APPLICATION OF NEURAL NETWORK MODELS FOR FORECASTING OF PAVEMENT CRACK INDEX AND PAVEMENT CONDITION RATING

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Errata Sheet

On page 7, the original text is:

$$RR = \frac{RN \times 20}{100} \tag{1.3}$$

where,

RR = Ride Rating (0 to 100 scale)

RN = Profiler Ride Number

Note: Ride Rating is actually calculated to a 100 scale and then reported on a 10 scale.

Now, the above text should be changed to:

$$RR = \frac{RN \times 20}{10} \tag{1.3}$$

where,

RR = Ride Rating (0 to 10 scale)

RN = Profiler Ride Number

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16. Abstract

Timely identification of undesirable crack, ride and rut conditions has been a critical step in pavement management at the network level. To date, many models have been developed for forecasting of pavement conditions with most of them focusing on a single index. Florida Department of Transportation (FDOT) forecasting models for roughness, skid resistance, or crack condition, etc. are such examples. The overall pavement surface condition is jointly determined by these individual pavement condition indices. This report summarizes the results of a research project that was initiated to implement a pavement condition prediction methodology using Artificial Neural Network (ANN). In this research effort, three individual ANN models were developed to forecast three key indices, including crack rating, ride rating, and rut rating. These indices have been used by FDOT for pavement evaluation purposes. Each individual model was trained and tested with the use of FDOT pavement surface condition database. Modeling results suggest that the ANN models developed in the research have the capability to satisfactorily forecast future individual pavement condition index up to a period of five years. As one of the implementation tasks, a software package was developed for easy implementation and use of the ANN predictive models.

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ABSTRACT

Timely identification of undesirable crack, ride and rut conditions has been a critical step in pavement management at the network level. To date, many models have been developed for forecasting of pavement conditions with most of them focusing on a single index. Florida Department of Transportation (FDOT) forecasting models for roughness, skid resistance, or crack condition, etc. are such examples. The overall pavement surface condition is jointly determined by these individual pavement condition indices. This report summarizes the results of a research project that was initiated to implement a pavement condition prediction methodology using Artificial Neural Network (ANN). In this research effort, three individual ANN models were developed to forecast three key indices, including crack rating, ride rating, and rut rating. These indices have been used by FDOT for pavement evaluation purposes. Each individual model was trained and tested with the use of FDOT pavement surface condition database. Modeling results suggest that the ANN models developed in the research have the capability to satisfactorily forecast future individual pavement condition index up to a period of five years. As one of the implementation tasks, a software package was developed for easy implementation and use of the ANN predictive models.

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CHAPTER 1

INTRODUCTION

Pavement condition performance models, which simulate the deterioration process of pavement conditions and provide forecasting of pavement conditions over time, play a pivotal role in pavement management system (PMS). Myriads of researches have been done with respect to pavement performance modeling. However, the pavement deterioration process is so complex that it is difficult and sometimes impossible to find an appropriate functional form as used in traditional modeling. Hence, a new approach, which can be categorized as “biologically-inspired”, is taking the territory from its traditional counterpart. Typical models in this category are neural networks and genetic algorithms. Neural network abstracts the underlying relationship between dependent and independent variables from the exemplar data pairs and express it as forms of weight matrix. The main objective of this research was to develop a pavement performance model applying neural network algorithm and implement the model in the Florida Department of Transportation (FDOT) pavement management system.

1.1 Background

Transportation Equity Act in the 21st Century (TEA-21) calls for coordinated efforts to collect, store, manage, and analyze transportation related data, which lay a solid foundation for the establishment of PMS. Due to the increasing challenges in pavement maintenance and rehabilitation, PMS has become a very beneficial management tool for highway agencies. The high expenditures incurred in highway construction imply a significant saving even from a slight improvement in management of the highway investment.

Pavement management typically operates at two levels, (1) network level and (2) project level. At the network level, a priority program and work schedules are developed within overall budget constraints. On the other hand, at the project level, specific physical improvements are implemented according to the network decisions. The key components of a PMS are inventory, analysis, output, and feedback. Pavement performance model, which acts as the hub of the analysis component, is the engine of the whole management activities. The activities include: at the network level, (1) prediction of the future conditions of the pavement, (2) prediction of the future funding needed to keep the pavement network at an acceptable level, (3) comparison of the effects of various funding scenarios on the pavement network, and (4) justification of annual budget for rehabilitation; at the project level, (1) identification of the candidate projects for rehabilitation, (2) generation of rehabilitation alternatives for each candidate project, (3) technical and economic analysis of each alternative, and (4) justification of project rehabilitation activities.

As it can be seen, the pavement performance model is not only a technical tool but also one that has significant economic implications. Traditionally, pavement performance has been referred to as serviceability performance, a concept defined by Carey and Irick, which represents performance as the history of pavement serviceability with time [1]. Since then, the concept of pavement performance has been widely analyzed and discussed by many researchers [2, 3, 4]. Typically, pavement performance models or pavement deterioration models relate pavement condition, represented by any one indicator of pavement condition, to a set of explanatory variables, such as traffic loads, environmental, design, construction, and maintenance practices to simulate the mechanism of the pavement deterioration process. If measured explanatory variables are furnished, pavement performance models can predict the future condition of the pavement, based on which future management activities are scheduled. In order to make a decision as to when maintenance activities are necessary, it is important to establish an action threshold in terms of the pavement condition. Usually, the rationale to set up the threshold is based on the deterioration rate. Empirically, the period of first several years after construction represents the slowest deterioration period for a pavement. As time progresses, pavement conditions become worse, and the deterioration rate begins to increase until it comes to a reflection point after which the pavement deteriorates so quickly that it is no longer efficient to renovate rather than rebuild it. However, the threshold value can vary depending on the rating systems and specific indicator that is used for pavement condition evaluation. A graphic illustration of the effect of maintenance activities on the pavement performance is shown in Figure 1.1.

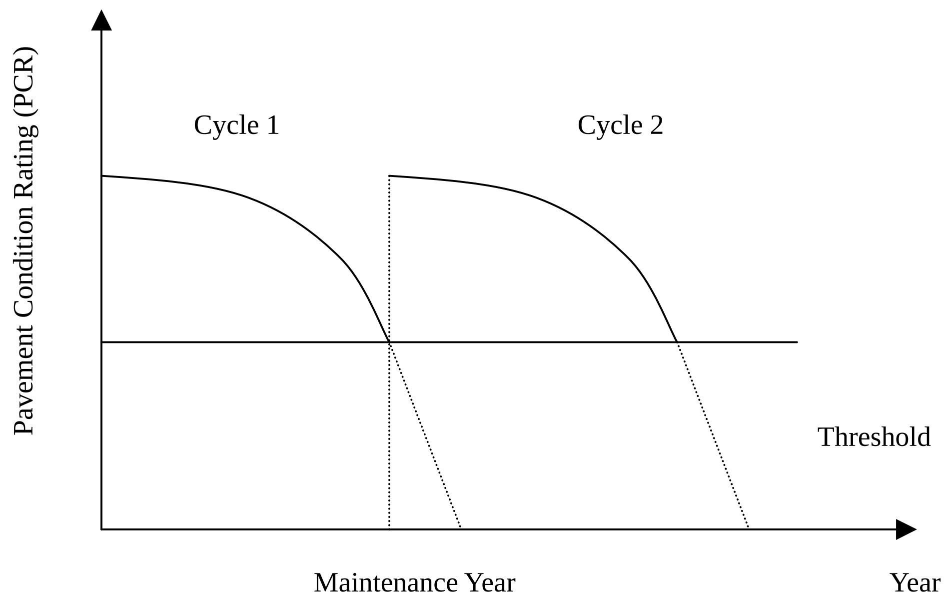


Figure 1.1 Illustration of the Effect of Maintenance Activities on Pavement Performance

1.2 FDOT Current Practice

Currently, FDOT uses three key pavement performance indices, which are crack index (CI), ride index (RD), and rut index (RT), to capture the different attributes of pavement surface conditions. In addition, FDOT uses a composite index called the pavement condition rating (PCR) to represent the overall pavement condition. PCR is defined as the minimum of the three key indices. It implies that the three indices are equally important and the lowest one represents the overall pavement condition. The indices of cracks, ride and ruts are rated on a 0-10 scale where 10 indicates the best condition and 0 the worst. If PCR is greater than the decision threshold of 6.4, the pavement is considered to be in a sound condition; or if PCR is equal to 6 and determined by ride rating, the pavement is not considered deficient when the speed limit is less than 45 mph. The following section provides a brief review of the FDOT rating procedure of each individual index.

1.2.1 Crack Rating

Visual survey has been employed to determine the pavement crack condition. A survey crew drives an inspection vehicle at a reduced speed to visually check the entire section and records the overall crack condition of the section. To facilitate crack data collection, three distinct types of cracking have been considered by FDOT:

> Class IB: this category includes hairline cracks that are 1/8 inch (3.18 millimeters) wide either in the longitudinal or transverse direction.
>
> Class II: this category includes cracks with open width from 1/8 inch (3.18 millimeters) to 1/4 inch (6.35 millimeters) either in the longitudinal or transverse direction. These cracks may have moderate spalling or severe branching. It is also included cracks with open with less than 1/4 inch (6.35 millimeters) which has formed cells less than 2 feet (0.61 meters) on that longest side (alligator cracking).
>
> Class III: this category includes cracks with open width 1/4 inch (6.35 millimeters) or greater and extending in a longitudinal or transverse direction and these those opened to the base or underlying material. It is also includes progressive Class II cracking resulting in severe spalling with chunks of pavement breaking out. Severe raveling (loss of surface aggregate) or patching would also be classified as Class III cracking.

The crack rating (CR) is obtained by subtracting the "negative deduct values" associated with various forms of cracking from 10 as shown in Eq.1.1

$$CR = 10 - (cw + co) \tag{1.1}$$

where,

cw = deduct value confined to wheelpaths

co = deduct value outside of Wheelpaths

Deduct values for flexible pavements are shown in Tables 1.1 and 1.2. A crack rating score of 10 indicates a pavement without observable distress or with only minor observable distress.

Table 1.1 Numerical Deductions for Cracking Survey (Confined to Wheelpaths (cw))

Percent of Pavement Area Affected by Cracking	Predominate Cracking Class		
	1B Cracking Deduct	II Cracking Deduct	III Cracking Deduct
00-05	0.0	0.5	1.0
06-25	1.0	2.0	2.5
26-50	2.0	3.0	4.5
51+	3.5	5.0	7.0

Table 1.2 Numerical Deductions for Cracking Survey (Outside of Wheelpaths (co))

Percent of Pavement Area Affected by Cracking	Predominate Cracking Class		
	1B Cracking Deduct	II Cracking Deduct	III Cracking Deduct
00-05	0.0	0.0	0.0
06-25	0.5	1.0	1.0
26-50	1.0	1.5	2.0
51+	1.5	2.0	3.0

Source: FDOT Flexible Pavement Condition Survey Handbook

1.2.2 Rut Rating

The rut defect score (RD) is obtained by subtracting the “deduct point” corresponding to the rut depth from 10 as shown in Eq.1.2.

$$RD = 10 - ra \qquad (1.2)$$

where, ra is the ultrasonic rutting deduct points, which can be found in Table 1.3.

The average rut depth (both wheelpaths combined) is extracted from the ultrasonic profiler report and coded as indicated on Table1.3. Manual rut depths are also recorded, if necessary.

Table 1.3 Ultrasonic Rutting Deduct Points (ra)

Rut Depth inches	Rut Depth mm	Range inches	Range mm	Defect Points	Code Value
0	0	0.00 - 0.06	0.00 – 1.59	0	0
1/8	3.18	0.07 – 0.19	1.60 – 4.76	1	1
1/4	6.35	0.20 – 0.31	4.77 – 7.94	2	2
3/8	9.53	0.32 – 0.44	7.95 – 11.11	3	3
1/2	12.7	0.45 – 0.56	11.12 – 14.29	4	4
5/8	15.88	0.57 – 0.69	14.30 – 17.46	5	5
3/4	19.05	0.70 – 0.81	17.47 – 20.64	6	6
7/8	22.23	0.82 – 0.94	20.65 – 23.81	7	7
1	25.4	0.95 – 1.06	23.82 – 26.99	8	8
1 1/8	28.58	1.07 – 1.19	27.00 – 30.16	9	9
1 1/4 +	31.75	1.20 +	30.17 +	10	10

Source: FDOT Flexible Pavement Condition Survey Handbook

1.2.3 Ride Rating

Ride Rating is calculated using profiler ride number, acquired from the outside wheel path. The expression for computing ride rating is as follows:

$$RR = \frac{RN \times 20}{100} \tag{1.3}$$

where,

RR = Ride Rating (0 to 100 scale)

RN = Profiler Ride Number

Note: Ride Rating is actually calculated to a 100 scale and then reported on a 10 scale.

The reviewing of FDOT rating procedures revealed considerable inconsistency in the rating systems of different indices used by FDOT. In order to assure consistency, three different models were developed with respect to the three key indices, crack index, rut index and rut index. The minimum value predicted by the three models is considered as the predicted PCR.

1.2.4 Forecasting Methods used by FDOT

Two mathematical forecasting methods are currently used by FDOT for each roadway segment: (1) mean deterioration rate and (2) simple linear regression. In practice, one of the methods that best fits the prior trend of the data will usually be chosen. However, since pavement performance is a nonlinear phenomenon in nature, neither of the two methods is appropriate in general. Hence, more accurate models based on sophisticated forecasting methodologies are needed for FDOT PMS.

1.3 Project Background

Four different objectives were achieved in a previous research conducted by Lu et al, University of South Florida (USF) leading to the development of a pavement crack performance model [5]. These objectives are:

1. Review of the existing models used to predict pavement crack condition,

2. Review of the FDOT database to identify available information that could be used for the model development,
3. Development of neural network model for crack forecasting based on historical information, and
4. Evaluation of the performance of the neural network model as compared with other existing models.

The previous research results and findings have demonstrated that the neural network method is an appropriate tool to model pavement crack performance. The previous research results are so inspiring that further research interest was mandated to implement the neural network method in FDOT's PMS. Thus, in 2000, FDOT and USF started a follow-up research, "Applications of Neural Network Models for Forecasting of Pavement Crack Index and Pavement Condition Rating". This research focused on application of the neural network model to pavement condition rating (PCR) and implementation of the model in FDOT PMS. In addition to the PCR forecasting model, three different neural network submodels were established and corresponding software that implement these neural network models were developed. This report summarizes the above research efforts.

CHAPTER 2

LITERATURE REVIEW

2.1 Review of Existing Pavement Performance Models

The last three decades witnessed an increasing interest in the development of pavement performance models. Although pavement performance models may take different forms, typically, they relate the indicators of pavement conditions, such as cracking index, roughness, or rutting, to explanatory variables such as traffic loads, environmental factors, cycle, age, and pavement structure. The purpose of a model is to establish a causal relationship between the pavement condition and these factors that is considered influencing performance of pavements. Three broad categories of pavement performance models currently exist. These are deterministic models, probabilistic models, and biologically-inspired models.

2.1.1 Deterministic Models

For deterministic models, the functional form is assumed to be explicitly specified. Deterministic models can be further divided into three subcategories, which are pure empirical models, mechanistic-empirical models, and expert system models.

1) Pure Empirical Models

Pure empirical model is one of the most widely used models for pavement performance forecasting. A massive database is required in the modeling effort. A typical empirical model takes the form of a non-linear polynomial curve that obeys specific boundary conditions as shown in Eq.2.1.

$$PCR = a_0 + a_1 X + a_2 X^2 + a_3 X^3 \tag{2.1}$$

where:

PCR = pavement condition rating,

X = pavement age in years, and

a_1, a_2, a_3, a_4 = regression parameters.

To assure the accuracy of such models, pavements need to be classified into families with each family having a unique set of parameters capturing its own characteristics.

2) Mechanistic-empirical Models

Historically, engineering knowledge of pavement behavior under traffic loading has been mostly based on mechanistic analyses of pavement structures. Mechanistic models are developed based on the mechanistic relationship among loading, stresses, strains, and deflections. Due to the complexity of the interactions among the factors relevant to pavement performance, few of this type of model have been successfully developed so far. Instead, the hybrid breed of mechanistic-empirical models becomes popular. The mechanistic-empirical model is the combination of empirical method and mechanistic knowledge. In particular, it involves a mechanistic model to calculate the pavement response (stresses, strains, deflections) under traffic loading, and an empirical function relating the pavement response to the pavement performance (cracking, roughness, and rutting etc.). An example of this model category is a pavement roughness model provided by Queiroz [6] as shown in Eq.2.2.

$$\log(QI) = 1.297 + 9.22(10^{-3})(AGE) + 9.08(10^{-2})(ST)$$

$$- 7.03(10^{-2})(RH) + 5.57(10^{-4}\}(SEN1)(\log N) \tag{2.2}$$

where:

QI = roughness (counts/km),

AGE = pavement age in years,

ST = surface type dummy variable (0 for as constructed and 1 for overlaid),

RH = state of rehabilitation indicator (0 for as constructed and 1 for overlaid),

$SEN1$ = strain energy at bottom of asphalt layer (10^{-4} kgf cm), and

N = cumulative equivalent single axle loads (ESAL).

By taking into account of the mechanistic characteristics of the pavement, the mechanistic-empirical models can perform better than the empirical models. A major drawback is that more efforts are needed in the acquisition of data.

3) Expert System Models

It is recognized that pure empirical models and mechanistic-empirical models are both massive data demanding models. In cases where data are deficient, experts can supplement knowledge. Expert models are developed based on the opinions of experienced engineers who are familiar with the deterioration patterns of different types of pavement. In practice, the amount of expert knowledge that enters these models varies depending on the highway agency. Some agencies may rely one hundred percent on expert opinions, while others may use contribution of 50% from expert opinion and 50% from databases. South Dakota Department of Transportation used this approach to develop their deterioration models (SD93-14). In South Dakota, first, a scaling system was applied to develop the deduct values associated with each severity and extent classifications associated with defined distress types. Then, experienced engineers were asked to provide estimates of the ages of pavements to reach particular conditions in terms of severity and extent for different distress type. With these data, a regression analysis was performed to determine the coefficients for the specified model, which could take the following form:

$$PPI = c + at^{b} \tag{2.3}$$

where:

PPI = pavement performance index,

c = the maximum value of the index,

a = slope of the deterioration curve,

t = age of the pavement, and

b = exponent coefficient of the curve.

2.1.2 Probabilistic Models

Inherent variability of material properties, environmental conditions, traffic characteristics, and the subjective nature of condition surveys cause the pavement performance to inherit characteristics of a stochastic process. Probabilistic models treat pavement condition measures such as PCR or crack index as a random variable. A popular probabilistic pavement performance model is the Markov chain model, which is an application of Markovian technique in pavement performance modeling. Markovian technique and its applications in pavement modeling was described in detail by Butt [7]. The technique requires developing a probability transition matrix to predict the pavement deterioration with time. The basic Markov chain model consists of initial stage probability and the transition matrix as shown in Eq.2.4.

$$P_i = P_0 (P)^i \tag{2.4}$$

where:

P_0 = the vector of initial state probability,

P_i = the vector of state probability of i^{th} duty cycle,

P = probability transition matrix, and

i = duty cycle.

The probability transition matrix P can be expressed as

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} & \ldots\ldots & p_{1n} \\ 0 & p_{22} & p_{23} & p_{24} & \ldots\ldots & p_{2n} \\ 0 & 0 & p_{33} & p_{34} & \ldots\ldots & p_{3n} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & 0 & 0 & 0 & \ldots\ldots & p_{(n-1)n} \\ 0 & 0 & 0 & 0 & \ldots\ldots & 1 \end{bmatrix} \tag{2.5}$$

where, $\sum_{j=i}^{n} p_{ij} = 1$, i = 1,2,3,……n-1.

The roadway condition, in terms of a particular indicator, is divided into n states, with 1 describing the best condition and n the worst. P_{ii} is the probability of a roadway staying in state i during one duty cycle and P_{ij} (i < j) is the probability of a roadway transiting down to the state j during one duty cycle. However, it is an arduous job to assign reasonable values for all probabilities in the P matrix. In practice, a simplified matrix is generally used. If the assumption is made that the pavement condition will not drop by more than one state in a single duty cycle, which is the general situation for most pavements under normal traffic loading, the probability transition matrix can be simply rewritten as

$$P = \begin{bmatrix} p_1 & q_1 & 0 & 0 & \ldots\ldots & 0 & 0 \\ 0 & p_2 & q_2 & 0 & \ldots\ldots & 0 & 0 \\ 0 & 0 & p_3 & q_3 & \ldots\ldots & 0 & 0 \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ 0 & 0 & 0 & 0 & 0 & p_{n-1} & q_{n-1} \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{2.6}$$

where, $p_i + q_i = 1$, i = 1,2,3,……,n-1

Wasantha Kumara et al described the application of the Markov model to predict the crack depth propagation in Florida’s asphalt pavements [8].

2.1.3 Biologically-inspired Models

Typical models in this category are genetic algorithm (GA) and artificial neural network (ANN) model. A genetic algorithm derives its concept from the process of evolution in nature. First, a population of characteristic candidates for the optimization problem is created. Each of these candidates is termed as an individual. Then, the individuals in the population go through a process of evolution. The evolution is usually achieved in a manner that is similar to the biological evolution: (1) evaluate the fitness of all individuals in the population; (2) create a new population through three key operations: crossover, reproduction, and mutation on individuals in old population; (3) discard the old population, and iterate using the new population. One iteration is referred to as a generation. The three operations play a crucial role in the process of evolution. Reproduction allows the copy of better individuals to appear in the new population. Crossover allows different individuals to be created in the successive generation by merging material from individuals from the previous generation. Mutation is the operation that can infuse new information in a random way to the genetic search process.

A recent application of genetic algorithm in the pavement performance modeling is done by Andrei et al [9]. In the research, a roughness performance model was developed by using the genetic programming algorithm. Various published LTPP distress data and early results of RO-LTPP data were utilized for the modeling. After running about 50 generations, the best model was finally obtained, which is expressed as:

$$R_t = R_{t-1} + \log_{10}(R_{t-1} + SN) \tag{2.7}$$

where,

R_t= roughness of pavement at age t,

R_{t-1} = roughness of pavement at age t-1, and

SN = structural number modified for subgrade strength.

As noticed, it is an iterative model. With the initial roughness R_0 and the pavement roughness condition at age t provided, R_t can be forecast iteratively. The research result suggests that evolutionary technique can be used successfully in engineering fields, especially in transportation engineering, where the available sample data are usually scarce and time-consuming to collect.

Another important biologically-inspired approach is artificial neural network (ANN). ANN stems from the understanding of the functioning of the brain. It can be regarded as the highly simplified models of the human brain system, which, however, emulates human brain abilities of learning, generalization, and abstraction. Up to now, many applications of ANN to pavement performance modeling have been attempted producing inspiring results.

2.2 Application of Artificial Neural Networks in Pavement Performance Modeling

A number of studies have involved the application of artificial neural networks to model pavement performance over time. To name a few, four applications relevant to this research are discussed herein.

Attoh-Okine et al. applied a neural network to develop a pavement roughness progression model [10]. The training data were generated from RODEMAN, a road deterioration and maintenance submodel of HDM-III. An empirical simulation model was used to generate roughness data. The neural network was then developed relating the pavement roughness to a set of factors causing pavement roughness: pavement structural deformation, incremental traffic loadings, extent of cracking and thickness of surface layer, incremental variation of rut depth, surface defects such as patching and potholes, and environmental and other non-traffic-related variables such as road age etc.. Three different architectures of the neural network with one, two and three layers, respectively, were examined. The back-propagation learning algorithm was used as the learning rule. The predicted results of the trained network were compared with the desired results in terms of the mean square error (MSE). It was concluded that the application of neural networks in pavement deterioration modeling is feasible when a large database of pavement condition is available. On the other hand, since the modeling was accomplished using simulated data, it was recognized that the model might not be general enough to perform well on other data sets, especially from pavements in service.

Shekharan developed ANN models to predict pavement conditions for five families of pavements: original flexible, overlaid flexible, composite, jointed, and continuously reinforced concrete pavements [11]. The pavement condition was represented by pavement condition rating (PCR), a composite index derived by combining the distresses and roughness, formulated for the Mississippi Department of Transportation. In this approach, Genetic Adaptive Neural Network Training (GANNT) algorithm is employed. The explanatory variables that have been chosen as inputs to the neural network models are pavement structure, pavement history represented by pavement age in years, traffic volume by cumulative 18-kip equivalent single axle loads. In order to account for quality of maintenance activities, and to some extent the traffic volume, the classification according to Federal Aid System (FAS) is also included in the list of explanatory variables. To substantiate the prediction capability of ANN, the same data with the same explanatory variables are employed for developing regression models. Finally, comparison was made on ANN and regression modeling. The author concluded that for modeling purposes, artificial neural network algorithms are, in general, found to be a better tool as compared to regression techniques, for the simple reason that artificial neural networks provide a flexible form of mapping and can take into account any functional form of equation.

Owusu-Ababio applied neural networks to model performance of thick asphalt pavement (thickness≥152.4 mm (6 in.)) [12]. The database used for this study was developed through a survey of the Wisconsin Department of Transportation district offices and selected city governments. The indicator of pavement condition used in this study was the pavement distress index (PDI), which range from 0 to 100 with 0 being the best and 100 being the worst. The main factors assumed to affect the performance of non-overlaid thick asphalt pavements include the pavement surface thickness, pavement age, traffic level (ESAL/day), base thickness, and roadbed condition. For comparison purposes, multiple linear regression (MLR) models were also developed. It was concluded that the ANN model outperforms the MLR model in terms of standard error and R square value.

In the research conducted by Lu et al USF, a neural network model was developed to forecast pavement crack condition [5]. In this study, the FDOT pavement condition database was used. Back propagation algorithm was employed for the network training. A three-layer neural network model was proposed for the modeling. Through trial and error, seven specific variables were selected as inputs. These are crack index time series variables, CI(t-2), CI(t-1), CI(t), which are the Crack Index in year t-2, t-1 and t, respectively, flexible type of pavement indicator (1 if flexible, 0 otherwise), rigid type of pavement indicator (1 if rigid, 0 otherwise), pavement cycle, and pavement age. As the output of neural network, the following year's crack index (CI(t+1)) was predicted. For comparison purposes, a corresponding AR model was also developed. The comparison result showed that neural network model was more accurate than the AR model in terms of root mean square error (RMSE), average error and R square value. As the result of the research, the authors (Lou et al, 2001) concluded that the proposed neural network model was an effective tool for pavement maintenance planning.

The literature review showed that ANN is a powerful modeling tool and began to receive increasing attention in modeling pavement performance over time. However, most of the researches focus on modeling single pavement index, such as crack, ride, or rut index, etc., with few centering on overall pavement condition. This study attempted to fill this void. As result of this research, ANN models were developed to forecast the overall pavement condition in Florida.

CHAPTER 3

METHODOLOGY

Three ANN models were developed in this study to forecast the overall pavement conditions, encompassing the individual crack, ride and rut ratings. They are (1) crack performance model, (2) ride performance model, and (3) rut performance model. FDOT uses a composite index (PCR) to represent overall pavement condition. PCR is defined as the minimum of crack, ride and rut indices. The minimum forecasted value from the three models is used to represent the forecasted PCR. The popular ANN training algorithm of standard Back-Propagation (BP) algorithm was employed for neural network training purpose. In the following sections techniques in modeling pavement performance over time are introduced first. Then, An in-depth review of ANN and BP algorithm are provided.

3.1 Techniques Applied in Pavement Performance Modeling

Primarily, there are two distinct types of models available for pavement condition forecasting. The first type is a static model and can be conceptually described by the following equation:

$$PI_t = f(S_t, M_t, T_t, E_t, t, etc.) \tag{3.1}$$

where,

PI_t = pavement condition index at age t,

S_t = pavement structural conditions at age t,

M_t = pavement materials characteristics at age t,

T_t = traffic conditions at age t, and

E_t = environmental conditions at age t.

Often, the development of such models is based on field and/or laboratory data and statistical analysis. As a result, formats of these models are generally complicated due to the multitude of variables associated. Further, these models may lack accuracy due to numerous uncertainties.

The second type, a dynamic model, can be described by the following equation:

$$PI_t = f(PI_{t-1}, PI_{t-2}, ..., PI_{t-N}) \tag{3.2}$$

Pavement condition at age t, PI_t, is forecasted using historical pavement condition data at ages *t-1, t-2, … , t-N*. This type of model is based on historical performance of pavement characteristics, irrespective of other variables used in the static model. By understanding the dynamics of the changing process over time, this type of model can forecast future conditions based on the past conditions. It is recognized that the structural condition is reflected in the historical changing process of pavement condition. Thus, if external and structural conditions are not significantly changed within a relative short time period, the model based on historical information could produce a reasonably accurate forecast of future pavement condition. This type of model is called time-series model, which has been successfully applied in transportation engineering.

A time-series model can describe time-dependent processes in which past data influence future data in the presence of underlying deterministic factors. These factors may be characterized by trends, cycles, and non-stationary behavior of the processes. It is these recurring patterns and relationships that the predictive models attempt to recognize. On the other hand, there is always certain level of randomness existing in the time-series. Both the deterministic trend and the randomness should be addressed in the forecasting model. A traditional statistical treatment of time series would include tests for randomness, analyses of series into component parts, smoothing, and the use of autoregressive models. However, the inherently nonlinear time series, such as that found in pavement condition deterioration process, are more suitable for analysis by the general nonlinear mapping provided by a neural network, than by linear based autoregressive models. Neural networks are nonlinear models that can be trained to map past and future data of a time-series, thereby uncovering the hidden relationships governing the data.

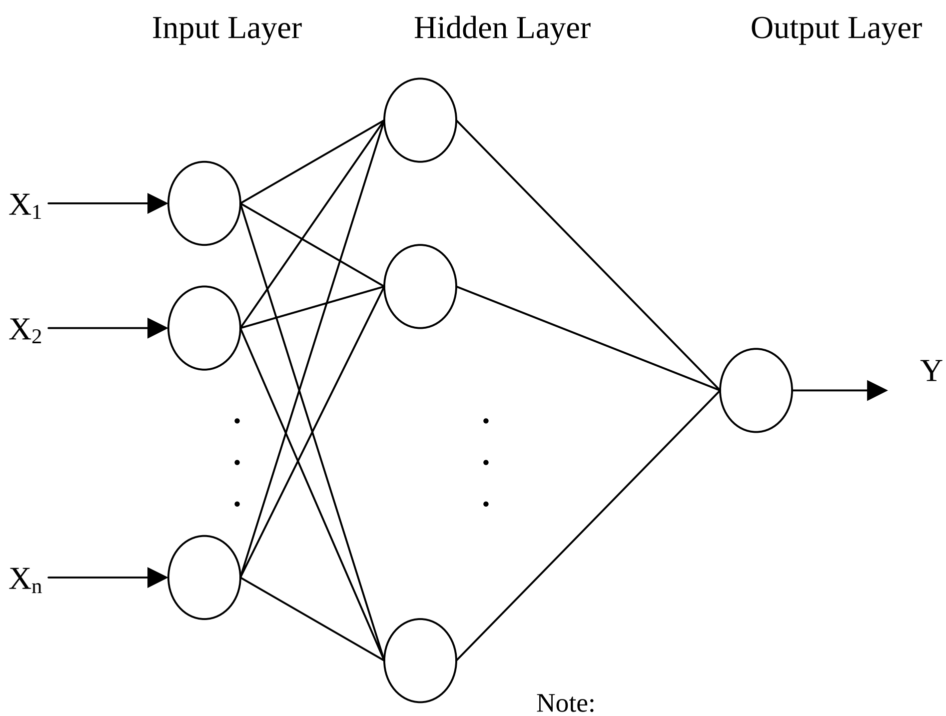
3.2 Artificial Neural Networks

An ANN is a parallel information-processing system that has certain performance characteristics similar to biological neural networks. A neural net consists of a large number of simple processing elements called neurons. Each neuron is connected to other neurons by means of directed links and each directed link has a weight associated with it. The weights acquired through the training process represent abstracted information from dataset, which is used by the net to solve a particular problem. Some functions that neural networks are able to perform include: (1) classification - making a decision on which category an input pattern belongs to, (2) pattern matching - according to the input pattern, the neural network produces corresponding output pattern, (3) pattern completion - presented with an incomplete pattern, the neural network produces the corresponding complete pattern, (4) optimization - provided with the initial values for a specific optimization problem, the neural network produces a set of variables that represent an acceptably optimized solution to the problem, and (5) simulation: presented with the current state vector of a system or time series, the trained network generates structured sequence or patterns that simulate behavior of the system with time.

The capability that neural network can execute such complicated tasks is attributed to its underlying parallel distributed computational “mechanism”. The mechanism is supported by three crucial and interacting components: (1) pattern of connection between neurons, which is referred to as architecture, (2) method of determining the weight of the connections, which is referred to as learning algorithm, and (3) neuron activation function. In order to construct a neural network for solving a particular problem, three components need to be determined first, including architecture, learning method, and neuron activation function.

