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A unified artificial neural network model for asphalt pavement condition prediction

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Most performance prediction models for asphalt pavements are either based on laboratory data or numerical distress data collected from field surveys. However, these models do not fully reflect the true performance of pavements in different traffic and environmental conditions. In the study reported in this paper, a multi-input unified prediction model based on an artificial neural network was developed by using a mixture of numerical and categorical features for in-service pavement test sections in the USA. Pavement age, cracking length and area, cumulative traffic loading, two functional classes of roads, four climatic zones and maintenance effects were considered as input variables while changes in the pavement condition index (PCI) were determined as the output. The developed model was found to be efficient in terms of processing time and accuracy in dealing with the complexity and non-linearity of multiple input parameters. The results showed that the model provided a high correlation between observed and predicted deterioration at the training stage. The testing and validation results also yielded high accuracy in predicting the PCI and could be combined with a pavement management system to plan timely and accurate maintenance strategies.

Notation

$f(k)$	tan sigmoid transfer function
I_i	input i
n	number of inputs
W_{j0}	bias
W_{ji}	weight
x	weighted sum
y	output

1. Introduction

A pavement management system is a tool that assists highway authorities in decision making procedures to maintain pavements in a serviceable and functional condition throughout their life. Building an effective and successful pavement management system requires the development of an accurate pavement deterioration prediction model for programming and prioritising preservation activities and allocating resources throughout the pavement's service life (Alharbi, 2018; Bianchini and Bandini, 2010). Improvement in the accuracy of the prediction model is vital for estimating desirable preservation activities and resources allocation, and makes a substantial difference to expenditure on pavement treatments (Bianchini and Bandini, 2010; Pan *et al.*, 2011; Yang *et al.*, 2002).

The perfect form of a deterioration prediction model is to find a causal relationship between an index of pavement performance and explanatory factors that influence pavement conditions. There are several requirements that should be considered in developing a reliable deterioration prediction model; they are long-term historical data of in-service pavements comprising all the variables affecting pavement performance, an acceptable model form considering non-linearity and interaction, and criteria to estimate model accuracy (Darter, 1980). In addition, the variables affecting pavement deterioration (e.g. traffic, distress quantity, pavement age, maintenance effects, environment, pavement construction and materials) should be combined and considered when modelling deterioration. These variables have numerical features and categorical features.

Highways agencies have applied several techniques to develop deterioration prediction models. Deterministic techniques have been used to predict a quantity of specific change in pavement life or a quantity of specific distress type (Abaza, 2004; Dalla Rosa *et al.*, 2017; Gulfam-E-Jannat *et al.*, 2016; Jain *et al.*, 2005; Khraibani *et al.*, 2012; Luo, 2013; Mahmood *et al.*, 2019; Ningyuan *et al.*, 2001; Obaidat and Al-Kheder, 2006; Prozzi and Madanat, 2004). Moreover, probabilistic methods have been applied to predict distributions of condition states or expected pavement lifetimes (Abaza, 2016a, 2016b; Anyala *et al.*, 2012; Bandara and Gunaratne, 2001; Hong and Prozzi, 2006; Hong and Wang, 2003; Jiménez and Mrawira, 2009; Lethanh and Adey, 2013; Park *et al.*, 2008). However, these models have limited abilities to overcome the degree of uncertainty in judgements, the non-linearity of distress progression and dealing with a large volume of distress data collected from sensor-based traffic speed investigations. To address these issues, artificial intelligence methods have been applied to develop prediction models of pavement deterioration (Bianchini and Bandini, 2010; Mahmood *et al.*, 2019).

Several studies have also applied various artificial neural network (ANN) or fuzzy logic or hybrid (i.e. neuro-fuzzy) techniques to predict changes in pavement roughness, distress progression or pavement condition (Alharbi, 2018; Attoh-Okine, 1994, 1999; Bianchini and Bandini, 2010; Heidari *et al.*, 2018; Lin *et al.*, 2003; Lou *et al.*, 2001; Mazari and Rodriguez, 2016; Okuda *et al.*, 2018; Owusu-Ababio, 1998; Roberts and Attoh-Okine, 1998; Terzi, 2007; Thube, 2012; Yao *et al.*, 2019).

2. Research objectives

As already noted, most prediction models estimate either the progression of a single distress type or multiple distress types. Only a few studies related to the prediction of overall pavement deterioration by using numerical distress data can be found in the literature. No previous study has considered categorical features such as functional class and climatic conditions. Therefore, the primary objective of this work was to develop a unified ANN deterioration prediction model for a flexible pavement using road category (functional class and traffic loading), climatic condition, pavement construction, maintenance records and numerical distress data. The aim was that the developed model will predict overall pavement conditions by evaluating changes in the pavement condition index (PCI) over the service life.

