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16. Abstract

Most mechanistic-empirical methods for determining the remaining life of an existing pavement rely on the use of deflection-based non-destructive evaluation (NDE) devices. This report describes a methodology based on Artificial Neural Networks (ANN) techniques to estimate the remaining life of flexible pavements given the occurrence of two possible failure modes: rutting and fatigue cracking. The ANN techniques are also used to develop models that predict the critical strains at the interfaces of the pavement. The inputs to all the models are the best estimates of the thickness of each layer and the surface deflections obtained from a Falling Weight Deflectometer test. Uncertainty in these variables is accounted for by the proposed methodology. The report also describes an approach to the production of pavement performance curves using the results of the ANN models.

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Artificial Neural Network-Based Methodologies for Rational Assessment of Remaining Life of Existing Pavements

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Mr. Ken Fults kindly authorized the use of the data from the TxMLS site for the case study presented in Chapter 6. Dr. Dar-Hao Chen generously shared the data with us.

Abstract

Most mechanistic-empirical methods for determining the remaining life of an existing pavement rely on the use of deflection-based non-destructive evaluation (NDE) devices. This report describes a methodology based on Artificial Neural Networks (ANN) techniques to estimate the remaining life of flexible pavements given the occurrence of two possible failure modes: rutting and fatigue cracking. The ANN techniques are also used to develop models that predict the critical strains at the interfaces of the pavement. The inputs to all the models are the best estimates of the thickness of each layer and the surface deflections obtained from a Falling Weight Deflectometer test. Uncertainty in these variables is accounted for by the proposed methodology. The report also describes an approach to the production of pavement performance curves using the results of the ANN models.

Executive Summary

One of the most common Nondestructive Evaluation (NDE) methods to collect pavement performance data is the Falling Weight Deflectometer (FWD) test. The seven peak-deflections, otherwise referred to collectively as a deflection bowl, provide some of the input used to determine the pavement layers' moduli, usually through a backcalculation process. Once the layer moduli of the pavement have been computed, the pavement's remaining life, using one of the many available models, can be estimated.

This report describes an alternative approach to the computation of the remaining life of a given section. The methodology is based on Artificial Neural Networks (ANN) techniques and statistical concepts. In the proposed approach the backcalculation process is omitted. In addition, it only uses data readily available to pavement engineers, such as the measured deflection bowls, the section layers thickness and the condition survey. No laboratory-derived properties are required.

The objectives of this project were, 1) to develop ANN models to compute the remaining lives of flexible pavements associated with the rutting and fatigue cracking failure modes, 2) to develop ANN models to predict the critical strains at the interfaces of the layers, 3) to account for the uncertainty in the variables used for predicting remaining life, 4) to develop pavement performance curves and their confidence bounds, and 5) to create a software tool that integrates the models developed.

The Artificial Neural Network theory is a branch of the more general field called Artificial Intelligence. The ANN theory aims at understanding the way the information is processed in the brain and to develop the mathematical relationships that would reproduce that process. To develop an ANN it is necessary to have a set of examples that show specific values of the independent variables and the corresponding values of the dependent variable(s). The examples are used to train and test the ANN model. In this work, each example consists of an input vector with nine elements that represent the thickness of the AC and base layers and the seven FWD readings and an output vector, whose only element defines the quantity that the model will predict. In this case, that quantity is any of the two critical strains at the interfaces of the layers or the remaining life of the pavement when it experiences either fatigue cracking or rutting.

Optimally, the examples could be obtained from actual field data that has been collected and "fed" into a PMS database. Nevertheless, this type of information is limited at the present time.

Therefore, a synthetic and comprehensive database was generated to simulate and cover a wide range of possible pavement sections. FWD tests and dual tandem loading on the pavement were simulated to obtain the deflection basin and the critical strains in a number of pavement sections. Furthermore, the Asphalt Institute models, for predicting the remaining life for rutting and fatigue cracking, were used to associate remaining life values to each section. At the end, a database with 360,000 exemplars was compiled. The data sets for training and testing the ANN models developed were sampled from this database.

