the structural condition of pavements as shown in Fig. 5. Normally, parameters from a FWD test were used to calculate pavement structure strains by back calculation method by ELMOD4.0 for determining elastic modulus (E), and then these E values are used in forward calculation by EVERSTRESS5.0 to determine strain.

2.4 Deflection basin parameters (DBPs).

DBPs are the parameters developed from the measured surface deflections (D) at various distances. DBPs which are used in this study consist of:

1. Surface Curvature Index (SCI), defined as: SCI = D_0-D_{300} [3-4]
2. Base damage index (BDI), defined as: BDI = D_{12}–D_{24} [4]
3. Maximum deflection (D_0) [5]
4. Area defined as: Area = $6(D_0+2D_{12}+2D_{24}+D_{36})/D_0$ [6]
5. Shape factors 1 (F_1) defined as: $F_1= (D_0 - D_{24})/D_{12}$ [6]
6. Shape factors 2 (F_2) defined as: $F_2= (D_{12} - D_{36})/D_{24}$ [6]

Fig. 3 Example of fatigue cracking

Fig. 4 Example of rutting

2.5 Artificial neural network (ANN)

ANN is a machine learning inspired by computer programs and designed to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience.

2.5.1 Forward propagation learning in ANN

Receiving input layer, then collecting weight for stimulating through hidden layer as shown in Fig. 6.

2.5.1 Forward propagation learning in ANN

Improving ANN from output data to input data by adjusting weight in each instance by error, and then the data will be improved to reduce error in ANN as shown in Fig. 6.

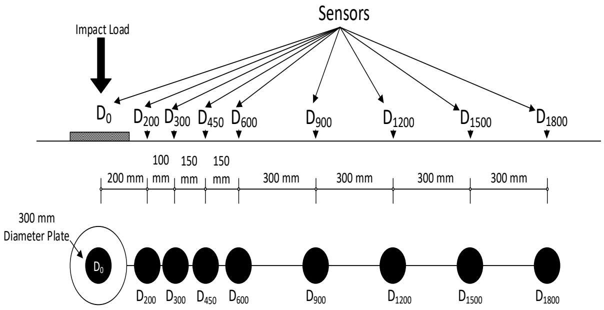


Fig. 5 FWD test with the measurements of surface deflections at various distance from the centre

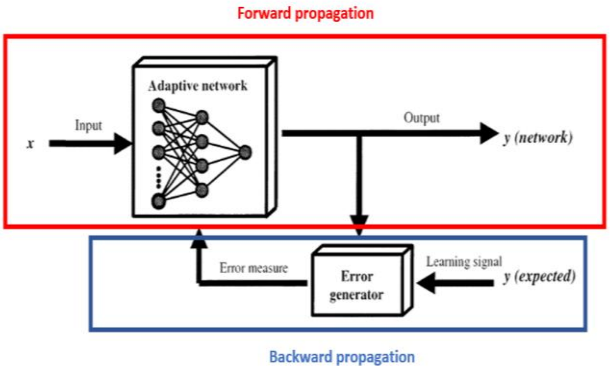


Fig. 6 Supervised network with forward-propagation and back propagation learning [7]

3. Methodology

The processes to predict the strains start from separating the pavement structure into three types, which are: i) thin surface pavement structure; ii) combined surface pavement structure; and iii) cement modified base pavement structure. There are two phases, which are: i) selection of relevant DPBs; and ii) verification of selected DBPs as shown in Fig. 7.

3.1 Architecture of ANN

Architecture of ANN consists of numbers of hidden layer and numbers of neuron as shown in Fig. 8 and 9 for seven DBPs and three DBPs, respectively.

3.2 Fitting network

Fitting network is the process to determine suitable network for ANN before using ANN to weight DBPs and predict pavement structure strains. There are three components as follows.

3.2.1 Function

Functions of network are used for fitting the network. Normally, Levenberg-Marquardt and Bayesian regularization were used to determine the data used in ANN as shown in Table 1.

3.2.2 Number of hidden layers

Hidden layers in ANN are used to increase performance of network.