3.2.1 Architecture

Significant effort is needed to determine the best architecture for the ANN models. This includes the determination of input and output variables, number of hidden layers, and number of hidden neurons in each hidden layers. Usually, a neural network with too few hidden neurons is unable to learn sufficiently from the training data set, whereas a neural network with too many hidden neurons will allow the network to memorize the training set instead of generalizing the acquired knowledge for unseen patterns [13]. Haykin recommends using two hidden layers; the first one for extracting local features and the second one for extracting global features [14]. However, with two hidden layers, a significant increase in the training time and corresponding decrease in the efficiency of training process could be experienced. Funahashi and Hornik et al. separately proved that any continuous function can be approximated with an arbitrary accuracy using the three-layered network [15,16]. Thus, from a theoretical viewpoint, a three-layered network is enough for function approximation. In practice, most neural network applications use only one hidden layer. Due to the still vague understanding of the impacts of the variation of ANN architecture, trial and error is conventionally employed to select the appropriate number of hidden neurons in the hidden layer for the problem under investigation. As an illustration, a typical three-layered neural network with one output neuron is shown in the Figure 3.1.



Note:

X_1, X_2,…, X_n = input to the neural network, and

Y = output of the neural network

Figure 3.1 A Typical Three-layered Neuron Network with One Output Neuron

3.2.2 Learning method

All learning methods can be classified into two categories: supervised learning and unsupervised learning. Supervised learning is a process that utilizes an external teacher and/or global information. Several popular supervised learning algorithms are error correction learning, reinforcement learning, stochastic learning, and hardwired systems. Supervised learning can be further classified into two subcategories: structural learning and temporal learning. Structural learning is concerned with finding the best possible input-output relationship for each individual pattern pair. Examples of structural learning include pattern matching and pattern classification. However, temporal learning is concerned with capturing a sequence of patterns necessary to achieve some final outcome. Examples of temporal learning include prediction, simulation, and control. In the case of unsupervised learning, external teacher or supervisor is not necessary. It relies only upon local information during the entire learning process by organizing presented data and discovering its emergent collective properties.

Back-propagation (BP) method, which was used in this research, falls into the category of supervised learning. It is one of the most popular learning methods for multiple-layer neural networks. Due to its generality, BP neural network can be used to tackle a wide array of problems. A detailed discussion of the BP method is presented in section 3.2.

3.2.3 Neuron activation function

A neural network consists of many neurons. Each neuron is an independent processing element (PE), having its own inputs and output. The term of "distributed parallel computation" is derived from the independence property of neurons. A typical neuron is shown in Figure 3.2.

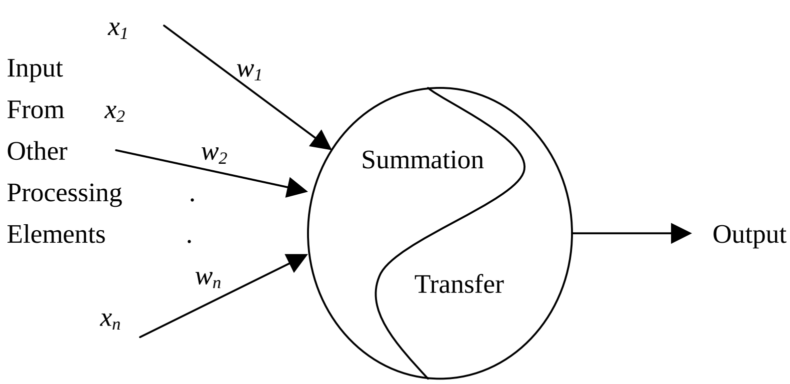


Figure 3.2 Diagram of Artificial Neuron

The output shown in Figure 3.2 is calculated by the following equation:

$$O_j = f(\sum_{i=1}^{n} x_i w_i) \tag{3.3}$$

where

x_i = the ith input,

w_i = the connection weight associated with ith input,

O_j = output of jth neuron, and

f = the transfer function.

As noticed, the processing of each neuron is simply a weighted summation plus a function transfer. Five typical transfer functions are generally used as neuron activation functions depending on the characteristics of the problem under study. These activation functions are linear, linear threshold, step, sigmoid and Gaussian. Among these, the most commonly used one is the sigmoid function due to its concise form and differentiability. The output of each neuron calculated by the sigmoid transfer function can be expressed as:

$$z = f(y) = \frac{1}{1+e^{-a(y)}} \tag{3.4}$$

$$y = \sum_{i=1}^{n} w_i x_i \tag{3.5}$$

where :

z = neuron output,

y = input to the transfer function,

a = gain of the sigmoid function,

n = number of element in the input vector,

x_i = ith element in the input vector, and

w_i = weight of connection i.

In this study the sigmoid function was employed as the neuron activation function.

3.2.4 Characteristics of neural network performance

In computational terms, a neural network exhibits a unique set of performance characteristics inherited from its parallel-distributed structure. By simulating the functionality of the human brain, neural network could possess:

(1) Learning ability: presented with examples, neural networks are capable of learning from examples. In other words, it can generalize information from the presented examples.

(2) Nonlinearity: neural network can perform nonlinear multi-dimensional mapping.

(3) Memorization: can memorize the patterns and restore the incomplete patterns.

(4) Adaptivity: can adapt itself to the environment by virtue of learning.

Of these characteristics, the most outstanding one is learning. The learning capability of ANNs is achieved by adjusting the signs and magnitudes of their weights according to learning rules that seek to minimize a cost or error function. BP neural network is the most widely used neural network. It provides a great opportunity for the multi-dimension vector mapping. Although powerful, the concept of BP network is very simple. The following section will focus on the organization of BP algorithm.

3.3 Back Propagation Method

Back-Propagation (BP) is an effective training method for multiplayer neural networks. Its appearance has played a major role in the re-emergence of neural networks as tools for solving a wide variety of problems especially after the downturn of neural networks due to limitations of single-layer neural networks. BP is simply the implementation of the gradient descend method to minimize the total squared error of the output computed by the network. However, the general nature of BP method implies that a BP trained network can be applied to solve problems in a wide spectrum of fields. Moreover, BP method presents a clear mathematical concept and ease of programming. These conveniences empower BP as a versatile and pragmatic mechanism to implement neural networks. Enormous software applications of neural network use BP as the embedded learning law. “Brainmaker” is one of these, and was employed in this research effort to develop the neural network models.

Compared with other neural network training methods, BP is a straightforward one. To facilitate understanding, a detailed mathematical derivation of BP method is presented as follows. To be general, a three-layer multiple-input-and-output neural network is shown in Figure 3.3 is used as an example to illustrate the derivation.

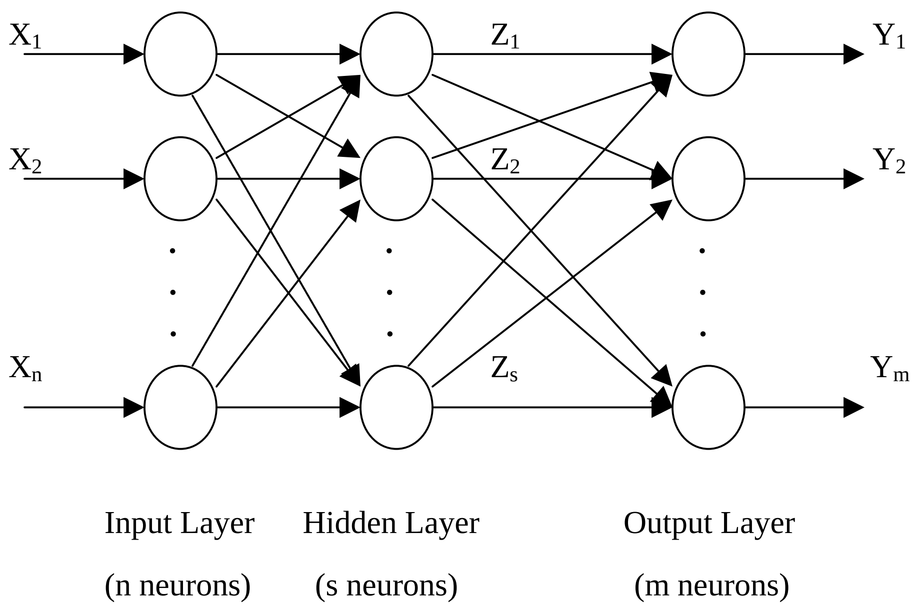


Figure 3.3 Back-propagation Network Structure

The following nomenclature will be used in the discussion.

Input vector: $X \in R^n, X = (X_1, X_2, ..., X_n)^T$

Output vector: $Y \in R^m, Y = (Y_1, Y_2, ..., Y_m)^T$

Intermediate Output vector of hidden layer: $Z \in R^s, Z = (Z_1, Z_2, ..., Z_s)^T$

Weight between the input layer and the hidden layer: $w_{ij}\,(i=1,2,...,n;\ j=1,2,...,s)$

Bias between the input layer and the hidden layer: $b_j\,(j=1,2,...,s)$

Weight between the hidden layer and the output layer: $w_{ik}\,(j=1,2,...,s; k=1,2,...,m)$

Bias between the hidden layer and the output layer: $b_k\,(k=1,2,...,m)$

Input sample: $X^{(1)}, X^{(2)}, ...X^{(p)}$

Expected output: $T^{(1)}, T^{(2)}, ...T^{(p)}$

Actual network output: $Y^{(1)}, Y^{(2)}, ..., Y^{(p)}$

To simplify the deduction, the bias is considered as a special weight with input as –1. Let the bias be the 1th element in the input vector, indicated by the subscript 0. Thus,

$$\begin{cases} b_j = w_{0j}, X_0 = -1 \\ b_k = w_{0k}, Z_0 = -1 \end{cases}$$

Therefore, the output of neurons for the hidden layer and output layer are:

$$Y_k = f\left(\sum_{j=o}^{s} w_{jk} Z_j\right), k = 1,2,...m \tag{3.6}$$

$$Z_j = f\left(\sum_{i=o}^{n} w_{ij} X_i\right), j = 1,2,...,s \tag{3.7}$$

It is assumed that the r^th^ sample in the training set propagates forward to the output as $Y_0, Y_1, ..., Y_{m-1}$, then half of sum of the square error for the r^th^ example is:

$$E_i = \frac{1}{2}\sum_{k=o}^{m-1}\left(T_k^i - Y_k^i\right)^2 \tag{3.8}$$

The total error for learning p examples is:

$$E_{total} = \frac{1}{2}\sum_{r=1}^{p}\sum_{k=1}^{m}\left(T_k^{(r)} - Y_k^{(r)}\right)^2 \tag{3.9}$$

Let

$$W = [w_{11}^{(1)}, w_{12}^{(1)},..., w_{ij}^{(1)},..., w_{ns}^{(1)}, w_{11}^{(2)}, w_{12}^{(2)},..., w_{jk}^{(2)},..., w_{sm}^{(2)}]$$

Given the rth training pattern pair, $E_{(r)}$ can be considered as a function of *W*. The relationship can be expressed as:

$$\varepsilon = E_{(r)} = \frac{1}{2}\sum_{k=0}^{m-1}\left(T_k^{(r)} - Y_k^{(r)}\right)^2 = g\left(W, T^{(r)}, X^{(r)}\right) \tag{3.10}$$

Thus,

$$E_{total} = \sum_{r=1}^{p} g\left(W, T^{(r)}, X^{(r)}\right) \tag{3.11}$$

Let w_{uv} be any weight in *W*. BP weight change is based on the following equation:

$$\Delta w_{uv} = -\sum_{r=1}^{p}\eta\frac{\partial\varepsilon}{\partial w_{uv}} \tag{3.12}$$

where η is learning rate.

By applying Eq.3.12, the updated weight can be derived as:

$$w_{jk}^{(2)}(l+1) = w_{jk}^{(2)}(l) - \eta\frac{\partial E_{total}}{\partial w_{jk}^{(2)}} \tag{3.13}$$

$$w_{ij}^{(1)}(l+1) = w_{ij}^{(1)}(l) - \eta\frac{\partial E_{total}}{\partial w_{ij}^{(1)}} \tag{3.14}$$

Now, one needs to solve $\frac{\partial E_{total}}{\partial w_{ij}^{(1)}}$ and $\frac{\partial E_{total}}{\partial w_{jk}^{(2)}}$.

As an example, if the sigmoid function is used, the gain of the function, *a*, can be set to 1.0 for simplicity. For the output layer, the rth training pattern pair and the kth output, Eq.3.4 becomes:

$$Y_k^{(r)} = f\left(u_k^{(r)}\right) = \frac{1}{1+e^{-u_i^{(r)}}} \tag{3.15}$$

where,

$$u_k^{(r)} = \sum_{j=0}^{s} w_{jk}^{(2)} Z_j^{(r)}$$

k=1,2,……,m

r=1,2,……,p

By incorporating Eq.3.9 and Eq.3.15, the partial derivative of E_{total} with respect to w_{jk} can be expressed as:

$$\frac{\partial E_{total}}{\partial w_{jk}^{(2)}} = \frac{\partial E_{total}}{\partial Y_k}\frac{\partial Y_k}{\partial u_k}\frac{\partial u_k}{\partial w_{jk}^{(2)}} = \sum_{r=1}^{p}\sum_{k=1}^{n}(T_k^{(r)} - Y_k^{(r)}) f(u_k^{(r)})(1 - f(u_k^{(r)}))Z_j^{(r)} \tag{3.16}$$

Notice $f(u_k^{(r)}) = Y_k^{(r)}$, the following equation can be derived:

$$\frac{\partial E_{total}}{\partial w_{jk}^{(2)}} = \sum_{r=1}^{p}\sum_{k=1}^{m}(T_k^{(r)} - Y_k^{(r)})Y_k^{(r)}(1 - Y_k^{(r)})Z_j^{(r)} \tag{3.17}$$

Let

$$\delta_{jk}^{(r)} = \sum_{k=1}^{m}(T_k^{(r)} - Y_k^{(r)})Y_k^{(r)}(1 - Y_k^{(r)}) \tag{3.18}$$

By substituting Eq.3.17 into Eq.3.13, one obtains:

$$w_{jk}^{(2)}(l+1) = w_{jk}^{(2)}(l) - \eta \sum_{r=1}^{p} \delta_{jk}^{(r)} Z_j^{(r)} \tag{3.19}$$

Similarly, for the hidden layer, the r^th training pattern pair and the j^th output, Eq.3.4 becomes:

$$Z_j^{(r)} = f(v_j^{(r)}) = \frac{1}{1+e^{-v_j^{(r)}}} \tag{3.20}$$

where,

$$v_j^{(r)} = \sum_{j=0}^{s} w_{ij}^{(1)} X_i^{(r)}$$

j=1,2,……,s

r=1,2,……,p

By incorporating Eq.3.20 and Eq.3.9, the partial derivative of E_{total} with respect to w_{ij} can be expressed as

$$\frac{\partial E_{total}}{\partial w_{ij}^{(1)}} = \frac{\partial E_{total}}{\partial Y_k} \frac{\partial Y_k}{\partial u_k} \frac{\partial u_k}{\partial Z_j} \frac{\partial Z_j}{\partial v_j} \frac{\partial v_j}{\partial w_{ij}^{(1)}}$$

$$= \sum_{r=1}^{p} \sum_{k=1}^{n} (T_k^{(r)} - Y_k^{(r)}) f(u_k^{(r)})(1 - f(u_k^{(r)})) w_{jk}^{(2)} (f(v_j^{(r)})(1 - f(v_j^{(r)})) X_i^{(r)}$$

Notice that $f(u_k^{(r)}) = Y_k^{(r)}$, and $f(v_j^{(r)}) = Z_j^{(r)}$. By incorporating Eq.3.18, the following equation can be derived:

$$\frac{\partial E_{total}}{\partial w_{ij}^{(1)}} = \sum_{r=1}^{p}\sum_{k=1}^{m}(T_k^{(r)} - Y_k^{(r)})Y_k^{(r)}(1-Y_k^{(r)})w_{jk}^{(2)}(Z_j^{(r)})(1-Z_j^{(r)})X_i^{(r)}$$

$$= \sum_{r=1}^{p}\sum_{k=1}^{m}\delta_{jk}^{(r)}w_{jk}^{(2)}Z_j^{(r)}(1-Z_j^{(r)})X_i^{(r)}$$

Let

$$\delta_{ij}^{(r)} = \sum_{k=1}^{m}\delta_{jk}^{(r)}w_{jk}^{(2)}Z_j^{(r)}(1-Z_j^{(r)}) \qquad (3.21)$$

By substituting Eq.3.21 into Eq.3.14, the following relation can be obtained:

$$w_{ij}^{(1)}(l+1) = w_{ij}^{(1)}(l) - \eta\sum_{r=1}^{p}\delta_{ij}^{(r)}X_i^{(r)} \qquad (3.22)$$

Eq.3.19 and Eq.3.22 are the weight adjustment equations for the hidden layer and input layer respectively. They will be used during the training process for adjustment of weights in order to reduce the total training error. The derivation above demonstrates a training approach commonly used by practitioners called the "batch training". In batch training, the weights are adjusted after all of samples are processed. Batch training can guarantee E_{total} to decrease gradually and speed up convergence as well. However, sometimes it may cause instability. To address this issue, a momentum term $\alpha\Delta w(n)$ is recommended by some practitioners to add to the adjustment. The additional momentum term improves the stability of the learning algorithm by properly directing the weight adjustment. After adding the momentum term, Eq.3.21 and Eq.3.22 become:

$$w_{jk}^{(2)}(l+1) = w_{jk}^{(2)}(l) - \eta(l)\sum_{r=1}^{p}\delta_{jk}^{(r)}Z_j^{(r)} + \alpha(l)\Delta w_{jk}^{(2)}(l) \qquad (3.23)$$

$$w_{ij}^{(1)}(l+1) = w_{ij}^{(1)}(l) - \eta(l)\sum_{r=1}^{p}\delta_{ij}^{(r)}X_i^{(r)} + \alpha(l)\Delta w_{ij}^{(1)}(l) \qquad (3.24)$$

In practice, Eq.3.23 and Eq.3.24 are used as weight adjustment rules for the BP network training.

3.4 ANN Model Implementation

There are two forms of implementation, hardware and software. The hardware implementation involves neuron realization by using VLSI, optic, or molecular technologies. Software implementation involves software simulation and algorithm-based applications. This research project falls in the latter category of algorithm-based application, which actually applies the neural network algorithm as a means to model the vague mechanism underlying the pavement deterioration process over time.

CHAPTER 4

DATABASE AND DATA PREPROCESSING

This chapter contains a detailed review of the database structure and data preprocessing. The FDOT database contains detailed information on highway pavement conditions on Florida state roads. The database includes variables such as crack, roughness, rutting, roadway identification (RDWYID), section begin mileage (BMP) and section end mileage (EMP), roadway side, roadway age, roadway type, number of lanes, district, system, maintenance cycle, etc. Data preprocessing is the prelude to the ANN modeling process, and it involves adding missing data, deleting irretrievable data, and transferring original database into the formats appropriate for the modeling purposes.

4.1 Database Review

FDOT highway pavement condition survey database was used in this study for both modeling and software implementation purposes. The databases include three time-series, crack index, ride index and rut index, from year 1976 to year 2001. For various purposes, the database was used in this research in two different formats. The one used for modeling purposes in the modeling stage is shown in Table 4.1. The data preprocessing for modeling purposes was based on this first format of the database. The second format of the database as shown in Table 4.2 was used for forecasting purposes at the software implementation stage, which will be discussed later. These two formats can be easily converted to one another by simply running a SAS program developed for this purpose.

Each pavement section recorded in the database is identified by the location, pavement type, and maintenance cycle, etc. The distribution of pavement sections across different maintenance cycles, pavement types and pavement age is shown in Figures 4.1 and 4.2.

Table 4.1 Database Format for Modeling Purposes

BMP	EMP	RDWYID	RDWYSIDE	LANES	DISTRICT	YEAR	AGE	CYCLE	TYPE	CRACK	RUT	RIDE
21.941	25.946	1010000	L	2	1	1976	1	1	1	10	8	9
21.941	25.946	1010000	L	2	1	1977	2	1	1	10	8	8.5
21.941	25.946	1010000	L	2	1	1978	3	1	1	10	8	8.6
21.941	25.946	1010000	L	2	1	1979	4	1	1	10	8	8.5
21.941	25.946	1010000	L	2	1	1980	5	1	1	*	*	*
21.941	25.946	1010000	L	2	1	1981	6	1	1	10	8	8.8
21.941	25.946	1010000	L	2	1	1982	7	1	1	10	9	8.6
21.941	25.946	1010000	L	2	1	1983	8	1	1	10	8	8.7
21.941	25.946	1010000	L	2	1	1984	9	1	1	*	*	*
21.941	25.946	1010000	L	2	1	1985	10	1	1	*	*	*
21.941	25.946	1010000	L	2	1	1986	11	1	1	9.4	7	8.5
21.941	25.946	1010000	L	2	1	1987	12	1	1	9.4	7	8.8
21.941	25.946	1010000	L	2	1	1988	13	1	1	9.4	7	9
21.941	25.946	1010000	L	2	1	1989	14	1	1	9.4	7	9.2
21.941	25.946	1010000	L	2	1	1990	15	1	1	8.4	7	8.7
21.941	25.946	1010000	L	2	1	1991	16	1	1	8.5	7	8.5
21.941	25.946	1010000	L	2	1	1992	17	1	1	8.5	8	8.8
21.941	25.946	1010000	L	2	1	1993	18	1	1	8.5	8	8.6
21.941	25.946	1010000	L	2	1	1994	19	1	1	8.5	8	8.7
21.941	25.946	1010000	L	2	1	1995	20	1	1	8.5	8	8.7
21.941	25.946	1010000	L	2	1	1996	21	1	1	8.5	8	8.5
21.941	25.946	1010000	L	2	1	1997	22	1	1	7.5	8	8.7
21.941	25.946	1010000	L	2	1	1998	23	1	1	7.5	8	8.6
21.941	25.946	1010000	L	2	1	1999	24	1	1	7.5	8	8.4
21.941	25.946	1010000	L	2	1	2000	25	1	1	7.5	8	8.3
21.941	25.946	1010000	L	2	1	2001	26	1	1	7.5	8	8.4

Note: “ * ” : missing data point.

Table 4.2 Database Format for Forecasting Purposes

BMP	**EMP**	**RDWYID**	**RDWYSIDE**	**SYSTEM**	**LANES**	**DISTRICT**	**COUNTY**	**TYPE**	**CYCLE**
0	0.491	1010000	L	1	2	1	01	1	2
0	7.777	1010000	R	1	2	1	01	1	1
0.491	4.98	1010000	L	1	2	1	02	4	1
4.98	7.777	1010000	L	1	2	1	03	1	1
7.777	10.306	1010000	L	1	2	1	04	1	1
7.777	8.685	1010000	R	1	2	1	05	1	2
8.685	10.879	1010000	R	1	2	1	06	1	2
10.306	11.842	1010000	L	1	2	1	07	1	2
10.879	11.924	1010000	R	1	2	1	08	1	2
AGE	**CRK1976**	**… …**	**CRK2001**	**RUT1976**	**… …**	**RUT2001**	**RIDE1976**	**… …**	**RIDE2001**
19	*	**… …**	5.5	*	**… …**	8	*	**… …**	6.5
24	*	**… …**	6	*	**… …**	7	*	**… …**	8.7
19	*	**… …**	4.7	*	**… …**	*	*	**… …**	7.8
24	*	**… …**	7	*	**… …**	8	*	**… …**	8
21	8	**… …**	1	4	**… …**	8	6.4	**… …**	8.2
8	8	**… …**	8.5	4	**… …**	9	6.4	**… …**	8.2
9	8	**… …**	8.5	4	**… …**	9	6.4	**… …**	8.7
6	7.7	**… …**	8.5	2	**… …**	9	5	**… …**	8.5
11	7.7	**… …**	7	2	**… …**	8	3.2	**… …**	8.3

Note: “ * ” : missing data point. “ … … ” : elapses of time series of crack index, ride index and rut index between year 1976 and year 2001.

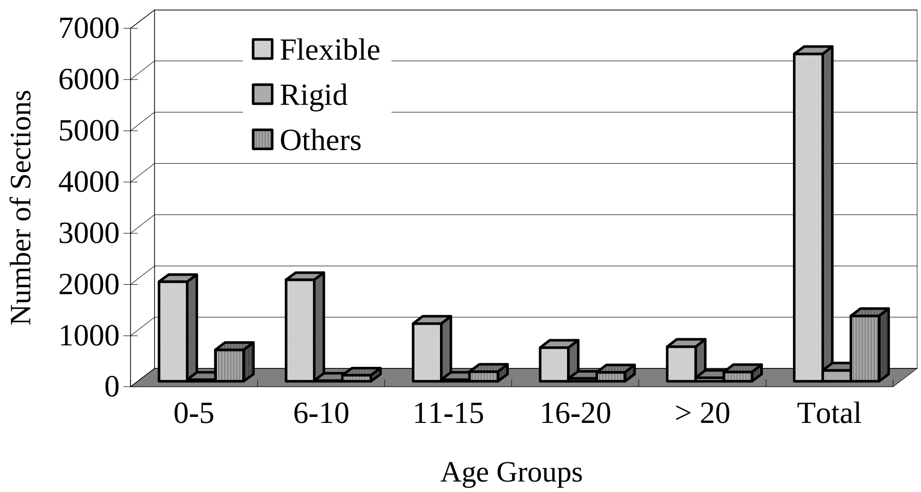


Figure 4.1 Distribution of Sections across Types and Age Groups

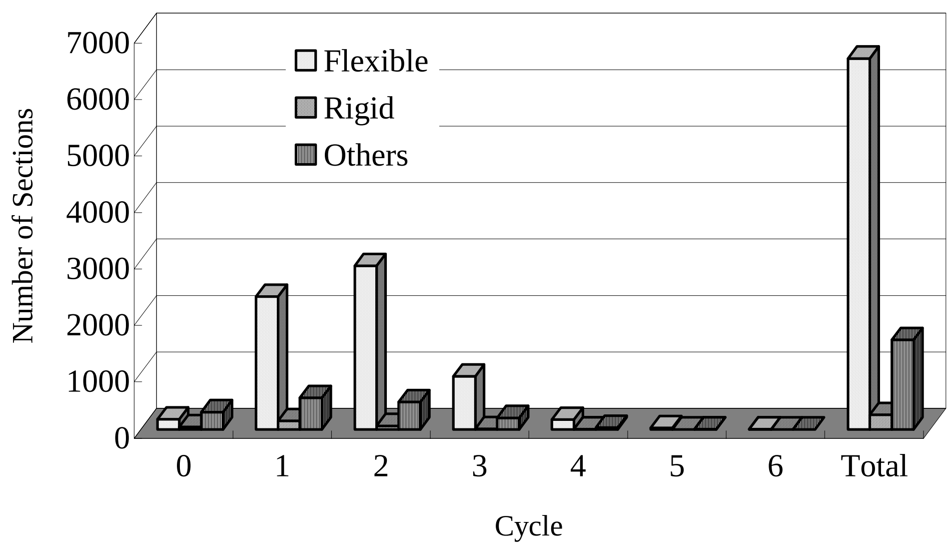


Figure 4.2 Distribution of Sections across Types and Cycles

In addition to the distribution information discussed herein, two major defects were observed during data mining. One is the missing of data points, which may be caused by discontinuous survey activities; another is irrational oscillation of the time series of pavement index data. Logically, pavement conditions should deteriorate over time, which is generally seen by the decreasing pavement distress index with time. However, sometimes increases are observed in the database. Therefore, it is necessary to preprocess the database prior to modeling and forecasting stages in order to screen off the illogical information that exists in the database.

4.2 Data Preprocessing

Two major approaches were used to preprocess the database for neural network modeling. The first step was to supplement the missing data points in the observations by means of linear interpolation. Table 4.1 shows a portion of the original database, which includes missing data points as indicated by *. Table 4.3 shows the database after missing points are added by linear interpolation. The added points are shown as data marked by *. Once the missing data points were added, moving average was carried out to smoothen the time series of index data. The objective of smoothening was to reduce or eliminate the illogical signals of the time-series data. For example, in case of the crack index, the moving average was computed by the following equation using a three-step moving range:

$$crack(t) = \frac{crack(t-1) + crack(t) + crack(t+1)}{3} \tag{4.1}$$

where crack(t) is the measured crack index at time t. In order to depict the benefit of using the moving average technique to improve the time series of index data, comparison plots of time series of crack index of both original and moving average data are shown in Figure 4.3. In addition, the database modified after moving averaging was executed is shown in Table 4.4.