Four ANN models were developed for a three-layer flexible pavement. Two of the models predict the rutting and fatigue cracking remaining lives according to the Asphalt Institute equations. The other two models predict the maximum tensile and compressive strains at the layer interfaces. The models have proven to be accurate in their predictions.

To describe the continuous performance of a pavement with time or alternatively with passing traffic, the pavement performance curve (PPC) has been proposed. In general, the development of a PPC is based on the widely accepted Weibull type curve. An approach that uses the predictions of the ANN models in the construction of PPCs has also been developed. The proposed approach also allows the definition of confidence bounds for the PPC. The bounds are obtained using a Monte Carlo simulation algorithm.

All the models and algorithms developed have been integrated into a software tool. The beta version of the software is being developed under Windows 95, using C^{++} development-programming language. The software development follows a modular approach.

The proposed methodology has been initially validated with data obtained from one of the Texas Mobile Load Simulator (TxMLS) test sites. Results of the measured and predicted degradation of the section match closely.

Artificial Neural Network technology has proven to be a feasible and practical modeling approach in the development of models to assess the integrity of pavements using data that is readily available to the pavement engineer. This is particularly advantageous because other approaches require information from laboratory tests, making the assessment more tedious and time consuming. Another advantage of an ANN model over traditional approaches is that the remaining life can be calculated without having to backcalculate the elastic moduli of each pavement layer.

Implementation Statement

The software developed is ready for limited implementation. We recommend that staff member of the Design Division utilizes this program along with the existing methodologies for evaluation purposes, and for providing recommendations for future improvements.

We also recommend training courses for a few members of the districts to determine the ease of use and to recommend means to make it more accurate and more practical for their use.

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Chapter 1

Introduction

Periodical assessment of the overall structural health of pavements is an integral factor in optimizing the maintenance and rehabilitation strategies of the highway networks around the country. For the past several years, many techniques have been developed to monitor pavement performance. Most of these techniques use non-destructive evaluation (NDE) procedures. Significant amount of effort has been placed to develop low cost simple non-destructive tests (NDT) for measuring pavement properties. These properties are collected and maintained in a Pavement Management System (PMS). The information contained in a PMS is frequently used by engineers to assess the integrity of the pavements and to determine their remaining (future useful) lives. This type of assessment is conducted at both the network and project level. Accurately predicting the integrity and remaining life of pavements is of utmost importance in planning short-term and long-term maintenance, rehabilitation and reconstruction strategies.

One of the most common NDE methods to collect pavement performance data is the falling weight deflectometer (FWD). The seven peak deflections, otherwise referred to collectively as a deflection bowl, provide some of the input used to determine the pavement layers' moduli, usually through a backcalculation process. Once the layer moduli of the pavement have been computed, it is then possible to estimate the pavement's remaining life using one of the many available models (Huang, 1993).

Despite the straightforwardness of this approach, several concerns still exist over its rationality. Some of those concerns are: 1) the weaknesses in the existing backcalculation procedures, 2) the uncertainty in the assumed input parameters, such as the thickness and Poisson's ratio of paving layers and subgrade, and 3) the uncertainty in the measured responses, such as the magnitude of applied load and the resulting deflections.

Another concern is the applicability of the current models developed to predict the performance of a pavement section. For instance, in the case of flexible pavements, the cracking of the pavement is related to the tangential strain level at the bottom of the AC. These critical strains are typically calculated using layered theory and backcalculated moduli. Small variations in moduli would significantly affect the predicted remaining life from these models. Vennalaganti et al. (1994a) performed extensive sensitivity studies on the effects of the variability of input pavement and traffic parameters on two popular models for computing the performance of a pavement subjected to fatigue (Finn et al., 1977) and to rutting (Shook et al., 1982). The main conclusion was that the remaining life of a pavement is more rationally modeled using a probabilistic model than using a single deterministic quantity. Deterministic models of pavement performance are being improved by many states and under federal programs. In general the existing remaining life models are functions of the backcalculated moduli and the computed strains at the interfaces of the pavement layers.