3. Database

The long-term pavement performance (LTPP) database is a public and online database established as part of the Strategic Highway Research Program in 1987. The database includes data on pavement condition collected from manual and/or automated inspections of pavement distress for each segment. It is a comprehensive programme that includes distresses (e.g. cracking, pothole, patching and rutting), serviceability requirements (e.g. skid resistance, roughness, texture and ride quality) and structural data such as service life (FHWA, 2012).

Furthermore, to study behaviour under real-life traffic loading, in-service pavement sections are built and investigated. The in-service pavement sections are classified into two main groups: general pavement studies and specific pavement studies. The general pavement studies comprise a study series on about 800 in-service test sections in all states of the USA and Canada, whereas the specific pavement studies consider specific parameters relating to new construction, treatment and rehabilitation activities. Seven modules – inventory, monitoring, traffic, materials testing, climatic, preservation and rehabilitation – are the main contents of the LTPP database (FHWA, 2012). General pavement studies data, including historical data of pavement conditions, maintenance and rehabilitation, traffic, climatic effect, design and construction, were considered in this study.

4. Methodology

4.1 ANNs

ANNs are a computational approach devised to mimic the technique in which the human brain processes data. ANNs collect their experience by identifying relationships and forms in the information. They learn through knowledge with proper learning exemplars just as humans do, not from programming. They can provide an effective tool for solving complex problems and addressing non-linearity (Agatonovic-Kustrin and Beresford, 2000; Attoh-Okine, 1999; Eldin and Senouci, 1995).

ANNs are composed of many individual elements, called artificial neurons, connected with weights to create a neural structure. They are also recognised as processing elements as they process data. Each processing element includes weighted inputs, a single output and a transfer function. A processing element is an equation that makes a balance between the inputs and the output (Agatonovic-Kustrin and Beresford, 2000). A model of a neuron is shown in Figure 1. The strength of each input (I_0, I_1, I_2, I_3, …, I_n) to the neuron is decided by the weights (W_{j0}, W_{j1}, W_{j2}, W_{j3}, …, W_{jn}), where weight W_{j0} is called bias, which helps the activation function to reach a correct fit of inputs with the output (y); the subscript j denotes the column number of the input vector (Jang *et al.*, 1997). The inputs are multiplied with the respective weights and the addition of those values, called the weighted sum, is found by the summation function.

The weighted sum is then passed to a suitable activation function that calculates the output value of a neuron in a hidden layer. The activation function used within the Levenberg–Marquardt optimisation algorithm, which was employed in this work, is the hyperbolic tangent sigmoid (tan sigmoid) transfer function. The model is composed of inputs, weights, bias and a neuron, and the output is referred to as the perceptron. A feed-forward neural network (NN) formed by multiple layers of perceptrons is called a multi-layer perceptron (MLP). Figure 2 depicts the MLP, which has several layers; that is, several neurons along a vertical column. The number of neurons in the input layer is fixed by the number of input parameters present in the data. Similarly, the number of neurons

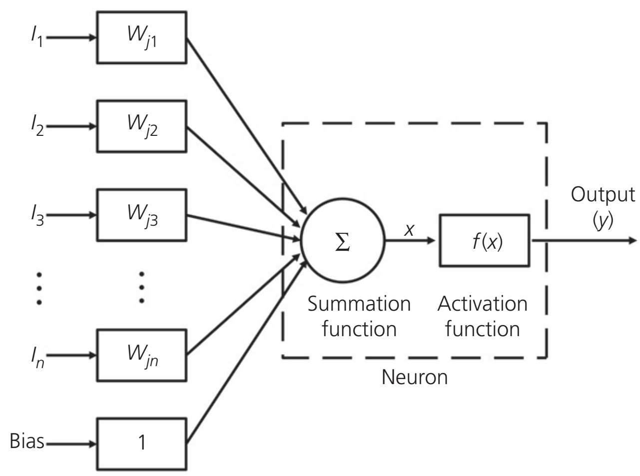

Figure 1. Model of a neuron

in the output layer is decided by the number of outputs required. For a regression task, as in the present work, a single neuron in the output layer suffices (Jang *et al.*, 1997).

Figure 2 shows that there are several hidden layers, whose configuration is usually determined in a trial-and-error fashion. Furthermore, it should be noted that the neurons in any given layer are connected to every neuron in the previous and next layers. Hence, a network such as that shown in Figure 2 is also known as a fully connected network. The following equations show how the output (y) is produced at the output of a neuron shown in Figure 2 for a number of inputs (I_1, I_2, I_3, …, I_n).

