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A PAVEMENT DETERIORATION MODEL USING RADIAL BASIS FUNCTION NEURAL NETWORKS

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A pavement deterioration model (PDM) applying Radial Basis Function Neural Networks (RBFNN) is presented in this paper. The RBFNN architectures are designed to be used to develop PDM based on the database that has at least two point history condition data, and are also designed as sequential PDM where the future pavement condition can be predicted using only information about present MCI value and age of pavements. The pavement condition prediction results are compared with actual measured MCI value and other existing methods. The results indicate that proposed RBFNN architectures have good capability to be used to predict future performance of pavements, and its application is very flexible and less time consuming.

Key Words : *pavement deterioration model, radial basis function neural networks*

1. INTRODUCTION

Pavement Management Systems (PMS) are developed and widely used in the world to get consistent and cost effective decision in road network maintenance. The fundamental part of PMS that has great influence on the reliability of the final results of PMS itself is the pavement deterioration model. In PMS, this model is mainly used to determine the future maintenance needs of pavement sections, budget planning, and the life cycle cost analysis.

Various pavement deterioration models have been developed and used over the years. These models can be categorized into two groups: the deterministic model and the probabilistic model.

In the deterministic deterioration models, the regression techniques are mainly used, and various regression functions are used to model the pavement condition deterioration over the time [1)-8)]. The curve-fitting techniques have also been evaluated for modeling the pavement condition deterioration[9)]. The regression techniques are applicable only to specific conditions of climates, materials, construction techniques, and others[10)].

The Markov deterioration model is the probabilistic approach that has been studied and developed by many researchers. This model is characterized by transition probability matrix (TPM) that predicts the pavement deterioration over time. The TPM can be constructed by assuming that an element of TPM, p_{ij}, is the same as the proportion of roads in state i that moves to state j in a specified cycle if one rehabilitation action is applied[11)-15)]. It also can be constructed using expected value methods[10)], econometric methods[16),17)], and reliability analyses and the Monte Carlo simulation technique[18)].

Some studies on the application of artificial neural networks in pavement deterioration have been reported[19), 20)], and multilayer perception with the error back propagation technique for model parameter estimation was commonly used. The back propagation technique, however, suffers from slow convergence times, and may become trapped at a local minimum of the chosen optimization criterion during the learning procedure if a gradient descent algorithm is used[21)].

In the development of pavement deterioration model, an adequate database is necessary. However, many new pavement database systems have only limited history condition data. The development of pavement deterioration model must be aimed to solve this problem.

This study attempts to apply Radial Basis Function Neural Networks (RBFNN) in the pavement deterioration model. In contrast with back propagation technique, the RBFNN is guaranteed to converge to globally optimum parameter and has fast convergence time[21]. Furthermore, its application can be designed to develop the pavement deterioration model using the limited history condition data and can be used to all climatic conditions, materials, construction techniques and others.

The purposes of this study are: (1) to propose the RBFNN architectures that are used to develop the sequential pavement deterioration model based on the database that has at least two point history condition data; (2) to evaluate the flexibility of the proposed method.

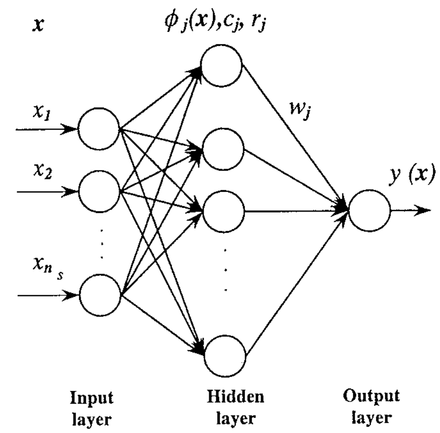

Fig.1 Radial basis function neural networks

2. METHODOLOGY

In this study, the pavement deterioration model using RBFNN was developed for two different condition of database, i.e. the database that has long history condition data, and the new database that has only two point history condition data. Before application of the model, the data was grouped into several pavement families and the data screening was applied. The methodology and the elements of the model are discussed as the following.

(1) Radial basis function neural networks

a) The topology of RBFNN

A RBFNN is a feedforward neural network that consists of three layers: input layer, hidden layer and output layer. **Fig. 1** shows a typical architecture of a RBFNN. In the topology of networks, a RBFNN is similar to a special case of multilayer feedforward neural networks, but different in terms of node characteristics and learning algorithm.

There is no calculation in input layer nodes. The input layer nodes only pass the input data to the hidden layer. The input layer consist of n_s nodes where input vector $\boldsymbol{x} = (x_1, x_2, \ldots, x_{n_s})$. The hidden layer consists of n nodes and each hidden node $j = 1, 2, \ldots, n$ has a center value c_j. Each hidden layer node performs a nonlinear transformation of the input data onto new space through the radial basis function. The most common choice for the radial basis function is a Gaussian function, given by

$$\phi_j(x) = \exp(-\| x - c_j \|^2 / r_j^2) \qquad (1)$$

where $\| x - c_j \|$ represents the Euclidean distance between input vector (x) and the radial basis function center (c_j). r_j is the width of radial basis function.

The output layer operation is linear, given by

$$y(x) = \sum_{j=1}^{n} w_j \cdot \phi_j(x) \qquad (2)$$

where w_j are the connection weight of hidden layer to output layer and n is number of hidden node.

Since the RBFNN output is a simple linear combination, the parameter solution can be obtained using linear optimization methods. Therefore, it has fast convergence time and is guaranteed to converge to global optimum parameter. Moody et al.[22] demonstrated that the radial basis function networks learn faster than multi layer perception network. Park and Sandberg[23] proved theoretically that radial basis function network are capable of universal approximation and learning without local minima, therefore it is guaranteed to converge to global optimum parameter.

Training of RBFNN involves determination of the following parameters.

- Number of hidden layer nodes.
- The center and the width of each radial basis function in each node.
- The connection weight of hidden layer to output layer.

b) Training Methodology

The orthogonal least squares (OLS) learning algorithm[21] was used to determine the center and the optimum number of hidden nodes. The OLS algorithm is operating in a forward selection manner. The procedure chooses the radial basis function center one by one in a rational way until an adequate network has been constructed. Once the optimum numbers of the hidden nodes and their centers are found, the connection weights can be determined. In this study, the same width was applied for all radial basis functions in hidden nodes.

The OLS learning algorithm[21] in determining the center and optimum number of hidden unit are described as the following.