3.2.3 Number of neurons

Number of neurons were used to train ANN and develop ANN, like the number of workers in the field site. Summary of the architecture of ANN in this study is shown in Table 2.

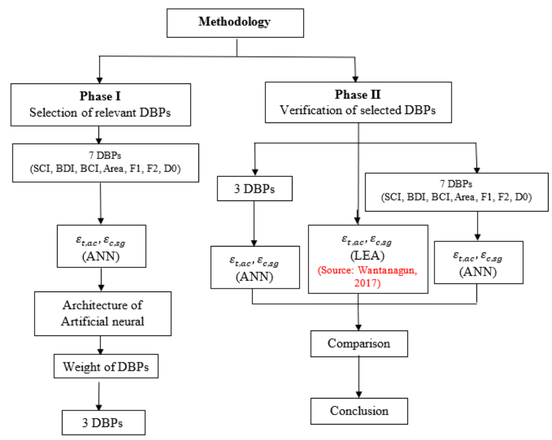


Fig. 7 Methodology used in this study

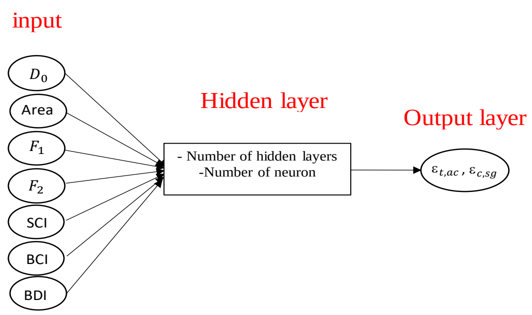


Fig. 8 Architecture of ANN with 7 DBPs

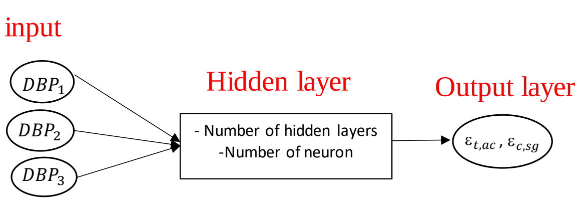


Fig. 9 Architecture of ANN with 3 DBPs

Table 1 Functions of network of ANN

Function	Levenberg-Marquardt	Bayesian regularization backpropagation
Code	Trainlm	Trainbr
Time	shorter	longer
Sampling	Training, Validation, Testing	Training, Testing
Performance	Mean Squared Error (MSE) and Regression values (R)	Mean Squared Error (MSE) and Regression values (R)

Table 2 Summary of architecture of ANN

Type of pavement	Type of strain	Function	No. Hidden layer	No. Neuron
Cement Modified	Horizontal	Trainbr	2	30,30
	Vertical	Trainbr	2	20,20
Combined surface	Horizontal	Trainbr	2	21,21
	Vertical	Trainbr	2	22,22
Thin surface	Horizontal	Trainbr	2	11,11
	Vertical	Trainbr	2	8,8
All type	Horizontal	Trainbr	2	14,14
	Vertical	Trainlm	2	7,7

After selecting the architectures of ANN for used to train DBPs, trend of regression correlation will show the state of ANN as under fitting, good fitting, or over fitting, as shown in Figs. 10, 11, and 12, respectively. Under fitting state is the state of ANN with low predictive accuracy. Good fitting state is the state of ANN with suitable prediction accuracy. Over fitting state is the state of ANN with more predictive accuracy than necessary.