The weighted sum x is given by

1. $$x = \sum_{i=0}^{n} W_{ji} I_i$$

where W_{ji} is the weight, I_i is the input I and n is the number of inputs.

The tan sigmoid transfer function is given by

2. $$f(k) = \frac{2}{1 + e^{-2k}} - 1$$

Equation 1 can be written as

3. $$x = \sum_{i=1}^{n} W_{ji} I_i + W_{j0} I_0$$

where $W_{j0} = -b$ and $I_0 = 1$.

Hence the weighted sum x is

4. $$x = \sum_{i=1}^{n} W_{ji} I_i - b$$

Plugging x into Equation 2 gives

5. $$f(x) = \frac{2}{1 + e^{-2x}} - 1$$

Therefore, the output y is given by

6. $$y = \frac{2}{1 + e^{-2x}} - 1$$

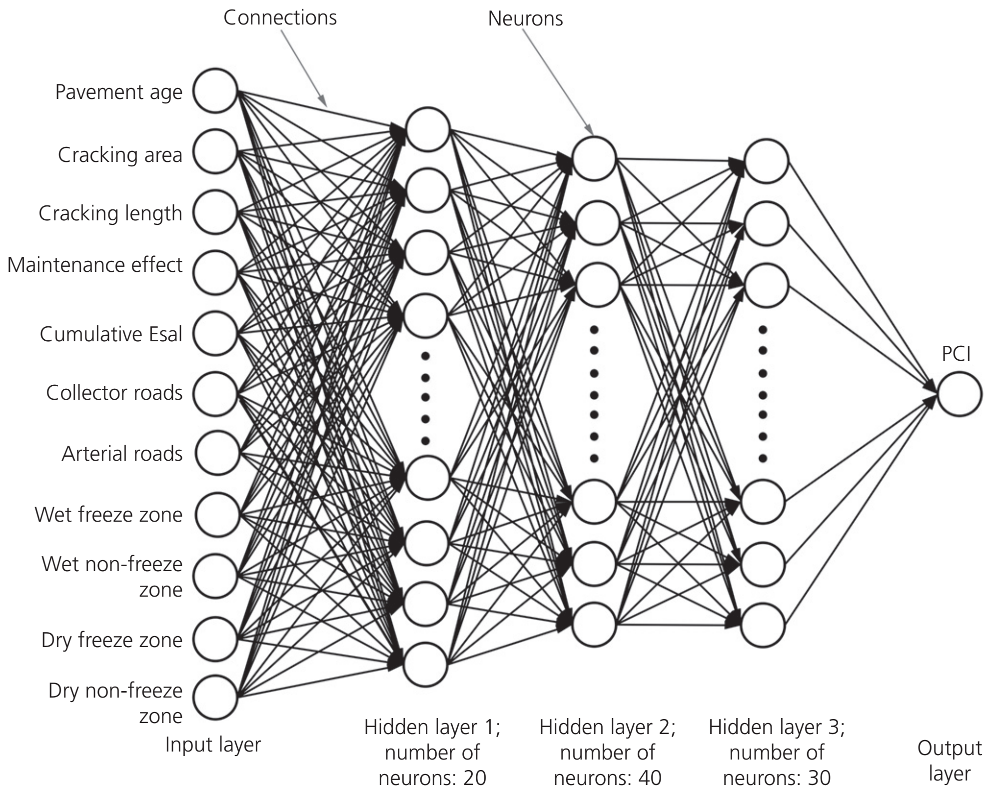

Figure 2. Architecture of the NN for the pavement deterioration model. Esal, equivalent single-axle load

In the development of ANN models, a generalisation ability should be included. Generalisation is known as the ability of a NN to recognise characteristics that are common to a sample of existing data and keep them in the network. The capability of retention is linked to the nodal weights. The weights and biases need to be tuned during training of the model, either in a supervised manner, where a human guides the network with inputs with labelled data and the expected outputs, or in an unsupervised manner, where the network is expected to perform the task on its own. Then, the NN efficiently employs these characteristics to perform forecasting for formerly unseen examples. The objective of training and testing is to estimate the architecture of the NN with the best generalisation ability.

Usually, a NN with only a few hidden neurons is unable to be trained effectively from a training data set, while a NN with a large number of hidden neurons will permit the network to learn the training set rather than generalising the attained experience for hidden patterns (Lou *et al*., 2001). An effective ANN is decided by variables of the network called hyperparameters – these are the number of hidden neurons, the number of hidden layers, the rate at which the weights are updated (called the learning rate), how much data are fed into the network to learn at a time (referred to as the batch size) and the number of times the whole data set is shown to the network to learn (called epochs).