Table 4.3 Database after Adding Missing Data Points by Interpolation

BMP	EMP	RDWYID	RDWYSIDE	LANES	DISTRICT	YEAR	AGE	TYPE	CYCLE	CRACK	RUT	RIDE
21.941	25.946	1010000	L	2	1	1976	1	1	1	10	8	9
21.941	25.946	1010000	L	2	1	1977	2	1	1	10	8	8.5
21.941	25.946	1010000	L	2	1	1978	3	1	1	10	8	8.6
21.941	25.946	1010000	L	2	1	1979	4	1	1	10	8	8.5
21.941	25.946	1010000	L	2	1	1980	5	1	1	*10	*8	*8.7
21.941	25.946	1010000	L	2	1	1981	6	1	1	10	8	8.8
21.941	25.946	1010000	L	2	1	1982	7	1	1	10	9	8.6
21.941	25.946	1010000	L	2	1	1983	8	1	1	10	8	8.7
21.941	25.946	1010000	L	2	1	1984	9	1	1	*9.8	*7.7	*8.6
21.941	25.946	1010000	L	2	1	1985	10	1	1	*9.6	*7.3	*8.6
21.941	25.946	1010000	L	2	1	1986	11	1	1	9.4	7	8.5
21.941	25.946	1010000	L	2	1	1987	12	1	1	9.4	7	8.8
21.941	25.946	1010000	L	2	1	1988	13	1	1	9.4	7	9
21.941	25.946	1010000	L	2	1	1989	14	1	1	9.4	7	9.2
21.941	25.946	1010000	L	2	1	1990	15	1	1	8.4	7	8.7
21.941	25.946	1010000	L	2	1	1991	16	1	1	8.5	7	8.5
21.941	25.946	1010000	L	2	1	1992	17	1	1	8.5	8	8.8
21.941	25.946	1010000	L	2	1	1993	18	1	1	8.5	8	8.6
21.941	25.946	1010000	L	2	1	1994	19	1	1	8.5	8	8.7
21.941	25.946	1010000	L	2	1	1995	20	1	1	8.5	8	8.7
21.941	25.946	1010000	L	2	1	1996	21	1	1	8.5	8	8.5
21.941	25.946	1010000	L	2	1	1997	22	1	1	7.5	8	8.7
21.941	25.946	1010000	L	2	1	1998	23	1	1	7.5	8	8.6
21.941	25.946	1010000	L	2	1	1999	24	1	1	7.5	8	8.4
21.941	25.946	1010000	L	2	1	2000	25	1	1	7.5	8	8.3
21.941	25.946	1010000	L	2	1	2001	26	1	1	7.5	8	8.4

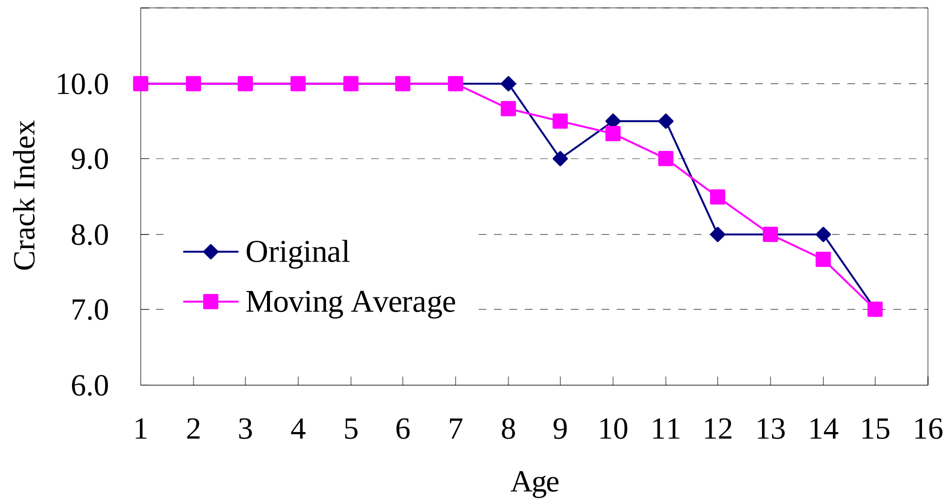


Figure 4.3 Comparison between Original Series and the Moving Average Series

Table 4.4 Database Modified Using the Moving Average Technique

BMP	EMP	RDWYID	RDWYSIDE	LANES	DISTRICT	YEAR	AGE	TYPE	CYCLE	CRACK	RUT	RIDE
21.941	25.946	1010000	L	2	1	1976	1	1	1	10	8	9
21.941	25.946	1010000	L	2	1	1977	2	1	1	10	8	8.7
21.941	25.946	1010000	L	2	1	1978	3	1	1	10	8	8.5
21.941	25.946	1010000	L	2	1	1979	4	1	1	10	8	8.6
21.941	25.946	1010000	L	2	1	1980	5	1	1	10	8	8.7
21.941	25.946	1010000	L	2	1	1981	6	1	1	10	8.3	8.7
21.941	25.946	1010000	L	2	1	1982	7	1	1	10	8.3	8.7
21.941	25.946	1010000	L	2	1	1983	8	1	1	9.9	8.2	8.6
21.941	25.946	1010000	L	2	1	1984	9	1	1	9.8	7.7	8.6
21.941	25.946	1010000	L	2	1	1985	10	1	1	9.6	7.3	8.6
21.941	25.946	1010000	L	2	1	1986	11	1	1	9.5	7.1	8.6
21.941	25.946	1010000	L	2	1	1987	12	1	1	9.4	7	8.8
21.941	25.946	1010000	L	2	1	1988	13	1	1	9.4	7	9
21.941	25.946	1010000	L	2	1	1989	14	1	1	9.1	7	9
21.941	25.946	1010000	L	2	1	1990	15	1	1	8.8	7	8.8
21.941	25.946	1010000	L	2	1	1991	16	1	1	8.5	7.3	8.7
21.941	25.946	1010000	L	2	1	1992	17	1	1	8.5	7.7	8.6
21.941	25.946	1010000	L	2	1	1993	18	1	1	8.5	8	8.7
21.941	25.946	1010000	L	2	1	1994	19	1	1	8.5	8	8.7
21.941	25.946	1010000	L	2	1	1995	20	1	1	8.5	8	8.6
21.941	25.946	1010000	L	2	1	1996	21	1	1	8.2	8	8.6
21.941	25.946	1010000	L	2	1	1997	22	1	1	7.8	8	8.6
21.941	25.946	1010000	L	2	1	1998	23	1	1	7.5	8	8.6
21.941	25.946	1010000	L	2	1	1999	24	1	1	7.5	8	8.4
21.941	25.946	1010000	L	2	1	2000	25	1	1	7.5	8	8.4
21.941	25.946	1010000	L	2	1	2001	26	1	1	7.5	8	8.4

Table 4.5 Format of the Transformed Database for Crack Forecasting

AGE	TYPE	CYCLE	CI(t-4)	CI(t-3)	CI(t-2)	CI(t-1)	CI(t)	CI(t+n)	RT_Avg	RT_Det	RD_Avg	RD_Det
5	1	1	10	10	10	10	10	10	8	0	8.7	0
6	1	1	10	10	10	10	10	10	8.1	0	8.6	0
7	1	1	10	10	10	10	10	9.9	8.1	0	8.6	0
8	1	1	10	10	10	10	9.9	9.8	8.2	0.1	8.7	0
9	1	1	10	10	10	9.9	9.8	9.6	8.1	0.2	8.7	0.3
10	1	1	10	10	9.9	9.8	9.6	9.5	8	0.4	8.6	1
11	1	1	10	9.9	9.8	9.6	9.5	9.4	7.7	0.5	8.6	1.2
12	1	1	9.9	9.8	9.6	9.5	9.4	9.4	7.5	0.5	8.6	1.2
13	1	1	9.8	9.6	9.5	9.4	9.4	9.1	7.2	0.4	8.7	0.7
14	1	1	9.6	9.5	9.4	9.4	9.1	8.8	7.1	0.5	8.8	0.3
15	1	1	9.5	9.4	9.4	9.1	8.8	8.5	7	0.7	8.8	0.1
16	1	1	9.4	9.4	9.1	8.8	8.5	8.5	7.1	0.9	8.8	0
17	1	1	9.4	9.1	8.8	8.5	8.5	8.5	7.2	0.9	8.8	0
18	1	1	9.1	8.8	8.5	8.5	8.5	8.5	7.4	0.6	8.8	0
19	1	1	8.8	8.5	8.5	8.5	8.5	8.5	7.6	0.3	8.7	0
20	1	1	8.5	8.5	8.5	8.5	8.5	8.2	7.8	0	8.7	0
21	1	1	8.5	8.5	8.5	8.5	8.2	7.8	7.9	0.3	8.7	0
22	1	1	8.5	8.5	8.5	8.2	7.8	7.5	8	0.7	8.6	0
23	1	1	8.5	8.5	8.2	7.8	7.5	7.5	8	1	8.6	0
24	1	1	8.5	8.2	7.8	7.5	7.5	7.5	8	1	8.6	0
25	1	1	8.2	7.8	7.5	7.5	7.5	7.5	8	0.7	8.5	0

After interpolation and using the moving average, the database preprocessing was completed. As a result of database preprocessing, a transformed database consisting of new variables was formed. Table 4.5 shows some of these variables.

4.3 Formation of Datasets for Training, Testing, and Validation Purposes

After the data-preprocessing task was completed, another task called formation of datasets was carried out. The objective of this step was to form three datasets in a format that can be instantaneously used for network training, testing, and validation respectively. Preparation of the training, testing, and validation dataset is the crucial step in successfully completing and deploying the ANN models. To achieve this, the transformed database was converted into another reduced database by excluding the redundant variables. Then, the reduced database was divided into two datasets. One dataset included all of the historical pavement index information except the latest year, which would be used for training and testing purposes. The second dataset contained only the latest year data, which would be used for validation purposes. To obtain the training and testing datasets, the dataset used for training and testing purpose was again divided into two subsets, one containing 80% of data in the dataset which would be used for network training and the remaining 20% of data would be used for network testing. According to the database partitioning, the validation dataset could be considered as statistically independent from the datasets that were used for training and testing purposes. Hence, the verification of the ANN model by using validation dataset can be considered as a touchstone to examine the performance of the developed ANN models from an implementation point of view. To reduce computational efforts, a SAS program was developed to automatically preprocess the database and generate the three datasets for network training, testing and validation purposes. Finally, the variables included in the training, testing, and validation datasets are shown in Table 4.6, 4.7, 4.8, 4.9, and 4.10 respectively.

Table 4.6 Variables Included in the N-year Crack-Forecasting Model (Models for Flexible Pavements)

Variables		**Description**
Crack(t-4)	Input	Crack Index for the year (t-4)
Crack(t-3)	Input	Crack Index for the year (t-3)
Crack(t-2)	Input	Crack Index for the year (t-2)
Crack(t-1)	Input	Crack Index for the year (t-1)
Crack(t)	Input	Crack Index for the year t (current year)
Crack(t+n)	Output	Crack Index for the year (t+n)
Ride_Avg	Input	(Ride(t-4) + Ride(t-3) + Ride(t-2) + Ride(t-1) + Ride(t))/5
Ride_Det	Input	Ride(t-4) - Ride(t)
Rut_Avg	Input	(Rut(t-4) + Rut(t-3) + Rut(t-2) + Rut(t-1) + Rut(t))/5
Rut_Det	Input	Rut(t-4) - Rut(t)
Age	Input	Section age since the last major improvement activity
Cycle	Input	Pavement improvement cycle of roadway section

Table 4.7 Variables Included in the N-year Ride-Forecasting Model (Models for Flexible Pavements)

Variables		Description
Ride(t-4)	Input	Ride Index for the year (t-4)
Ride(t-3)	Input	Ride Index for the year (t-3)
Ride(t-2)	Input	Ride Index for the year (t-2)
Ride(t-1)	Input	Ride Index for the year (t-1)
Ride(t)	Input	Ride Index for the year t (current year)
Ride(t+n)	Output	Ride Index for the year (t+n)
Crack_Avg	Input	(Crack(t-4)+Crack(t-3)+Crack(t-2)+ Crack(t-1) + Crack(t))/5
Crack_Det	Input	Crack(t-4)-Crack(t)
Rut_Avg	Input	(Rut(t-4)+Rut(t-3)+Rut(t-2)+Rut(t-1)+Rut(t))/5
Rut_Det	Input	Rut(t-4)–Rut(t)
Age	Input	Section age since the last major improvement activity
Cycle	Input	Pavement improvement cycle of roadway section

Table 4.8 Variables Included in the N-year Rut-Forecasting Model (Models for Flexible Pavements)

Variables		Description
Rut(t-4)	Input	Rut Index for the year (t-4)
Rut(t-3)	Input	Rut Index for the year (t-3)
Rut(t-2)	Input	Rut Index for the year (t-2)
Rut(t-1)	Input	Rut Index for the year (t-1)
Rut(t)	Input	Rut Index for the year t (current year)
Rut(t+n)	Output	Rut Index for the year (t+n)
Crack_Avg	Input	(Crack(t-4)+Crack(t-3)+Crack(t-2)+Crack(t-1)+Crack(t))/5
Crack_Det	Input	Crack(t-4)-Crack(t)
Ride_Avg	Input	(Ride(t-4)+Ride(t-3)+Ride(t-2)+Ride(t-1)+Ride(t))/5
Ride_Det	Input	Ride(t-4)-Ride(t)
Age	Input	Section age since the last major improvement activity
Cycle	Input	Pavement improvement cycle of roadway section

Table 4.9 Variables Included in the N-year Crack-Forecasting Model (Models for Rigid Pavements)

Variables		Description
Crack(t-4)	Input	Crack Index for the year (t-4)
Crack(t-3)	Input	Crack Index for the year (t-3)
Crack(t-2)	Input	Crack Index for the year (t-2)
Crack(t-1)	Input	Crack Index for the year (t-1)
Crack(t)	Input	Crack Index for the year t (current year)
Crack(t+n)	Output	Crack Index for the year (t+n)
Ride_Avg	Input	(Ride(t-4)+Ride(t-3)+Ride(t-2)+Ride(t-1)+Ride(t))/5
Ride_Det	Input	Ride(t-4)-Ride(t)
Age	Input	Section age since the last major improvement activity
Cycle	Input	Pavement improvement cycle of roadway section

Table 4.10 Variables Included in the N-year Ride-Forecasting Model (Models for Rigid Pavements)

Variables		Description
Ride(t-4)	Input	Ride Index for the year (t-4)
Ride(t-3)	Input	Ride Index for the year (t-3)
Ride(t-2)	Input	Ride Index for the year (t-2)
Ride(t-1)	Input	Ride Index for the year (t-1)
Ride(t)	Input	Ride Index for the year t (current year)
Ride(t+n)	Output	Ride Index for the year (t+n)
Crack_Avg	Input	(Crack(t-4)+Crack(t-3)+Crack(t-2)+Crack(t-1)+Crack(t))/5
Crack_Det	Input	Crack(t-4)-Crack(t)
Age	Input	Roadway section age since last major improvement activity
Cycle	Input	Pavement improvement cycle of roadway section

It must be noted that each N-year model can represent 5 different models with N=1,2,3,4,5. Once the formation of datasets for training, testing, and validation was completed, network modeling can performed as discussed in the next chapter. In view of irregularity of the data in the database, the database preprocessing is the crucial step for the model development. To guarantee the reliable performance of neural network for forecasting task, it is important that quality data be utilized for network training. As result of database preprocessing, illogical data variation is corrected and corresponding datasets are formed that can be directly used by neural network for network training, which will be discussed in next chapter.

CHAPTER 5

MODEL DEVELOPMENT

This chapter presents the modeling framework design and procedures used for the development of each ANN model. Similar to the traditional modeling process, where the objective is to estimate a set of coefficients for a particular function form of specification, the main objective of ANN modeling in this research was to attain a set of weight matrices, which is the abstracted underlying knowledge from the example data after many loops of training. However, to use neural network to solve a particular real-life problem, a framework needs to be first designed according to the characteristics of the problem under study. The objective of the framework design is to determine whether a nested ANN architecture is necessary and how the components of the architecture communicate with each other. After completion of the framework design, the next stage was to design the architecture of each ANN sub-model. The design process of ANN architecture is actually a decision-making process, which includes determining the number of layers, the number of neurons in each layer, variables to be included in input layer and output layer, etc. After finishing the ANN architecture design, the ANN architecture needs to be trained, tested and validated.

Training a neural network involves repeatedly presenting a set of example data pairs to the neural network. The neural network adapts its weights according to the learning law. The result of training is a set of weight matrices, which store the knowledge gained from the example data set. Testing the neural network is almost as same as training it, except that the trained network is presented with the examples it had not seen during the training, and no weight adjustments are made during testing. For this project, the data used in training and testing did not include the latest year data in the database. The only difference between validation and testing is that validation uses the latest data, which is an independent dataset from training and testing, but testing uses the same historical dataset that did not include the latest year data as training does. The following sections present procedures used for the modeling and the detailed efforts and results of the model development.

5.1 Model Framework Design

To enhance the performance of the ANN models developed in the research, two types of models were developed. The first one was the model for flexible pavements, and the second one was the model for rigid pavements. For flexible pavements, three sub-models were developed for the indices of crack, ride and rut respectively. For rigid pavements, two sub-models were developed for the indices of crack and ride respectively. The PCR model was a *de facto* combination of these sub-models, as shown in Figures 5.1 and 5.2.

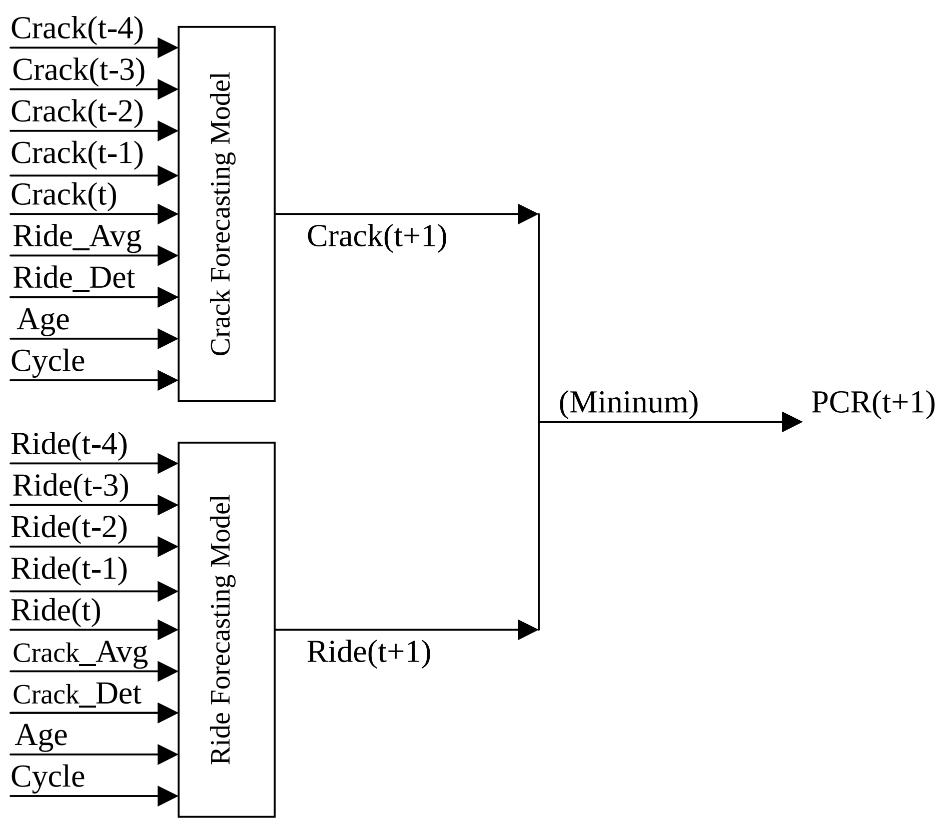


Figure 5.1 Architecture of PCR forecasting model (Rigid Pavements)

Note: the variables in Figure 5.1 are defined in Tables 4.9 and 4.10.

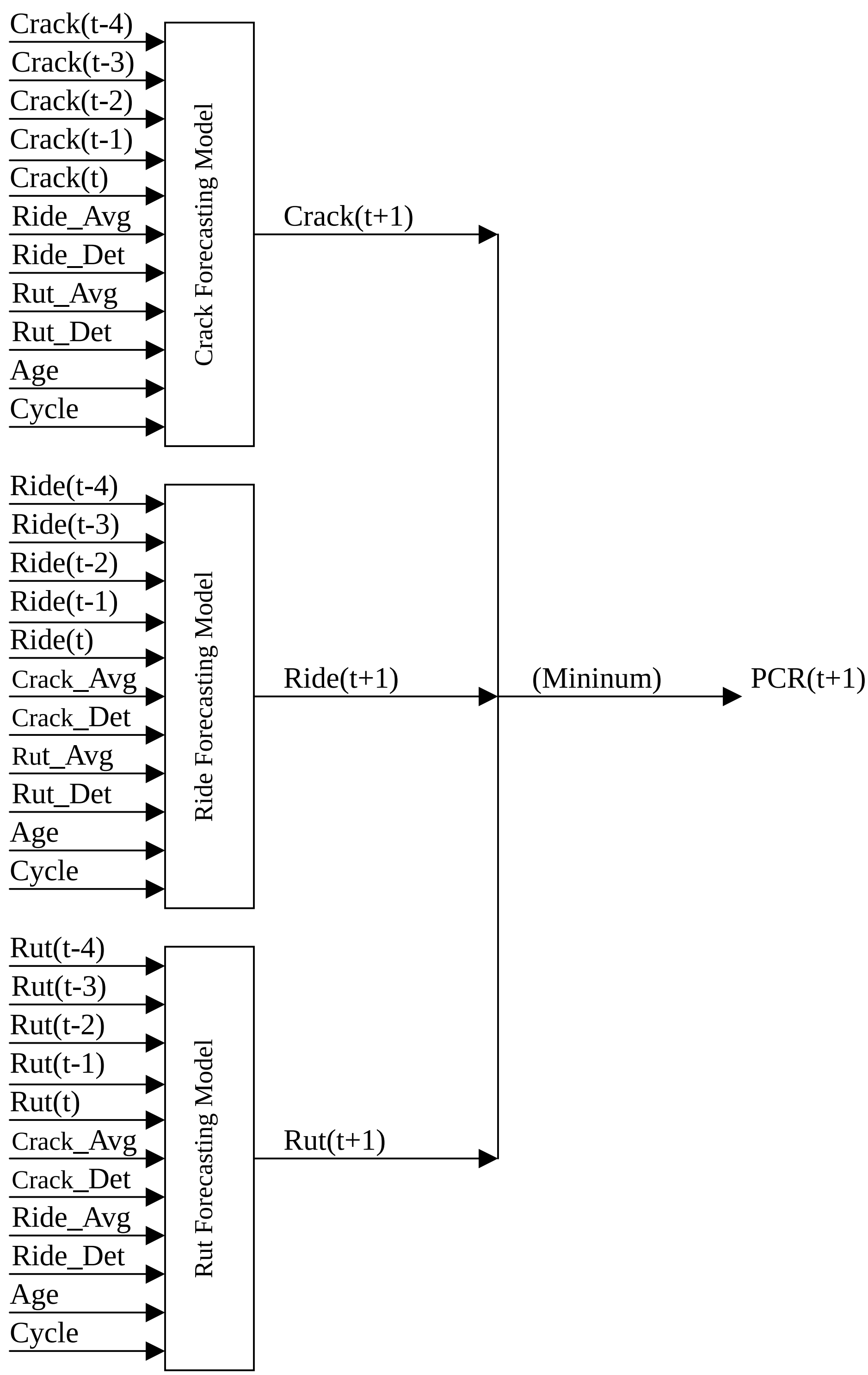


Figure 5.2 Architecture of PCR Forecasting Model (Flexible Pavements)

Note: the variables in Figure 5.2 are defined in Tables 4.6, 4.7, and 4.8.

5.2 ANN Modeling Procedures

5.2.1 Model Architecture

The selection of ANN architecture is not a straightforward decision-making process. Most of the time, trial and error combined with engineering judgment is jointly employed to determine the appropriate architecture for a particular problem. As an illustration, Table 5.1 shows the training and testing errors resulting from typical network architectures for 1-year crack index forecasting model. Similar to the traditional models, variables that appear in the output layer are the dependent variables, which are defined according to the problem under study. Variables that appear in the input layer are independent variables. It is not difficult to decide what variables should be included in the input layer since it is straightforward to select input layer variables that are considered highly correlated with the output variables from the available set of variables. To do this, a statistical test can be performed to distinguish these variables that are significantly correlated with the output variables, or use trial and error to select the architecture that produces minimum training and testing error. However, selection of the number of neurons in the hidden layer is not as simple as the selection of input variables in the input layer. In practice, a sequential number of hidden neurons were tried, and the number that produces the minimum root-mean-square test error is usually selected. As an example, the selection of the number of hidden neurons for the 5-year flexible crack model is shown in Figure 5.3. The root-mean-square test error is plotted against the number of hidden neurons. According to Figure 5.3, the architecture with 22 hidden neurons produced the structure with the best performance for the 5-year flexible crack model. In the practice of selecting number of hidden neurons, not all trials of different number of hidden neurons result in clear-cut trend as shown in Figure 5.3. An inclusive situation was often met that different trails with the same parameter setting produce different results. This instability poses a difficult situation to make decision on the best number of hidden neurons during the network training. As experienced in the process of network training, 11 hidden neurons and 22 hidden neurons produced best result most of time for model training for rigid and flexible type of pavements, respectively, regardless of different forecasting time-windows.

Table 5.1 Training and Testing Errors of Different Network Architectures

Model	Inputs	Output	Architecture	RMS Error	
				Training	Testing
1	CI(t-1), CI(t)	CI(t+1)	2-6-1	0.1063	0.0983
2	CI(t-1), CI(t)	CI(t+1)	2-6-6-1	0.159	0.1604
3	CI(t-2), CI(t-1), CI(t)	CI(t+1)	3-7-1	0.0751	0.0774
4	CI(t-2), CI(t-1), CI(t)	CI(t+1)	3-7-7-1	0.1031	0.1108
5	CI(t-3),CI(t-2),CI(t-1),CI(t)	CI(t+1)	4-8-1	0.0802	0.075
6	CI(t-3),CI(t-2),CI(t-1),CI(t)	CI(t+1)	4-8-8-1	0.1227	0.1341
* 7	CI(t-2), CI(t-1), CI(t), Type, Age, Cycle	CI(t+1)	7-12-1	0.0631	0.0593
8	CI(t-4), CI(t-3), CI(t-2), CI(t-1), CI(t)	CI(t+1)	5-10-1	0.0481	0.0564
9	CI(t-4), CI(t-3), CI(t-2), CI(t-1), CI(t), Cycle, Age	CI(t+1)	7-10-1	0.0481	0.0551
** 10	CI(t-4), CI(t-3), CI(t-2), CI(t-1), CI(t), RD_avg, RD_det, RT_avg, RT_det, Cycle, Age	CI(t+1)	11-22-1	0.0367	0.0445
** 11	CI(t-4), CI(t-3), CI(t-2), CI(t-1), CI(t), RD_avg, RD_det, Cycle, Age	CI(t+1)	9-18-1	0.0356	0.0442

Note: * The architecture selected for from previous research project [5].

** The model architecture selected for the current research project (Model 10 for flexible pavements and Model 11 for rigid pavements).

The indication "*l-m-n-o*" for the neural network architecture as shown in Table 5.1 denotes a two-hidden-layer neural network structure with *l* neurons in the input layer, *m* neurons in the first hidden layer, *n* neurons in the second hidden layer, and *o* neurons in the output neurons. The indication "*l-m-n*" denotes a one-hidden-layer neural network structure with *l* neurons in the input layer, *m* neurons in the hidden layer, and *n* neurons in the output layer.

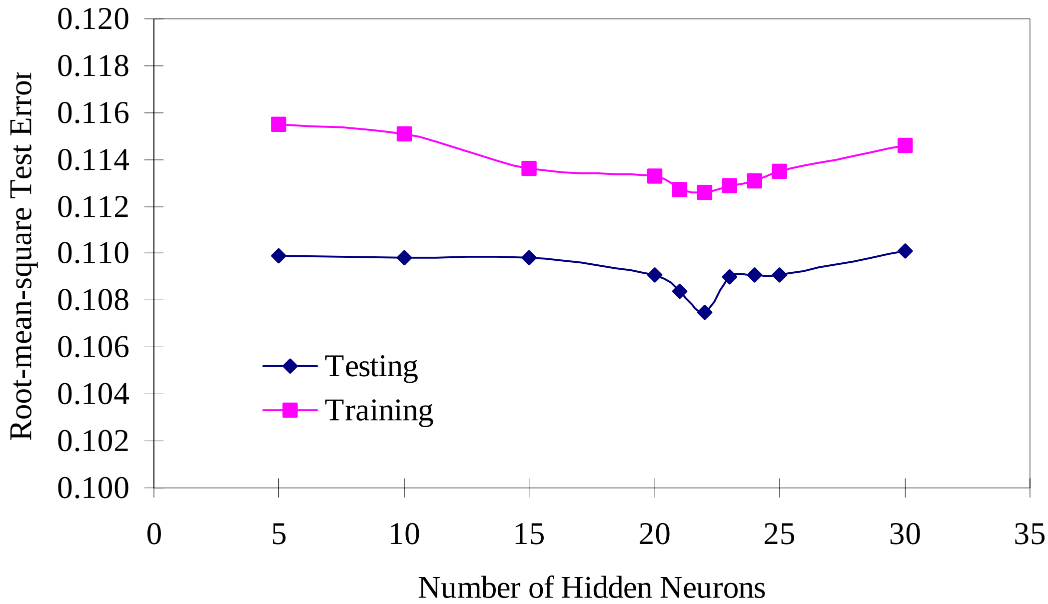


Figure 5.3 Root-mean-square Errors with Different Number of Hidden Neurons

5.2.2 Training, Testing, and Validation

Given the architecture of ANNs, the weights of links among the neurons are resolved through the training process. The training process involves presenting all example pattern pairs in the training dataset to the network and adjusting the weights of the connections according to the weight adjustment rule as defined by Eqs.3.23 and 3.24. The training process is considered complete when the total error, as defined in Eq.3.9, reduces to an acceptable threshold level, which is predefined according to characteristics of the problem under study. After completion of the training procedure, the trained network is exposed to the testing dataset to check if the training is successful. The testing data pairs are fed into the trained ANN, and the testing error is calculated. If the testing error is still within the acceptable level, the ANN model is considered a reasonable model. After the training and testing, the last and also the most critical step is to verify the model using a validation data set. Again, if the error incurred in the validation process is still acceptably small, the model can be treated as a practical model, and ready for the real-life implementation.

5.3 Architectures of Neural Network Models Used in the Research

This section presents the neural network architectures used in the research project. The procedure to select the architectures was described in previous section. After a laboring process of trial and error, the architectures selected for the neural network sub-models are detailed in Table 5.2, and the schematic architectures are shown in Figures 5.4-5.8, where t represents current year and n represents the number of years for which forecasts are made.

As result of model development, 25 submodels were established with 10 models for rigid pavements and 15 models for flexible pavements. 10 models for rigid pavements included: 1-year crack model, 2-year crack model, 3-year crack model, 4-year crack model, 5-year crack model, 1-year ride model, 2-year ride model, 3-year ride model, 4-year ride model, and 5-year ride model. 15 models for flexible pavements included: 1-year crack model, 2-year crack model, 3-year crack model, 4-year crack model, 5-year crack model, 1-year ride forecasting model, 2-year ride model, 3-year ride model, 4-year ride model, 5-year ride model, 1-year rut model, 2-year rut model, 3-year rut model, 4-year rut model, and 5-year rut model. The model year as identified for each models above relates to forecasting time window with respect to the current year. For example, 1-year crack model is used for the crack index forecasting for the next “one” year with respect to the current year. The same terminology applies to all other models.

Table 5.2 Selected Network Architectures

<table>
<tr><th colspan="2">Model</th><th>Inputs</th><th>Output</th><th>Architecture</th></tr>
<tr><td rowspan="3">Flexible Pavements</td><td>Crack</td><td>CI(t-4), CI(t-3), CI(t-2), CI(t-1), CI(t), RD_avg, RD_det, RT_avg, RT_det, Cycle, Age</td><td>CI(t+1)</td><td rowspan="3">11-22-1</td></tr>
<tr><td>Ride</td><td>RD(t-4), RD(t-3), RD(t-2), RD(t-1), RD(t), CI_avg, CI_det, RT_avg, RT_det, Cycle, Age</td><td>RD(t+1)</td></tr>
<tr><td>Rut</td><td>RT(t-4), RT(t-3), RT(t-2), RT(t-1), RT(t), CI_avg, CI_det, RD_avg, RD_det, Cycle, Age</td><td>RT(t+1)</td></tr>
<tr><td rowspan="2">Rigid Pavements</td><td>Crack</td><td>CI(t-4), CI(t-3), CI(t-2), CI(t-1), CI(t), RD_avg, RD_det, Cycle, Age</td><td>CI(t+1)</td><td rowspan="2">9-18-1</td></tr>
<tr><td>Ride</td><td>RD(t-4), RD(t-3), RD(t-2), RD(t-1), RD(t), CI_avg, CI_det, Cycle, Age</td><td>RD(t+1)</td></tr>
</table>

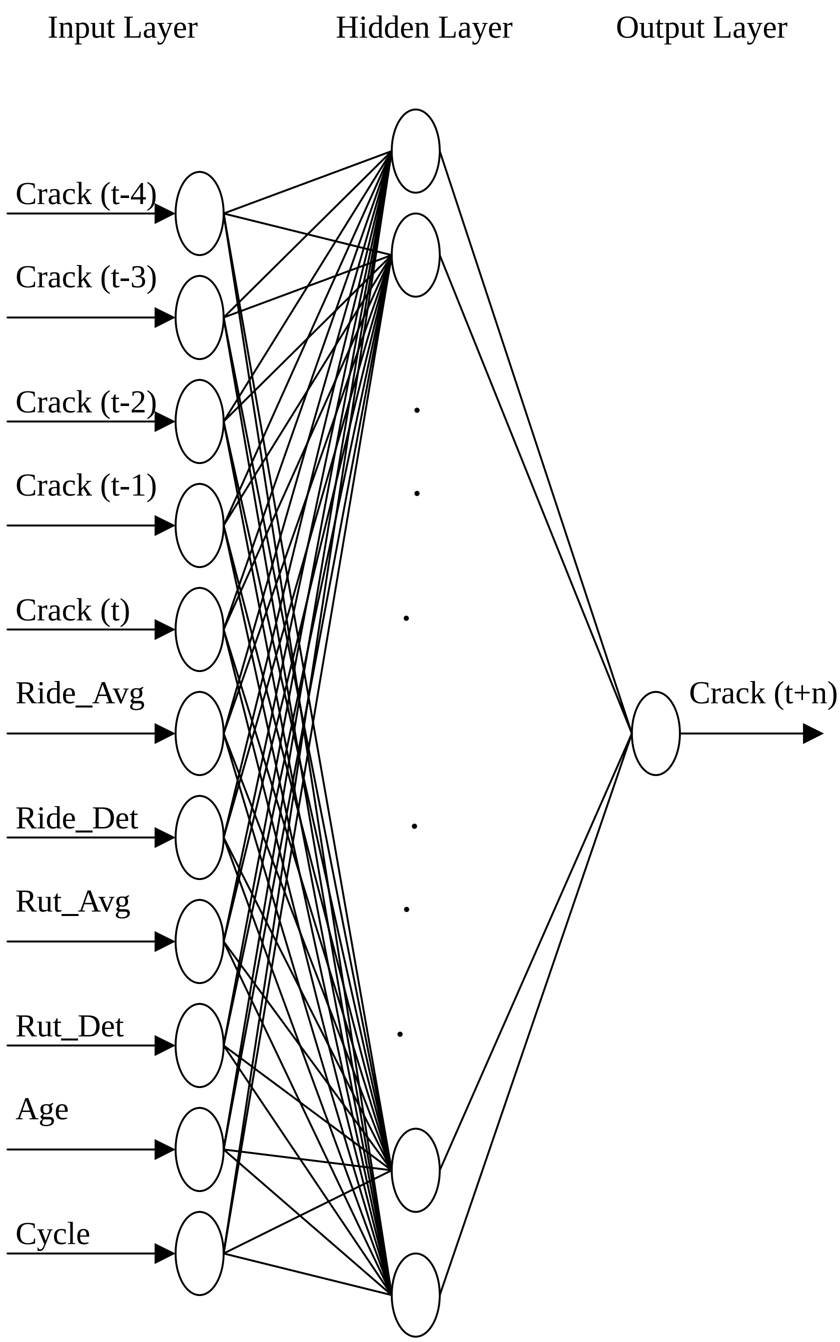


Figure 5.4   Architecture of Crack Forecasting Model (Flexible Pavements)