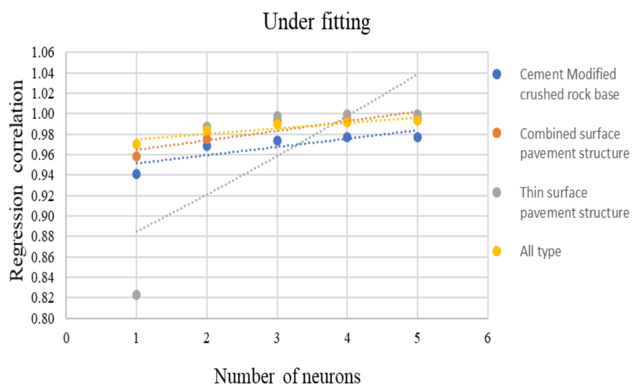


Fig. 10 Under fitting state

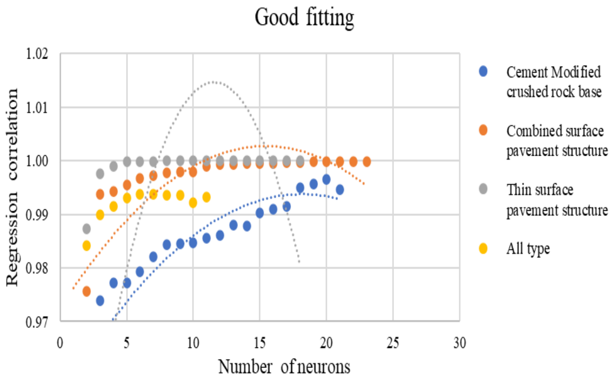


Fig. 11 Good fitting state

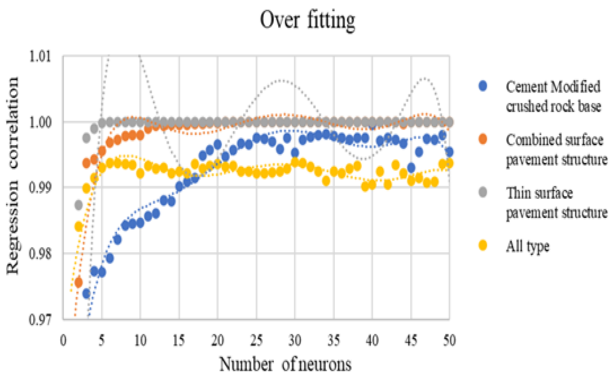


Fig. 12 Over fitting state

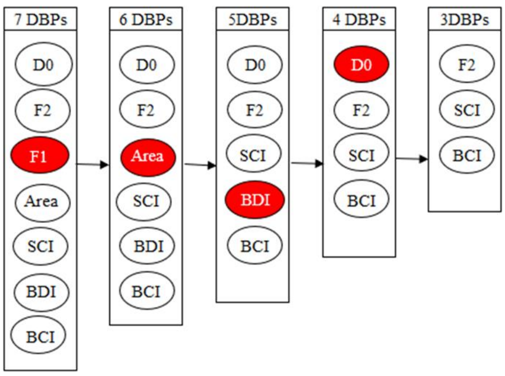


Fig. 13 Example of weighting DBPs for $\varepsilon_{t,ac}$ cement modified crushed rock base

3.3 Weighting DBPs

Weighting is the process to determine the influence of each DBP in each type of pavement structure. Fig. 13 shows an example and details of weighting DBPs for horizontal tensile strain at bottom of asphalt concrete for cement modified crushed rock base from seven DBPs to three DBPs. For an example of weighting, decreasing seven DBPs to six DBPs, F1 made ANN performance the best compared with excluding other DBPs. Then, weight six DBPs to five DBPs and run the processes again until obtain the best performance of three DBPs. After that, R-square and RMSE of ANN with seven DBPs, three DBPs will be compared together.

4. Results and discussion

Results and discussion consist of summary of the most relevant three DBPs of each type of pavement, comparison of R-square and RMSE of ANN with seven DBPs and three DBPs, comparison of R-square for prediction of ANN with seven DBPs, ANN with three DBPs and Wantanagun [1], and the accuracy of successfully developed ANN.

4.1 Summary of the most relevant three DBP

Summary of the most relevant three DBPs used to predict the strains, R-square and root mean square error (RMSE) are shown in Tables 3 and 4, respectively.

4.2 Comparison R^2 and RMSE between ANN with 7DBPs and ANN with 3DBPs of the predicted strain

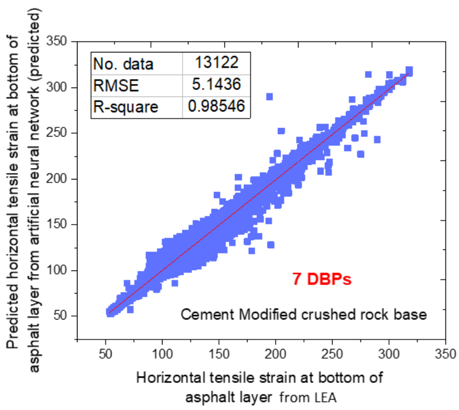
This part shows the comparison of accuracy to predict strain between representative ANN with seven DBPs and ANN with the most relevant three DBPs.