4.2 Input parameters

In developing a prediction model for pavement deterioration, the existence and use of the most influential parameters affecting pavement deterioration were considered. These parameters are pavement age, pavement design and construction, traffic loading, environmental effect, and the effect of maintenance and rehabilitation (Al-Mansour *et al*., 1994; Fwa, 2006). These factors are now briefly described in turn.

Due to the ageing process, adverse climatic impacts and their interaction with traffic on pavement conditions accelerate over time. Pavement age should be estimated from the date of construction or the date of the most recent rehabilitation (Fwa, 2006).

Pavement design and construction have the most substantial effects on the performance of a pavement. In general, pavement design and construction comprises two key parts – the layer thickness of the asphalt and the type of pavement (e.g. flexible and rigid) (Fwa, 2006). The design and construction of high-capacity arterial roads and low- to moderate-capacity collector roads are different because arterial roads have the highest level of service at the maximum speed for the longest mileage. Therefore, in this study, both arterial and collector roads were selected as inputs of the prediction model to consider the effects of pavement design and construction on deterioration.

Moreover, traffic load repetition, axle load type, volume and vehicle type also affect pavement deterioration. These factors are combined to be expressed as an equivalent single-axle load (Esal) in prediction models (Al-Mansour *et al*., 1994; Fwa, 2006).

Environmental variation has a significant effect on pavement deterioration. Temperature, which is a climatic effect, causes cracking in age-hardened brittle asphalt surfaces in the cold season and rutting in pavement surfacing under traffic loads in the hot season. Furthermore, freeze–thaw cycles and levels of precipitation also have an impact on pavement performance (Al-Mansour *et al*., 1994; Fwa, 2006).

Finally, maintenance actions are performed to minimise the deterioration level of a pavement structure or are applied in an emergency to preserve the pavement structure at an acceptable level. Occasionally, when pavement sections comprise several types of distress, it may be economical to rehabilitate either by inlay, overlay or reconstruction of the pavement rather than preservative treatment. Therefore, both inlay and overlay actions (thickness) were used as input parameters.

4.3 Model development

To develop the pavement deterioration ANN model, pavement condition data were collected from the online LTPP database (FHWA, 2012). Table 1 shows the total number of sections and data samples that were considered to develop the deterioration prediction model. As inputs, the following 11 explanatory variables were considered – pavement age, cracking area, cracking length, cumulative Esal, maintenance effect (inlay and/or overlay thickness), four climatic zones (dry freeze, dry non-freeze, wet freeze, wet non-freeze) and two functional classes (collector and arterial). The PCI is an indicator, ranging from 0 to 100, used to evaluate pavement deterioration based on three main factors – type of distress, severity of distress and distress. The PCI was used utilised as the dependent variable. Table 2 shows an example of data samples, including inputs and output of the pavement-deterioration-based ANN model. The categorical variables belonging to the four climatic zones and the two functional classes were converted into binary values using the 'one-hot encoding' method, which checks whether the input belongs to one of the six categorical variables defined.

An example of hot encoding performed for three categorical variables (A, B and C) is shown in Table 3. The correlation between the input parameters is depicted in Table 4, which is

Table 1. Summary of total number of pavement sections and data samples

Sections	59
Samples	838

Table 2. Example of data including inputs and output of the deterioration-based ANN model

Section ID	Data sample	Inputs											PCI (output)
		Pavement age	Cracking area	Cracking length	Maintenance effect	Cumulative Esal	Collector roads	Arterial roads	Wet freeze zone	Wet non-freeze zone	Dry freeze zone	Dry non-freeze zone	
1001	1	0	0	0	0	131	0	1	1	0	0	0	100
	2	16.8	0	161.5	0	334	0	1	1	0	0	0	75
	3	22.5	0	7	0	1248	0	1	1	0	0	0	27
7775	1	0	0	0	0	140	1	0	0	0	1	0	100
	2	3.06	0	226.3	0	384	1	0	0	0	1	0	79

Table 3. Example of 'one-hot encoding' method

Check	*A*	*B*	*C*
Is *A*?	1	0	0
Is *B*?	0	1	0
Is *C*?	0	0	1

the correlation matrix. It is clear that no two pairs of inputs had a perfect linear relationship, other than the variables arterial roads and collector roads. The correlation coefficient between arterial roads and collector roads was −1 because there were only two types of roads available and both types were taken into account and hot encoded as 1 or 0. Further, the pairs of inputs wet freeze–wet non-freeze, wet freeze–dry freeze, wet freeze–dry non-freeze, wet non-freeze–dry freeze and dry-freeze–dry non-freeze showed a moderate negative linear relationship with values of −0.28051, −0.55743, −0.267, −0.34186 and −0.3254, respectively. Here too, there are four variables with hot encoding, which can be covered by three independent variables alone. The rest of the correlation coefficients occupying the other off-diagonal elements of the matrix were very small numbers, thus showing a weak linear relationship between the input pairs.