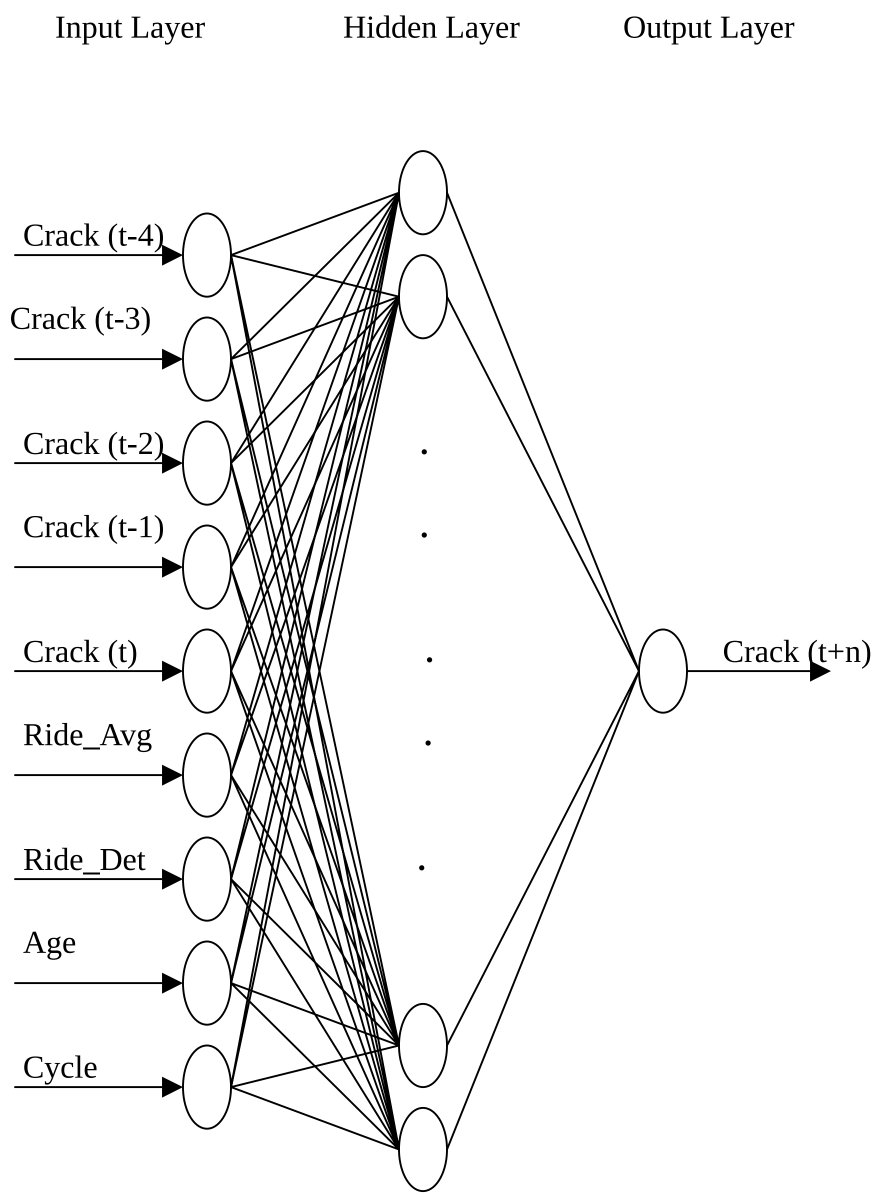


Figure 5.5 Architecture of Crack Forecasting Model (Rigid Pavements)

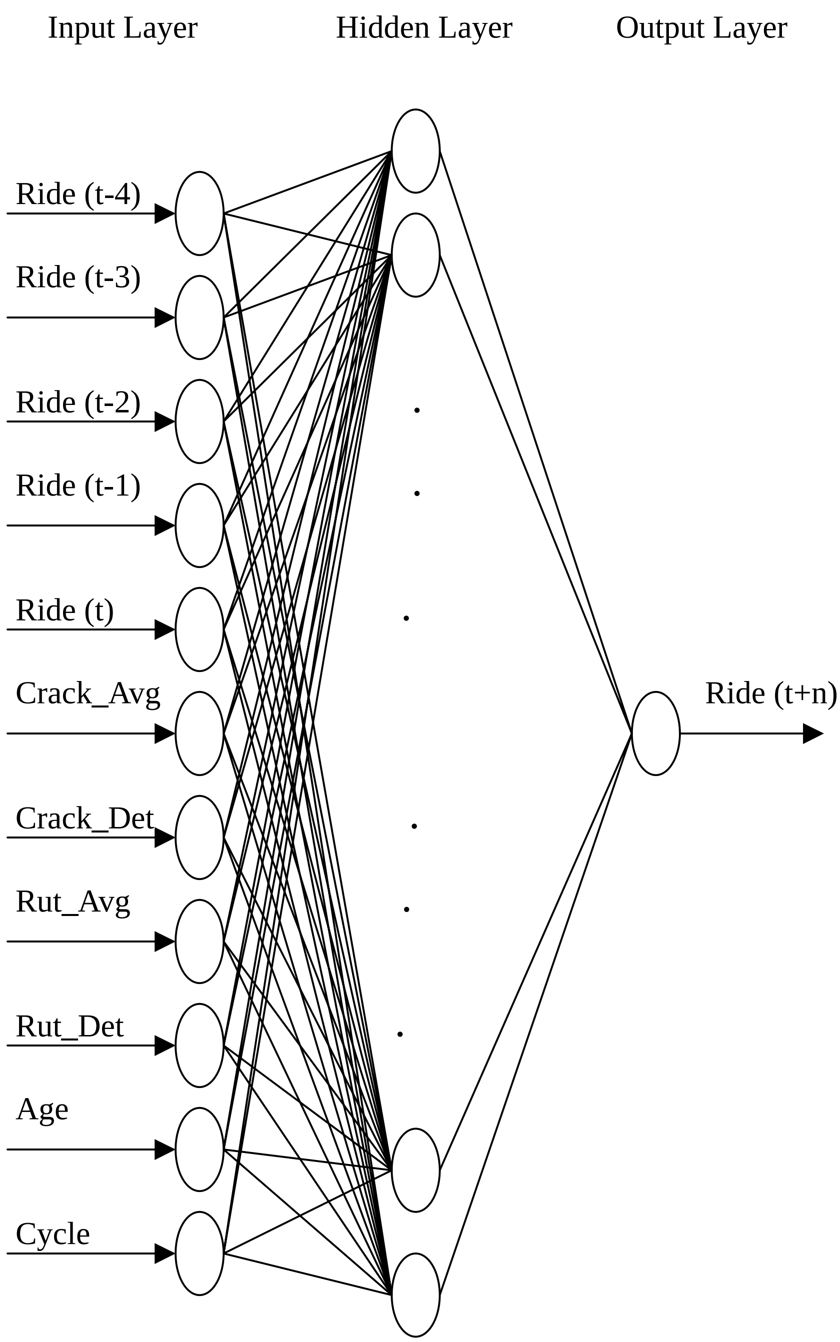


Figure 5.6 Architecture of Ride Forecasting Model (Flexible Pavements)

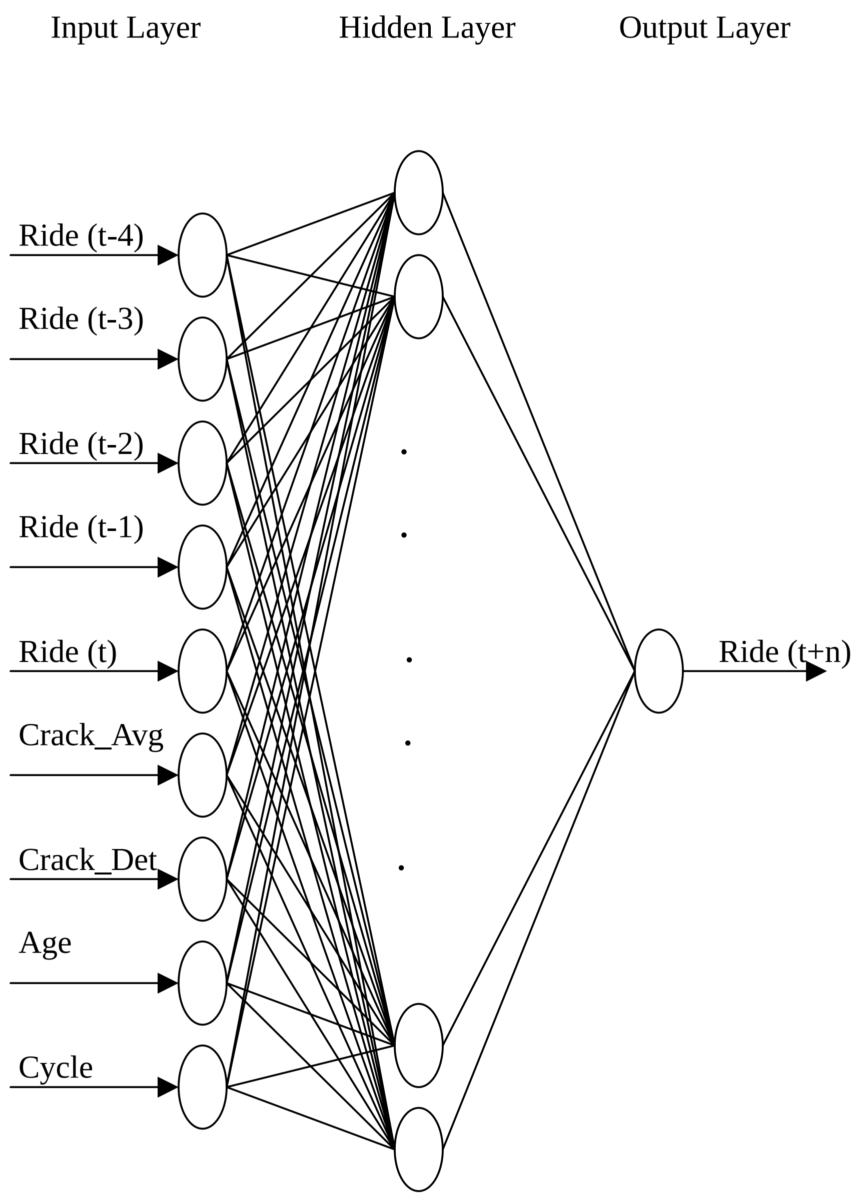


Figure 5.7 Architecture of Ride Forecasting Model (Rigid Pavements)

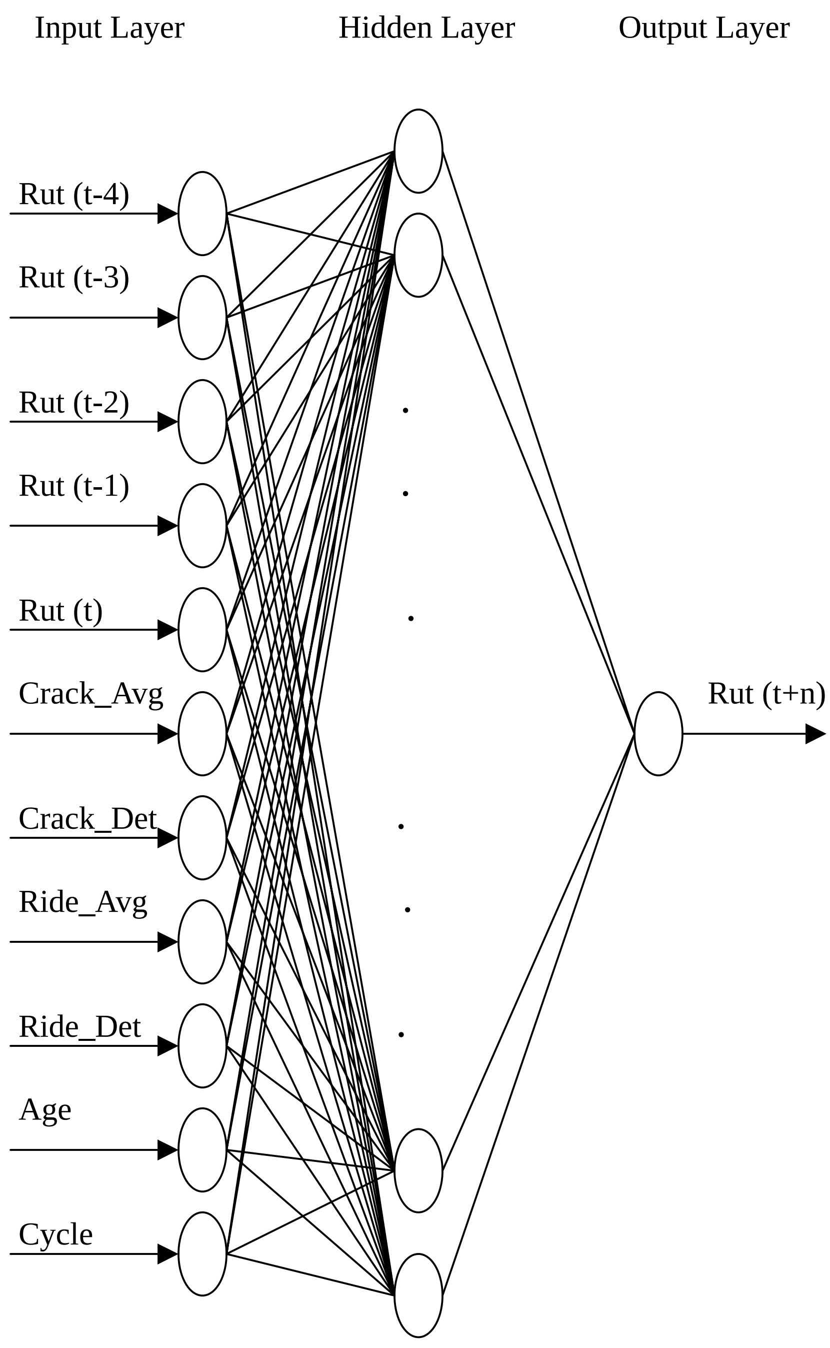


Figure 5.8 Architecture of Rut Forecasting Model (Flexible Pavements)

CHAPTER 6

PERFORMANCE EVALUATION OF ANN MODELS

After completing the training and testing processes, the neural network attains the capability of simulating pavement condition deterioration mechanism and thereby forecasting the future pavement condition. Then, the subsequent step is to evaluate the performance of the developed neural network models. For this purpose, the validation dataset, which includes only the 2001 pavement data, was used. To obtain unbiased evaluations, irrational data that are showed improved pavement condition with time were discarded. Only these roadway sections with year 2000 PCR indices equal or greater than that of year 2001 were used for model evaluation purposes.

6.1 Model Comparison

To evaluate the performance of ANN models, three autoregressive (AR) models were developed as well to forecast the three key indices, CI, RT, and RD for the purpose of comparison. In the AR models, the three distress indices after n years (CI(t+n), RT(t+n), and RD(t+n)) were forecasted by linearly extrapolating corresponding CI, RT, and RD in the previous three years. The forecasted PCR value is the minimum of values of three individual indices. Table 6.1 shows the comparison of forecasting errors of ANN model and AR model. It can be seen that the ANN model was more accurate than the AR model in terms of average absolute error and the root-mean-square error (RMSE).

Average absolute error is calculated using Eq.6.1.

$$\text{Average Absolute Error} = \frac{\sum_{i=1}^{n} |o_i - p_i|}{n} \tag{6.1}$$

where,

n = number of observations,

o_i = observed value of observation i, and

p_i= predicted value of observation i.

RMSE is calculated using Eq.6.2.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(o_i - p_i)^2}{n}} \tag{6.2}$$

where,

RMSE = root mean square error,

n = number of observations,

o_i = observed value of observation i, and

p_i= predicted value of observation i.

Table 6.1 PCR Forecasting Errors of ANN Model and AR Model

Years of Forecast		Average Absolute Error	RMSE
1 year	ANN	0.0479	0.0664
	AR	0.1268	0.1969
2 year	ANN	0.0644	0.0913
	AR	0.1699	0.2436
3 year	ANN	0.0791	0.1118
	AR	0.1892	0.2723
4 year	ANN	0.0889	0.1284
	AR	0.2127	0.2977
5 year	ANN	0.1054	0.1496
	AR	0.2312	0.3215

6.2 Goodness of Fit

Goodness of fit is a commonly used approach to evaluate performance of models. In this research, the performance of PCR forecasting models were further evaluated by comparing the goodness of fit of the ANN models and AR models. For comparison purpose, the R^2 values were calculated using Eq.6.3.

$$R^2 = 1 - [\sum (PCR_{act} - PCR_{pred})^2 / \sum (PCR_{act} - PCR_{avg})^2] \quad (6.3)$$

where,

PCR_{act} = actual value of PCR;

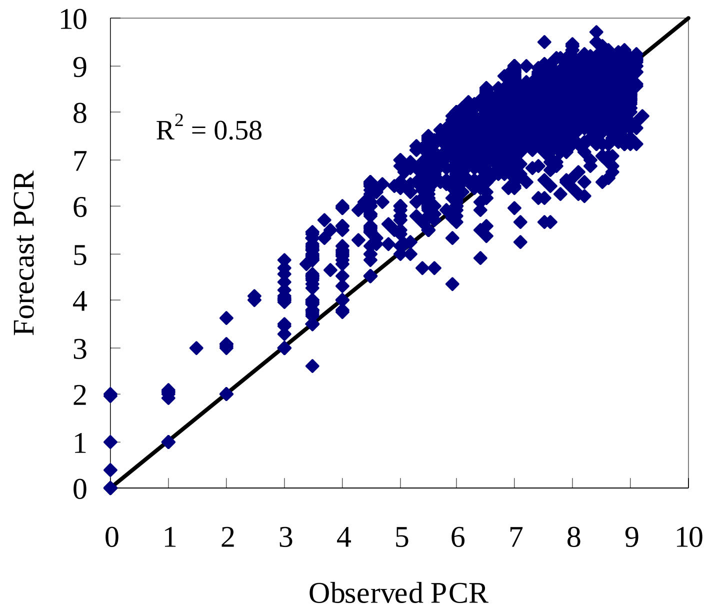
PCR_{pred} = value of PCR predicted by neural network model; and

PCR_{avg} = average value of PCR.

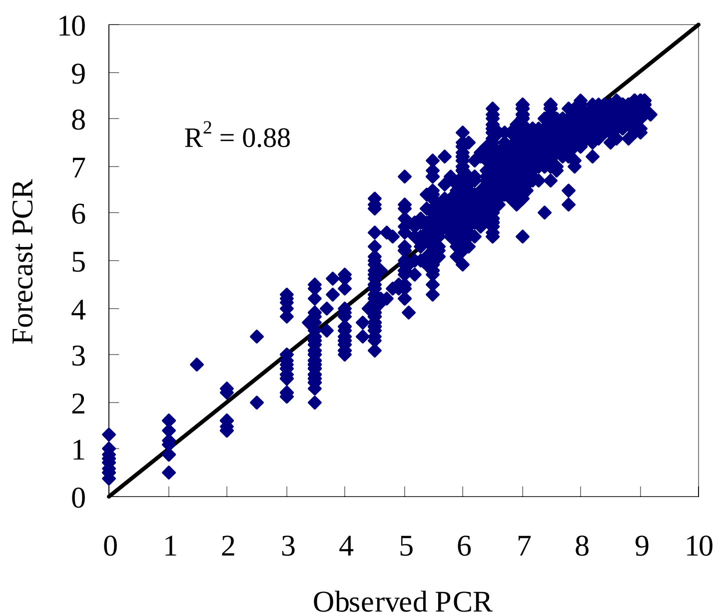
The goodness of fit shows that the ANN models have higher R^2 values than that of corresponding AR models. Moreover, the AR models become useless when the forecasting interval exceed two years because the R^2 turned out to be negative. Table 6.2 summarizes goodness of fit in terms of R^2 for each model. As an illustration, one-year forecasting correlation graphs are shown in Figures 6.1 and 6.2.

Table 6.2 R^2 Comparisons of ANN Model and AR Model

Model and Years of Forecast		Goodness of Fit (R^2)	
		Flexible Pavements	Rigid Pavements
1 year	ANN	0.88	0.79
	AR	0.58	0.39
2 year	ANN	0.76	0.55
	AR	0.29	0.2
3 year	ANN	0.59	0.52
	AR	-0.22	-0.15
4 year	ANN	0.48	0.4
	AR	-0.49	-0.28
5 year	ANN	0.38	0.2
	AR	-0.74	-0.14

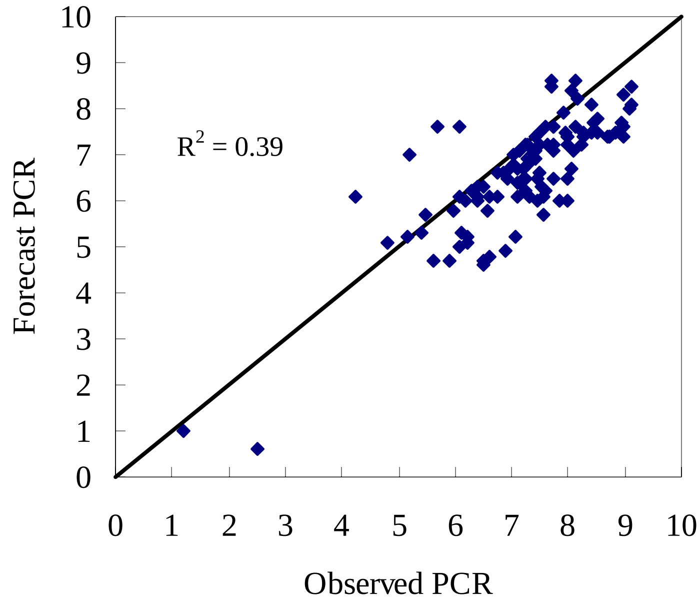


a) AR Model

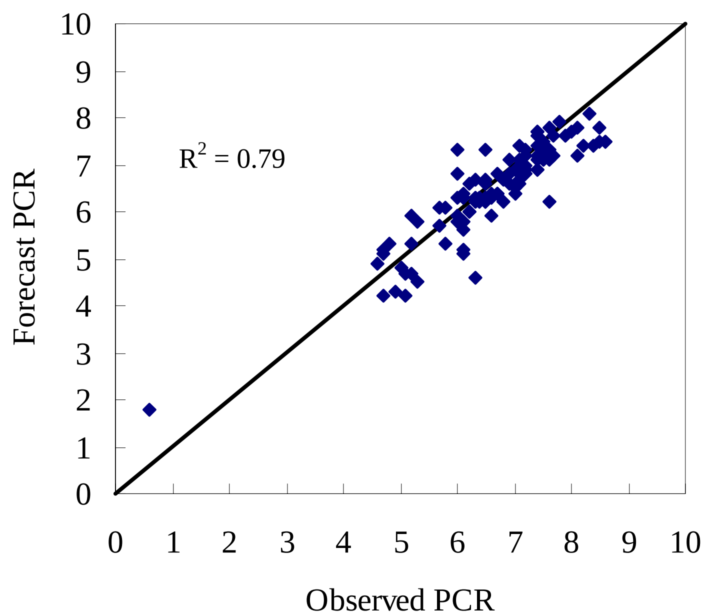


b) ANN Model

Figure 6.1 Goodness of Fit (Flexible Pavements, One-year Forecasting)



a) AR Model

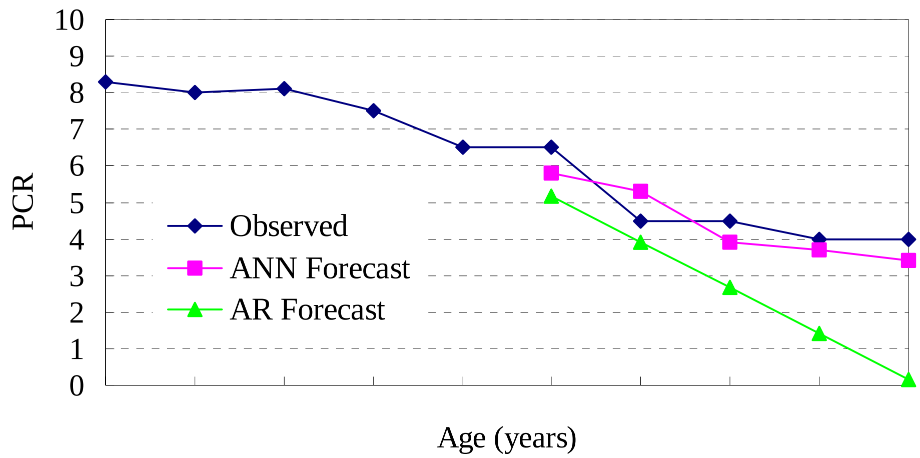


b) ANN Model

Figure 6.2 Goodness of Fit (Rigid Pavements, One-year Forecasting)

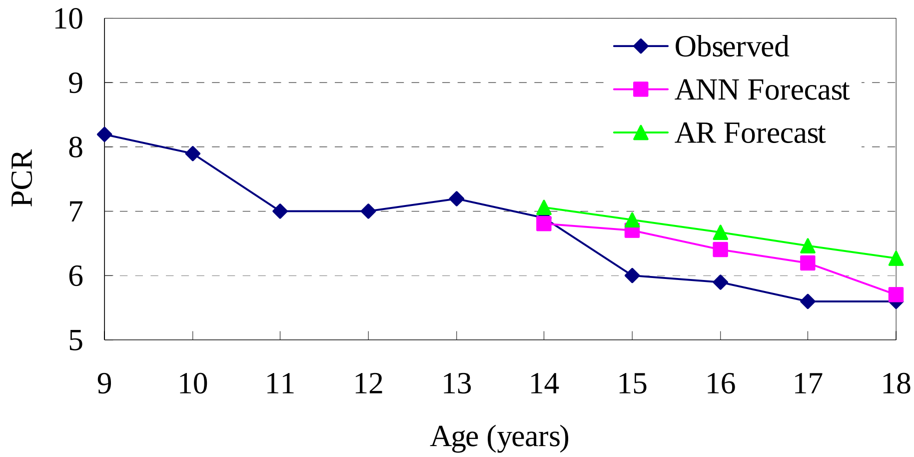
6.3 Case Study of Individual Sections

Several typical sections which were not included in the training process were initially set aside for the case study. The forecasts of two of the sections are plotted on the same graph for comparison purposes as shown in Figure 6.3. It has been found that the ANN model and AR model had comparable forecasting accuracy for 1-year future and 2-year future forecasting. However, when forecasting models were used to forecast future PCR values (say 3, 4, and 5 years from today), the ANN model outperformed the AR model. This pattern becomes pronounced when pavements tend to deteriorate at a higher rate. From the comparison, it can be seen that the forecasts of AR model tend to lag behind the observed values, which often occurs in the conventional time-series models. Again the comparison showed that the pavement deterioration is a nonlinear process over time in nature. It is suitable to use ANN for the pavement performance modeling.



a) Section 1, Flexible Pavement, Cycle 2

Figure 6.3 Case Study of Individual Pavement Sections



b) Section 2, Rigid Pavement, Cycle 1

Figure 6.3 Case Study of Individual Pavement Sections

6.4 Lane-Mile Deficiency Forecast

PCR is the criterion used by FDOT to make a decision on whether a pavement section is deficient or not. Accordingly, if the PCR of a section is rated equal or lower than 6.4, the section is considered to be deficient. A deficient section should be considered for rehabilitation according to the budget constraints. Deficient lane miles is defined as the total lane miles of pavement sections with PCR equal to or less than 6.4. The latest available year 2001 data is used to validate the ANN models for forecasting deficient lane miles. The forecasted year 2001 deficient lane miles were compared to those forecasted by AR models and the observed year 2001 deficient lane miles. The comparison results for one-year to five-year forecasting are shown in Tables 6.3 to 6.7.

Table 6.3 Comparison of Observed and One-year Forecast of Deficient Lane Miles Using ANN Models and AR Models

FDOT Districts	Observed	Forecast		Forecasting Error	
		ANN	AR	ANN	AR
1	1191.25	1263.36	527.99	72.11	-663.26
2	1573.95	1496.54	508.86	-77.41	-1065.09
3	1322.14	1120.52	383.56	-201.63	-938.59
4	1081.29	1207.48	300.25	126.19	-781.04
5	1230.67	1249.44	438.12	18.78	-792.55
6	352.18	390.09	95.24	37.91	-256.93
7	559.64	584.04	164.27	24.4	-395.38
Total	7311.13	7311.47	2418.29	0.35	-4892.84

Table 6.4 Comparison of Observed and Two-year Forecast of Deficient Lane Miles Using ANN Models and AR Models

FDOT Districts	Observed	Forecast		Forecasting Error	
		ANN	AR	ANN	AR
1	1191.25	1363.11	429.27	171.86	-761.98
2	1573.95	1650.8	359.52	76.85	-1214.43
3	1322.14	1188.05	126.63	-134.1	-1195.52
4	1081.29	1105	197.33	23.71	-883.96
5	1230.67	1423.53	267.37	192.87	-963.3
6	352.18	385.02	69.95	32.85	-282.23
7	559.64	531.11	68.06	-28.53	-491.58
Total	7311.13	7646.63	1518.13	335.5	-5792.99

Table 6.5 Comparison of Observed and Three-year Forecast Deficient Lane Miles Using ANN Models and AR Models

FDOT Districts	Observed	Forecast		Forecasting Error	
		ANN	AR	ANN	AR
1	1191.25	1408.88	269.73	217.62	-921.52
2	1573.95	1726.34	232.99	152.39	-1340.96
3	1322.14	1318.42	101.99	-3.73	-1220.15
4	1081.29	1208.39	116.24	127.09	-965.05
5	1230.67	1422.61	143.21	191.94	-1087.46
6	352.18	356.5	73.32	4.32	-278.86
7	559.64	514.61	47.95	-45.04	-511.69
Total	7311.13	7955.74	985.43	644.61	-6325.69

Table 6.6 Comparison of Observed and Four-year Forecast Deficient Lane Miles Using ANN Models and AR Models

FDOT Districts	Observed	Forecast		Forecasting Error	
		ANN	AR	ANN	AR
1	1191.25	1208.55	141.36	17.29	-1049.9
2	1573.95	1436.12	121.26	-137.83	-1452.69
3	1322.14	867.98	164.04	-454.17	-1158.11
4	1081.29	794.43	74.35	-286.86	-1006.94
5	1230.67	1009.8	111.2	-220.86	-1119.47
6	352.18	310.27	64.64	-41.91	-287.53
7	559.64	383.32	73.84	-176.32	-485.8
Total	7311.13	6010.47	750.7	-1300.66	-6560.43

Table 6.7 Comparison of Observed and Five-year Forecast Deficient Lane Miles Using ANN Models and AR Models

FDOT Districts	Observed	Forecast		Forecasting Error	
		ANN	AR	ANN	AR
1	1191.25	914.65	122.04	-276.6	-1069.21
2	1573.95	1246.58	204.35	-327.37	-1369.6
3	1322.14	850.36	208.11	-471.79	-1114.04
4	1081.29	619.5	147.45	-461.79	-933.84
5	1230.67	818.32	184.54	-412.35	-1046.13
6	352.18	271.26	57.31	-80.92	-294.87
7	559.64	380.85	104.75	-178.79	-454.89
Total	7311.13	5101.52	1028.54	-2209.61	-6282.59

According to the definition of "forecasting error" (forecasted deficient lane miles minus observed deficient lane miles), AR models tend to produce unacceptable larger error than ANN models and always overestimate pavement condition as forecasting errors are all negative. This fact seems to reveal that AR model is not a suitable tool for pavement performance modeling since pavement deterioration is a nonlinear process in nature and pavement condition deteriorates faster as time progresses. As compared to AR models, ANN models produce balanced forecasting error within acceptable range. Therefore, ANN models are considerably more accurate than the AR models in terms of forecasting accuracy.

The deficient lane-mile comparison showed only the overall deficiency forecasting. When it comes to the details of individual sections, two types of forecasting errors need to be identified, over-estimation error and under-estimation error. Over-estimation is defined as the incorrect model estimate on the subject section that is actually deficient but forecast as not. Under-estimation is defined as incorrect model estimate on the subject section that is actually not deficient but forecast as deficient. For the section-by-section forecasting comparison, these two types of errors caused by ANN and AR models are summarized in the Tables 6.8 to 6.12 for one-, two-, three-, four-, and five-year forecasting, respectively.