Table 3 Summary of the most relevant three DBPs of each type of pavement

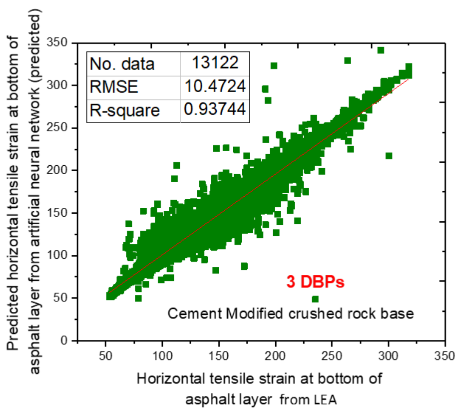
Type of pavement	Type of strain	No. of DBPs	Input
Cement Modified crushed rock base	Horizontal	7	SCI ,BDI ,BCI ,F1 ,F2 ,Area ,D0
		3	F2, SCI, BCI
	Vertical	7	SCI ,BDI ,BCI ,F1 ,F2 ,Area ,D0
		3	BCI ,Area ,D0
Combined surface pavement structure	Horizontal	7	SCI ,BDI ,BCI ,F1 ,F2 ,Area ,D0
		3	F1 ,BDI ,BCI
	Vertical	7	SCI ,BDI ,BCI ,F1 ,F2 ,Area ,D0
		3	BDI ,Area ,D0
Thin surface pavement structure	Horizontal	7	SCI ,BDI ,BCI ,F1 ,F2 ,Area ,D0
		3	Area, BCI,BDI
	Vertical	7	SCI ,BDI ,BCI ,F1 ,F2 ,Area ,D0
		3	SCI, F2, D0
All type	Horizontal	7	SCI ,BDI ,BCI ,F1 ,F2 ,Area ,D0
		3	Area,BDI ,BCI
	Vertical	7	SCI ,BDI ,BCI ,F1 ,F2 ,Area ,D0
		3	SCI ,BDI ,D0

Table 4 Summary of R-square and RMSE in each set of DBPs of each type of pavement

Type of pavement	Type of strain	No. of DBPs	R^2	RMSE
Cement Modified crushed rock base	Horizontal	7	0.9855	5.1436
		3	0.9374	10.4725
	Vertical	7	0.9931	6.5418
		3	0.9508	17.1503
Combined surface pavement structure	Horizontal	7	0.9997	1.7150
		3	0.9969	5.3444
	Vertical	7	0.9999	1.7391
		3	0.9952	11.5579
Thin surface pavement structure	Horizontal	7	1.0000	0.1557
		3	0.9999	0.7220
	Vertical	7	1.0000	0.7503
		3	0.9947	7.8599
All type	Horizontal	7	0.9884	9.2125
		3	0.9710	14.4052
	Vertical	7	0.9875	16.7213
		3	0.9654	27.5315



(a)



(b)

Fig. 14 Comparison of ANN with: (a) 7 DBPs and (b) 3 DBPs of $\varepsilon_{t,ac}$, cement modified crushed rock base

Fig. 14 shows comparison of R-square and RMSE of ANN with seven DBPs (a) and three DBPs (b) of $\varepsilon_{t,ac}$ in cement modified crushed rock base. Performance of ANN with seven DBPs is better than ANN with three DBPs due to R-square and RMSE of seven DBPs are equal to 0.9855 and 5.1436, respectively. Meanwhile ANN with three DBPs (i.e., F2, SCI, and BCI), the R-square and RMSE are equal to 0.9374 and 10.4724, respectively.