In its simplest definition, backcalculation is an iterative process that requires varying a set of moduli until a best match between the measured FWD deflection bowl and calculated deflection bowl is obtained. The problem with the backcalculation process is the nonuniqueness of the results. A good match between the deflections does not guarantee that the backcalculated moduli are reasonable for that section and, as a consequence, the remaining life of the section could be grossly under or over estimated.

This report presents an alternative approach to the computation of the remaining life of a given section. Our methodology is based on Artificial Neural Networks techniques and statistical concepts. In the proposed approach, the backcalculation process is omitted. In addition, it only uses data readily available to pavement engineers, such as the measured deflection bowls, the section layers thickness and the condition survey. No laboratory-derived properties are required.

Objective

The objective of this project were:

1) to develop neural network models which will rapidly and reliably predict the remaining lives of flexible pavements,

2) to develop neural network models that rapidly and reliably predict the critical strains which are used in existing remaining lives models.

3) to improve and integrate an algorithm for estimating the uncertainty in the predicted remaining life from the uncertainty in the geometric and material variables of the section,

4) to develop a pavement performance curve, which incorporates the results of the ANN models, condition survey and traffic,

5) to develop a state of the art modular software that incorporates items 1 through 4 and provide results manifested with sophisticated graphical user interface (GUI) designed, specifically, to complement TXDOT decision-making practices.

In this report, the results from the efforts made during the past two years of the project are summarized. The ongoing success of this project has been due to the cooperative effort between UTEP and TXDOT personnel. TXDOT personnel have provided valuable input at several stages of the project to keep the methodology practical.

Organization

Chapter 2, of this report introduces the background information on FWD, ANN models, and remaining life models. In chapter 3, the process of generating a database of pavement sections is discussed. Chapter 4 shows the process of creating artificial neural networks models that estimate the remaining life of flexible pavements as well as the critical strains at the interfaces of a pavement section. Chapter 4 also contains a methodology to incorporate ANN model results in the definition of pavement performance curves. It also discusses the effect of uncertainty of the input variables on the uncertainty of the estimated variables. Chapter 5 describes the software under development. Finally, Chapter 6 includes a case study that demonstrates the use of the methodology presented in this report. The last chapter contains the conclusions of the research effort in this project. An extensive literature review of neural network applications to pavements is included in Appendix A. Appendix B shows a typical run of the software under development.

Chapter 2

Background

Falling Weight Deflectometer

The Falling Weight Deflectometer, as shown in Figure 2.1, is a pavement evaluation instrument designed to monitor its conditions. The FWD produces a transient impulse loading force on the pavement and seven seismic deflection transducers, usually placed 305 mm (12 in.) apart on the surface of the pavement, to measure the resulting pavement deflections.

The impulse load is produced by dropping a mass from various heights. The seven seismic transducers (geophones), which are controlled by the data acquisition equipment that is integrated with the FWD, measure the time histories of deflections. Extracted from the time histories are seven peak deflections that define the deflection basin (Stokoe et al., 1991). These deflections provide part of the input to the methodology developed under this project.