The training input-output pairs are in the form of $\{\boldsymbol{x}(t), \boldsymbol{d}(t)\}$, t=1, 2, …, N where N is the number of training patterns, $\boldsymbol{x}(t)=[x_1(t),\ldots,x_{n_s}(t)]^T$ is the input vector, and $\boldsymbol{d}(t)$ is desired output vector. Initially, all the training data $\{\boldsymbol{x}(t)\}$ are considered as candidates for center. Therefore, the initial number of centers M is equal to N. The network output in Eq. (2) can be considered as a special case of linear regression model.

$$d(t) = \sum_{i=1}^{M} p_i(t)\theta_i + \varepsilon(t) \tag{3}$$

where $d(t)$ is the desired output and is also called the dependent variable, the θ_i is the weight between the ith node to output node, $p_i(t)$ are known as regressors which are fixed functions of the input vector $\boldsymbol{x}(t)$:

$$p_i(t) = p_i(\boldsymbol{x}(t)). \tag{4}$$

$\varepsilon(t)$ is the error signal which is assumed to be uncorrelated with the regressor $p_i(t)$.

The geometric interpretation of the least squares (LS) method is best revealed by arranging Eq. (3) for t = 1 to N in the following matrix form:

$$\boldsymbol{d} = \boldsymbol{P}\boldsymbol{\theta} + \boldsymbol{E} \tag{5}$$

where

$$\boldsymbol{d} = [d(1) \ldots d(N)]^T \tag{6}$$

$$\boldsymbol{P} = [\boldsymbol{p}_1 \ldots \boldsymbol{p}_M],$$

$$\boldsymbol{p}_i = [p_i(1) \ldots p_i(N)]^T,\ 1 \le i \le M \tag{7}$$

$$\boldsymbol{\theta} = [\theta_1 \ldots \theta_M]^T \tag{8}$$

$$\boldsymbol{E} = [\varepsilon(1) \ldots \varepsilon(N)]^T \tag{9}$$

The OLS method involves the transformation of the set of $\boldsymbol{p}_i$ into a set of orthogonal basis vectors, and uses only the significant ones to form the final RBFNN. The number of significant basis vector in final network, Ms, is much less than initial number M. The regression matrix $\boldsymbol{P}$ can be decomposed into

$$\boldsymbol{P} = \boldsymbol{W}\boldsymbol{A} \tag{10}$$

where $\boldsymbol{A}$ is M x M triangular matrix with 1's on the diagonal and 0's below the diagonal, that is,

$$A = \begin{bmatrix} 1 & \alpha_{12} & \alpha_{13} & \Lambda & \alpha_{1M} \\ 0 & 1 & \alpha_{23} & \Lambda & \alpha_{2M} \\ 0 & 0 & O & O & M \\ M & & O & 1 & \alpha_{(M-1)M} \\ 0 & \Lambda & 0 & 0 & 1 \end{bmatrix} \tag{11}$$

and $\boldsymbol{W}$ is an N x M matrix with orthogonal columns $\boldsymbol{w}_i$ such that

$$\boldsymbol{W}^T \boldsymbol{W} = \boldsymbol{H} \tag{12}$$

where $\boldsymbol{H}$ is diagonal with elements h_i:

$$h_i = \boldsymbol{w}_i^T \boldsymbol{w}_i = \sum_{t=1}^{N} w_i(t)\, w_i(t),\quad 1 \le i \le M. \tag{13}$$

The space spanned by the set of orthogonal basis vectors $\boldsymbol{w}_i$ is the same space spanned by the set of $\boldsymbol{p}_i$, and Eq. (5) can be rewritten as

$$\boldsymbol{d} = \boldsymbol{W}\hat{\boldsymbol{g}} + \boldsymbol{E} \tag{14}$$

The orthogonal LS solution $\hat{\boldsymbol{g}}$ is given by

$$\hat{\boldsymbol{g}} = \boldsymbol{H}^{-1}\boldsymbol{W}^T \boldsymbol{d} \tag{15}$$

or

$$g_i = \boldsymbol{w}_i^T \boldsymbol{d}/(\boldsymbol{w}_i^T \boldsymbol{w}_i),\quad 1 \le i \le M \tag{16}$$

The quantities $\hat{\boldsymbol{g}}$ and $\hat{?}$ satisfy the triangular system.

$$\boldsymbol{A}\hat{?} = \hat{\boldsymbol{g}}. \tag{17}$$

The classical Gram-Schmidt and modified Gram-Schmidt methods[24] can be used to derive Eq. (17) and thus to solve for $\hat{?}$. The $\hat{?}$ is the weights between hidden nodes to output node. In the case of RBF networks, the number of data points $\boldsymbol{x}(t)$ is often very large and centers are to be chosen as a subset of the data set. In general the number of all candidate regressors, M, can be very large and an adequate modeling may only require M_s ($<<M$) significant regressors. These significant regressors can be selected using the OLS algorithm operating in forward regression manner. Because $\boldsymbol{w}_i$ and $\boldsymbol{w}_j$ are orthogonal for $i \neq j$, the sum of squares or energy of $d(t)$ is

$$\boldsymbol{d}^T\boldsymbol{d} = \sum_{i=1}^{M} g_i^2 \boldsymbol{w}_i^T \boldsymbol{w}_i + \boldsymbol{E}^T\boldsymbol{E}. \tag{18}$$

If $\boldsymbol{d}$ is the desired output vector after its mean has been removed, then the variance of $d(t)$ is given by

$$N^{-1}d^Td = N^{-1}\sum_{i=1}^{M} g_i^2 w_i^T w_i + N^{-1}E^TE. \qquad (19)$$

It is seen that $\sum g_i^2 w_i^T w_i / N$ is the part of the desired output variance which can be explained by the regressors and E^TE/N in the unexplained variance of $d(t)$. Thus $g_i^2 w_i^T w_i / N$ is the increment to the explained desired output variable introduced by w_i, and an error reduction ratio due to w_i can be defined as

$$[err]_i = g_i^2 w_i^T w_i / \left(d^T d\right), \quad 1 \le i \le M. \qquad (20)$$

This ratio offers a simple and effective means of seeking a subset of significant regressors in a forward selection manner. The regressors selection procedure is summarized as follows:

- At the first step, for $1 \le i \le M$, compute

  $$w_1^{(i)} = p_i$$
  $$g_1^{(i)} = \left[w_1^{(i)}\right]^T d / \left(\left(w_1^{(i)}\right)^T w_1^{(i)}\right)$$
  $$[err]_1^{(i)} = \left(g_1^{(i)}\right)^2 \left(w_1^{(i)}\right)^T w_1^{(i)} / \left(d^T d\right)$$

  Find

  $$[err]_1^{(i_1)} = \max\{[err]_1^{(i)},\ 1 \le i \le M\}$$

  and select

  $$w_1 = w_1^{(i_1)} = p_{i_1}.$$

- At the kth step where $k \ge 2$, for $1 \le i \le M,\ i \ne i_1, \Lambda, i \ne i_{k-1}$, compute

  $$\alpha_{jk}^{(i)} = w_j^T p_i / \left(w_j^T w_j\right), \qquad 1 \le j \le k$$
  $$w_k^{(i)} = p_i - \sum_{j=1}^{k-1} \alpha_{jk}^{(i)} w_j$$
  $$g_k^{(i)} = \left(w_k^{(i)}\right)^T d / \left(\left(w_k^{(i)}\right)^T w_k^{(i)}\right)$$
  $$[err]_k^{(i)} = \left(g_k^{(i)}\right)^2 \left(w_k^{(i)}\right)^T w_k^{(i)} / \left(d^T d\right)$$

  Find

  $$[err]_k^{(ik)} = \max\{[err]_k^{(i)},\ 1 \le i \le M, i \ne i_1, \ldots, i \ne i_{k-1}\}$$

  and select

  $$w_k = w_k^{(ik)} = p_{ik} - \sum_{j=1}^{k-1} \alpha_{jk} w_j$$

  where $\alpha_{jk} = \alpha_{jk}^{(ik)},\ 1 \le j \le k$.

- The procedure is terminated at M_sth step when

$$1 - \sum_{j=1}^{M_s} [err]_j < \rho \qquad (21)$$

where $0 < \rho < 1$ is a chosen tolerance. This gives rise to a subset model containing M_s significant regressors.

The tolerance ρ is an important instrument in balancing the accuracy and the complexity of the final network. The accuracy improves with increasing complexity of network. Ideally, the value of the tolerance should be larger than, but very close to $\sigma_\varepsilon^2/\sigma_d^2$, where σ_ε^2 is the variance of the residuals and σ_d^2 is the variance of the measured data. At the outset, however, σ_ε^2 is not known. An initial guess is assigned to ρ and an estimate of σ_ε^2 can be computed during the selection process. After a few trials, an appropriate estimate for $\sigma_\varepsilon^2/\sigma_d^2$ can be found.

(2) Data used and family of pavement

a) Data used

The pavement data from "the report of the structural design of asphalt pavements, technical memorandum of Japan Public Works Research Institute[25]", and " the database of Hokuriku Region Pavement Management Support system " were used in this study.

There are about 157 pavement sections data in the report of the structural design of asphalt pavements[25]. This report contains detailed information about pavement material and thickness, pavement condition data, rehabilitation records, and traffic data. The pavement sections have about ten years history condition data, and there is a variation in interval time of data collection.

The pavement condition data in Hokuriku region are collected every three years. The data contained in this database include pavement condition data, maintenance history, pavement material types, traffic, pavement geometric, and road map. Because the database of Hokuriku Region Pavement Management Support system is new, the pavement sections have only two point history condition data, which were collected after overlay of asphalt concrete, reconstruction or new construction. A total of about 5564 pavement sections data of route 8 in Hokuriku region were retrieved to develop the model.

In both database, Maintenance Control Index (MCI) are used to assess the condition of pavements. The MCI was developed by Japanese

Table 1 The pavement families developed in this study.

Database	Pavement family	Action applied	Material type	Traffic level
The report of the structural design of asphalt pavement	1	AC overlay	AC surface Asphaltic base Granular subbase	C
	2	AC overlay	AC surface Asphaltic base Granular subbase	B
Hokuriku Region	3	AC overlay	AC surface Bitumen - stabilized base Granular subbase	D
	4	Routine maintenance (new road or reconstruction)	AC surface Bitumen - stabilized base Granular subbase	D
	5	AC overlay	AC surface Granular base Granular - subbase	D

Ministry of Construction to evaluate the condition of surfaces of national highways in Japan.

b) Pavement families

Pavement sections with similar characteristics were grouped into a pavement family. The criteria used for the pavement family selection were maintenance actions, pavement material types and traffic levels. Two types of maintenance actions were included in the analysis: routine maintenance (for new roads and reconstruction) and overlays. Most of pavement sections in both database have the asphalt concrete surface layer, bound or granular base, and granular subbase, therefore, the pavement material type was classified based on these material types. Traffic volumes were characterized by four levels: A, B, C, and D[26].

After pavement families have decided the proposed model uses the age of pavements to predict the deterioration of pavement. The successful development of pavement deterioration model using similar method have been reported by several researchers [8), 9), 10), 27)]. George, et al.[1] indicate that age is the most significant factor that influence pavement deterioration, and yearly ESAL and structural number are only minor important. Age can be determined precisely for any pavements and play a pivotal role in prediction pavement deterioration.

In this study, the structural aspects are implicitly included in pavement material type classification. The structural parameter such as structural number and CBR are not included in our model because of lack of structural data range in the database used. The similar condition may be found in other pavement database in Japan.

The proposed method can be used to develop pavement deterioration model using the database from any individual geographic location where the climatic or environmental condition is implicitly included. In this study, the pavement deterioration model of Hokuriku region was developed. The data in the report of the structural design of asphalt pavements[25] was collected from several regions in Japan. Because the lack of data of each region, all the data was used, and the criteria used were maintenance actions, material types and traffic levels. However, if enough data is available, the pavement deterioration of each region can be developed.

The pavement families that can be developed from the report of the structural design of asphalt pavements[25] and route 8 of Hokuriku region database, are summarized in **Table 1**. It is assumed that the pavement sections in the same pavement family more or less will have similar deterioration performance.

The data screening was applied to each pavement family data before the data was used in the pavement deterioration model. The purposes of the data screening are:

- To filter out the pavement segment data that showed improved condition without any record of maintenance activity.
- To separate the abnormal sections those show the consecutive small variation in MCI or show the rapid declines in MCI.