4.3 Comparison of R^2 from ANN and Wantanagun [1]

Fig. 15 shows comparison of R-square of ANN with seven DBPs, ANN with three DBPs, and Wantanagun [1]. ANN with seven DBPs gave the best R-square at 0.9855 and 0.9931 for $\varepsilon_{t,ac}$ and $\varepsilon_{c,sg}$, respectively. ANN with three DBPs has R-square more than that of Wantanagun [1] at 0.9374 and 0.9508 for $\varepsilon_{t,ac}$ and $\varepsilon_{c,sg}$, respectively. Meanwhile, study of Wantanagun [1] gave R-square at 0.9110 and 0.8830 for $\varepsilon_{t,ac}$ and $\varepsilon_{c,sg}$, respectively.

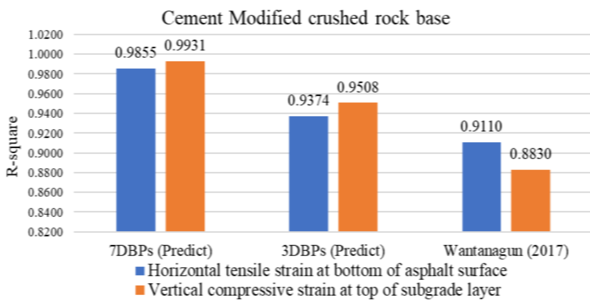


Fig. 15 Comparison R^2 of ANN with 7DBPs, ANN with 3DBPs and Wantanagun [1] for $\varepsilon_{t,ac}$ and $\varepsilon_{c,sg}$

4.4 Accuracy of successfully developed ANN

The successfully developed ANN has the following predictive performance and accuracy:

1. For cement-modified crushed rock base, the prediction with seven DBPs gave R-square at 0.9855 and RMSE at 5.1436 for $\varepsilon_{t,ac}$, and R-square at 0.9931 and RMSE at 6.5418 for $\varepsilon_{c,sg}$. The best performance three DBPs are F2, SCI, and BCI which gave R-square at 0.9374 and RMSE at 10.4724 for $\varepsilon_{t,ac}$ and the best performance three DBPs are BCI, Area, and D0 which gave R-square at 0.9508 and RMSE at 17.1503 for $\varepsilon_{c,sg}$.
2. For combined surface pavement structure, the prediction with seven DBPs gave R-square at 0.9997 and RMSE at 1.7150 for $\varepsilon_{t,ac}$, and R-square at 0.9999 and RMSE at 1.7391 for $\varepsilon_{c,sg}$. The best performance three

DBPs are F1, BDI, and BCI which gave R-square at 0.9969 and RMSE at 5.3444 for $\varepsilon_{t,ac}$ and the best performance three DBPs are BDI, Area, and D0 which gave R-square at 0.9952 and RMSE at 11.5579 for $\varepsilon_{c,sg}$.

3. For thin surface pavement structure, the prediction with seven DBPs gave R-square 1.0000 and RMSE at 0.1557 for $\varepsilon_{t,ac}$, and R-square at 1.0000 and RMSE at 0.7504 for $\varepsilon_{c,sg}$. The best performance three DBPs are Area, BCI, and BDI which gave R-square at 0.9999 and RMSE at 0.7220 for $\varepsilon_{t,ac}$ and the best performance three DBPs are SCI, F2, and D0 which gave R-square at 0.9508 and RMSE at 7.8599 for $\varepsilon_{c,sg}$.

4. For all type pavement structures, prediction with seven DBPs gave R-square at 0.9884 and RMSE at 9.2125 for $\varepsilon_{t,ac}$, and R-square at 0.9875 and RMSE at 16.7213 for $\varepsilon_{c,sg}$. The best performance three DBPs are Area, BDI, and BCI which gave R-square at 0.9710 and RMSE at 14.4052 for $\varepsilon_{t,ac}$ and the best performance three DBPs are BCI, Area, and D0 which gave R-square at 0.9654 and RMSE at 27.5315 for $\varepsilon_{c,sg}$.

5. Conclusion

For all types of pavements analyzed in this study, the R-square from ANN is higher than the one from Wantanagun [1]. Using ANN with seven DBPs is better than using ANN with three DBPs. The maximum error of prediction is around only 3% for ANN with seven DBPs and three DBPs.

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