Table 6.8 Comparison of Over- and Under-estimates of One-year forecast

FDOT Districts	Models	Observed deficiency	Over-estimates	Observed Non-deficiency	Under-estimates	Percent of Over-estimates	Percent of Under-estimates
1	ANN	1191.25	117.99	1629.7	190.101	9.9	11.66
	AR	1191.25	696.99	1629.7	33.73	58.51	2.07
2	ANN	1573.95	231.32	2211.81	153.91	14.7	6.96
	AR	1573.95	1075.53	2211.81	10.44	68.33	0.47
3	ANN	1322.14	313.1	1094.03	111.47	23.68	10.19
	AR	1322.14	938.71	1094.03	0.12	71	0.01
4	ANN	1081.29	132.66	2121.45	258.85	12.27	12.2
	AR	1081.29	786.53	2121.45	5.49	72.74	0.26
5	ANN	1230.67	216.49	2215.3	235.26	17.59	10.62
	AR	1230.67	797.99	2215.3	5.45	64.84	0.25
6	ANN	352.18	20.62	1025.19	58.53	5.85	5.71
	AR	352.18	264.39	1025.19	7.46	75.07	0.73
7	ANN	559.64	47.26	1305.36	71.66	8.44	5.49
	AR	559.64	395.96	1305.36	0.59	70.75	0.04
Total	ANN	7311.13	1079.43	11602.84	1079.78	14.76	9.31
	AR	7311.13	4956.11	11602.84	63.27	67.79	0.55

Table 6.9 Comparison of Over- and Under-estimates of Two-year forecast

FDOT Districts	Models	Observed deficiency	Over-estimates	Observed Non-deficiency	Under-estimates	Percent of Over-estimates	Percent of Under-estimates
1	ANN	1191.25	128.27	1629.7	300.12	10.77	18.42
	AR	1191.25	779.78	1629.7	17.79	65.46	1.09
2	ANN	1573.95	240.86	2211.81	317.71	15.3	14.36
	AR	1573.95	1241.46	2211.81	27.03	78.88	1.22
3	ANN	1322.14	261.04	1094.03	126.95	19.74	11.6
	AR	1322.14	1195.64	1094.03	0.12	90.43	0.01
4	ANN	1081.29	235.41	2121.45	259.12	21.77	12.21
	AR	1081.29	886.17	2121.45	2.21	81.95	0.1
5	ANN	1230.67	207.72	2215.3	400.58	16.88	18.08
	AR	1230.67	972.14	2215.3	8.84	78.99	0.4
6	ANN	352.18	41.28	1025.19	74.13	11.72	7.23
	AR	352.18	289.69	1025.19	7.46	82.26	0.73
7	ANN	559.64	94.63	1305.36	66.09	16.91	5.06
	AR	559.64	491.79	1305.36	0.21	87.88	0.02
Total	ANN	7311.13	1209.2	11602.84	1544.7	16.54	13.31
	AR	7311.13	5856.65	11602.84	63.65	80.11	0.55

Table 6.10 Comparison of Over- and Under-estimates of Three-year forecast

FDOT Districts	Models	Observed deficiency	Over-estimates	Observed Non-deficiency	Under-estimates	Percent of Over-estimates	Percent of Under-estimates
1	ANN	1191.25	164.09	1629.7	381.72	13.77	23.42
	AR	1191.25	938.33	1629.7	16.81	78.77	1.03
2	ANN	1573.95	319.5	2211.81	471.89	20.3	21.34
	AR	1573.95	1345.92	2211.81	4.96	85.51	0.22
3	ANN	1322.14	300.89	1094.03	297.16	22.76	27.16
	AR	1322.14	1220.28	1094.03	0.12	92.3	0.01
4	ANN	1081.29	222.86	2121.45	349.96	20.61	16.5
	AR	1081.29	966.66	2121.45	1.61	89.4	0.08
5	ANN	1230.67	209.78	2215.3	401.72	17.05	18.13
	AR	1230.67	1088.95	2215.3	1.48	88.48	0.07
6	ANN	352.18	82.6	1025.19	86.92	23.45	8.48
	AR	352.18	278.86	1025.19	0	79.18	0
7	ANN	559.64	138.39	1305.36	93.36	24.73	7.15
	AR	559.64	511.9	1305.36	0.21	91.47	0.02
Total	ANN	7311.13	1438.12	11602.84	2082.73	19.67	17.95
	AR	7311.13	6350.88	11602.84	25.19	86.87	0.22

Table 6.11 Comparison of Over- and Under-estimates of Four-year forecast

FDOT Districts	Models	Observed deficiency	Over-estimates	Observed Non-deficiency	Under-estimates	Percent of Over-estimates	Percent of Under-estimates
1	ANN	1191.25	265.74	1629.7	283.04	22.31	17.37
	AR	1191.25	1055.03	1629.7	5.14	88.56	0.32
2	ANN	1573.95	442.85	2211.81	305.02	28.14	13.79
	AR	1573.95	1493.68	2211.81	41	94.9	1.85
3	ANN	1322.14	498.49	1094.03	44.32	37.7	4.05
	AR	1322.14	1218.02	1094.03	59.91	92.12	5.48
4	ANN	1081.29	385.66	2121.45	98.8	35.67	4.66
	AR	1081.29	1009.71	2121.45	2.77	93.38	0.13
5	ANN	1230.67	446.73	2215.3	225.87	36.3	10.2
	AR	1230.67	1142.47	2215.3	23	92.83	1.04
6	ANN	352.18	107.58	1025.19	65.67	30.55	6.41
	AR	352.18	304.69	1025.19	17.16	86.52	1.67
7	ANN	559.64	218.38	1305.36	42.06	39.02	3.22
	AR	559.64	501.93	1305.36	16.13	89.69	1.24
Total	ANN	7311.13	2365.43	11602.84	1064.77	32.35	9.18
	AR	7311.13	6725.52	11602.84	165.1	91.99	1.42

Table 6.12 Comparison of Over- and Under-estimates of Five-year forecast

FDOT Districts	Models	Observed deficiency	Over-estimates	Observed Non-deficiency	Under-estimates	Percent of Over-estimates	Percent of Under-estimates
1	ANN	1191.25	412.85	1629.7	136.25	34.66	8.36
	AR	1191.25	1082.62	1629.7	13.41	90.88	0.82
2	ANN	1573.95	534.47	2211.81	207.1	33.96	9.36
	AR	1573.95	1533.23	2211.81	163.62	97.41	7.4
3	ANN	1322.14	637.31	1094.03	165.53	48.2	15.13
	AR	1322.14	1247.28	1094.03	133.24	94.34	12.18
4	ANN	1081.29	538.67	2121.45	76.88	49.82	3.62
	AR	1081.29	1016.35	2121.45	82.51	93.99	3.89
5	ANN	1230.67	595.11	2215.3	182.76	48.36	8.25
	AR	1230.67	1155.78	2215.3	109.65	93.91	4.95
6	ANN	352.18	134.77	1025.19	53.84	38.27	5.25
	AR	352.18	318.23	1025.19	23.36	90.36	2.28
7	ANN	559.64	315.2	1305.36	136.41	56.32	10.45
	AR	559.64	497.02	1305.36	42.13	88.81	3.23
Total	ANN	7311.13	3168.37	11602.84	958.76	43.34	8.26
	AR	7311.13	6850.5	11602.84	567.91	93.7	4.89

It is noted that the ANN models have comparable over- and under-estimation error. However, AR models are prone to over-estimation, with much higher over-estimation error than under-estimation error. Although the ANN models tended to have higher under-estimation error than AR models, it was not justified that the AR models are better than ANN models in terms of forecasting capability because AR models had unacceptable higher over-estimation error as compared to under-estimation error with over 50% higher over-estimation error, which is actually impracticable for real-life forecasting application. ANN models produced more accurate, consistent and uniform forecasting than AR models. Therefore, ANN models are considered more reliable and better than AR models in terms of forecasting capability.

CHAPTER 7

SOFTWARE IMPLEMENTATION

7.1 Software Architecture

As crucial part of the research, significant effort was made for implementing the ANN models in the FDOT PMS. As result of the implementation effort, a software system called IPPFS (Integrated Pavement Performance Forecasting System) was developed. The IPPFS developed for this research contains four major operational modules: data preprocessing, pavement condition forecasting using ANN models, data postprocessing, and model upgrading. The software architecture is shown in Figure 7.1. As noticed, the direction indicated by the arrow is the direction that the information flows. Provided with the FDOT original database, the first module is designed to preprocess the database, which included adding missing data and use of the moving average. Then, the processed database is fed into the second module, which uses the developed ANN models to forecast the future pavement condition. Following the forecasting, the third module is used to summarize the forecasted results in formats that can be easily understood and directly used by FDOT for budget planning at the network level and rehabilitation activities at the project level. The last module is used to upgrade the model parameters, which are ANN matrices. This module is important since it ensure the model keep up with the information in the newly collected data. To integrate the four major modules in the forecasting system, a main interface program is needed. Considering the popularity and convenience of programming, a widely used programming language, Visual Basic, is employed to code the main interface program.

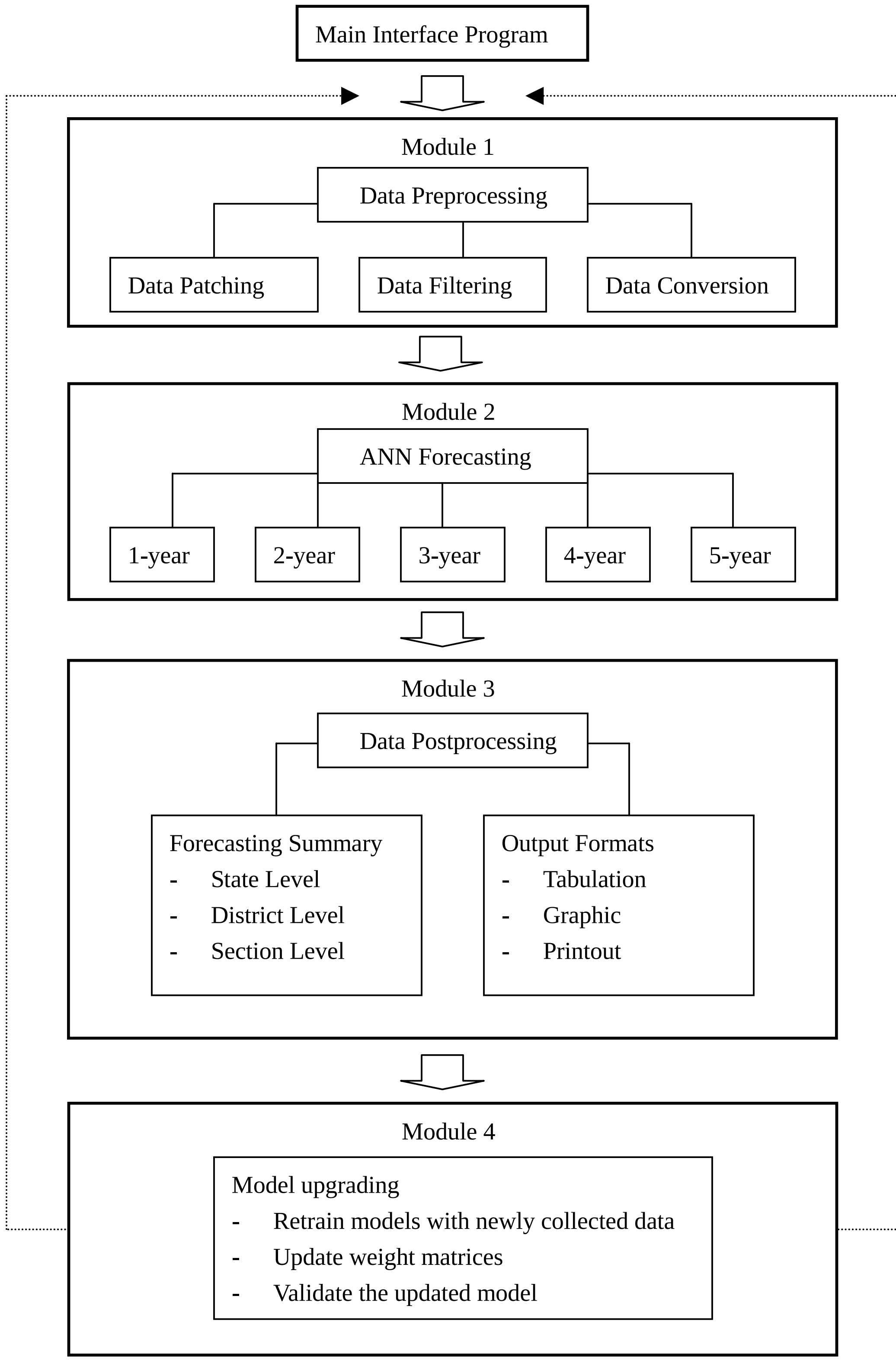


Figure 7.1 Software Architecture

7.1.1 Data Preprocessing Module

To minimize the practice inconvenience, the original FDOT pavement condition survey database, which is in SAS format, is the original input to the software. The database selection interface is shown in Figure 7.2. Users are required to select the database in the correct format, which is crucial for this module to work properly. As part of the software package, a user manual documents the detail of the format requirement for the input database. In addition to the input database, users are required to select the forecasting base year of their interest. The base year is the year from which the forecasting occurs. A SAS program was developed to preprocess the database, which is called by main interface program when necessary. The function of the SAS program is to carry out the three data preprocessing tasks: data patching, data filtering, and data conversion.

Data patching: this step is to add missing data point, if needed, in the database.

Data filtering: this step is to filter out high-frequency noise existing in the time series of pavement index data.

Data Conversion: this step is to convert the data format of the original database into the format that can be directly used for the neural network modeling and forecasting.

The output of this module is the preprocessed database, which will be used as input to the next module, the ANN forecasting module.

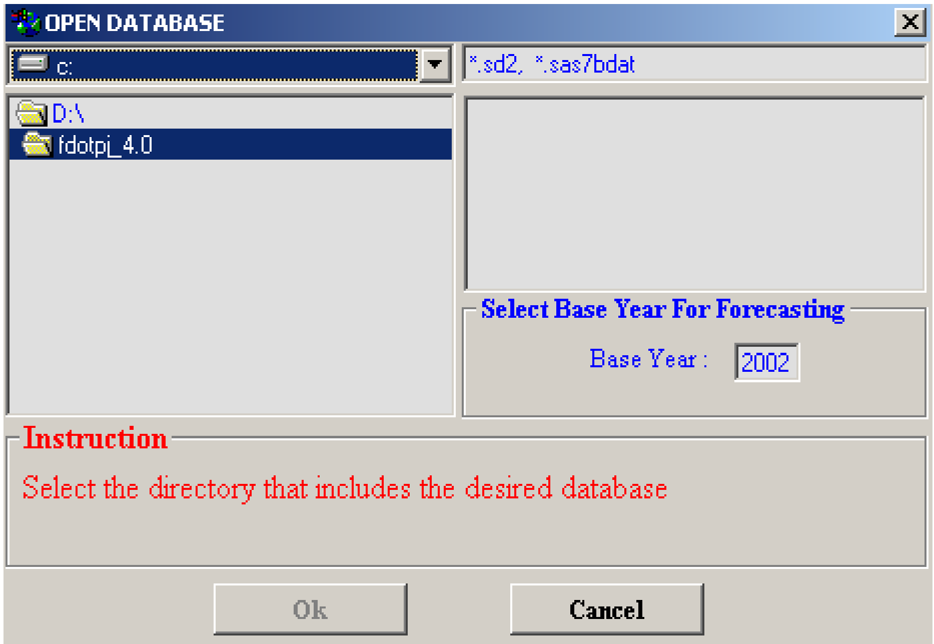


Figure 7.2 Database Selection Interface

7.1.2 ANN Forecasting Module

This module consists of 25 ANN forecasting models as shown in Table 7.1. Each model has an associated text file to store its weight matrix. The advantage of using external text file for storage of ANN weight matrix is the convenience of updating the weight matrix. It is can be achieved easily by using any text editor.

To facilitate the forecasting process, Users were provided with a user-friendly interface that allows them to select the forecasting detail of their interest. Specifically, users can select the forecasting time window from one to five years and the forecasting level of details: state or district. According to the user's selection, the main program is able to call the corresponding ANN models to perform the user-interested forecasting. The forecasting interface is shown in Figure 7.3. As one may notice, there is "years to deficiency" option in the forecasting scenarios selection box. This function provides another format of forecast: the number of years that one particular pavement section can serve prior to deficiency. This information becomes crucial when FDOT is interested in the comparison of different budget alternatives.

Table 7.1 ANN Model Classifications

Pavement Type	Pavement Index	Forecast Interval	Description
Flexible	Crack	1 year	1-year Crack Index Forecasting Model
		2 years	2-year Crack Index Forecasting Model
		3 years	3-year Crack Index Forecasting Model
		4 years	4-year Crack Index Forecasting Model
		5 years	5-year Crack Index Forecasting Model
	Ride	1 year	1-year Ride Index Forecasting Model
		2 years	2-year Ride Index Forecasting Model
		3 years	3-year Ride Index Forecasting Model
		4 years	4-year Ride Index Forecasting Model
		5 years	5-year Ride Index Forecasting Model
	Rut	1 year	1-year Rut Index Forecasting Model
		2 years	2-year Rut Index Forecasting Model
		3 years	3-year Rut Index Forecasting Model
		4 years	4-year Rut Index Forecasting Model
		5 years	5-year Rut Index Forecasting Model
Rigid	Crack	1 year	1-year Crack Index Forecasting Model
		2 years	2-year Crack Index Forecasting Model
		3 years	3-year Crack Index Forecasting Model
		4 years	4-year Crack Index Forecasting Model
		5 years	5-year Crack Index Forecasting Model
	Ride	1 year	1-year Ride Index Forecasting Model
		2 years	2-year Ride Index Forecasting Model
		3 years	3-year Ride Index Forecasting Model
		4 years	4-year Ride Index Forecasting Model
		5 years	5-year Ride Index Forecasting Model

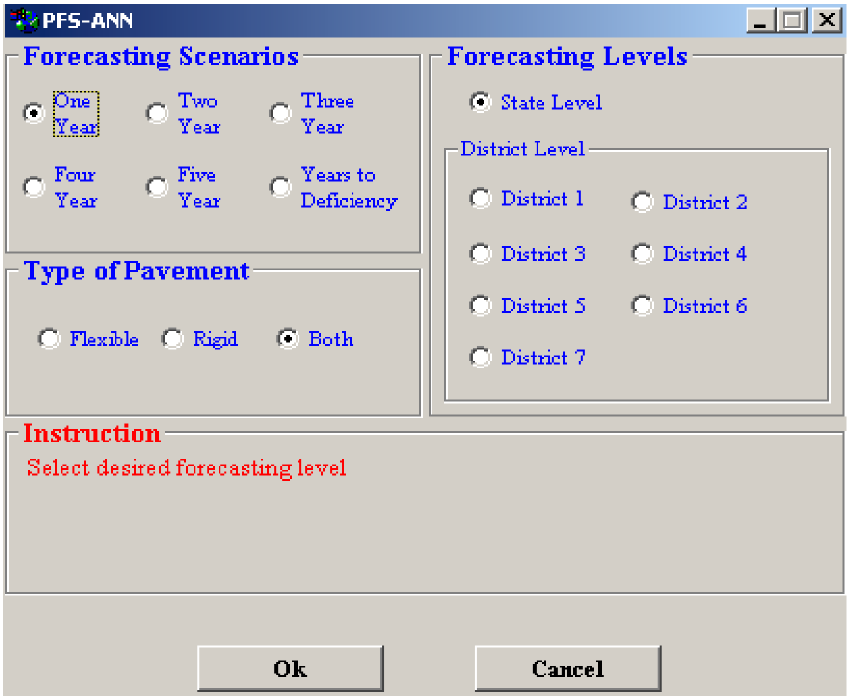
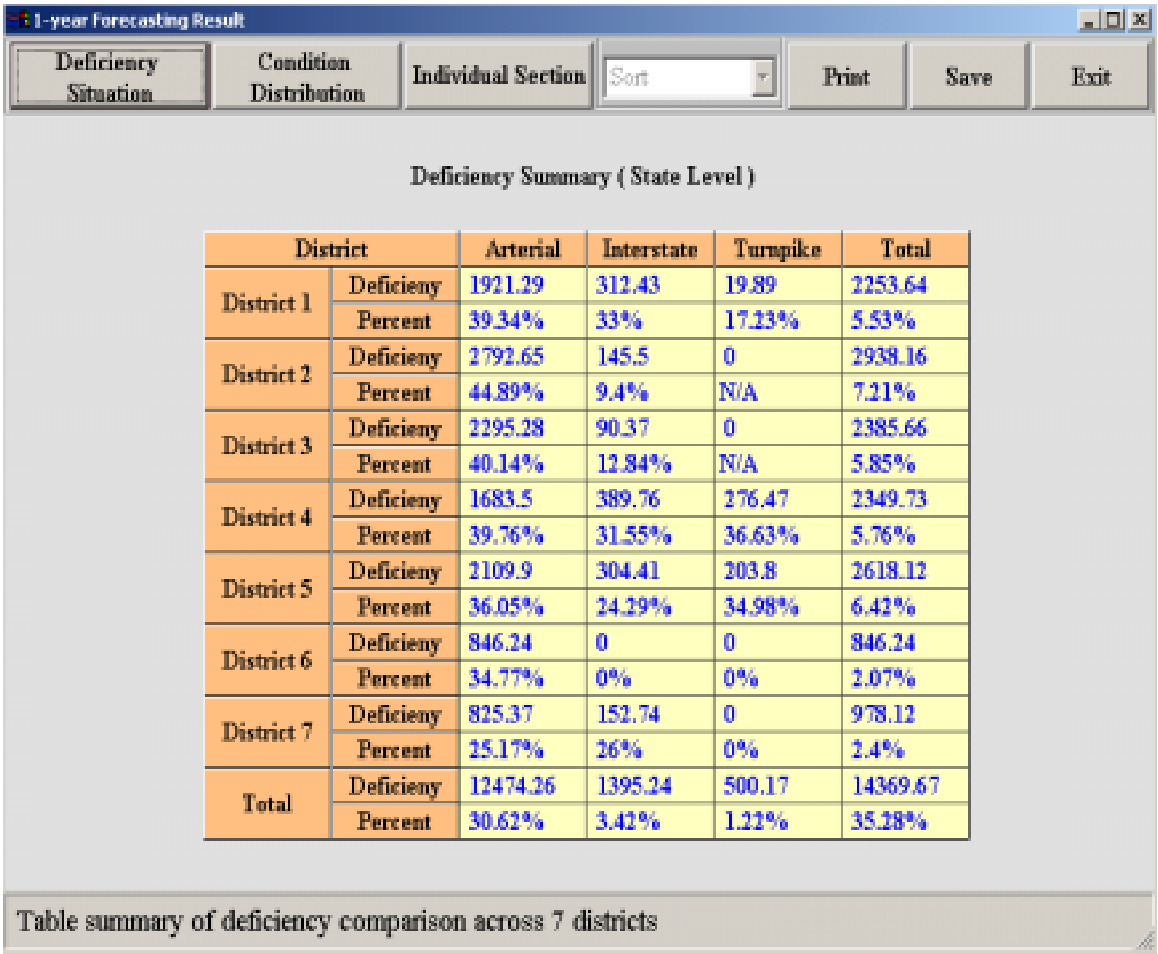


Figure 7.3 Forecasting Interface

7.1.3 Data Postprocessing Module

In this module, the forecasted results are summarized in two levels; state level and district level. At the state level, lane-mile deficiency forecasts for 7 districts are provided. At the district level, lane-mile deficiency forecasts for 3 systems, which are arterial, interstate, and turnpike, are provided. Considering convenience of users, a detailed list of section-by-section forecasting is provided in addition to the two levels of forecasts. As output of the module, the forecast results are presented in three formats: table, graphic, and listing. Users can either print out the output or simply save the outputs into files for later checks. The major output interfaces are shown in Figure 7.4, 7.5, and 7.6.



District		Arterial	Interstate	Turnpike	Total
District 1	Deficieny	1921.29	312.43	19.89	2253.64
	Percent	39.34%	33%	17.23%	5.53%
District 2	Deficieny	2792.65	145.5	0	2938.16
	Percent	44.89%	9.4%	N/A	7.21%
District 3	Deficieny	2295.28	90.37	0	2385.66
	Percent	40.14%	12.84%	N/A	5.85%
District 4	Deficieny	1683.5	389.76	276.47	2349.73
	Percent	39.76%	31.55%	36.63%	5.76%
District 5	Deficieny	2109.9	304.41	203.8	2618.12
	Percent	36.05%	24.29%	34.98%	6.42%
District 6	Deficieny	846.24	0	0	846.24
	Percent	34.77%	0%	0%	2.07%
District 7	Deficieny	825.37	152.74	0	978.12
	Percent	25.17%	26%	0%	2.4%
Total	Deficieny	12474.26	1395.24	500.17	14369.67
	Percent	30.62%	3.42%	1.22%	35.28%

Figure 7.4   Tabulation of Deficiency Summary

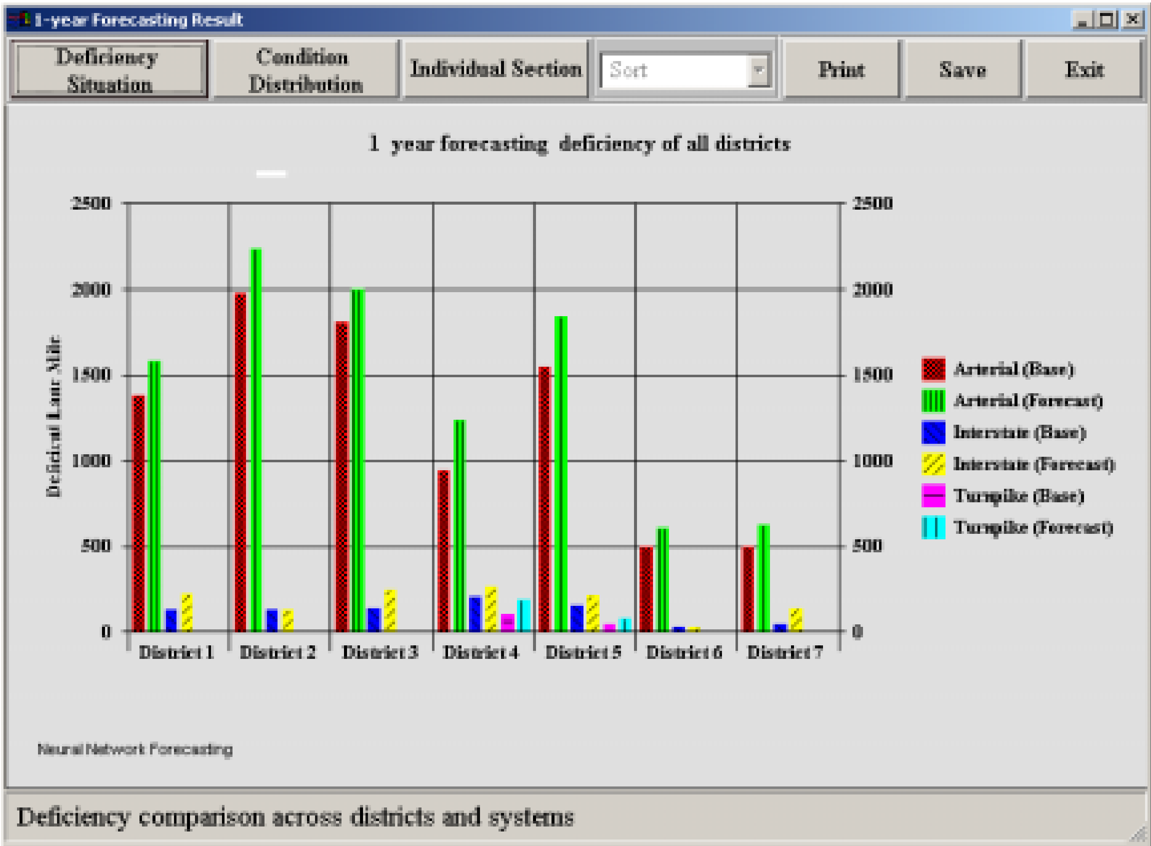


Figure 7.5 Distribution of Lane-mile Deficiency

Figure 7.6 Distribution of Overall Pavement Condition

7.1.4 Pavement Deficiency Forecasts for the Next Five Years Using the developed ANN Models

In this section, the developed ANN models was applied to forecast the pavement overall deficiency condition in the future in terms of PCR. Since the latest available data in the database is year 2001 data, forecasting of pavement deficiency condition from 2002 to 2006 was performed using the developed ANN models. The results are summarized in Table 7.2 and Figure 7.7.

Table 7.2 Forecasts of Deficient Lane Miles for Year 2002 to 2006

Districts	Total Lane Miles	Deficient Lane Miles / Percentage				
		2002	2003	2004	2005	2006
1	5767.26	2013.7	2343.63	2790.94	2817.31	2978.22
		34.90%	40.60%	48.40%	48.90%	51.60%
2	7823.91	2537.67	3078.82	3499.87	3570.23	4039.64
		32.40%	39.40%	44.70%	45.60%	51.60%
3	6364.52	2242.74	2621.89	2719.1	2696.41	3290.09
		35.20%	41.20%	42.70%	42.40%	51.70%
4	5916.9	1917.1	2049.25	2731.41	2864.66	3075.04
		32.40%	34.60%	46.20%	48.40%	52.00%
5	7296.72	2111.05	2813.49	3493.53	3643.41	4050.93
		28.90%	38.60%	47.90%	49.90%	55.50%
6	2851.69	734.63	741.2	838.82	942.3	1055
		25.80%	26.00%	29.40%	33.00%	37.00%
7	4057.8	825.11	1086.68	1308.55	1324.1	1691.71
		20.30%	26.80%	32.20%	32.60%	41.70%
Total	40078.79	12381.99	14734.97	17382.21	17858.41	20180.64
		30.90%	36.80%	43.40%	44.60%	50.40%

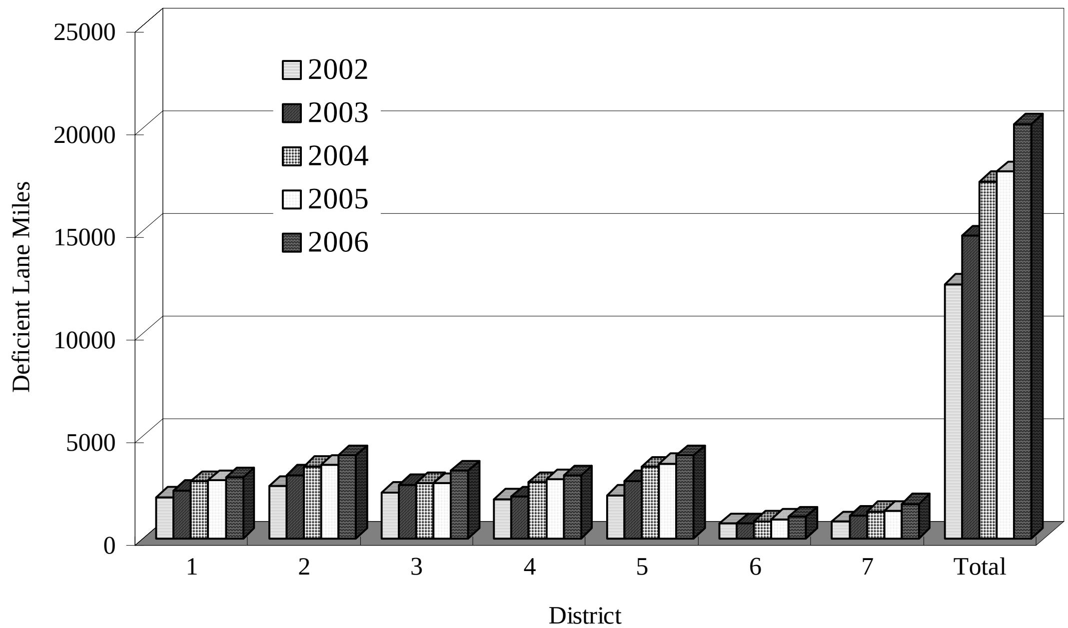


Figure 7.7 Deficient Lane Mile Forecasts for Year 2002, 2003, 2004, 2005 and 2006

CHAPTER 8

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

8.1 Summary

This report documents the research that was conducted to develop appropriate pavement performance forecasting models based on artificial neural networks and the corresponding software that can implement these models in FDOT's PMS. As a key component of PMS, pavement performance models play a crucial role in PMS at the network level where forecasting results provide key information for FDOT to make decisions on overall maintenance and budget plans. Therefore, improved accuracy of pavement performance models could make a considerable difference in the expenditure on pavement maintenance and rehabilitation. Although many highway agencies still use regression models in their PMSs, it is noticeable that some agencies are attempting to use more advanced and accurate models in their PMSs. In the presence of an extensive pavement database, with a multitude of variables involved, ANN models can be advantageous as they do not require an explicit function form to be pre-specified. Although the training algorithm of the neural network may be complicated, development of neural network model is usually accomplished by using professional software.

This research is a continuing effort of the previous research " Road Surface Crack Condition Forecasting Using Neural Network Work" conducted by University of South Florida. In the previous research, crack-index forecasting models were developed using neural network technique. The developed crack-index models can perform one to three year forecasting for crack index with acceptable accuracy. Inspired by the result of the previous research study, this research focused on development and implementation of PCR forecasting model with the use of FDOT pavement surface condition survey database. As the result of the research, 25 ANN models were developed with each model focusing on a pavement distress index (crack, ride, or rut) forecasting for a specific time window (one, two, three, four, or five years). Modeling using neural network is a time-consuming process. To reduce the modeling effort, “BrainMaker”, a popular neural network training software, was utilized for neural network training. After the training process is completed, the ANN model stores all the gained knowledge in its weight matrix. Then this matrix can be used by the neural network to forecast the future pavement condition at a reasonable accuracy.