The model development can be summarised as follows.

(*a*) Selection of the explanatory variables (age, cracking area and length, cumulative Esal, maintenance effect, climatic zones and functional classes).
(*b*) For each pavement section, collection of historical condition data and also all the required data for step (*a*) from the online LTPP database.
(*c*) For each section, calculation of the PCI for each survey year using the Paver system.
(*d*) Use of the one-hot encoding method to convert the categorical variables (four climatic zones and two functional classes) into binary values.
(*e*) Use of the ANN method to develop a deterioration prediction model using Matlab software.

Modelling pavement deterioration considering 11 input factors that affect pavement deterioration is a complex problem. In addition, there are non-linear relationships between the dependent and independent variables. Therefore, the ANN technique was used to address these issues and find all potential interactions without complicated equations. Figure 2 shows the ANN architecture of the pavement deterioration model.

The ANN used in this study is known as a shallow network, composed of MLPs of around two or three hidden layers in the context of supervised learning. The weights and biases are initialised randomly and tuned using the backpropagation method, which first calculates the error function from the decision of the output layer in the feed-forward path and the target values

Table 4. Correlation coefficient of the inputs used

Input	Input										
	Pavement age	Cracking area	Cracking length	Maintenance effect	Cumulative Esal	Collector roads	Arterial roads	Wet freeze	Wet non-freeze	Dry freeze	Dry non-freeze
Pavement age	**1**	0.147046	0.224161	0.069974	0.295475	−0.22612	0.226122	0.075752	−0.11667	0.008382	0.005912
Cracking area	0.147046	**1**	0.105648	−0.06354	−0.05039	−0.01104	0.01104	0.120757	0.0929	−0.12865	−0.07546
Cracking length	0.224161	0.105648	**1**	−0.13518	−0.04114	0.017676	−0.01768	0.079831	0.082052	−0.07794	−0.08148
Maintenance effect	0.069974	−0.06354	−0.13518	**1**	0.051448	−0.00736	0.00736	0.027277	0.04364	−0.02773	−0.04243
Cumulative Esal	0.295475	−0.05039	−0.04114	0.051448	**1**	−0.13116	0.131159	−0.2476	−0.07699	0.395858	−0.15265
Collector roads	−0.22612	−0.01104	0.017676	−0.00736	−0.13116	**1**	**−1**	0.071626	0.189618	−0.10562	−0.14201
Arterial roads	0.226122	0.01104	−0.01768	0.00736	0.131159	**−1**	**1**	−0.07163	−0.18962	0.10562	0.142005
Wet freeze	0.075752	0.120757	0.079831	0.027277	−0.2476	0.071626	−0.07163	**1**	**−0.28051**	**−0.55743**	**−0.267**
Wet non-freeze	−0.11667	0.0929	0.082052	0.04364	−0.07699	0.189618	−0.18962	**−0.28051**	**1**	**−0.34186**	−0.16375
Dry freeze	0.008382	−0.12865	−0.07794	−0.02773	0.395858	−0.10562	0.10562	**−0.55743**	**−0.34186**	**1**	**−0.3254**
Dry non-freeze	0.005912	−0.07546	−0.08148	−0.04243	−0.15265	−0.14201	0.142005	**−0.267**	−0.16375	**−0.3254**	**1**

provided. The calculated error is then sent backwards through the MLPs. The weights and biases are adjusted towards minimising the error at the output layer and the feed-forward path action is activated using the adjusted weights and biases. This forward and backward operation is continued until the minimum error value possible is achieved.

To train the ANN, the Levenberg–Marquardt optimisation algorithm was chosen to implement a feed-forward NN since it is an effective algorithm for training a feed-forward NN (Agatonovic-Kustrin and Beresford, 2000). This algorithm utilises the Jacobian for calculations, which imposes a condition for the mean squared error (MSE) or sum of squared errors for performance measurement of the NN, hence the performance of the network is measured based on the MSE between the targets and predictions. Modelling of the network was accompanied by the early stopping technique, which specifies a criterion to stop training when the expected conditions are met. This method stops training from consuming training time and power redundantly. The conditions used in the early stopping criterion were the maximum number of epochs (1000), zero error between targets and predictions, the value of the minimum performance gradient (1×10^{-7}) and increasing validation error for six continuous epochs from the lowest value achieved during training validation.