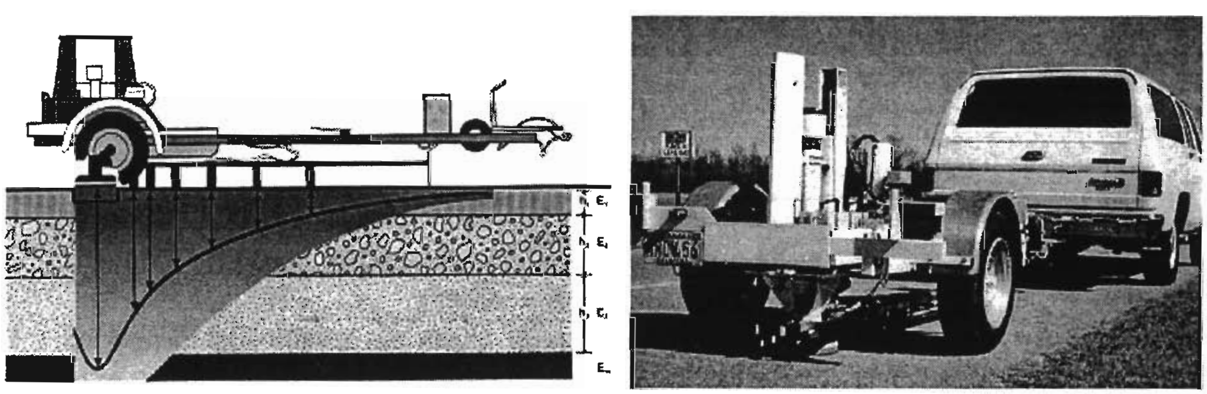


Figure 2.1 - Schematic of Falling Weight Deflectometer

Artificial Neural Networks in Pavement Engineering

The Artificial Neural Network (ANN) theory is a branch of the more general field called Artificial Intelligence. The ANN theory aims at understanding the way the information is processed in the brain and to develop the mathematical relationships that would reproduce that process (Smith, 1993). An artificial neural network is modeled to resemble the human's brain capability to think and learn through perception, reasoning and interpretation. A brain is composed of networks of neurons that receive input signals from other neurons. When a certain level of excitation is reached, a neuron "fires" an output signal that acts as an input to other connecting neurons. The type of relationship between the input and the output of a neuron can be described mathematically using a number of algorithms (Freeman and Skapura, 1991).

Figure 2.2 graphically shows a model for an ANN and its main components. In an analogy to a biological neural network, the neurons are replaced by artificial neurons also called processing elements (PEs). In general, an ANN consists of at least three layers of interconnected PEs: the input, hidden, and output layers. The number of PEs in the input layer is the same as the number of input variables that are used to predict the desired output (independent variables). The PEs in the output layer represent the variables to be predicted (dependent variables). The input and output layers are connected through one or several intermediate layers of PEs, also called hidden layers. The number of hidden PEs within these layers is decided by trial and error depending on the complexity of the problem.