As a part of the research, the results from the ANN model were compared with those from a commonly used AR model. To meet FDOT needs in long-term pavement performance forecasting and decision-making, one to five year forecasts were carried out using both ANN model and AR model, in which both models were used to forecast the deficient lane mileage for year 2001. The forecasts were then compared against the observed deficiency of lane mileage in year 2001. The comparison showed that ANN models produced comparable over- and under-estimation errors. AR models produced significantly unbalanced estimation errors with unreasonably higher over-estimation error than under-estimation error; and ANN models perform much better than the regression models in terms of forecasting accuracy.

For implementation purposes, the weight matrix obtained by the training process will be stored in an easy-to-read text file, which will be used by the developed software to forecast the future pavement condition. This facilitates convenient updating of the ANN model by simply updating the text file that stores the weight matrix. A software package was developed using Visual Basic and SAS language. A preprocessing module was developed using SAS language since the input database will be the original FDOT pavement surface distress condition database, which is in SAS format. Main interface program and other function modules were developed using Visual Basic. The software is user-friendly and can be mastered without special training.

8.2 Conclusions

This research study involved developing ANN models for PCR forecasting. Based on the foregoing analysis, the ANN model provided an effective alternative to the current pavement performance forecasting models. The characteristics of ANN models coincide with the very nature of the pavement deterioration mechanism. By undergoing training with historical pavement condition data, the trained ANN models can extract underlying information contained within the historical database and then make reasonable forecasts of pavement condition in the future. This has been verified by comparing model forecasts with year 2001 pavement evaluations.

The theoretical foundation of ANN provides a solid support for pavement condition forecasting. By learning the dynamics of pavement condition deterioration history, the ANN model can extract the underlying information contained within the database and then make reasonable forecasts of pavement condition in the future. This has been verified by the ANN forecasts comparing to 2001 observations.

As found in this research, the original FDOT pavement condition survey database is not suitable to be used directly for the ANN model development. Accordingly, a data preprocessing procedure was necessary to rectify the database, which includes adding missing data, using moving averages of data in the database, transforming the database into formats that can be directly used for ANN modeling purpose. A module coded in SAS was developed in order to accomplish these tasks automatically.

Although the ANN training algorithm itself is complicated, the theory behind it is simple – gradient decent. In view of its effectiveness as a model tool, many neural network software packages, such as BrainMaker, Matlab neural toolbox, etc., are available to simplify the training process and reduce the training efforts.

To implement the ANN models in FDOT's PMS, a software package was developed by using a popular programming language, Visual Basic. The software includes three modules, which will perform three major functions: preprocessing of database, one to five year forecasting, and summarization of results. A commercial professional software, BrainMaker, was used in this research for the ANN model training. Use of external software does not cause an inconvenience because the neural network training can be accomplished by using any network training software and separate text files are used to store the trained network weight matrices. In practice, FDOT needs to update the network weight matrix at regular intervals by retraining the ANN models using newly available data. In order to update the weight matrix, FDOT only needs to update the text file of the weight matrix. It is hoped that the developed software would aid FDOT in managing Florida's pavement network in a more efficient way.

With the above consideration in mind, it was concluded in this research that the proposed neural network model was an effective tool for pavement maintenance planning process in a PMS. Not only does it improve the forecasting accuracy, but it can be easily updated by retraining the ANN models with newly collected data. In view of the limitations of the existing models, neural networks offer an attractive alternative for the problem at hand. Pavement performance based on historical database is likely to play a key role in PMS. We hope that the neural networks will prove useful as a means of modeling pavement performance and building useful mathematical models for pavement management.

8.3 Recommendations

Data preprocessing is the crucial part of the research for successful ANN modeling due to the sensitivity of the ANN model to the data used for training purpose. It is recommended that survey procedure be as uniform and consistent as possible over time and data should be double check for the irregularity before adding to the database.

The ANN models were developed based on FDOT's historical pavement surface distress condition survey database. The pavement condition deterioration pattern may change over time. It is much helpful to compare the model forecasts with the surveyed data each year and retrain the ANN models with newly collected data every a specific time frame, say five years. By retraining the ANN models with newly obtained data, the ANN models can keep learning the updated information and adjust its hidden weights to ensure the forecasting accuracy.

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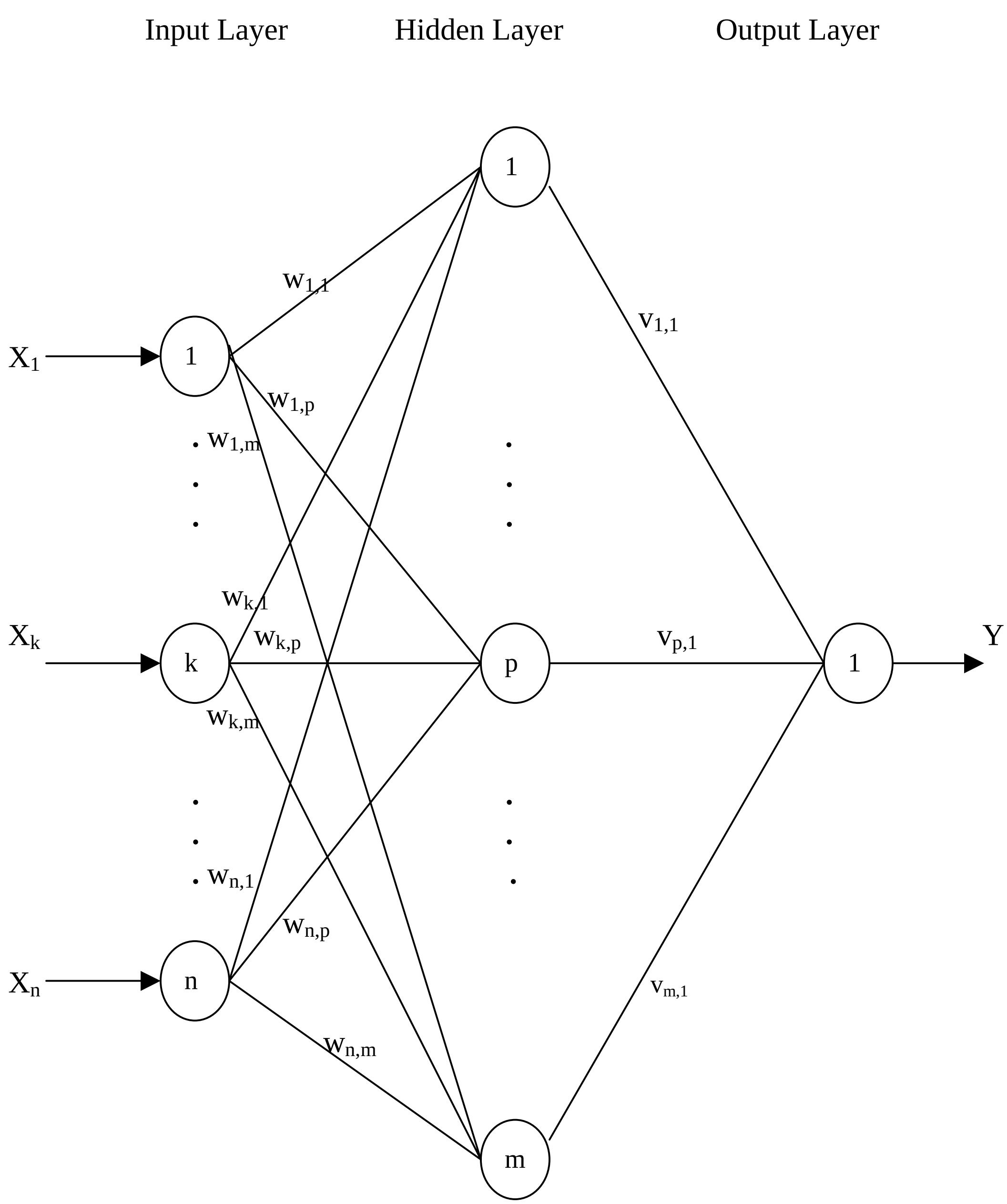
APPENDIX A

Format of Weight Matrix



Note:

w_{ij} = weight of the ith neuron in the input layer to the jth neuron in the hidden layer

v_{ij} = weight of the ith neuron in the hidden layer to the jth neuron in the output layer

This notation will be used to interpret the weight matrix as follows

APPENDIX A-1

Weight Matrix of the 1-year ANN Crack Model

Flexible Pavements

Input Hidden Weight Matrix

	$W_{1,1}$	$W_{2,1}$	$W_{3,1}$	$W_{4,1}$	$W_{5,1}$	$W_{6,1}$	$W_{7,1}$	$W_{8,1}$	$W_{9,1}$	$W_{10,1}$	$W_{11,1}$	$W_{12,1}$
$W_{1,1}$	0.3980	0.6264	-0.0676	-0.9708	-2.3574	0.9974	-1.3026	0.4102	-2.4024	-0.1530	-0.3914	0.6682
$W_{1,2}$	2.6984	2.5120	4.9222	3.4154	1.3176	4.8142	1.3396	0.5102	1.1836	2.2466	3.1386	3.8526
$W_{1,3}$	-0.1120	1.9842	0.9616	-3.8696	-0.4964	-0.5350	0.8764	0.9564	1.4664	-0.1710	-1.3452	0.7772
$W_{1,4}$	0.1806	-0.2116	0.2710	0.7224	1.5482	-0.3580	-1.8640	-0.4274	-1.9804	-1.0264	-1.2600	-0.2142
$W_{1,5}$	0.6770	1.4152	-1.3400	1.2196	1.5082	-1.9054	-0.7880	0.0656	2.9464	-1.1580	0.3992	-2.6154
$W_{1,6}$	-3.5656	-1.3060	-1.0684	-1.0280	0.5130	0.6652	1.4154	1.1532	0.5456	-1.2440	1.9282	2.0556
$W_{1,7}$	-0.3350	-0.4082	0.6726	-2.0434	2.6040	1.5300	0.2394	1.3664	-0.9520	0.5022	-1.1330	-2.3820
$W_{1,8}$	-2.2994	-3.1060	-0.5616	-2.8790	-2.5986	-0.2960	-1.2886	-1.7914	0.2156	0.6850	2.9502	-2.8246
$W_{1,9}$	2.2960	2.2162	0.3196	-0.7830	-0.3890	-1.1726	2.1896	-0.4722	-0.2434	0.9600	-0.0742	-0.3474
$W_{1,10}$	-3.5436	-0.8276	-2.5410	-1.4582	-0.7562	-1.3534	-4.1424	-2.5642	-1.9380	-0.3496	-1.5240	-5.7564
$W_{1,11}$	0.2686	-2.2044	-3.8604	-3.1066	-2.1420	-3.3526	0.0516	-1.1974	-0.3340	-2.7206	-0.0244	-4.9596
$W_{1,12}$	-3.7134	-2.7126	-1.8970	-1.7672	-0.7424	-3.7992	-0.1014	-2.7636	0.0282	-2.6650	0.9220	-4.6400
$W_{1,13}$	0.2506	0.4086	0.4570	0.1660	0.1080	-0.1252	-0.0540	0.0140	-0.0414	0.0616	0.0010	0.0584
$W_{1,14}$	-0.5222	-0.3270	-0.1382	-0.4208	-1.1804	-0.5062	-0.1096	-0.2136	0.7124	0.3396	1.4564	-1.6336
$W_{1,15}$	0.0716	0.0592	0.0322	-0.4384	-1.0350	-0.4472	0.2646	-0.4110	0.1510	-0.1106	-0.2240	0.1712
$W_{1,16}$	-0.0326	0.1222	-0.0266	-0.3036	-0.6124	-0.2014	0.1356	-0.2064	-0.2404	-0.1030	-0.2992	-0.0686
$W_{1,17}$	-1.9374	-1.8464	-0.9554	-0.9096	0.1294	-2.7294	-0.0460	-2.7102	0.0276	-1.0354	0.9206	-4.6664
$W_{1,18}$	-3.1262	-2.2452	-2.0760	-1.0954	-0.1786	-2.4676	0.1100	-2.1242	-0.8332	-1.7182	-0.5696	-4.1552
$W_{1,19}$	-1.0100	-0.8608	-0.9710	-0.8308	-2.2666	0.0360	-0.0164	-0.2124	0.7704	-0.2744	0.5600	-0.9842
$W_{1,20}$	-3.6922	-2.7436	-1.7694	-1.7706	-0.7706	-3.7432	-0.0050	-2.6684	0.0408	-4.4406	0.8852	-4.6992
$W_{1,21}$	-0.9740	-0.8352	-0.8746	-0.7696	-0.8866	-0.8884	-0.0442	-0.8494	0.4626	-1.0820	0.9126	-0.4166
$W_{1,22}$	0.1142	0.3474	0.3336	0.2124	0.0456	-0.1914	-0.1220	-0.0264	-0.1274	0.0162	0.1642	-0.2650

Hidden Output Weight Matrix

$W_{1,1}$	$W_{2,1}$	$W_{3,1}$	$W_{4,1}$	$W_{5,1}$	$W_{6,1}$	$W_{7,1}$	$W_{8,1}$	$W_{9,1}$	$W_{10,1}$	$W_{11,1}$	$W_{12,1}$
[-2.4508	-0.4114	-2.1656	1.7216	1.6176	0.7050	2.5022	0.2884	2.1170	-0.5142	-0.3574	-0.8826

$W_{13,1}$	$W_{14,1}$	$W_{15,1}$	$W_{16,1}$	$W_{17,1}$	$W_{18,1}$	$W_{19,1}$	$W_{20,1}$	$W_{21,1}$	$W_{22,1}$	$W_{23,1}$
-0.3556	-0.5034	-1.2860	-0.8684	-0.1026	0.2674	-0.9008	-0.8730	-1.7690	-0.2564	-0.1316]

APPENDIX A-2

Weight Matrix of the 1-year ANN Ride Model

Flexible Pavements

Input Hidden Weight Matrix

-0.1564	0.0822	-0.0206	-0.7546	-1.4250	0.4030	-4.0408	-0.3944	-1.6812	0.0408	-1.1542	-0.1356
-0.1740	-0.3242	4.0076	1.5170	0.5186	2.7350	-0.7534	-1.5882	1.9774	-1.7264	2.8192	2.0754
0.2796	1.8504	2.1770	-5.0304	-0.9730	-1.1392	0.6560	0.6950	0.8690	0.2300	-0.4496	0.9122
0.3112	-0.1466	-0.0136	0.9986	1.0710	-1.1484	-0.8272	-0.5056	-0.9620	-0.3844	-1.5744	-0.1362
0.9200	1.7892	-1.3144	1.8522	1.4546	-1.7466	-0.6740	-0.0032	2.9292	-1.5442	0.8822	-2.5910
-2.7170	-0.3444	-0.6836	0.1964	1.6640	0.8826	3.5896	1.4322	0.0730	0.0032	3.0270	2.7720
-0.3220	-0.2832	0.2314	-1.8222	2.3912	1.2024	0.0664	1.2372	-1.5508	0.9550	-1.4264	-2.7986
3.1506	0.2508	0.3022	-3.1594	0.4684	-7.2430	5.6634	1.8994	3.6720	-2.3254	-1.9940	6.9432
1.7770	2.2420	0.5690	0.1642	0.0864	-1.7296	1.1830	-1.0800	-0.8624	0.6376	0.1520	-1.7900
-0.7442	1.0746	-3.0246	-0.4934	-2.5306	1.0076	-3.0372	-1.5290	-1.0764	-0.3584	0.1632	-0.6752
2.6730	0.2852	-0.2054	-0.7590	-0.6544	-2.1906	-2.3122	-0.0176	0.3762	-2.1192	-0.0256	-3.1644
-1.3806	-1.1564	-0.0630	-1.5810	-1.8082	-6.5912	-3.9934	-4.5376	0.7442	-1.9570	2.8452	5.9944
1.0056	1.0060	1.9074	0.4720	0.2806	0.5904	-1.5334	0.0186	1.1144	-0.5014	-0.8994	-1.5530
0.1220	0.3034	0.0132	-0.7566	-0.8666	-0.1400	-0.1382	-0.3624	-0.0500	-0.2930	-0.6164	0.4182
0.2164	0.3404	-0.0002	-0.8896	-1.0720	-0.2536	-0.2412	-0.4806	-0.0674	-0.4192	-0.6470	0.6110
0.1264	0.2762	-0.1132	-0.6810	-0.8176	-0.3026	-0.2942	-0.4844	-0.2122	-0.1122	-0.5632	0.4826
0.0874	0.1494	0.3586	-0.0340	-0.7162	-0.9640	-3.1692	-1.8340	0.6984	-1.6540	1.9586	-0.8586
-0.2966	0.8222	1.4066	-0.3304	-0.2604	-3.5564	-2.6280	-1.4152	3.2460	-1.0494	2.2790	-6.9120
-1.8756	-1.7530	-1.7512	-0.1940	-0.5062	-3.0416	3.4886	-1.9154	0.5596	2.9236	-0.2396	-5.6726
-0.0272	0.0742	0.3516	-0.0544	-0.7172	-1.5324	-2.4782	-1.6394	0.6244	-1.0982	1.3904	-0.3642
-7.4572	-7.1786	-6.8572	-5.1386	-5.1720	-5.0766	0.0010	-7.0734	1.5016	2.8244	3.6820	-4.5114
0.1822	0.2992	0.0016	-0.5302	-0.7144	-0.3380	-0.1190	-0.4260	-0.1600	-0.2326	-0.5204	0.3100

Hidden Output Weight Matrix

[-1.0742 -0.2712 -3.0142 1.1906 1.6424 1.1312 1.3194 0.1726 1.0012 0.5262 -1.7110 0.5124
-0.0070 -0.6810 -0.7832 -0.7810 -1.3114 -0.8808 1.7220 -1.4242 -0.8612 -0.6946 0.0208]

APPENDIX A-3

Weight Matrix of the 1-year ANN Rut Model

Flexible Pavements

Input Hidden Weight Matrix

-0.0406	0.7714	0.9946	-2.3500	-2.0172	1.0014	-1.1904	0.1282	-2.6286	0.1450	-0.5534	1.2084
-3.6024	-0.7010	2.5620	1.8722	1.9462	-2.5534	5.3862	-2.9608	3.1974	4.1786	3.8142	-1.9232
-0.4232	2.1586	2.0874	-5.2910	0.0966	-0.5400	0.1546	0.4734	1.5536	0.1584	-0.1146	0.2914
0.9720	0.1714	0.2434	1.8524	1.4420	-1.2310	-1.4062	-0.7636	-1.5910	-1.7390	-1.1616	-1.1260
-0.6530	-0.6570	-2.5896	-0.0780	-0.5096	-4.6782	-0.4042	-2.3030	1.5346	-0.9894	-0.5564	-5.8480
-3.7362	-1.5010	-0.2842	-0.1856	0.9308	3.6490	-0.9114	0.7708	1.5926	-1.1522	-0.6194	6.9314
0.2282	-0.3176	0.6492	-1.7040	2.0720	0.9916	0.4284	1.2336	-0.9634	1.3120	-1.7520	-2.6534
3.0570	0.9646	1.6208	-1.0836	-2.2906	7.0534	-0.0210	2.3182	0.4424	2.4226	4.7686	7.2354
2.5826	2.4164	0.7632	0.0374	-0.0332	-0.9664	1.6726	0.0970	0.4006	2.2934	-0.2436	0.3722
0.0824	1.3174	-0.6904	0.1196	-1.0022	1.6702	-5.5340	-0.0804	0.2290	0.5530	1.4532	-1.9602
3.4706	0.5730	-0.9310	-0.2834	-0.2344	-0.8608	0.6734	0.8314	-1.5302	-0.5342	0.0660	-2.5932
-0.7972	0.3426	-0.2080	-0.2542	-0.3276	-1.1134	-0.4466	-0.6584	-0.1554	-1.2384	-0.7372	-0.1206
0.6920	0.8794	0.5224	-0.4242	-0.3142	-0.0914	0.0380	-0.5462	-0.9144	-0.9530	0.3790	-0.0130
0.3502	0.6508	0.3126	-0.6994	-0.6464	-0.7164	-0.8186	-1.1184	0.2400	-1.2108	0.3872	-1.0202
0.0108	0.5190	0.3954	-0.4232	-0.2896	-0.3900	-0.0102	-0.5634	-1.7950	-0.8542	0.0752	-0.0992
0.2274	0.7090	0.2576	-0.4834	-0.3164	-0.4150	-0.1874	-0.5470	-1.8792	-0.9694	0.1712	-0.3296
-1.4156	-0.3204	-0.5812	-0.9702	-0.3008	-2.1084	-0.6890	-1.3730	0.1684	-1.3856	-0.8584	-1.9402
-0.2874	0.1908	0.2990	-0.2644	-0.0844	-2.4244	0.1032	-0.9404	0.0646	-0.8094	0.1280	-2.1664
0.3806	0.7042	0.2876	-0.3374	-0.2750	-0.3396	-0.0534	-0.6086	-1.9362	-0.8584	0.1636	-0.2080
-1.4102	-0.4440	-0.4434	-0.9196	-0.9324	-2.1130	-0.9314	-1.0236	0.1682	-1.4012	-1.2472	-1.6580
1.6300	2.1382	0.8550	-0.7916	-1.4334	-0.8690	0.4640	1.0396	0.0086	-0.8690	-1.4516	-3.6406
0.2984	0.7708	0.4490	-0.1662	-0.2096	0.0392	-0.0194	-0.1614	-0.9742	-1.0124	0.1792	0.5090

Hidden Output Weight Matrix

[-2.3310 -0.0380 -3.2890 2.1314 2.9172 0.9690 0.4482 0.0252 1.7696 0.5960 0.7856 -1.8272
-0.4284 -1.6776 -0.5606 -0.5826 -3.7326 -2.5584 -0.5014 -5.0846 -0.5776 -0.3044 0.2816]

APPENDIX A-4

Weight Matrix of the 2-year ANN Crack Model

Flexible Pavements

Input Hidden Weight Matrix

0.4184	0.6030	0.0380	-0.8084	-2.1810	1.1100	-1.2242	0.3790	-2.4280	-0.1264	-0.3384	0.5726
-0.1492	-0.3014	2.7862	1.8520	0.2604	2.5374	0.6032	-1.7960	0.2602	1.8642	1.2872	1.0934
-0.2402	1.7690	0.9292	-3.8294	-0.5340	-0.3034	0.5220	0.8754	1.6010	0.0006	-0.9576	0.6746
0.3200	-0.0524	0.3850	0.8908	1.6232	-0.7352	-1.7796	-0.4900	-1.9942	-1.1882	-1.7480	-0.2634
0.8856	1.6000	-1.2300	1.2686	1.3042	-2.1300	-0.5560	-0.0246	3.2402	-1.2410	0.5994	-2.4700
-2.9390	-0.7770	-0.8050	-0.6984	0.7166	0.8582	1.0912	1.5670	0.3360	-1.0462	1.3408	2.6770
-0.1666	-0.2560	0.7042	-2.0402	2.5650	1.3520	0.1412	1.4602	-1.1240	0.6180	-1.4170	-2.2208
-0.4464	-1.4480	1.0230	-1.2456	0.6984	1.7186	0.5812	-0.5656	0.6008	1.7114	2.5166	-1.0082
3.1076	3.0224	1.0604	0.0066	0.2954	-0.9214	1.6502	-0.1606	-0.6182	1.1614	-0.7162	0.3960
-2.0170	-0.1552	-2.3476	-1.6514	-1.8630	-0.1950	-3.8480	-0.8526	0.3008	-0.6626	-0.4976	-3.3336
2.2296	-0.2652	-1.9936	-1.6172	-1.0300	-1.8522	0.1934	0.5570	-1.0836	-2.5480	0.1180	-3.0784
-1.0262	-0.9760	-0.6622	-0.9032	-0.3614	-1.5864	-0.1014	-0.5792	0.0282	-1.8142	0.4514	-1.8934
-0.2832	-0.1730	-0.1812	-0.3764	-0.3924	-0.3412	-0.2606	-0.3014	-0.0922	0.0500	-0.1420	-0.1556
-1.2384	-1.1742	-1.1266	-1.1520	-1.0232	-0.8414	0.3292	-1.2066	-0.0004	-0.3980	-0.4200	-1.2916
-0.2314	-0.1392	-0.0932	-0.5320	-0.8914	-0.3840	-0.0146	-0.3390	0.3036	-0.0234	-0.1422	-0.1164
-0.2256	-0.0916	-0.2034	-0.3750	-0.5444	-0.4072	-0.3240	-0.2842	-0.0372	-0.0402	-0.1602	-0.1470
-0.8166	-0.7760	-0.3794	-0.7300	-0.5116	-0.7640	-0.0460	0.1306	0.0276	-1.9292	0.3676	-1.2496
-2.0714	-2.0084	-2.0356	-1.9012	-1.3472	-1.6506	0.1100	-1.1304	0.0646	-1.4556	-0.4422	-2.2550
-0.2626	-0.1208	-0.2224	-0.2532	-0.4454	-0.4552	-0.0374	-0.4540	-0.0536	0.1112	-0.1034	-0.1894
-1.4722	-1.4570	-0.9804	-1.0520	-0.8674	-1.5596	-0.0050	-0.4782	0.0408	-1.8434	-0.0262	-2.0174
-0.2212	-0.2562	-0.1908	-0.2040	-0.3492	-0.3810	-0.0576	-0.3080	-0.1562	-0.0184	-0.1044	-0.0854
-0.2636	-0.1170	-0.2042	-0.3362	-0.5836	-0.3196	-0.1654	-0.2402	-0.1250	-0.0204	-0.2144	-0.2256

Hidden Output Weight Matrix

[-2.1170 -0.8442 -2.0682 1.6202 1.2406 0.2152 2.0040 0.7106 1.8422 0.0650 0.2232 -0.2326
-0.6892 -0.4654 -1.0304 -0.7296 -0.3244 -0.2574 -0.7374 -0.1942 -0.6106 -0.7404 -0.5722]

APPENDIX A-5

Weight Matrix of the 2-year ANN Ride Model

Flexible Pavements

Input Hidden Weight Matrix

0.0870	0.2276	-0.0982	-0.6440	-1.7110	0.7644	-1.2156	0.1984	-2.6250	-0.3872	-0.4364	0.0908
-0.0344	-0.1144	3.1560	1.9326	0.1654	1.9692	1.1204	-2.3850	0.7882	1.6126	0.1686	0.6974
-0.0562	1.6576	0.9210	-3.6834	-0.3912	-0.7592	0.5186	0.7792	1.0966	0.0432	-1.4692	0.4304
0.3682	0.0500	0.2956	0.5286	1.1870	-0.6562	-1.6894	-0.6744	-1.9174	-0.8362	-1.3786	-0.2912
1.1040	1.8736	-1.1082	1.2694	1.3922	-1.7164	-0.3816	-0.2302	3.2852	-1.1900	0.9570	-2.3490
-3.4972	-1.4286	-1.3456	-0.8800	0.4620	0.0676	0.4272	0.9062	-0.1224	-0.1706	1.2650	0.8354
-0.4194	-0.2834	0.6650	-2.1564	2.7396	1.7186	0.1850	1.3854	-1.1192	0.8256	-0.9604	-2.3190
2.6130	0.9204	2.4374	0.1300	1.0270	5.4922	1.4136	3.3210	2.2314	0.6026	2.5154	3.9442
2.0454	2.2120	0.3716	-0.6386	-0.1584	-1.1494	1.6132	-0.4980	-0.6914	1.0176	-0.6690	-0.5596
-1.0984	0.3834	-2.0806	-1.2210	-1.6082	-0.9204	-3.9304	-1.8322	0.5342	-0.2092	0.5964	-4.0506
2.2760	0.1674	-1.5754	-1.0510	-0.8308	-1.8586	0.1470	0.0630	-0.5942	-2.0074	1.4404	-2.9080
-2.3730	-1.7484	-1.9208	-1.5522	-0.7666	-2.5176	-0.7224	-2.2812	0.1262	-0.5894	0.6702	-3.2720
1.2140	1.2560	1.7152	0.8826	0.9084	1.5064	0.7476	0.9908	0.1656	-0.0810	-0.5364	2.5442
0.6696	0.0726	0.7346	0.6052	-0.7600	2.1770	0.6542	1.4566	0.0010	0.1030	0.0020	3.6046
-0.1212	-0.0884	-0.0402	-0.4980	-0.8986	-0.2544	-0.2002	-0.2484	0.2822	-0.1450	-0.3340	0.0236
0.0660	0.0062	0.2022	-0.0822	-0.4956	-0.3592	0.0926	-0.6044	-0.0880	0.0500	-0.8862	-1.1264
-1.3782	-1.4204	-1.2970	-0.6276	-0.4192	-2.6884	-0.8986	-2.0646	0.1242	-1.0180	-0.0174	-2.7982
-1.1294	-0.4260	-0.5850	0.2094	0.0944	-1.6500	0.1100	-1.6416	0.0646	-0.0172	0.0302	-2.9842
0.8426	1.3842	0.7750	1.3092	1.8306	0.1936	-0.1652	-0.8846	0.0460	2.8670	-0.0040	-0.5982
-1.9354	-1.8492	-2.3724	-1.6200	-0.8680	-2.6992	-0.7410	-2.2852	0.2322	-0.7950	-1.0666	-3.8080
-0.3870	-0.4590	-0.4184	-0.1460	0.1660	-0.0008	-0.3492	-0.0922	0.2422	0.0776	-0.3124	-0.1262
1.3142	1.3790	1.8484	1.0772	0.9602	1.8130	0.7266	1.2066	-0.8764	0.0576	-0.0764	2.9742

Hidden Output Weight Matrix

[-1.5920 -0.8410 -1.4700 1.1094 1.5204 0.4972 2.4866 0.0836 0.8174 0.2826 -0.8124 -0.1220
-0.0646 0.0914 -0.9442 -0.4064 -0.5076 -0.4106 0.3552 -0.1312 0.3144 -0.0384 -0.4654]

APPENDIX A-6

Weight Matrix of the 2-year ANN Rut Model

Flexible Pavements

Input Hidden Weight Matrix

0.1980	0.4608	1.5266	0.2770	-3.7406	0.6930	-0.8346	0.7508	-2.1152	0.1536	-1.0596	0.0262
-0.8330	-1.1064	2.6262	1.6234	-1.4526	1.1242	0.5116	-2.3126	0.8770	1.6432	1.2752	-0.3766
-0.4146	1.8762	2.1832	-2.9614	-2.7032	-0.6362	0.7786	1.6566	1.2254	-0.0132	-1.0520	0.7190
0.2972	0.1940	-0.0508	0.2520	2.2108	-0.6656	-1.4340	-0.8950	-1.5694	-0.8376	-0.9464	-0.5704
1.2564	2.0476	-1.3608	1.0860	1.9426	-2.0964	-0.4220	-0.4252	2.6244	-0.3122	0.8136	-2.9100
-2.6954	-0.3682	-0.8342	-0.7496	1.5282	1.5154	0.9256	0.7452	0.6386	0.4416	-0.7826	3.7036
0.0590	-0.1256	-0.5566	-3.1592	4.4110	1.3864	0.0610	0.9142	-1.1244	1.1640	-0.8604	-2.2740
1.6870	-2.5684	-0.1056	-4.2254	-0.9608	-7.9480	-0.5272	5.9626	0.4424	1.2492	-6.5964	-0.5604
4.5214	4.1866	1.9604	0.6830	1.3856	0.3702	2.1686	-0.1072	0.4076	2.0296	0.0114	0.9682
-3.9472	-1.9272	-4.6094	-3.0900	-1.7290	-5.5700	-4.3134	-7.2126	-1.8026	1.3022	-3.8542	7.4002
3.5486	1.6186	2.3162	2.2200	-0.3234	-0.5830	-1.2274	2.6430	-7.6342	-6.9556	5.6982	1.2462
-1.6642	-0.8972	-1.4908	-1.4862	-0.2266	-3.7820	-1.5620	-4.1236	-0.0130	0.1240	-1.0710	-4.1612
-0.7116	-0.5610	-0.1444	-0.4130	-1.4554	0.0660	-0.4802	0.5664	-1.4316	-0.0540	-0.0830	1.1170
0.6826	0.7292	1.5402	1.7662	-0.1524	-0.9516	-0.8254	-0.0384	1.8432	-0.4634	-0.0410	-6.6650
-0.5814	-0.6356	0.0340	-0.2106	-1.6132	-0.3212	-0.2384	0.1054	-1.0086	0.0180	-0.1546	0.7708
-0.6808	-0.5972	-0.1608	-0.4042	-1.5632	0.1008	-0.3890	0.4570	-1.1836	-0.0040	-0.1422	0.9746
-1.2354	-1.1114	-0.7030	-0.5656	-1.8144	-3.0392	-1.5226	-1.7164	-0.3430	-1.4932	-2.4094	-2.4696
-1.6816	-0.4290	-0.8470	-0.9452	-0.0334	-4.9300	-0.7094	-4.4054	0.1202	0.6594	-1.5452	-5.4632
-1.1456	-0.3656	-0.8520	-0.9342	0.6490	-3.2712	0.2940	-3.3670	-0.7446	-0.6924	-0.4772	-4.0610
4.1470	5.1610	7.1716	7.1556	7.2590	0.1756	-4.1564	5.6174	-0.0316	-1.9842	-6.1464	-1.7324
-0.9562	0.0026	-0.3402	-0.2792	0.7324	-2.2542	0.2930	-2.5710	0.0832	-0.7130	-0.2796	-3.6612
-0.6906	-0.5212	-0.1352	-0.3606	-1.4674	-0.0920	-0.6186	0.5824	-1.1326	-0.1450	-0.1956	0.8912