(3) The architecture of pavement deterioration model using RBFNN

To develop the pavement deterioration model of each pavement family, the pavement deterioration architectures using RBFNN were proposed. These are shown in **Fig. 2** and **Fig. 3**. Both architectures can be used to develop pavement deterioration based on the database that has long history condition data or only two point history condition data. The RBFNN shown in **Fig. 2** is used if there is a variation in interval time of data collection in the database, and RBFNN in **Fig. 3** is used if the database has the same interval time of data collection.

The input data of proposed RBFNN architecture are preceding MCI, age and Δ age. The age is a time of life duration of pavements since construction, reconstruction or overlay. The preceding MCI is the MCI value at this age. The Δ age is the interval time of data collection when RBFNN is in training, and is the age difference between the preceding MCI and the next MCI when optimum RBFNN is used to predict the future pavement condition. In PMS, the same interval analysis period is commonly used.

The RBFNN as shown in **Fig. 2** and **Fig. 3** are designed as a sequential pavement deterioration model. In this model, after the optimum RBFNN has

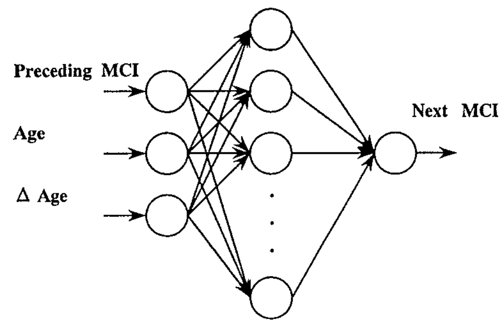

Fig. 2 The RBFNN architecture for database that has variation in interval time of data collection.

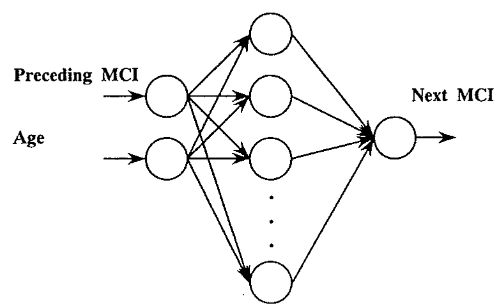

Fig. 3 The RBFNN architecture for database that has the same interval time of data collection

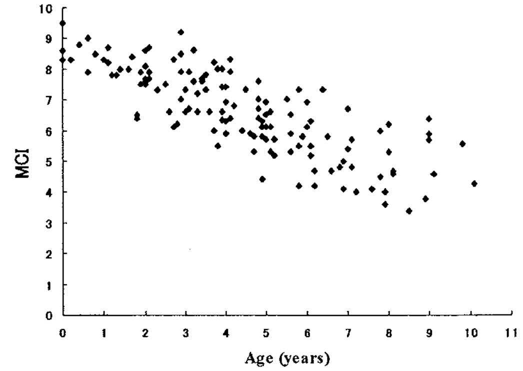

Fig. 4 The scatter plot of age versus MCI of pavement family 1

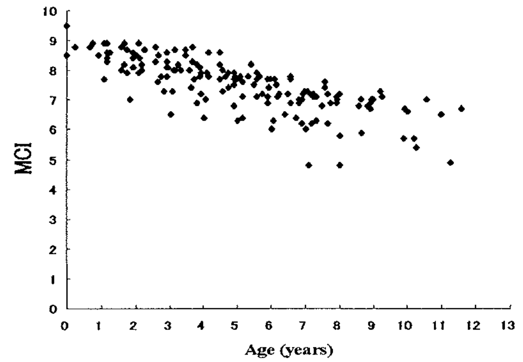

Fig. 5 The scatter plot of age versus MCI of pavement family 2

been calculated, the RBFNN is used to predict the next MCI value of the pavement section. This predicted MCI value is then used as the preceding MCI value to predict the next consecutive MCI value. The process is repeated until the desired prediction period is reached.

3. RESULTS AND DISCUSSION

(1) Pavement deterioration model based on the long history condition data.

The data in the report of the structural design of asphalt pavements[25] has variation in interval time of data collection, therefore the RBFNN architecture in **Fig. 2** was applied to this data. The pavement deterioration model of pavement family 1 and 2, as shown in **Table 1**, were developed.

Pavement family 1 consists of 33 pavement section data sets with 190 history condition data points, and pavement family 2 consists of 23 pavement section data sets with 145 history condition data points. The scatter plot of the age versus MCI for pavement of family 1 and 2 are shown in **Fig. 4** and **Fig. 5**, respectively.

Pavement section data of family 1 were divided into two subsets: a training set consists of 29 pavement section data sets (164 data points), and a testing set consists of 4 pavement section data sets (26 data points) that were selected randomly. A training set of pavement family 2 consists of 21 pavement section data sets (132 data points) and the testing set consists of 2 pavement section data sets (13 data points) that were selected randomly. The training data set was used to train RBFNN, and the testing set was used to evaluate the capability of the model to predict the pavement deterioration.

a) RBFNN optimization

The same width was applied for all radial basis functions in hidden nodes. In order to find the optimum width, a number of widths were applied in RBFNN optimization. Root mean squared error (RMS) between the predicted MCI value of RBFNN and actual MCI value of training data was used as a criteria to select the optimum width. **Fig. 6** shows the plot of width versus RMS of RBFNN of pavement family 1. The width with minimum RMS

Table 2 The results of pavement deterioration prediction of testing sections of pavement family 1.

Test Section 1 (Code 3914)		Test Section 2 (Code 5418)		Test Section 3 (Code 6115)				Test Section 4 (Code 3913)		Prediction		
Actual		Actual		Actual		Corrected RBFNN		Actual		Age	MCI	
Age	MCI	Age	MCI	Age	MCI	Age	MCI	Age	MCI		RBFNN	Reg.
0	9.5	0	9.5	0	9.5			0	9.5	0	9.5	9.3
2.0	7.5	1.8	7.0	3.3	8.5	3.3	8.5	1.3	8.2	1	8.3	8.6
2.9	6.4	2.7	6.5	4.2	8.4	4.3	7.8	2:3	7.0	2	7.4	7.9
4.0	6.0	3.7	6.0	5.7	7.4	5.3	6.5	3.3	6.8	3	6.8	7.3
5.0	5.2	4.7	5.4	6.5	6.8	6.3	6.0	4.3	6.4	4	6.5	6.3
6.0	4.8			7.6	5.6	7.3	5.6	5.3	5.1	5	5.9	6.2
7.0	4.2			8.5	5.5	8.3	4.9	6.3	4.7	6	5.4	5.7
7.9	3.9					9.3	4.7	7.2	4.3	7	4.9	5.3
8.9	3.7									8	4.3	5.0
9.8	3.6									9	4.0	4.7
										10	3.8	4.5

Reg. : the results of regression analysis, where MCI= 9.3 - 0.768 age + 0.029 age^2.