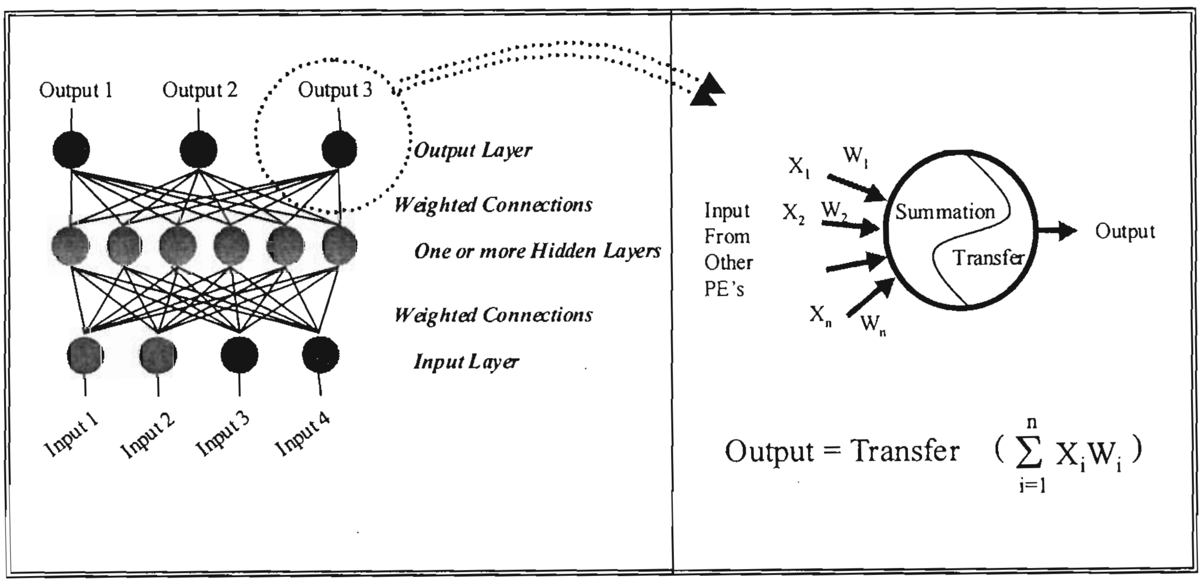


Figure 2.2 - Components of an Artificial Neural Network

In most types of ANN, the PEs between two adjacent layers are usually interconnected. The strength of each connection is expressed by a numerical value called a weight. The weights are determined through a "training" process that consists of presenting input and output examples to the network. The ANN is supposed to learn the relationship between the input and the output by adapting the weights of the connections. A number of algorithms have been developed to conduct the training process (NeuralWare, 1993). In this work the commonly used "backpropagation" model was implemented.

During the training of a backpropagation neural network, information is transferred in two phases: the forward phase and the backward phase. In the forward phase, the input is presented and propagated forward through the network to compute an output value for each PE. In the backward phase, for each PE in the network, the current output is compared to the desired output and the difference or error is computed. Starting at the output layer and ending at the input layer, the error is gradually propagated back through each node in the network using a predefined learning rule. During this process, the weights of the connections are also modified until the error is minimized (NeuralWare, 1993). Once the network is trained, the development process is completed.

The use of ANN is not new in pavement engineering. Several applications have already been published in the specialized literature. Some of those applications include: 1) parameter determination, such as the pavement section moduli; 2) assessment of the condition of the pavement and 3) selection of maintenance strategies. Appendix A gives a summary of publications on the subject. It shows the type of application for the ANN models, the input variables used, the predicted variables, and the size of the databases used to generate training (input examples) and testing files.

Remaining Life Models

A pavement, either flexible or rigid, may develop several modes of failure during its service life. Therefore, its integrity at a given point in time depends on the type of failure it is exhibiting. When no distress is visible, the prediction of the remaining life of a pavement requires *a priori* identification of its possible failure modes. The most common structural failure types observed in flexible pavements are rutting and fatigue cracking.

In most design and evaluation methodologies of flexible pavements, loads on the surface of the pavements are considered to produce two critical strains (tensile and compressive). Figure 2.3 below shows the location of the critical strains for a three-layer flexible pavement.

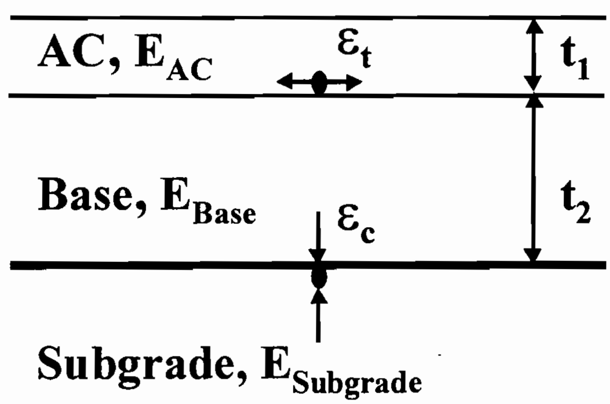


Figure 2.3 - Three-Layer Flexible Pavement Section

The first critical strain, horizontal tensile strain, ε_t, develops at the bottom of the asphalt layer and it has been shown to be a measure of the fatigue cracking of a pavement. The second critical strain, the vertical compressive strain, ε_c, develops at the top of the subgrade layer and has direct relation to the permanent deformation or rutting that results on top of the surface of the pavement.