5. Results

To develop the network-level pavement deterioration prediction model for flexible pavements, 11 explanatory variables and one response variable were defined. The input variables of the pavement deterioration model are age, cracking area, cracking length, inlay and/or overlay thickness, cumulative Esal, collector roads, arterial roads, wet freeze zone, wet non-freeze zone, dry freeze zone and dry non-freeze zone. The output variable of the deterioration model is the PCI.

The pavement deterioration model was formulated using an ANN and was created using Matlab's NN toolbox. The ANN modelling comprised three steps: training, validation and testing. During the training process, the network was adjusted by learning from a data examples set called the training set. In the validation stage, network generalisation was measured and set to stop training when generalisation halted improvements. After the training stage, testing was performed to measure the network performance.

In this research, the data set collected from the LTPP comprised 838 samples. For the training set, 586 samples (approximately 70%) were randomly chosen; the residual data were separated into a validation set and a testing set of 126 samples each. Training was performed according to two different strategies with three approaches. The first strategy was to align the training with a single hidden layer while changing the number of neurons in the layer. The second strategy was to increase the number of neurons for an increased number of layers.

Table 5. Network performance for different numbers of hidden neurons

Number of hidden neurons	Number of iterations	*R*			
		Training	Validation	Testing	All
10	19	0.902	0.857	0.899	0.897
20	12	0.899	0.850	0.907	0.892
30	22	0.938	0.848	0.735	0.863
40	11	0.916	0.774	0.771	0.879
50	10	0.899	0.898	0.821	0.886
60	19	0.933	0.874	0.794	0.902
70	11	0.898	0.685	0.527	0.799
80	10	0.916	0.939	0.818	0.904
90	13	0.926	0.878	0.739	0.891
100	16	0.941	0.912	0.734	0.895
110	14	0.972	0.746	0.528	0.852
120	11	0.930	0.821	0.856	0.900
130	12	0.936	0.738	0.735	0.851
140	11	0.932	0.763	0.770	0.880
150	17	0.948	0.753	0.776	0.866

Table 6. Samples of performance of the network with two hidden layers composed of 6–30 neurons

Number of hidden neurons		Number of iterations	*R*			
First layer	Second layer		Training	Validation	Testing	All
12	18	11	0.9285	0.9061	0.8642	0.9148
12	15	26	0.9237	0.9045	0.8695	0.9114
15	9	8	0.8991	0.8952	0.8846	0.8946
15	21	11	0.9217	0.9192	0.8539	0.9108
15	24	21	0.9336	0.8383	0.9086	0.9180
15	30	12	0.9261	0.8435	0.8894	0.9092
18	15	6	0.9038	0.8834	0.8952	0.8998
24	18	8	0.9025	0.9127	0.8535	0.8955
27	27	6	0.9127	0.8959	0.8772	0.9043
30	9	16	0.9196	0.8973	0.8696	0.9077

Table 7. Samples of performance of the network with two hidden layers composed of 30–70 neurons

Number of hidden neurons		Number of iterations	*R*			
First layer	Second layer		Training	Validation	Testing	All
30	50	11	0.9065	0.8657	0.8823	0.8988
30	70	8	0.9217	0.8746	0.9181	0.9134
40	30	6	0.9258	0.8575	0.8928	0.9101
40	40	8	0.9231	0.8971	0.8604	0.9078
50	30	8	0.9110	0.8856	0.8943	0.9018
50	50	6	0.9274	0.8622	0.8546	0.9064
60	30	6	0.9233	0.8921	0.8446	0.9095
70	30	7	0.9169	0.8729	0.8059	0.8891
70	40	8	0.9301	0.8736	0.8462	0.9105
70	60	9	0.9086	0.8956	0.8949	0.9030

In the first approach, an ANN configuration with a single hidden layer was trained by changing the number of neurons from ten to 150 in steps of ten to examine and identify the best network performance. The analysis showed that 120 hidden neurons produced the best performance, as shown in Table 5. Secondly, an ANN configuration with two hidden layers was utilised by changing the number of neurons in each layer through a grid approach in which both layers were changed

Table 8. Samples of performance of the network with three hidden layers composed of 10–50 neurons

Hidden neurons				***R***			
First layer	Second layer	Third layer	**Number of iterations**	Training	Validation	Testing	All
10	20	40	11	0.9252	0.8998	0.8692	0.9133
10	30	10	8	0.9257	0.9077	0.7690	0.9023
10	30	20	5	0.8981	0.9075	0.9002	0.9001
10	30	50	9	0.9217	0.9064	0.8197	0.9038
10	40	40	10	0.9129	0.9114	0.8708	0.9040
10	50	30	8	0.9237	0.9004	0.8166	0.9075
20	10	20	17	0.9361	0.9149	0.8390	0.9180
20	40	30	12	0.9335	0.9101	0.8583	0.9165
50	20	10	10	0.9177	0.9038	0.8703	0.9071
50	50	20	6	0.9113	0.9064	0.8709	0.9022