Hidden Output Weight Matrix

[-2.0406 -1.4126 -1.5986 1.2250 1.1382 0.9726 2.7722 -0.2134 1.6760 4.0334 0.0410 3.8110
-0.4524 -1.5580 -0.8332 -0.5308 -3.8902 3.6524 3.7274 -0.1714 3.7264 -0.5364 -0.5954]

APPENDIX A-7

Weight Matrix of the 3-year ANN Crack Model

Flexible Pavements

Input Hidden Weight Matrix

0.0040	0.7634	0.9560	-0.1064	-4.1944	0.6252	-0.5630	0.7230	-1.6992	-0.3642	-0.5400	1.3012
-0.7744	0.3960	3.9602	3.3402	1.1626	1.0084	-5.7786	-1.3642	0.0844	0.7026	4.3372	4.7230
-0.5486	2.0946	1.7512	-3.2812	-2.3046	-0.3736	1.0184	1.0626	1.9930	-0.1970	-1.1596	1.5930
0.2642	-0.4590	-0.4534	0.1722	2.7210	-0.7874	-2.0686	-0.6880	-1.9676	-1.3272	-0.9830	-0.8330
0.2834	1.1220	-1.8074	1.4412	3.7184	-2.1806	-0.3734	-0.1936	2.7880	-0.3046	-0.4166	-3.3506
-6.4206	-4.3214	-4.6944	-4.8352	-3.0202	-1.8460	1.7410	-1.2536	1.2030	-1.9244	-0.1836	-1.5036
0.3084	-0.5180	-0.5266	-2.9676	4.9056	1.0308	-0.0252	1.4676	-1.3476	0.2874	-0.3156	-3.3350
-3.5542	-4.5870	-2.4240	-4.6802	-2.3066	-1.5022	1.6060	-2.9390	0.7752	0.2876	2.2536	-5.2926
4.9940	4.5460	1.9106	0.9244	1.7820	-0.0172	3.1886	0.8622	-0.5142	1.2052	-0.9492	1.9290
-6.9934	-3.1986	-2.3742	-0.0672	1.2770	-6.1864	-6.1846	-3.0382	0.7072	-6.1456	-5.9946	3.0644
-5.7586	7.7452	6.4322	-7.7796	-7.4302	-4.9560	4.1120	-5.1104	-1.4042	-0.8570	3.6664	6.3044
-4.9304	-5.0712	-4.8012	-4.6004	-2.2660	-5.0686	0.9604	-4.6134	-1.5424	-4.3304	-1.8584	-5.6314
-0.8116	-0.3930	0.1002	0.0294	-0.4772	-0.3570	-2.3150	-0.0260	-0.4720	-0.0362	0.0944	-0.3994
4.7070	5.4574	-7.7490	-7.7054	-7.0314	7.7382	-0.1096	-3.8260	0.1470	-2.6508	-3.8202	4.2752
-0.4900	0.0344	0.3906	-0.0066	-1.4094	-0.4410	-0.6192	-0.0256	0.0634	0.2408	0.4440	0.3766
-0.7106	-0.4342	0.0934	0.2100	-0.5162	-0.3736	-2.0100	-0.0450	-0.5454	-0.0500	-0.0506	-0.5696
6.1914	-7.5708	-5.0374	-5.4456	-7.7264	-7.9802	-0.0460	-5.8710	0.0276	2.5332	-3.6730	3.6374
6.8270	-7.1330	-5.9074	-3.8826	-2.6062	4.5544	0.1100	-4.3174	0.0646	0.6890	-4.7980	2.8032
-3.4100	-3.6330	-3.9982	-4.0966	-3.4744	-2.8744	0.6242	-2.4040	0.3172	-2.7902	-1.9014	-4.4252
-0.0274	1.5908	1.6270	1.5484	6.9250	-0.2572	-0.0050	5.2102	0.0408	1.7606	-5.5804	-2.3108
-7.7720	-7.7296	-7.6546	-7.6272	-7.5692	4.8666	-0.0442	-4.0062	0.0086	-7.5324	-3.6870	-7.6924
-0.7332	-0.3562	0.1396	0.2390	-0.5624	-0.4240	-2.0656	-0.0400	-0.6552	-0.0560	-0.0384	-0.5352

Hidden Output Weight Matrix

[-1.9486 -0.4862 -1.3086 1.1376 1.5982 2.9462 2.5952 3.4574 2.1650 1.7216 -0.5862 3.3614
-0.8812 0.2320 -1.1008 -1.0224 -0.6806 -0.3962 3.2386 0.0990 -0.1524 -0.9752 -0.4044]

APPENDIX A-8

Weight Matrix of the 3-year ANN Ride Model

Flexible Pavements

Input Hidden Weight Matrix

-0.5154	-0.4308	-0.6706	-1.2570	-2.3292	0.8372	-1.8732	-0.1456	-2.4826	-0.1892	-0.9162	-0.5790
0.7922	0.9746	4.3250	2.8980	1.0642	3.1436	1.1782	-2.4214	0.5060	3.9160	5.3410	0.9514
-0.2256	1.7536	0.9024	-3.6662	-0.7260	-0.2726	0.0292	1.1500	1.1094	-0.1880	-1.1536	0.8506
0.4350	0.2224	0.2826	0.5906	1.3380	-0.8808	-1.7916	-1.0036	-1.8650	-0.6924	-1.2116	-0.5774
1.1182	1.9730	-0.9350	1.4308	1.7716	-2.0050	-0.1852	-0.6344	3.5354	-0.7984	1.4420	-2.6902
-3.9810	-1.7062	-1.5870	-1.3890	0.1096	-0.9684	-0.6694	0.0930	0.1124	-1.5970	3.0262	-0.1080
-0.3616	-0.2720	0.7624	-1.9812	3.3790	1.4000	-0.0684	1.2122	-1.0324	0.8826	-1.8794	-2.7586
3.8100	5.3610	7.9442	5.4856	6.8484	-2.0332	3.2494	-7.8016	-1.1874	0.2644	-0.1874	-3.6864
2.8806	3.0970	0.9766	-0.0562	0.4322	-0.9912	1.9908	-0.2260	-0.8714	1.1206	0.7004	0.0256
-1.2384	0.1094	-2.2210	-2.0908	-2.7196	-2.6526	-2.9626	-2.4206	0.5606	-2.0590	0.6210	-6.5230
3.5052	1.1744	-0.9508	-0.5696	-0.0922	-1.3352	1.4890	1.6154	-0.9786	-5.6206	2.2622	-3.3120
-1.9320	-2.2092	-1.6894	-1.5610	-0.2726	-4.8808	-1.0862	-2.7036	-2.1254	-2.5146	2.7704	-4.8464
0.0354	-0.0472	-0.0352	-0.3934	-0.6714	-0.1046	-0.4236	-0.2496	-0.1342	0.0670	-1.6662	-0.2100
0.2604	0.4156	0.6374	0.5840	-0.0824	-0.6204	0.3020	-1.0540	0.0380	0.2572	-0.4010	-2.1526
-0.2704	-0.0822	-0.1706	-0.6634	-1.2700	-0.0326	-0.3144	-0.2936	0.1502	0.0302	0.1282	-0.1356
-0.0436	-0.0482	-0.3710	-0.6480	-1.0272	-0.0326	-0.5746	-0.1236	0.4584	0.1202	-1.2180	0.4282
0.3624	0.6536	0.8142	0.3872	0.2722	-1.1952	0.3362	-0.8792	-0.9434	-0.1710	-0.3606	-3.0076
-0.1026	0.9632	1.6576	0.8508	0.8354	-2.9050	-0.0386	-2.5890	-1.4252	-1.3430	6.6824	-7.2532
0.1650	0.2160	0.1056	0.0380	0.0260	-5.4046	-0.0164	-5.3694	0.0460	-2.5482	-0.0040	-7.9186
-2.2374	-2.3780	-1.6360	-1.6880	-0.4934	-4.7124	-1.0356	-2.4404	-2.0650	-2.4356	2.3906	-4.9854
0.2714	0.3292	0.5932	0.3156	-0.3750	-0.9882	0.6082	-1.0312	-0.1416	0.2632	-0.5308	-1.9660
-0.0026	-0.0152	-0.2406	-0.5008	-0.9508	-0.0352	-0.4554	-0.2172	0.2976	-0.0110	-1.6364	0.0664

Hidden Output Weight Matrix

[-1.8260 -0.7900 -1.0740 1.0290 1.3510 2.0904 2.2472 -0.0242 1.1514 -1.0662 0.3510 2.1954
-0.5836 -0.3302 -1.3022 -0.5922 -0.6894 -0.5406 -0.1176 2.2734 -0.5554 -0.6364 -0.5782]

APPENDIX A-9

Weight Matrix of the 3-year ANN Rut Model

Flexible Pavements

Input Hidden Weight Matrix

0.0940	0.9880	1.1164	-0.5634	-3.3434	0.8910	-2.7286	-0.2122	-4.5064	-1.5736	-1.8234	-0.6314
-1.0584	-0.2200	2.5062	0.9490	0.4920	0.5682	0.9310	-2.4042	-2.3422	0.3582	1.5786	-2.8922
-1.3682	2.1584	2.8596	-3.5600	-3.6090	0.0116	2.2186	0.1476	-0.1546	0.6396	-1.2714	1.6684
0.9572	0.4686	-0.1166	0.4634	2.3704	-1.0150	-0.7816	-0.2100	-1.8692	-1.4084	-2.0882	-0.7076
0.9684	1.6840	-1.6672	1.7452	2.4120	-1.9374	1.2440	0.7462	4.2892	-0.8604	0.9436	-2.3134
-1.7780	-0.4506	-1.4344	-1.0554	1.7096	5.5444	0.4466	5.9956	2.3734	1.6680	-1.8514	-6.8308
0.2100	-0.1684	-0.5670	-2.5944	3.8542	0.7352	-0.1766	1.6882	-0.1054	1.6430	-0.4592	-3.4430
-4.1024	-4.3924	-1.7170	-4.3110	-4.9980	-4.8242	-2.8012	-5.0924	-1.9960	-1.8464	7.5850	7.3444
4.2176	5.2344	0.6486	2.4762	3.3224	7.7350	2.5008	4.2410	-5.8834	-7.3236	-1.2704	0.5784
-6.2190	-4.0322	-6.2150	-6.0490	-7.1426	5.2076	1.3674	3.1992	-4.9020	-1.0656	5.4154	-7.7494
3.0012	0.5072	-0.8540	-0.6474	-0.8810	-2.0932	-0.6134	0.4862	-4.6382	-3.1882	1.6210	-7.3072
-1.4640	-1.0290	-1.0092	-0.7524	0.4792	-3.5082	-1.4762	-1.8170	1.9272	0.2814	-0.6686	-3.3494
-0.0574	0.2452	-0.7172	-0.3832	0.3610	-1.1492	1.1508	-1.0392	-0.8700	0.0852	0.0170	-1.5750
-2.0082	-2.0680	-2.4472	-2.3124	-1.5260	-3.8040	-0.0154	-2.5384	1.6454	1.1550	-0.5842	-3.6076
0.1770	0.2408	-0.4214	-0.2434	0.4302	-0.9310	0.4784	-0.9466	-1.2094	-0.2110	-0.1296	-1.7256
-0.0686	1.0794	-0.0950	0.3406	1.0874	-0.4240	0.4436	-1.1310	-2.5484	-0.3200	0.4814	-1.8270
1.3276	-1.5134	-2.7790	-3.9224	-1.5382	4.2502	-0.1160	-5.9174	2.2610	-1.6736	-6.0372	5.1966
-3.1784	-1.9664	-1.5396	-1.3424	-2.8690	-5.1324	-1.2808	-4.5114	-1.6040	-1.5208	0.6234	-5.3030
0.0622	-0.0086	-1.0766	0.1254	1.7984	-1.3612	-0.0684	-0.9074	1.1910	0.1602	-0.1922	-2.1610
-3.1350	-1.9000	-1.4040	-1.9410	-3.3154	-3.5156	-1.2546	-4.7310	-1.4712	-2.2324	-1.1844	-5.0108
7.8192	-5.2494	-5.1924	-3.1490	-3.2926	-2.0390	-0.9732	2.6032	0.6262	-5.7820	-4.9694	0.1322
-6.8116	-4.9232	-4.8394	-5.3242	7.6006	-0.0060	-2.6486	1.8532	7.8130	-5.9750	2.4642	-3.4592

Hidden Output Weight Matrix

[-2.2986 1.4374 -2.0794 1.2290 0.5900 0.8882 1.3420 -4.4844 0.2982 3.7456 -5.4192 5.8502
4.9846 -0.0982 5.0930 1.5854 0.4642 6.6208 5.0586 6.6426 2.1982 -2.2756 -1.4306]

APPENDIX A-10

Weight Matrix of the 4-year ANN Crack Model

Flexible Pavements

Input Hidden Weight Matrix

0.4850	1.3704	0.9646	-0.6334	-4.1974	0.8694	-0.2100	0.6644	-1.7026	-0.2290	-0.7600	0.8140
-1.9046	-1.2566	2.4142	1.3044	-0.6170	0.7640	-1.5508	-1.3610	0.2436	0.8290	4.2224	-0.9946
-0.3904	2.3462	1.7726	-3.5090	-1.9182	-0.5576	1.0600	1.2306	1.2172	-0.1702	-0.5500	0.3710
-0.2520	-1.0370	-0.4430	0.8582	4.5046	-0.7346	-2.6496	-1.1246	-2.9962	-1.4086	-0.2954	-2.0504
-0.0790	0.6470	-1.8904	1.7844	5.0020	-2.1126	-0.4822	-0.0104	2.7902	-0.1170	0.6852	-4.3342
-3.8744	-0.6534	-0.3482	-0.4794	-0.0814	0.8734	0.9034	1.6582	0.3308	0.0794	-0.0056	1.3342
-0.4932	-1.0894	-0.1206	-2.0370	5.2408	1.0882	-0.3220	1.3322	-1.6666	0.6266	-0.9212	-3.6966
-2.2522	-3.2106	-0.7626	-3.1082	-1.3780	-0.0552	0.5466	3.0184	0.2782	5.0080	-2.4344	-5.4364
3.8914	3.7440	1.8754	1.0340	1.9290	-0.4952	0.9264	-0.1896	-0.8324	1.6874	-1.5012	0.5730
-3.0466	-0.6490	-3.0486	-2.1310	-2.1002	-1.0576	-5.7320	-2.1744	0.7534	-1.0136	0.2796	-5.0414
2.2292	-0.0802	-2.0444	-2.2784	-3.2454	-2.1142	-0.5666	0.3296	-1.3580	-2.8542	0.1442	-2.9980
-1.1732	-0.8222	-0.8706	-1.2010	-2.4712	-1.9532	-1.5926	-0.2804	-0.3686	-0.1432	-0.4120	-1.3324
-0.5834	-0.4446	-0.3596	-0.8712	-1.5534	-1.1132	-0.9500	0.1234	0.2184	0.2792	-0.1914	-0.9100
-0.8132	0.2070	0.0472	-0.2466	-1.2482	-0.9086	-2.0850	0.2692	0.4674	0.2554	-0.5742	0.4070
-1.4010	-1.1886	-1.1266	-1.5740	-2.3456	-1.6416	0.5900	-0.2754	-0.1872	-0.4522	0.1540	-1.6832
-1.6106	-1.2492	-1.3700	-1.6294	-2.2470	-1.6850	0.5476	-0.4408	-0.5262	-0.5408	0.0974	-1.8410
-1.2612	-0.8782	-0.8424	-1.2834	-2.4860	-1.7844	-1.5510	-0.3346	-0.3984	-0.6006	-0.4446	-1.4186
-1.6330	-1.0102	-0.9684	-1.3270	-2.3720	-1.9260	-1.2506	-0.5896	-0.4116	-0.4556	-0.6800	-1.5964
-1.6450	-0.8476	-0.9004	-1.2266	-2.5352	-1.9244	-1.5302	-0.6794	-0.4260	-0.3530	-0.0934	-1.4554
-0.7208	-1.9224	-3.9400	-4.4608	-4.5762	-3.9422	-2.0276	-3.1076	0.1486	-3.0644	-2.6350	-3.2182
-0.2874	-0.0194	0.0108	-0.3676	-1.4214	-1.0930	-1.6236	-0.3784	-0.4414	-0.5314	0.4410	-0.3992
-1.2770	-0.2520	-0.1910	0.1356	-1.1760	-0.7042	-1.8236	-0.8656	0.5814	1.0044	0.7508	1.3474

Hidden Output Weight Matrix

[-1.2816 -0.4226 -0.9762 1.3604 2.1726 -0.4844 2.0494 -0.1740 1.6108 -3.6886 7.8580 -4.5354
-1.3450 -0.7280 -1.4506 -1.5286 -4.5456 -4.4982 -4.5590 2.9912 -3.0364 -0.7394 -0.6456]

APPENDIX A-11

Weight Matrix of the 4-year ANN Ride Model

Flexible Pavements

Input Hidden Weight Matrix

-0.1736	-0.1004	-0.5704	-0.9776	-1.8220	0.7056	-1.6234	-0.0670	-2.5154	-0.3014	-0.0484	0.0452
-0.0606	-0.4480	2.4656	1.6106	0.0810	1.4814	0.4476	-2.7846	0.0596	2.2976	0.3432	-0.6674
-0.2216	1.6000	0.5994	-3.9600	-0.5502	-0.2684	0.4902	1.3312	2.0222	-0.3906	-0.8608	1.4162
0.3066	0.0608	0.3316	0.3970	0.8270	-0.9640	-1.7046	-0.5354	-2.1022	-1.1676	-1.4126	-0.7352
0.9654	1.9050	-0.9924	1.4854	1.5450	-2.2250	-0.4820	-0.1584	3.2530	-1.2780	1.3214	-2.8222
-4.6470	-2.4200	-2.2066	-2.4874	-0.6730	-2.5250	0.9686	-0.9834	0.0876	0.3932	3.3672	-1.9680
-0.2984	-0.2700	0.7846	-2.0652	2.6700	1.2814	0.0490	1.3206	-1.4370	1.1734	-1.4984	-2.6674
6.2736	5.5252	-7.9992	5.5174	7.1946	-5.1444	2.6900	6.0552	2.5702	3.4044	2.5154	-5.4600
3.4920	3.6736	1.8582	0.7816	0.9202	-0.2764	2.1270	-0.3540	-0.6804	1.2226	-0.7560	0.5646
0.1242	2.2156	-0.2920	0.0952	-0.5346	1.3374	-2.9086	-0.2716	0.6820	-0.3310	0.5472	-2.2920
1.8576	-0.5670	-2.3524	-1.9666	-1.4808	-3.6076	-0.1684	-0.2956	-1.4510	-1.9790	-0.2054	-5.6352
0.2014	0.7686	0.6152	0.2786	-0.0226	-2.5122	1.6610	-1.6842	-0.4564	-2.3090	-0.5964	-1.4536
-0.1756	-0.2482	-0.2964	-0.7062	-0.8332	-0.1140	-0.4850	0.0534	-0.2070	0.4466	0.2692	0.0914
-0.1664	-0.1902	-0.1392	-0.5454	-0.7280	-0.1824	-0.3172	-0.0252	-0.6650	0.5250	-0.1846	0.1440
-0.0952	-0.1932	-0.1780	-0.6216	-0.9112	-0.4180	-0.4792	-0.2802	0.1456	0.1960	0.6034	0.0316
-0.0830	-0.2262	-0.3946	-0.6734	-0.8806	-0.1574	-0.3856	-0.0946	-0.1682	0.3586	0.4308	0.1426
0.5920	0.2762	0.0852	-0.2584	0.3142	-0.9282	0.7420	-0.1746	-0.4436	-0.9200	-0.3610	-1.2434
0.7704	0.6970	0.3362	-0.0832	-0.1942	-0.4886	0.8352	-0.5250	0.1408	-0.7320	0.1674	-1.8830
-0.7750	-0.7492	-0.9154	-0.6304	-0.8516	-2.3000	-0.0606	-1.7992	-0.6708	-0.1730	0.4442	-2.0174
-0.8344	-0.1894	-0.7724	-1.0476	-1.3286	-2.8356	0.2670	-1.5036	-0.2020	-2.0492	0.6904	-2.2756
-0.1930	-0.2572	-0.2874	-0.6308	-0.8876	-0.2270	-0.5422	-0.1630	-0.1924	0.2608	0.4380	0.1408
-0.1072	-0.1716	-0.3424	-0.5246	-0.8466	-0.3472	-0.5446	-0.0156	-0.0116	0.2674	0.4882	-0.1276

Hidden Output Weight Matrix

[-1.8082 -0.2400 -1.8036 0.7296 1.4452 1.7492 1.5814 0.0356 2.0402 0.3412 1.0524 -0.7974
-0.6970 -0.5466 -1.0242 -0.7352 -0.5112 -0.4540 -3.9754 -2.0432 -0.8894 -0.8708 -0.4314]

APPENDIX A-12

Weight Matrix of the 4-year ANN Rut Model

Flexible Pavements

Input Hidden Weight Matrix

-0.9408	-0.3890	-0.9086	-1.6702	-3.7456	-0.2974	-2.3240	-1.3490	-4.1326	-0.7372	-1.3832	-1.5206
1.1306	-1.3050	0.6552	-0.0330	-2.9472	-2.6480	4.8892	-2.1832	0.8500	-3.2722	-1.6976	-7.8466
-0.3640	2.2576	1.7754	-3.6134	-1.9962	-0.6202	1.2000	0.1776	1.3512	-0.1512	-0.9502	1.5984
0.9162	0.2336	0.4966	1.0426	2.2466	-0.3512	-1.5114	-0.2260	-1.9126	-1.4740	-0.7450	-0.2386
1.5190	1.7106	-1.4020	1.0504	1.8344	-1.4530	1.1508	0.8880	3.0114	-0.5606	0.9306	-2.4432
-1.5560	0.5000	0.3882	0.7112	2.4700	2.2182	-0.0724	3.1044	-1.1992	0.3146	0.0764	2.9542
-0.0864	-0.6760	0.3092	-2.7072	2.1366	1.3452	0.7742	1.4734	0.6196	1.1030	-0.7986	-2.1936
-1.1194	-1.7484	0.2540	-2.3326	-1.9430	-1.3082	0.3334	-5.1126	-0.2416	-0.8646	4.3902	-6.8234
6.7804	0.7172	-1.0936	-0.0386	-1.5600	6.8222	2.8894	7.3306	-3.8334	4.5906	0.8564	-6.6392
-6.0140	-2.7972	-6.9202	-3.6470	-4.2210	-6.4896	-3.4306	-7.2262	-0.0354	0.2080	-0.2030	6.0130
2.1484	-0.0520	-2.0670	-1.6706	0.3074	-3.4440	-0.3732	-1.0916	-0.8922	-1.1012	-0.7834	-4.9610
0.1332	0.4884	0.0170	0.4266	1.4910	-1.9182	-0.3596	-0.7362	-1.2374	0.7232	-0.2302	-2.6240
-1.3276	-1.7222	-1.0106	-1.5416	-0.3486	-2.5594	1.3108	-2.4920	-0.2904	0.9808	0.1810	-3.1812
-1.2810	-1.6842	-0.9446	-1.4680	-0.3304	-2.7716	1.1990	-1.7422	-0.3004	1.0008	0.1910	-3.2210
1.4844	1.6212	1.0652	-0.1066	-2.2614	-1.8364	5.4146	-0.1904	-2.7336	-1.8814	3.5836	-3.6324
5.7382	3.2094	3.0954	-1.3110	-6.4420	-0.6902	-4.7064	3.6710	0.0064	-5.0830	0.0472	5.6814
-0.7230	-0.5430	-0.3016	0.4504	1.5408	-0.8450	0.5230	-0.2480	0.3608	-0.6686	-0.6036	-2.4410
-1.9122	-1.9852	-2.4296	-0.5200	0.7090	-5.4554	-0.9924	-1.8430	-1.4180	-1.3522	-1.1322	-7.6536
-0.2204	-0.0314	-0.2444	0.2154	1.3536	-2.2250	1.0764	-0.6422	0.5256	-0.2546	-0.7464	-2.2184
-0.3666	-0.0066	-0.2114	-0.6910	1.1936	-0.5354	-1.4950	-0.7852	-0.2022	-1.5860	-1.2792	-1.6608
0.2534	-0.1410	-0.4130	0.8808	1.3864	-0.2772	-0.7850	-1.0862	0.5162	0.4874	-0.7196	-3.4814
3.0808	3.8350	3.3602	3.8550	2.4444	-0.4514	-1.6656	1.3542	-4.7030	-2.5930	2.3102	-2.8600

Hidden Output Weight Matrix

[-3.9912 0.2462 -2.1026 0.8500 1.3460 0.9804 1.1342 -4.2920 0.0584 5.2912 4.6044 2.0592
4.8204 4.8270 -0.4720 0.2142 4.4836 6.0776 3.6030 4.4774 4.6412 -0.4080 -1.2950]

APPENDIX A-13

Weight Matrix of the 5-year ANN Crack Model

Flexible Pavements

Input Hidden Weight Matrix

-3.5616	-1.7602	-1.1800	-5.3364	0.9724	-1.5490	-1.6014	-1.6636	-2.6136	-1.5316	0.5350	4.6444
-5.3750	-4.3274	-0.8606	-2.2182	-4.6166	-0.7954	3.0950	-3.6162	0.3764	2.1716	1.6706	-2.5636
-3.6026	0.2940	0.6320	7.0960	-0.3920	-1.7710	-1.1494	-0.3050	-0.2876	0.7966	0.9936	5.2120
1.7160	-1.5546	2.2344	2.4992	1.5676	7.0762	-1.4836	6.2236	-3.1256	-7.3682	-5.9156	-0.9924
0.7234	1.7308	0.4762	7.8204	0.8766	-0.7230	1.4126	0.5252	-1.0830	1.5244	-0.4772	7.2124
-5.2690	-2.8072	-3.4962	-1.3610	5.4736	-5.3874	-1.3366	-2.7836	-0.4670	-2.1674	-1.0436	4.7630
2.9532	4.9810	6.0766	3.0672	-6.3584	4.5516	-2.3514	-6.4350	-4.6120	-0.3342	-5.0170	-3.0680
-4.3492	-5.4840	-4.3908	7.5826	-6.9272	-4.5786	6.4020	0.4556	-4.9854	-4.7342	-1.1784	-5.9294
0.3742	-0.0176	-1.3662	0.2204	-7.9974	-1.4654	0.1364	-0.4162	-1.3712	-0.2446	-0.9710	-4.4660
-5.3756	-2.8942	-5.4272	-7.0580	-7.9976	-2.8526	-6.2232	-3.0470	0.9774	-1.1570	-0.3376	-2.9466
2.3460	0.3902	-0.6930	0.4040	2.7334	-3.8144	6.0608	-0.2096	-5.5576	-3.3740	-6.7844	6.9562
-5.3110	-4.5260	-3.9956	-2.9080	-1.3372	-5.0810	2.2036	-4.2552	1.2156	-4.6430	2.6808	-7.0042
-2.5434	-2.4522	-2.4322	-3.9064	-5.9934	-1.9304	-3.0012	-0.6982	-2.0310	-2.9670	1.0866	-3.1844
-6.0924	-5.2414	-5.0424	-3.9708	-3.2464	-3.0104	-3.8284	-2.2312	-1.3866	-3.0306	0.8204	-7.9140
-0.1532	-0.7152	-1.6264	-2.1216	-2.3396	0.3534	-2.5470	1.2708	-1.5834	-2.1966	0.2816	-2.8102
-0.8666	0.6856	1.5876	0.3840	-1.9342	0.2542	-3.0732	1.4482	-1.9550	-0.7742	0.3144	-1.6156
-4.2886	-5.7800	-1.5922	2.4960	-7.9906	-3.4516	-4.0770	-0.7560	-0.4642	0.0770	-1.0020	0.7260
-4.5144	-2.8556	-2.7450	-2.7904	-3.4370	-4.2344	0.3594	-1.0652	1.4830	-0.0440	2.7224	-4.1096
-7.8134	-6.4776	-7.4324	-7.9954	3.3016	-3.7070	-2.3454	-4.9056	1.6926	-3.5714	0.0544	-3.9600
-0.8554	-3.4576	0.0044	2.5592	6.5656	-3.4406	-4.4614	0.6046	-0.6884	-4.2582	-0.6636	0.6136
-0.1682	-0.7362	-0.2500	1.3136	4.5284	0.0500	-0.0634	0.3886	-0.3490	0.4908	-0.0242	-5.0694
-5.6944	-3.6080	-3.4544	-5.5180	-7.9962	-3.7294	1.1762	-1.2686	-0.2714	0.9002	3.3050	-1.8034

Hidden Output Weight Matrix

[-1.7290 2.0872 -3.3570 -0.2624 5.3946 0.2300 0.4926 -0.4520 -5.7850 -6.0684 0.3700 2.5004
-5.6122 -0.0756 7.2920 -1.7970 0.5276 -4.1960 -6.7094 1.0150 4.8036 -7.7930 -3.6006]

APPENDIX A-14

Weight Matrix of the 5-year ANN Ride Model

Flexible Pavements

Input Hidden Weight Matrix

0.0602	0.1662	-0.1404	-0.7114	-1.2350	0.6660	-1.4474	-0.1702	-2.9832	-0.4022	-0.6572	-0.5362
-1.0522	-1.4700	1.7862	0.9672	-0.6950	1.1174	0.8276	-2.2480	-0.1966	1.9636	1.5942	-0.3166
-0.1744	1.8544	0.8960	-3.7752	-0.3400	-1.0084	1.1494	0.4654	1.0454	-0.8170	-1.7602	0.5624
0.3906	-0.0594	0.3884	0.6152	1.3554	-0.7852	-1.9100	-0.8700	-2.0342	-1.2234	-0.2366	-0.7756
1.2744	1.8976	-1.0640	1.3270	1.5196	-2.2850	-0.1930	-0.6930	3.7684	-1.5582	1.5402	-2.9676
-3.0532	-0.6808	-0.7564	-1.0264	-0.5116	0.9412	-0.1190	1.3408	0.5316	0.4056	-0.1220	3.5042
-0.4750	-0.5914	0.7012	-1.8536	3.1314	1.5152	-0.2240	1.1108	-0.9254	1.2104	-0.3254	-3.0810
2.8240	1.6956	4.2312	1.8330	3.4212	4.9736	2.9004	3.6092	2.3632	3.4846	0.4650	5.8866
3.0330	3.1160	1.0694	-0.1206	0.1122	-1.0204	1.9708	-0.7446	-0.0210	1.4872	-1.8372	-0.4490
-0.3686	1.0074	-1.5794	-1.2820	-2.3532	-0.6146	-3.8114	-1.1740	0.8262	-1.6746	-0.4908	-3.8374
1.4446	-2.0102	-3.8162	-3.8030	-3.4534	-5.6360	-1.5704	-1.7046	-1.7544	-3.2872	-2.7000	-7.2444
-5.4260	-5.3708	-5.5114	-7.2576	-5.3220	-7.5830	-5.6826	-7.4066	-1.9384	-3.6382	1.9976	6.6022
-0.3282	-0.4600	-0.3700	-0.7706	-0.8280	-1.4146	0.8524	-0.7772	-0.6846	-0.4234	0.7140	-1.9202
-0.0584	-0.0176	0.0360	-0.2242	-0.5504	-0.9586	0.8956	-0.8686	-0.5800	-0.3824	0.9086	-1.6992
-0.3336	-0.2122	-0.1916	-0.4170	-0.8660	-0.4110	-0.4672	-0.4774	-0.4152	0.0800	0.2196	0.2576
0.1934	-0.1486	-0.1596	-0.2982	-0.7350	-0.6220	-0.6502	-0.2896	-0.6674	0.0106	0.3626	-0.1462
0.1102	0.2094	-0.2820	-0.4292	-0.5870	-1.5296	0.7020	-0.7974	-0.4190	-0.4022	2.0604	-2.3192
-0.3470	-0.1566	-0.8040	-0.8734	-1.0952	-1.7320	0.1820	-1.0710	-0.1100	-1.0572	2.5274	-1.7484
-3.1720	-4.8204	-4.9320	-5.0452	-4.9520	7.4140	-3.6356	-5.0082	-1.6896	-3.4214	-0.1794	7.1382
-2.7464	-2.6570	-2.6312	-2.7506	-1.1984	-6.3250	0.4862	-6.3572	-1.8024	-0.0446	3.8326	7.8912
-0.5296	-0.5776	-0.5902	-0.6012	-0.3526	-1.6584	-1.7466	-1.7614	-0.0160	-1.3234	2.6324	-2.0284
-0.5540	-0.6190	-0.6850	-0.9920	-1.3194	-1.8206	0.2750	-1.4962	-0.7572	-1.0024	0.6826	-3.3354