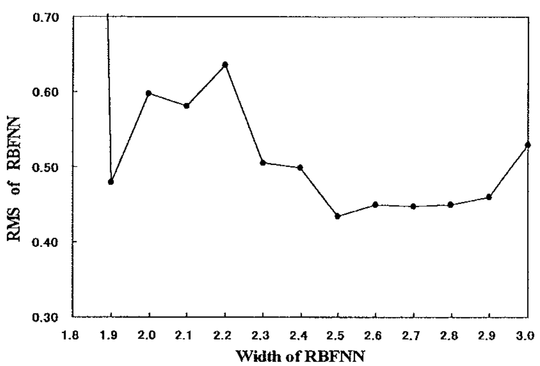

Fig. 6 The width versus RMS of RBFNN of pavement family 1

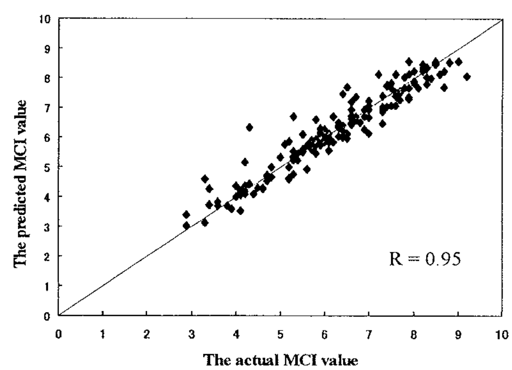

Fig. 7 The predicted versus actual MCI of pavement family 1

of RBFNN was chosen as the optimum width. The optimum width of pavement family 1 is 2.5 and the number of hidden nodes of RBFNN is 50. This means that from 164 training data points, 50 selected data points with width = 2.5 are used as centers to get the optimum RBFNN. Using similar way, the optimum width of pavement family 2 is 2.2 and the number of hidden nodes is 39.

The predicted MCI values of training data, along with the actual MCI values for pavement family 1 and 2 are shown in **Fig. 7** and **Fig. 8**, respectively. The coefficient of correlation of pavement family 1 and 2 are 0.95 and 0.91, respectively.

b) Comparison between the results of testing data with actual rating and regression analysis results.

In PMS, the same interval analysis period is applied and usually a yearly basis of analysis is used. Therefore, in the evaluation of the results of proposed model, the Δ age = 1.0 year is used. To evaluate the predicted results using RBFNN, the MCI results of testing data were compared with

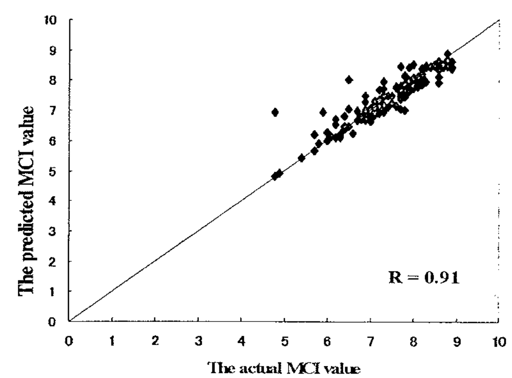

Fig. 8 The predicted versus actual MCI of pavement family 2

actual MCI values and regression analysis results. **Table 2,** and **Figs. 9** to **12** respectively show the results comparison of testing sections of pavement family 1. The regression function that best fit with the data is quadratic function. This was found after evaluation of various functions includes: linear, quadratic, cubic, exponential, compound, logistic

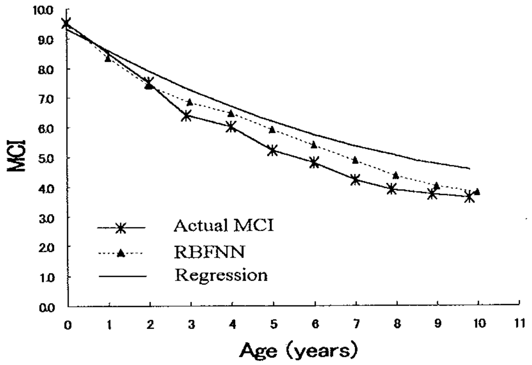

Fig. 9 Pavement performance curve of test section 1 of pavement family 1

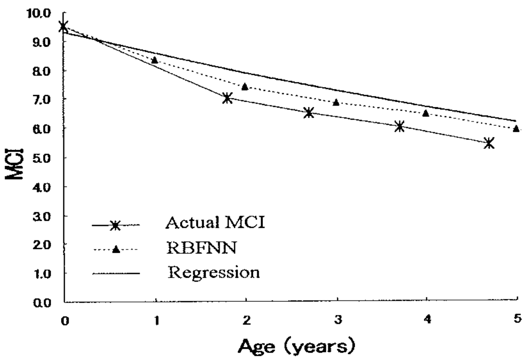

Fig. 10 Pavement performance curve of test section 2 of pavement family 1

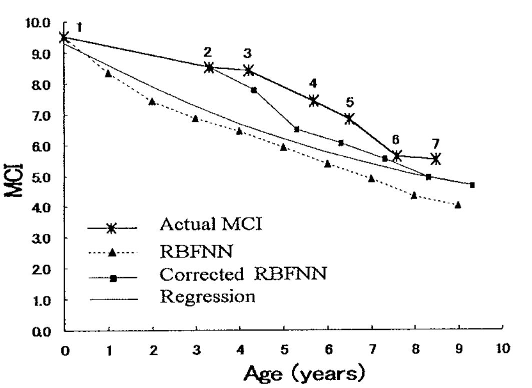

Fig. 11 Pavement performance curve of test section 3 of pavement family 1

and growth. This regression function represents the general trend of pavement deterioration of pavement family 1.