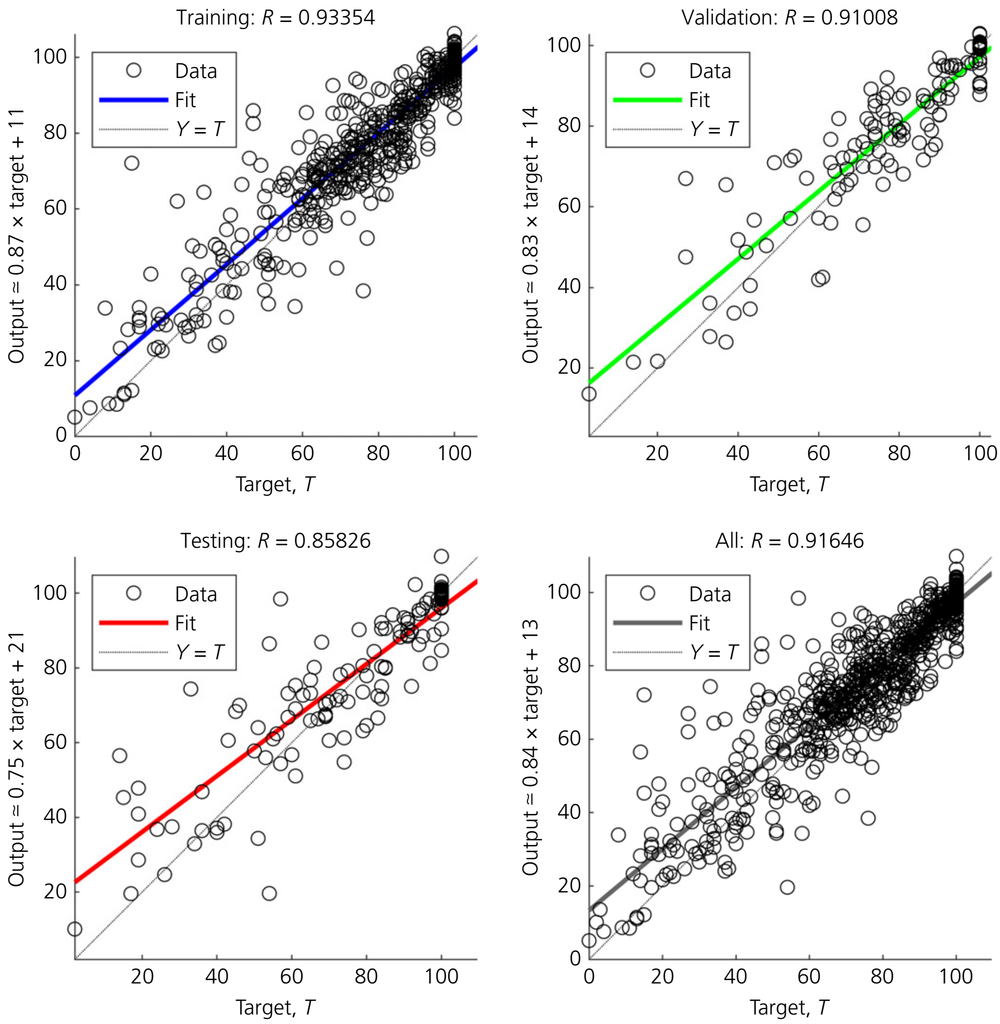

Figure 3. Accuracy of the selected pavement-deterioration-based ANN model

from six neurons to 30 neurons by adding three neurons in each loop. Initially, the first layer was kept at six neurons, the neurons on the second layer were changed to finish a complete loop and the performance was recorded. Then, the number of neurons in the first layer was increased by three and the network was trained and examined by changing the number of