Hidden Output Weight Matrix

[-0.9330 -0.3612 -0.9308 1.0262 1.0426 -1.1534 2.1062 -0.3074 2.2146 -0.8000 0.1542 -0.0320
-1.2706 -0.9286 -1.0400 -0.8126 -1.2970 -2.2074 0.2416 -0.9130 -1.9270 -0.7504 -0.9696]

APPENDIX A-15

Weight Matrix of the 5-year ANN Rut Model

Flexible Pavements

Input Hidden Weight Matrix

-2.1784	-1.3236	-1.4804	-2.3786	-6.3406	-1.0562	-2.7830	-1.7492	-4.6640	-1.1554	0.1554	-1.9422
-3.8370	-2.9060	0.2334	-1.3484	-5.4446	-2.5704	-0.4452	-6.5740	-3.1744	-0.3604	1.9326	-4.4364
-7.4764	-4.3330	-4.6480	7.1112	-6.4814	4.9424	0.2484	7.7790	0.9744	-2.9554	0.5504	4.8736
0.8990	-0.3750	-0.5872	0.5542	4.3896	-0.0708	-0.0316	-0.0790	-1.0774	-1.5942	-0.9886	-1.6182
0.1830	0.8642	-1.6912	0.8674	1.8946	-1.2452	-0.1004	0.1204	1.3006	0.2954	0.9562	-1.9250
-2.8410	-0.8540	-0.5534	-0.0836	2.2782	-0.6314	-2.6352	-0.2656	0.7000	-0.3464	0.1760	0.9652
-0.2044	-0.4034	0.5090	-2.4908	3.1206	1.0046	-1.6790	0.6710	0.7830	1.1666	0.1244	-2.7870
-0.0846	-1.6532	0.3622	-1.9480	1.6280	0.2920	1.6434	-2.0810	1.6820	0.9570	1.4292	-1.8140
0.0880	0.5952	-0.8146	-0.9622	2.3670	-0.3114	2.4250	-1.2156	2.6832	3.3320	-3.3770	5.8442
-1.8652	-1.6000	-2.9362	-2.3604	-3.3700	-4.1072	-3.3730	-4.6204	0.6576	-1.5680	0.0340	-7.3550
-1.0202	-1.9526	-3.7172	-1.8360	-0.5702	-6.8294	0.2712	-5.4540	-0.7754	-3.4086	-0.5970	4.4160
0.3450	0.0754	-0.0080	0.0492	2.4136	-1.3180	-1.7390	-1.7708	0.4840	0.2030	-0.8870	-2.8256
7.3404	-5.2940	-3.9452	-3.8596	-4.0554	-0.8776	5.1464	3.1272	1.2860	-3.2520	-3.5034	-2.4442
1.4956	-1.0462	-0.8992	-0.9154	1.0322	-1.0672	0.9854	-1.5312	1.2606	0.3912	-4.1680	0.1564
-0.3514	-1.8960	-1.5824	-3.5474	-5.4256	-3.6246	-6.5530	-4.9086	-3.6106	-5.1746	-0.4274	4.3696
6.9340	-5.9734	-5.6872	-5.2108	-6.1634	-1.3816	3.6616	2.0976	-1.8140	-6.8492	-0.0702	-3.6852
-0.0452	0.3126	0.6696	1.1020	3.9392	-1.5944	0.6662	-0.7722	-2.6844	1.0290	1.0556	-3.2306
3.5296	-2.3246	-4.2130	-4.1156	0.9760	-2.2970	0.9634	-1.6910	0.7860	0.3844	6.4786	-2.5742
-1.4120	0.2356	-0.2154	1.4906	2.3426	-6.4816	-1.7564	-5.5630	0.5770	-1.4732	-2.1924	5.5884
0.2922	-0.0572	0.1090	-0.0042	2.3870	-1.1122	-1.3396	-1.8236	0.5576	0.0752	-1.1210	-2.8356
-4.4640	-2.6616	-1.0452	0.3196	-0.4454	6.5652	-4.1190	7.3666	-3.7814	-0.2632	-2.1910	-0.5760
2.3308	0.8874	-0.2506	-0.9120	-1.1230	0.2712	-0.9384	0.1184	2.4690	-0.3026	-5.3620	-2.4256

Hidden Output Weight Matrix

[-7.0208 7.7056 0.3966 1.7494 0.8482 0.4464 1.3284 4.0910 -0.2106 -3.9454 0.0534 1.8152
1.1140 0.6242 -3.0094 6.5384 0.9762 0.9500 0.3476 1.9274 0.6974 0.1844 -2.1290]

APPENDIX A-16

Weight Matrix of the 1-year ANN Crack Model

Rigid Pavements

Input Hidden Weight Matrix

-0.5540	-0.8052	-0.2250	-0.3094	-0.3734	-2.4184	-0.1090	-0.6810	0.0322	1.7226
1.3220	-0.7926	-2.3196	-0.8360	0.2912	-0.7042	-0.3894	-0.2646	-0.0844	0.8902
-0.3650	1.4046	0.0472	-0.2506	-1.6122	0.0360	-2.0380	2.0294	2.1282	1.8246
-1.9280	-1.3730	1.4910	-0.4104	0.7112	0.6080	4.0670	-1.8994	-1.3250	2.5836
0.7054	-2.4774	2.8940	0.0416	1.8352	-0.3936	-0.0606	-0.2244	0.1570	-1.8610
0.0016	-0.3416	1.2572	-0.7830	-2.6014	0.2304	1.9112	0.8312	-0.5584	1.2166
-0.8506	-4.9652	0.9082	-0.2050	-1.1836	-2.4940	-2.5402	-2.1462	-2.6116	-2.7826
0.0212	1.9286	-1.2346	0.5040	-3.3812	0.0820	0.0672	-0.5824	0.2570	0.2592
2.4222	1.4708	-0.1816	1.6808	-0.1586	-2.2716	0.1056	0.4452	1.6504	0.5352
-0.3394	2.0300	1.5444	-2.9256	2.0506	-0.0744	0.6822	1.1476	0.8622	-0.5840
-1.1456	-0.8446	-0.6406	-0.5464	-0.1690	-0.9222	0.1956	0.1666	-0.1112	-2.3942
-1.1600	-0.9982	-0.7452	-0.5946	-0.2610	-0.9872	0.1586	0.1782	0.2456	-2.3234
-0.4126	-0.4066	-0.1946	-0.1534	0.0604	-0.2606	0.6242	0.5970	0.8812	-0.5550
-1.2332	-0.7606	-0.6524	-0.6016	-0.1386	-0.9194	0.2184	0.4110	0.0214	-2.3452
-1.1814	-0.7426	-0.7144	-0.5686	-0.1066	-0.8312	0.1792	0.0206	0.0256	-2.3316
-0.6724	-0.5894	-0.4556	-0.2908	-0.0690	-0.3886	0.1292	0.5372	0.2434	-1.3552
-1.5052	-1.0800	-0.9900	-0.9896	-0.9286	-2.7014	-1.6214	-2.7384	-2.5854	-2.8240
-1.1566	-0.7890	-0.6712	-0.5884	-0.2180	-0.7262	0.2134	-0.0872	-0.0660	-2.4372

Hidden Output Weight Matrix

[-1.8102 -1.3450 0.8580 0.9806 3.1824 -1.9134 -1.0456 -1.7180 -0.5150 1.3690 0.4656 0.4344
0.3616 0.4212 0.4114 0.2174 -0.4364 0.4372 -1.0496]

APPENDIX A-17

Weight Matrix of the 1-year ANN Ride Model

Rigid Pavements

Input Hidden Weight Matrix

-0.7886	-0.9910	-0.0490	-0.3036	-0.2122	-2.0780	-0.1342	-0.6956	-0.3062	1.5952
1.1306	-1.0254	-2.2920	-0.8824	0.4114	-0.2350	-0.5504	-0.3900	0.1508	0.7294
-0.1092	1.7024	-0.0222	-0.1054	-1.7366	0.0206	-2.5496	1.9666	3.7222	1.8374
-0.9974	0.0172	2.7414	0.6862	1.4452	-0.9076	4.9480	-1.1504	0.8664	5.0536
1.7006	-1.9420	2.8472	-0.3042	1.0366	-1.0114	-0.1594	-0.8196	-1.2266	-1.7408
-0.6180	-0.8510	1.1456	-0.7552	-2.4666	0.3994	1.4204	0.9202	-0.1656	0.7732
-0.2672	-3.8996	0.9030	-0.2192	-1.6252	-2.1930	-1.4766	-2.0276	-2.3912	-2.6096
-0.4600	1.6510	-1.1826	0.4714	-3.2020	0.3792	0.2350	-0.0960	-0.3696	0.2726
2.3064	1.4714	0.0480	1.7120	0.1112	-2.1520	-0.0196	1.3144	2.0760	-0.0344
-0.0300	2.1924	1.4094	-2.9160	1.9066	-0.3466	0.7716	1.1474	1.0214	-0.6702
-0.5036	-0.5510	-0.9210	-0.4440	-0.4026	-2.3694	-1.4626	-2.4592	-2.4394	-2.5184
0.3108	0.5232	0.2686	0.5226	0.4430	-0.2246	0.0900	0.1892	-0.1140	-0.0452
0.2454	0.3252	0.3016	0.4026	0.4156	-0.0970	0.2002	0.1922	0.0060	0.0134
-0.1602	0.0284	-0.1114	0.1362	0.1976	-0.7974	0.9602	0.1956	0.5584	-0.6860
-1.0334	-1.4376	-1.0342	-0.9664	-0.9410	-2.4624	-1.9600	-2.4766	-1.8894	-2.4844
0.2890	0.4766	0.3966	0.4716	0.4532	-0.1642	0.0546	0.2612	-0.1246	-0.1666
-0.9552	-1.0384	-1.0176	-1.0072	-0.9460	-1.5590	-0.5134	-1.5764	0.0472	-2.6710
-0.0332	0.0208	-0.1414	0.1164	0.1210	-0.6746	0.9682	0.2794	1.0512	-1.0010

Hidden Output Weight Matrix

[-1.5400 -0.8602 0.5504 0.4308 2.3776 -1.3814 -0.1902 -1.2276 -0.7580 0.8534 -0.0180 0.6756 0.6234 0.2156 -0.1494 0.6652 -0.1672 0.2236 -1.4700]

APPENDIX A-18

Weight Matrix of the 2-year ANN Crack Model

Rigid Pavements

Input Hidden Weight Matrix

-0.9624	-1.2206	-0.5242	-0.5146	-0.2882	-2.6664	0.0194	-0.4902	0.0106	1.4014
1.1276	-1.0308	-2.5144	-0.9796	0.3222	-0.6364	-0.2580	-0.1690	-0.1072	0.8926
-0.0984	1.7326	0.2408	-0.1704	-1.6732	-0.0062	-2.7892	1.6606	2.3100	2.0076
-1.5200	-0.9334	1.8376	-0.1646	0.7364	0.6308	3.6980	-1.8706	-1.0442	2.8744
1.0436	-2.2410	3.1490	0.2312	1.9586	-1.1046	0.3492	-0.4150	-0.2482	-1.8642
-0.2812	-0.5734	0.9960	-1.0010	-2.8950	0.6044	1.7642	0.7102	-0.1032	1.1622
0.2280	-3.8730	1.0810	-0.0366	-1.2708	-0.7542	-0.7794	-0.4640	-0.7374	-1.0692
-0.3814	1.5062	-1.5002	0.3590	-3.3310	-0.1444	0.1330	-0.3404	-0.5052	-0.3408
2.4314	1.6164	0.0774	1.9606	0.2552	-2.1802	0.3564	1.5972	1.1114	0.4726
-0.5826	1.7750	1.2842	-3.1400	1.8108	-0.4326	0.7544	1.2846	1.5342	-0.7340
-0.5270	-0.5656	-0.3236	-0.2844	-0.1284	-0.7280	-0.2262	-0.5890	0.0036	-0.7602
-0.2842	-0.0642	-0.1646	-0.0054	0.0806	-0.4894	-0.1394	0.0994	0.1186	-0.5490
0.0434	0.0382	0.2096	0.2182	0.2922	-0.1106	-0.0916	0.0212	0.3216	-0.1732
-0.2596	-0.0680	0.0864	0.1160	0.2940	-0.2950	-0.0770	0.0390	0.3256	-0.4516
-0.3464	-0.1930	-0.1844	-0.0212	0.1754	-0.3834	-0.1242	0.1112	0.2034	-0.5560
-0.1202	0.0274	0.1742	0.1640	0.1950	-0.2660	-0.1662	0.1574	0.3508	-0.3922
-0.1490	-0.1842	0.0084	0.1036	0.3042	-0.3252	-0.1282	0.0556	0.4206	-0.6114
-0.1252	-0.0762	-0.0556	0.0026	-0.0822	-0.0652	-0.5792	-0.5906	-0.4900	-0.2810

Hidden Output Weight Matrix

[-1.3976 -1.1836 0.5574 0.5280 3.1802 -1.9814 -0.2352 -1.0370 -0.9974 1.1704 -0.0354 0.1694
0.3402 0.2812 0.1884 0.2854 0.2874 -0.2124 -1.5176]

APPENDIX A-19

Weight Matrix of the 2-year ANN Ride Model

Rigid Pavements

Input Hidden Weight Matrix

-1.0934	-1.3176	-0.5594	-0.5182	-0.2034	-2.4994	-0.0930	-0.4340	0.1560	1.4014
1.0544	-1.0642	-2.4166	-0.7624	0.6250	-0.6076	-0.3070	0.1244	0.0704	0.8942
0.0424	1.7794	0.2026	-0.2334	-1.8782	0.0924	-2.6694	1.5136	2.1426	2.3562
-1.3810	-0.8208	1.9026	-0.1362	0.6196	0.5964	3.8426	-1.8614	-1.2374	3.0610
1.9030	-1.5980	3.2680	-0.1816	0.9220	-0.2830	0.2870	-1.1764	-0.5292	-0.7562
-0.7022	-0.9120	0.8800	-0.8010	-2.3956	0.1064	1.7834	1.4100	0.0020	0.5870
0.6080	-3.4944	1.2564	0.2536	-1.2162	-0.3000	-0.1506	-0.0146	-0.3080	-0.6242
-0.6780	1.2694	-1.6162	0.2536	-3.2766	-0.2712	0.0000	-0.1744	-0.6860	-0.5908
2.3794	1.5990	0.2030	2.1626	0.5816	-2.0912	0.2016	1.9352	1.6932	0.7046
-0.2074	2.1322	1.4604	-3.1330	1.6180	-0.2534	0.7644	1.0444	1.1184	-0.5392
0.0380	-0.0040	0.0792	0.0892	0.1066	-0.2476	0.1012	0.0306	-0.0444	-0.3052
0.0594	0.1990	0.0080	0.0790	-0.0240	-0.2552	0.0222	0.0142	-0.0466	-0.2146
0.1846	0.1736	0.2032	0.1604	0.1442	0.0144	0.1304	0.0272	-0.0800	-0.0580
-0.0296	0.1194	0.0990	0.0664	0.1054	-0.1808	0.1024	-0.0360	-0.0424	-0.2300
0.0034	0.0914	-0.0030	0.0832	0.0990	-0.2292	0.0340	0.0242	0.1374	-0.2332
0.1280	0.2224	0.1980	0.1386	0.0914	-0.1042	-0.0036	0.0934	-0.0954	-0.1244
0.0916	0.0082	0.0306	0.0536	0.1122	-0.2802	0.0422	-0.0194	0.1724	-0.3966
0.0706	0.0966	0.0480	0.0714	0.0136	-0.0420	0.1114	0.0106	0.0212	-0.2712

Hidden Output Weight Matrix

[-1.2670 -0.8196 0.6892 0.3742 2.2262 -1.0054 -0.1824 -0.6476 -1.0614 0.5924 0.2032 0.2244
0.3142 0.2020 0.1752 0.2890 0.2014 0.1642 -1.5936]

APPENDIX A-20

Weight Matrix of the 3-year ANN Crack Model

Rigid Pavements

Input Hidden Weight Matrix

-0.9506	-1.2800	-0.5816	-0.6216	-0.5394	-2.7472	-0.1056	-0.1044	-0.3196	1.4412
1.0764	-1.2214	-2.6464	-1.1734	0.0180	-0.8060	-0.2930	-0.1296	-0.4700	0.9144
-0.1584	1.7374	0.1932	-0.1384	-1.6346	0.0630	-2.7530	1.6720	2.2770	1.7572
-1.6834	-1.0526	1.7834	-0.1386	0.7966	0.6210	3.8544	-2.1860	-1.2440	2.3586
1.2366	-2.0680	3.2292	0.4084	2.2800	-0.4614	0.4572	-0.5192	-0.2692	-1.8946
-0.3842	-0.7462	0.8944	-1.1642	-3.1908	0.3484	1.5774	0.5384	-0.2796	1.3252
-0.6334	-4.7330	0.3472	-0.3264	-1.4886	-1.2196	-0.9902	-0.9522	-1.2140	-1.5294
-0.4480	1.3864	-1.5874	0.2162	-3.4300	-0.3552	0.0100	-0.4660	-1.1774	-0.1556
2.5180	1.6552	0.1694	2.0040	0.3490	-2.2982	0.2764	1.5242	1.0300	0.5794
-0.8352	1.5374	1.0246	-3.4666	1.5094	-0.2860	0.8154	0.9108	1.2560	-0.8942
-0.8560	-0.8504	-0.5264	-0.4880	-0.2436	-0.7302	-0.0606	-0.9274	-1.0526	-1.1920
-0.6332	-0.4894	-0.6164	-0.3322	-0.2024	-0.7820	-0.1510	-0.9794	-1.0306	-1.1642
-0.5600	-0.5610	-0.4676	-0.3244	-0.2286	-0.4686	-0.2640	-0.7152	0.0996	-0.8924
-0.7812	-0.6316	-0.5856	-0.4186	-0.3056	-0.8032	-0.2566	-0.8920	0.0104	-1.0312
-0.9624	-0.8634	-0.7124	-0.6284	-0.1366	-0.7324	-0.5186	-1.0062	-0.6754	-1.1662
-0.9184	-0.8026	-0.6022	-0.6464	-0.4530	-0.8576	-0.3886	-0.8366	-0.4880	-1.1202
-0.8772	-0.9382	-0.6824	-0.6570	-0.1392	-0.7376	-0.4980	-1.0722	-0.6600	-1.3452
-0.1332	-0.1952	-0.1662	-0.2000	-0.1642	-0.0332	-0.4444	-0.6740	-0.7624	-0.1680

Hidden Output Weight Matrix

[-1.5896 -1.4308 0.5450 0.8482 3.3612 -2.4486 -0.3640 -0.8480 -1.1070 0.7386 -0.1980 -0.2586
-0.0434 -0.1142 -0.2808 -0.1736 -0.2812 -0.3616 -1.5294]

APPENDIX A-21

Weight Matrix of the 3-year ANN Ride Model

Rigid Pavements

Input Hidden Weight Matrix

-1.1366	-1.5892	-0.8664	-0.7690	-0.5556	-2.2570	-0.7182	-0.3762	0.3584	1.0012
1.3144	-0.7670	-2.0332	-0.4724	0.8152	-0.5640	-0.9204	0.0686	0.2734	0.1324
-0.1530	1.6340	-0.1186	-0.5762	-2.0260	-0.3014	-2.0192	1.6836	2.7230	2.0834
0.5614	1.1376	3.8414	1.7866	2.5406	-1.0092	3.2882	-1.5866	0.6494	4.9156
1.9880	-1.6432	3.2272	-0.4624	0.7974	-0.4496	-0.0252	-0.9400	-0.8390	-0.7336
-0.6572	-0.9008	1.0952	-0.5422	-2.2634	0.5132	1.6340	1.3710	-0.0584	1.0924
1.0136	-3.1136	2.1564	1.0316	-0.3608	-2.3082	-1.4046	-1.5600	-1.8916	-2.6014
-1.0720	0.8766	-2.3240	-0.3974	-3.9232	0.5942	0.9574	0.5290	0.0342	0.4372
2.0862	1.2804	-0.3854	1.5824	-0.0382	-1.8714	-0.8076	1.8486	2.2894	1.4980
-0.2920	2.0660	1.3102	-3.2086	1.6156	-0.1456	0.5722	0.9772	0.8676	-0.0034
-0.0106	0.0986	0.1606	0.1446	0.2110	-0.0506	0.7608	0.1782	-0.6616	0.5096
0.2580	0.5382	0.5510	0.5972	0.5302	0.6980	0.5126	0.3156	0.1484	1.3476
0.0034	-0.0464	-0.0232	-0.0806	0.0734	-0.4140	0.6630	-0.0184	0.2520	-0.3226
0.0520	0.3340	0.3906	0.3686	0.4410	0.4136	0.7534	0.1306	-0.2234	0.8016
-0.0260	0.2226	0.0770	0.1334	0.2856	-0.4556	0.6174	0.0712	0.4260	-0.1732
-0.0394	0.1386	0.1740	0.1024	-0.0330	-0.3082	1.0254	0.3904	-1.4340	0.7034
0.4402	0.3572	0.3960	0.3962	0.0580	-0.9900	-0.0254	-1.5044	0.0520	-2.4584
0.1602	0.2914	0.2342	0.1630	0.0916	-0.4384	1.1130	0.2542	-1.3846	0.6704

Hidden Output Weight Matrix

[-1.2966 -0.6762 0.8086 0.3982 2.3810 -1.3430 0.1570 -0.6500 -0.9402 0.8716 0.1732 0.2264
0.3166 0.2710 0.2482 0.1540 0.0710 0.1680 -1.6462]

APPENDIX A-22

Weight Matrix of the 4-year ANN Crack Model

Rigid Pavements

Input Hidden Weight Matrix

-0.8932	-1.2326	-0.4900	-0.4726	-0.3916	-2.8142	0.1892	-0.3484	-0.1202	1.2676
1.2544	-0.9532	-2.4482	-0.9766	0.1854	-0.6862	-0.3512	-0.0426	-0.4966	0.8570
0.2294	2.0282	0.4670	0.0884	-1.4308	0.3852	-3.3416	2.1036	1.7530	2.5044
-1.5308	-0.8384	1.9572	0.1052	1.0820	0.7692	3.6822	-2.0122	-0.6496	2.5956
1.2256	-2.0216	3.1556	0.2012	2.1740	-0.3966	0.3614	-0.6292	-0.0850	-1.7062
-0.4000	-0.7324	0.8666	-1.2442	-3.3904	0.2046	1.7164	0.6534	-0.5196	1.0300
-0.7702	-4.8470	0.2272	-0.3874	-1.5120	-1.3246	-1.3340	-1.0694	-1.3544	-1.6500
0.0782	1.9002	-1.2324	0.6106	-3.3736	0.0214	0.4574	0.2892	-0.7136	0.0690
2.5206	1.6324	0.1196	2.0256	0.2424	-2.3710	0.2802	1.6712	1.3754	0.5764
-0.7854	1.5854	1.1026	-3.2722	1.8162	-0.1820	0.6208	0.8608	1.4204	-0.7204
-0.6842	-0.6950	-0.3546	-0.3196	-0.0304	-0.7230	-0.6182	-0.3370	-1.0156	-1.2286
-0.6560	-0.5024	-0.4260	-0.1004	-0.1574	-0.7552	-0.6554	-0.3786	-0.2766	-1.1820
-0.1674	-0.1360	0.0224	0.0410	0.2720	-0.0596	-0.5146	0.1210	-0.0374	-0.7520
-0.2306	-0.0186	0.0650	0.1462	0.3902	-0.1370	-0.6000	0.0982	-0.1052	-0.9784
-0.5286	-0.4194	-0.2430	-0.1304	-0.0436	-0.4802	-0.6526	-0.6032	-0.6746	-1.1646
-0.2340	-0.0620	0.0420	0.1022	0.2684	-0.1746	-0.6750	0.1522	-0.0646	-0.9064
-1.0126	-1.0854	-1.0250	-0.5096	-0.1736	-1.0652	-1.1170	-1.3972	-1.3308	-1.4944
-0.8604	-0.8114	-0.5876	-0.5382	-0.3310	-0.7422	-0.6042	-0.8280	-0.9808	-1.2792

Hidden Output Weight Matrix

[-1.3824 -1.0822 0.6596 0.9276 2.9890 -2.4206 -0.4240 -1.4132 -1.3630 0.9930 -0.0056 0.0086
0.2924 0.2834 -0.0240 0.2890 -0.1632 -0.0812 -1.5672]

APPENDIX A-23

Weight Matrix of the 4-year ANN Ride Model

Rigid Pavements

Input Hidden Weight Matrix

-0.9370	-1.1422	-0.3606	-0.2890	-0.0160	-1.8512	-0.0050	-0.5792	0.0310	2.1682
1.0866	-0.9380	-2.2734	-0.7132	0.7112	-0.3670	-0.3922	0.0014	-0.1000	0.9186
-0.0296	1.5960	0.0140	-0.4030	-2.1252	-0.4842	-2.5306	1.5124	3.0956	1.4204
-0.2700	0.2936	3.0484	0.9932	1.7466	0.3172	2.8834	-1.1672	0.0080	4.1986
2.1002	-1.4202	3.4980	0.0026	1.0436	-0.3642	0.3410	-0.7174	-0.3902	-0.8836
-0.6672	-0.7190	1.1040	-0.6572	-2.2180	0.5026	1.5906	1.3870	0.0034	0.9872
0.6144	-3.5016	1.2886	0.1656	-1.2454	-1.4310	-1.1866	-1.0736	-1.4260	-1.7114
-0.5020	1.5076	-1.3100	0.6170	-2.8370	0.5896	0.2336	0.0702	0.0804	0.2956
2.3866	1.6000	0.3312	2.3000	0.7026	-1.2062	0.3616	1.9106	1.8916	1.5252
-0.0004	2.1002	1.3120	-3.2302	1.4954	-0.6404	0.5816	1.1114	1.5110	-0.9580
-0.0902	-0.1216	-0.1740	-0.1760	-0.1466	-1.1740	0.1104	0.1850	-0.0002	-1.3344
0.1922	0.3262	0.0794	0.1446	0.0752	-0.3494	0.2526	0.2482	-0.0022	-0.4284
0.1236	0.1000	0.0086	-0.0408	-0.0240	-0.3962	0.3890	0.2782	-0.0350	-0.6460
0.2244	0.3800	0.2392	0.1972	0.2232	-0.1714	-0.2374	0.1466	0.0520	-0.5206
0.2814	0.0964	-0.0022	0.0574	0.0952	-1.3406	-0.8966	-0.6420	-0.6012	-1.4036
0.4074	0.4350	0.3794	0.3374	0.1808	-0.4244	0.2390	0.1502	0.1674	-0.4634
0.3574	-0.0202	0.0184	0.0186	0.0796	-1.4402	-0.3346	-0.9954	-0.3290	-1.5836
0.0922	0.1340	0.1108	0.1270	0.0800	-1.1834	-0.3666	-0.1530	-0.2100	-1.3926

Hidden Output Weight Matrix

[-1.5314 -1.0274 1.3540 0.1740 2.2622 -1.2304 -0.3526 -0.9866 -0.6730 1.3102
0.2196 0.5254 0.4396 0.5676 0.1242 0.6276 0.0440 0.1808 -1.6214]

APPENDIX A-24

Weight Matrix of the 5-year ANN Crack Model

Rigid Pavements

Input Hidden Weight Matrix

-0.9652	-1.3500	-0.7984	-0.8404	-0.7212	-3.3894	0.4076	-0.6860	-0.0224	0.8290
1.4516	-0.5980	-2.1956	-0.8352	0.0822	-0.9722	0.1892	-0.2708	-0.3470	1.1516
-0.4716	1.5864	-0.1994	-0.5508	-1.6056	0.4336	-3.3234	2.2850	2.9572	2.1620
-2.0740	-1.1386	1.8272	-0.0360	1.1308	0.6160	3.6886	-1.7906	-1.9162	2.0442
0.8934	-1.9762	3.2970	0.2466	2.2554	-0.2670	0.3316	-0.4002	-0.8582	-2.1146
0.3742	-0.0916	1.4930	-0.6046	-3.0094	-0.1486	2.4766	0.5012	-0.1956	1.7302
0.3902	-3.7802	1.2152	0.1120	-1.2460	-0.7008	-1.2226	-1.3044	-2.4300	-0.5540
0.4220	1.9632	-0.9234	0.8816	-3.1244	-0.5490	0.1794	-0.3594	0.3872	0.2024
2.1040	1.1960	-0.2456	1.6604	-0.1584	-3.1706	0.6162	1.5842	1.7220	-0.1086
-0.9134	1.4832	0.9722	-3.1726	1.9154	0.1402	0.4366	1.4110	1.6410	-1.0014
0.2082	-0.0784	-0.1836	-0.2942	-0.3874	-0.7020	0.0216	-0.9652	-2.4674	-0.4212
-1.3516	-1.2064	-0.8970	-0.3636	0.0112	-1.4312	-1.4464	-1.5020	-0.1782	-2.2920
-0.1480	0.0492	0.3184	0.4374	0.5736	0.5490	-0.1960	0.4230	0.0790	0.1790
-0.2562	0.1770	0.2870	0.4640	0.6852	0.4782	-0.1308	0.3860	0.0852	0.0946
0.6666	0.4754	0.1362	0.2444	0.0686	0.2040	-0.0108	-0.8730	-1.8810	1.0452
-0.2130	0.1110	0.3270	0.4312	0.5516	0.4390	-0.3766	0.5020	0.0944	0.2210
0.0972	-0.2286	-0.4014	-0.4756	-0.4080	-0.8636	0.1914	-1.0696	-2.3676	-0.0320
0.8460	0.6332	0.2856	0.4050	0.0814	0.3180	0.0316	-0.8884	-1.7540	1.0990

Hidden Output Weight Matrix

[-1.5544 -1.5462 1.2704 1.1300 3.2684 -2.7292 -0.9020 -1.5610 -1.5206 1.6784 -0.6296 -0.4034 0.6500 0.6430 -0.2336 0.6144 -0.8200 -0.3264 -1.5812]

APPENDIX A-25

Weight Matrix of the 5-year ANN Ride Model

Rigid Pavements

Input Hidden Weight Matrix

-1.1652	-1.3784	-0.5910	-0.5012	-0.1990	-2.5526	-0.1964	-0.4714	0.4906	1.4422
1.0522	-1.0786	-2.4490	-0.8266	0.5822	-0.6446	-0.3062	0.0216	0.2682	0.9206
0.0684	1.7952	0.2136	-0.2436	-1.8808	0.1312	-2.5856	1.6876	2.1406	2.3670
-1.4152	-0.8632	1.8430	-0.2150	0.5422	0.5602	3.8756	-2.0160	-1.5564	2.5772
1.8552	-1.6630	3.2260	-0.2826	0.7856	-0.1234	0.4502	-0.9334	-0.7472	-0.7874
-0.7208	-0.9206	0.8752	-0.8234	-2.3842	0.0040	1.8472	1.3834	0.2982	0.6576
0.4560	-3.6596	1.1450	0.0844	-1.3350	-0.3106	-0.2366	0.0334	-0.2886	-0.6044
-0.6582	1.3036	-1.5820	0.3440	-3.1944	-0.1910	-0.0636	-0.0542	-0.5156	-0.5946
2.3924	1.6074	0.1960	2.1690	0.5786	-1.9554	0.0972	1.8536	1.6972	0.7830
-0.2872	2.0300	1.3812	-3.2056	1.5184	-0.2932	0.8316	1.0774	1.0666	-0.5650
0.1422	0.0996	0.2000	0.1980	0.2190	-0.3514	-0.0454	-0.1632	-0.3650	-0.3392
0.0570	0.1902	0.0194	0.0856	-0.0094	-0.3090	0.0824	0.1430	-0.0696	-0.2582
0.2130	0.1940	0.2276	0.1746	0.1700	0.0474	0.2094	0.1408	-0.0692	-0.0040
0.2020	0.3366	0.3354	0.2930	0.3406	-0.2712	0.0132	-0.2430	-0.3044	-0.3064
0.1980	0.2860	0.2060	0.2660	0.2912	-0.2434	-0.0108	-0.1566	-0.2272	-0.2502
0.0404	0.1350	0.1310	0.0636	0.0160	-0.2062	0.0584	0.2210	-0.0706	-0.2424
0.0950	0.0120	0.0508	0.0510	0.1120	-0.2280	-0.0254	-0.0602	0.0472	-0.4346
0.2936	0.3210	0.2874	0.3036	0.2482	-0.1676	-0.0354	-0.2536	-0.3200	-0.3434

Hidden Output Weight Matrix

[-1.4008 -0.9022 0.5684 0.4090 2.1804 -0.5532 -0.2630 -0.6012 -0.9734 0.7780 0.0900 0.1796 0.2854 0.1676 0.0962 0.2124 -0.0122 0.1242 -1.7322]