From **Fig. 9**, it can be seen that the general trend of RBFNN deterioration prediction results, started from age = 0 and MCI = 9.5, is in good agreement

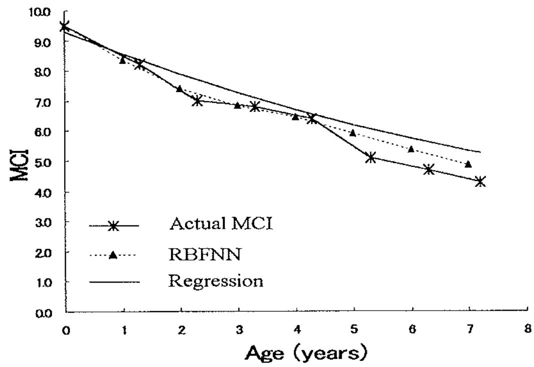

Fig. 12 Pavement performance curve of test section 4 of pavement family 1

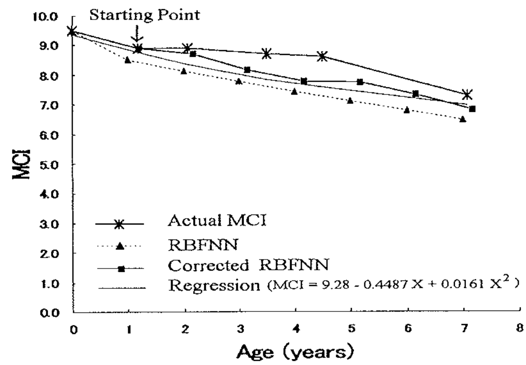

Fig. 13 Pavement performance curve of test section 1 of pavement family 2

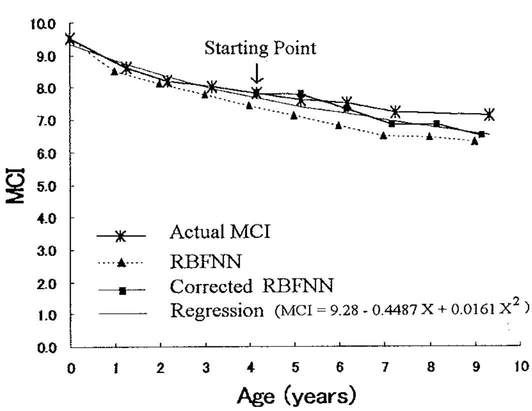

Fig. 14 Pavement performance curve of test section 2 of pavement family 2

with the actual MCI of test section 1, and the general trend of RBFNN model can give better results comparing with regression model. The similar facts were found from test sections 2 and 4 of pavement family 1.

It is well-known, the pavement sections in a pavement family that have the same age and initial MCI value, probably have the differences in future pavement condition deterioration. For test section 3, as shown in **Fig. 11**, it was found that the actual MCI is in bad agreement with general trend of RBFNN model. The general trend of RBFNN also has worse results comparing with the results of regression model. In our proposed model, however, if the training data contains a range of pavement ages and MCI values that represent the entire range exist in a pavement family, the correction can be made by using actual measured value as the preceding MCI to predict the next MCI value. For test section 3, the correction was done by using the actual measured MCI value and age of point 2 as starting point to predict the pavement deterioration. The results of corrected RBFNN are shown in **Fig. 11**.

From the **Fig. 11**, it can be seen that the results of corrected RBFNN are closer to actual MCI and have better results than the results of regression model.

As shown in **Figs. 13** and **14**, the similar facts as test section 3 of pavement family 1 are found from 2 testing sections of pavement family 2 where the corrected RBFNN results are in good agreement with actual MCI values.

The results indicate that the proposed RBFNN architecture can give satisfactory pavement deterioration prediction. However, as mentioned by Sebaaly et al.[5] and Hand et al.[28], a model is valid only when the range of parameter used in the model is within the range that it was developed. Every effort was made to maintain data sets that were representative of entire range of variables that could be encountered a particular pavement family.

The RBFNN is learning from training data and it is able to represent the existing data patterns in the training data. Because the training data contains a range of pavement ages with various MCI values, the optimum RBFNN can be used to predict the future condition of pavement sections using only information about age of pavement and its MCI value. It will be discussed in the next section.

c) The flexibility of pavement deterioration model using RBFNN

The architecture of proposed pavement deterioration model using RBFNN is designed as "Sequential Pavement Deterioration Model". In this model, if information about present MCI and age of pavement section are known, the future condition of pavement section can be predicted.

To evaluate this flexibility, the future condition of testing sections of pavement family 1 and 2 determined using RBFNN, started from a point located along the actual deterioration curve, was compared with the actual pavement deterioration. The location of the starting point was selected randomly. These are shown in **Figs. 15** to **20**.

The results indicate that pavement deterioration predictions, started from a point located along the actual deterioration curve, are in a good agreement with the actual measurement MCI. This indicates that the proposed pavement deterioration model using RBFNN can be used to determine the future pavement condition using only information about the present MCI value and the age of pavements.

(2) Pavement deterioration model based on the database that has two point history condition data.

Ideally, the database to develop the pavement deterioration model would consist of long history pavement condition data. However, the new

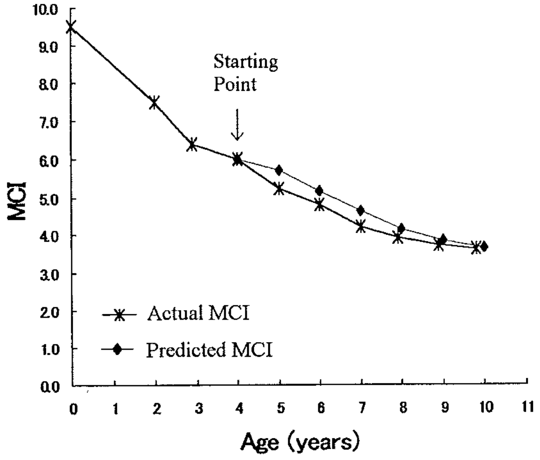

Fig. 15 Pavement performance prediction of testing section 1 of pavement family 1 using RBFNN start from a point located along deterioration curve.

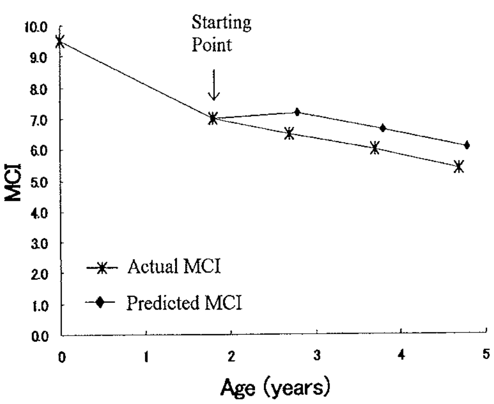

Fig. 16 Pavement performance prediction of testing section 2 of pavement family 1 using RBFNN start from a point located along deterioration curve.