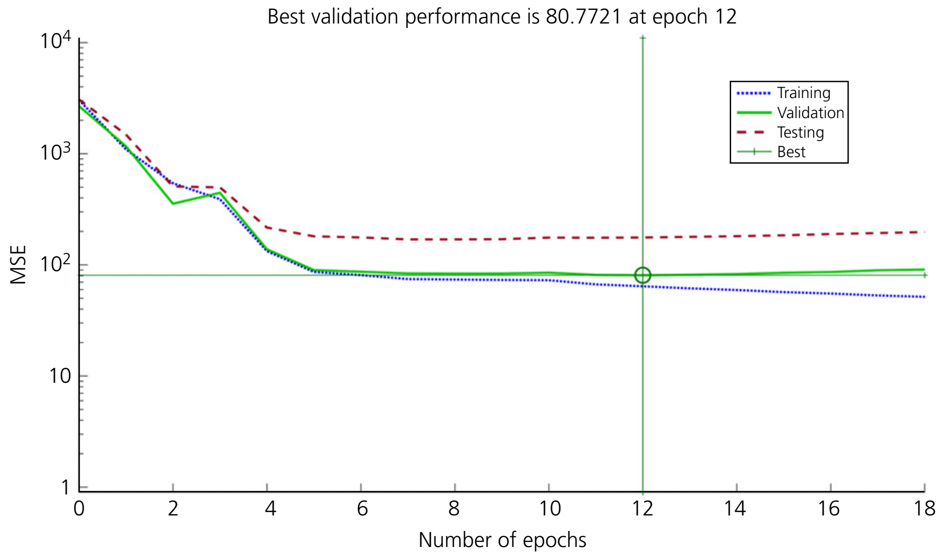

Figure 4. Performance of the selected pavement-deterioration-based ANN model

neurons in the second layer, in the range of 6–30. Similarly, the second layer was changed from six neurons to 30 neurons for each step change of the first layer, which resulted in 81 training occurrences. In this approach, the best result was obtained with 12 neurons in the first layer and 18 neurons in the second layer. Samples of performance are shown in Table 6.

Using the previous approach, an ANN with two hidden layers of 30–70 neurons with a step increment of ten neurons was produced into training, which resulted in 25 training occurrences. The best performance was observed when the ANN was trained with 30 neurons in the first layer and 70 neurons in the second layer (Table 7).

As the third approach, an ANN was established with three hidden layers, each comprising 10–50 neurons in increments of ten neurons for each step, and the same grid approach was applied as in the second approach. This method produced 125 training occurrences and the best performance was observed when the training was performed with the first layer made of 20 neurons, the second layer made of 40 neurons and the third layer made of 30 neurons. Some of the performance samples are shown in Table 8.

By comparing the results for the best performance from all three approaches, the NN with three hidden layers with 20 neurons in the first layer, 40 in the second and 30 in the third, was finalised as the optimum model. As shown in Table 8 and Figure 3, the accuracy values (R) were 0.9335, 0.9101, 0.8583 and 0.9165 for training, validation, testing and overall, respectively. Figure 4 shows that this pavement-deterioration-based ANN model showed the best performance, with a high accuracy of PCI prediction for training, validation, testing and all sets.

Table 9. Advantages and disadvantages of the unified ANN prediction model

Advantages	Disadvantages
Less statistical training for model formulation	Difficulty of interpretation of model parameters (black box)
Comprehensive and easy to implement	Not for all pavement types
High accuracy as there is a huge quantity of historical data	Not accurate for a shortage of availability of historical data
Capable of addressing all possible interactions between input parameters	Routine maintenance activities are not considered
Applicable at the network level	Not applicable at the project level

Based on all the preceding results, all the possible advantages and disadvantages of the developed model are summarised in Table 9.

6. Conclusions

Deterioration prediction based on an ANN model at network level was established to predict the PCI of in-service flexible pavements. All potential numerical distresses and road categorical data were considered in the model development. The categorical variables were converted into binary values by applying the one-hot encoding method. Information on asphalt concrete pavements on a granular base (general pavement studies) in the LTPP database (FHWA, 2012) was selected and separated into training, validation and testing sets.

The ANN model of pavement deterioration showed a high goodness of fit (R) between the observed and predicted PCIs (greater than 0.91 and 0.85 at the validation stage and testing stage, respectively), thus demonstrating the efficiency of the developed ANN model for predicting pavement deterioration. Based on the results, the developed model is comprehensive and easy to implement at network-level deterioration for specific roads and weather conditions.

The unified prediction model will be a beneficial tool that can assist highways agencies in accurately estimating future pavement deterioration. Furthermore, the unified prediction model of pavement deterioration can be easily incorporated with an algorithm of maintenance programming. Therefore, it can select the appropriate treatment strategy with less effort and time for a specific section of the pavement network. Additionally, as future work, this unified deterioration-prediction-based ANN model could be combined with evolutionary optimisation algorithms such as genetic algorithms and particle swarm optimisation to determine the optimal maintenance plan.

Although the unified ANN model shows good capability to predict the PCI, several limitations have been recognised and will be addressed in future research. The first improvement will be to incorporate, mathematically, the positive influence of preventive maintenance measures in the predictions of deterioration and PCI. Secondly, as the limited availability of past condition data reduces the model accuracy for collector roads, further efforts are underway to gather more data for similar types of road.

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