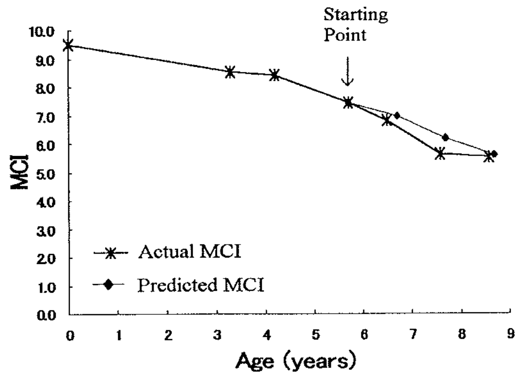

Fig. 17 Pavement performance prediction of testing section 3 of pavement family 1 using RBFNN start from a point located along deterioration curve.

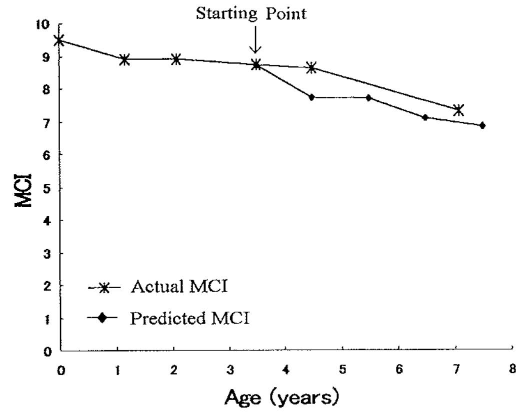

Fig. 19 Pavement performance prediction of testing section 1 of pavement family 2 using RBFNN start from a point located along deterioration curve.

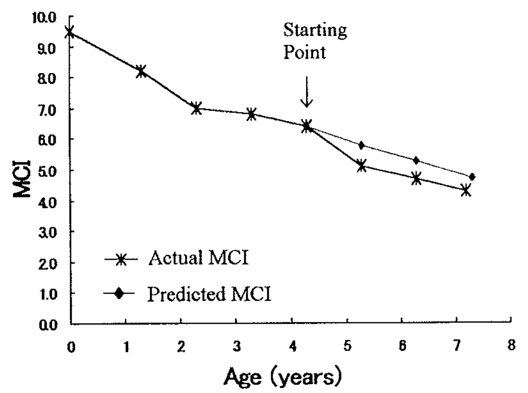

Fig. 18 Pavement performance prediction of testing section 4 of pavement family 1 using RBFNN start from a point located along deterioration curve.

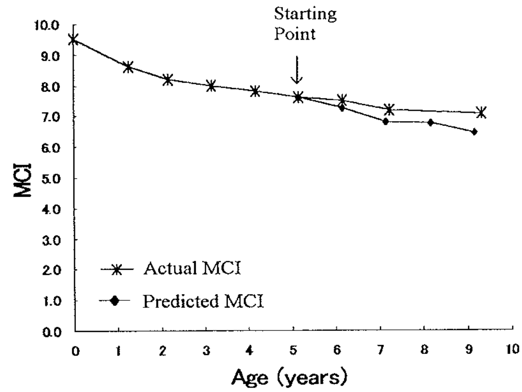

Fig. 20 Pavement performance prediction of testing section 2 of pavement family 2 using RBFNN start from a point located along deterioration curve.

database such as the Hokuriku region database has only two period history condition data collection. The RBFNN architectures as shown in **Fig. 2** and **Fig. 3** are also designed to develop the pavement deterioration model based on at least two point history pavement condition data. For Hokuriku region database, the RBFNN architecture as shown in **Fig. 3** was used because the database has the same interval time of data collection (3 years).

Fig. 3 indicates that the input data needed to predict the next pavement section condition are the pavement age and its MCI value. Although there are no long history data, fortunately a range of pavement ages and its MCI value, that is similar to a range of ages of long history condition data, can be found from the first period data collection because pavement sections have various pavement ages. An assumption was made that these sections represent the condition of pavement sections at various ages. The future condition of pavement sections for the next consecutive three years can be found from the second point of data collection. These data were then used to train the RBFNN model, and the optimum RBFNN were used to predict the future pavement condition using only information about present MCI value and age of pavement.

The pavement deterioration of pavement family 3 and 5 are presented in this section. The pavement family 3 consists of 59 pavements with various pavement ages and preceding MCI values, and the MCI values for the next consecutive three years. There are 67 pavement sections data in pavement family 2. The pavement deterioration of pavement family 4 is not developed for the time being due to

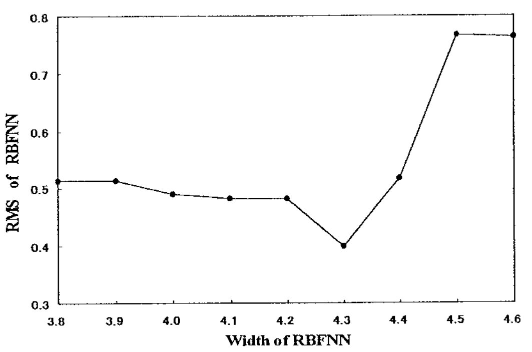

Fig. 21 The width versus RMS of RBFNN of pavement family 3.

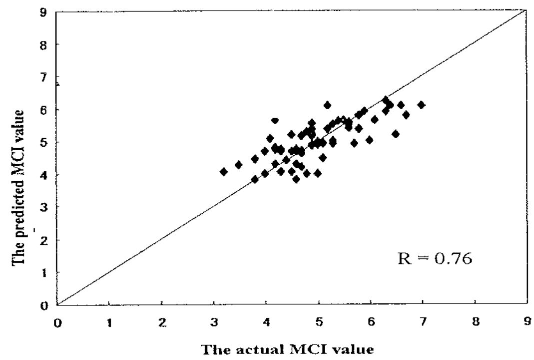

Fig. 23 The predicted versus actual MCI of pavement family 5

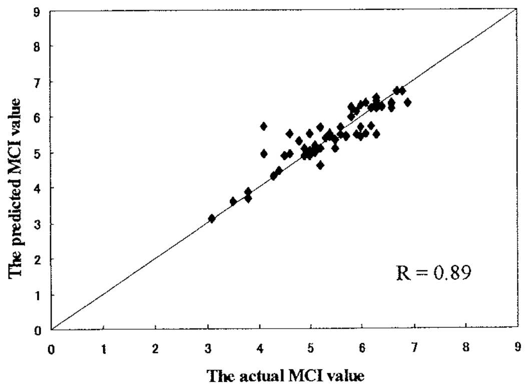

Fig. 22 The predicted versus actual MCI of pavement family 3

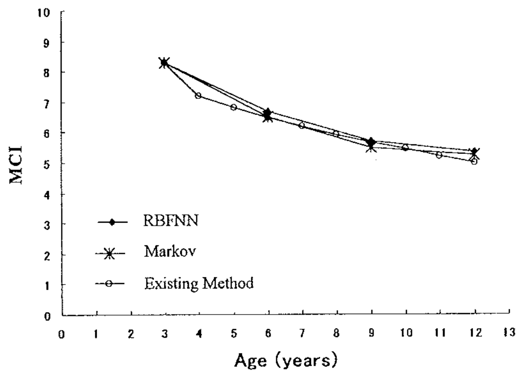

Fig. 24 Model comparisons for test section 1 of pavement family 3 (KP 4+540 to 600)

the lack of pavement parameter data distribution in the database.

a) RBFNN optimization

Fig. 21 shows the plot of width versus root mean squared error (RMS) between the predicted MCI value of RBFNN and actual MCI value of training data of pavement family 3. The optimum width found is 4.3 and the number of hidden nodes of RBFNN is 18. The plot of predicted MCI value of training data versus actual MCI value of pavement family 3 is shown in **Fig. 22**. The coefficient of correlation R = 0.89.

For pavement family 5, the optimum width is 3.3 and number of hidden nodes is 6. **Fig. 23** shows the plot of predicted MCI value of training data versus actual MCI value of pavement family 5. The coefficient of correlation R = 0.76.

b) Comparison between the RBFNN results with the Markov model and the existing model of Hokuriku region.

Because there are no long history condition data, to check the capability of the RBFNN pavement deterioration model, the comparison with the Markov model[14] and the existing model of Hokuriku region database[29] were conducted. The Markov model was developed using the same data that used to develop the RBFNN model, and the existing linear model was developed based on the pavement data in Hokuriku region. The pavement performance prediction comparison using five pavement sections data of route 8 in Hokuriku region were presented. **Figs. 24** to **26** and **Figs. 27** to **28** respectively show the model comparison of pavement family 3 and 5.

The results indicate that the three different models have the similar trend of pavement performance and are in close agreement. This likely indicates that the proposed RBFNN architecture can be used to predict the future performance pavement section.

4. CONCLUSIONS

The pavement deterioration model using the Radial Basis Function Neural Networks were proposed and evaluated. The results indicate that the proposed model has good capability to be used to predict the future performance of pavement

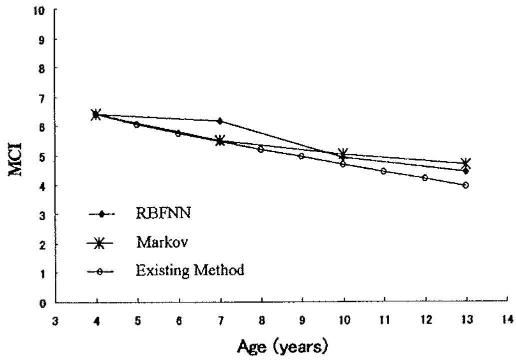

Fig. 25 Model comparisons for test section 2 of pavement family 3 (KP 17+600 to 700)

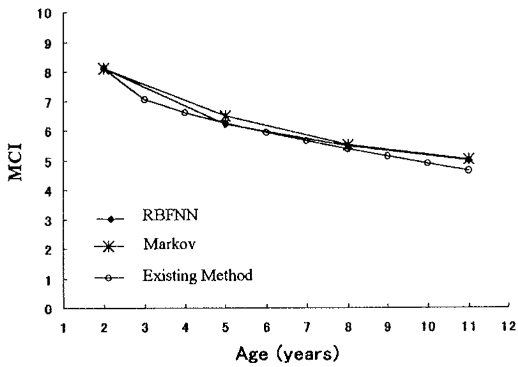

Fig. 26 Model comparisons for test section 3 of pavement family 3 (KP 56+100 to 200)

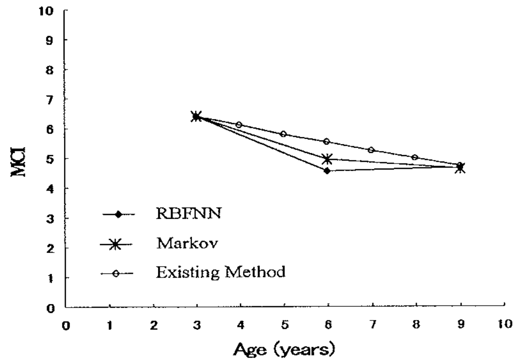

Fig. 27 Model comparisons for test section 1 of pavement family 5 (KP 27+500 to 600)

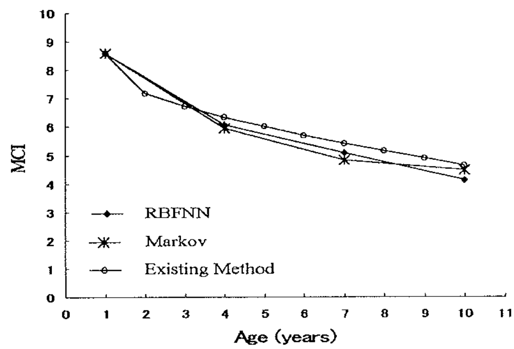

Fig. 28 Model comparisons for test section 2 of pavement family 5 (KP 12+900 to 12+1000)

sections. The advantages of the proposed model are as follows:

- The model is designed as sequential pavement deterioration model, where the future pavement condition can be determined only based on the information about the present MCI value and age of pavement.
- The model can be used to develop the pavement deterioration model using the database that have at least only two point history condition data.
- Since the proposed model is applying the RBFNN, the model has fast convergence time and guarantees convergence to global optimum parameter.

To get the best result of the pavement deterioration model, the range of parameter that used in RBFNN training must be adopted in the entire range of variables that could be encountered a particular pavement family.

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