Two general mathematical distress models are used to determine the remaining life of flexible pavements. These models take the following general forms (Huang, 1993): For the fatigue cracking failure mode,

$$N_f = f_1(\varepsilon_t)^{-f_2}(E_{AC})^{-f_3} \tag{2.1}$$

and for the rutting failure mode,

$$N_r = f_4(\varepsilon_c)^{-f_5} \tag{2.2}$$

where N_f is the number of repeated 80-KN (18-kip) equivalent single axle load (ESAL) the pavement can stand before fatigue cracking failure occurs. Parameter N_r is a similar quantity associated with the rutting of the pavement.

The constants f_1, f_2, f_3, f_4, and f_5 in Equations 2.1 and 2.2 are usually determined from field performance data, road tests, or laboratory tests. Table 2.1 gives the values developed by various institutions.

Table 2.1 - Fatigue Cracking Model and Rutting Model Parameters Used to Determine Remaining Life of a Flexible Pavement (from Huang, 1993)

	$N_f = f_1 (\varepsilon_t)^{-f2} (E_{AC})^{-f3}$			$N_r = f_4 (\varepsilon_c)^{-f5}$	
	f_1	f_2	f_3	f_4	f_5
Asphalt Institute	0.0796	3.291	0.854	*NA*	*NA*
Shell	0.0685	5.671	2.363	*NA*	*NA*
Shell (50% reliability)	*NA*	*NA*	*NA*	6.15E-7	4
Shell (85% reliability)	*NA*	*NA*	*NA*	1.94E-7	4
Shell (95% reliability)	*NA*	*NA*	*NA*	1.05E-7	4
Illinois Dept. of Transportation	5E-6	3	*NA*	3	*NA*
Transport and Road Research Laboratory	1.66E-10	4.32	*NA*	4.32	*NA*
U.K Research & Road Research Laboratory (85% reliability)	*NA*	*NA*	*NA*	6.18E-8	3.95
University of Nottingham	*NA*	*NA*	*NA*	1.13E-6	3.571
Belgian Road Research Center	4.92E-14	4.76	*NA*	3.05E-9	4.35

Chapter 3

Data Base of Pavement Section Parameters

To develop an ANN it is necessary to have a set of examples that show specific values of the independent variables and the corresponding values of the dependent variable(s). These examples are used to train and test the ANN model. In this work, each example consists of an input vector with nine elements that represent the thickness of the AC and base layers (t_1, t_2) and the seven FWD readings ($d_0 \ldots d_6$), and an output vector, whose only element defines the quantity that the model will predict. In this case, that quantity is any of the two critical strains at the interfaces of the layers (ε_t or ε_c) or the remaining life of the pavement when it experiences either fatigue cracking (N_f) or rutting (N_r).

Optimally, the examples could be obtained from actual field data that has been collected and "fed" into a PMS database. Nevertheless, this type of information is limited at the present time. Therefore, a synthetic and comprehensive database was generated to simulate and cover a wide range of possible pavement sections.

Data Base Generation

The overall process employed to generate a synthetic data base is graphically depicted in Figure 3.1. First, a simulation was conducted to generate a number of pavement sections [STEP 1]. The thickness of the AC and base layers and their corresponding elastic moduli defined each section. Wide ranges of possible thickness and moduli were initially established to cover most types of pavement sections. To generate these variables a Monte Carlo simulation approach was conducted (Ang and Tang, 1984) using the following assumptions: 1) the variables were not correlated, 2) the thickness of the subgrade was fixed at 610 cm (240 in.) to simulate a semi-rigid layer, and 3) the pavement section variables were simulated using a discrete uniform distribution. Some of these assumptions could be reviewed in the future as more evidence of the statistical relationships of the pavement section variables become available.

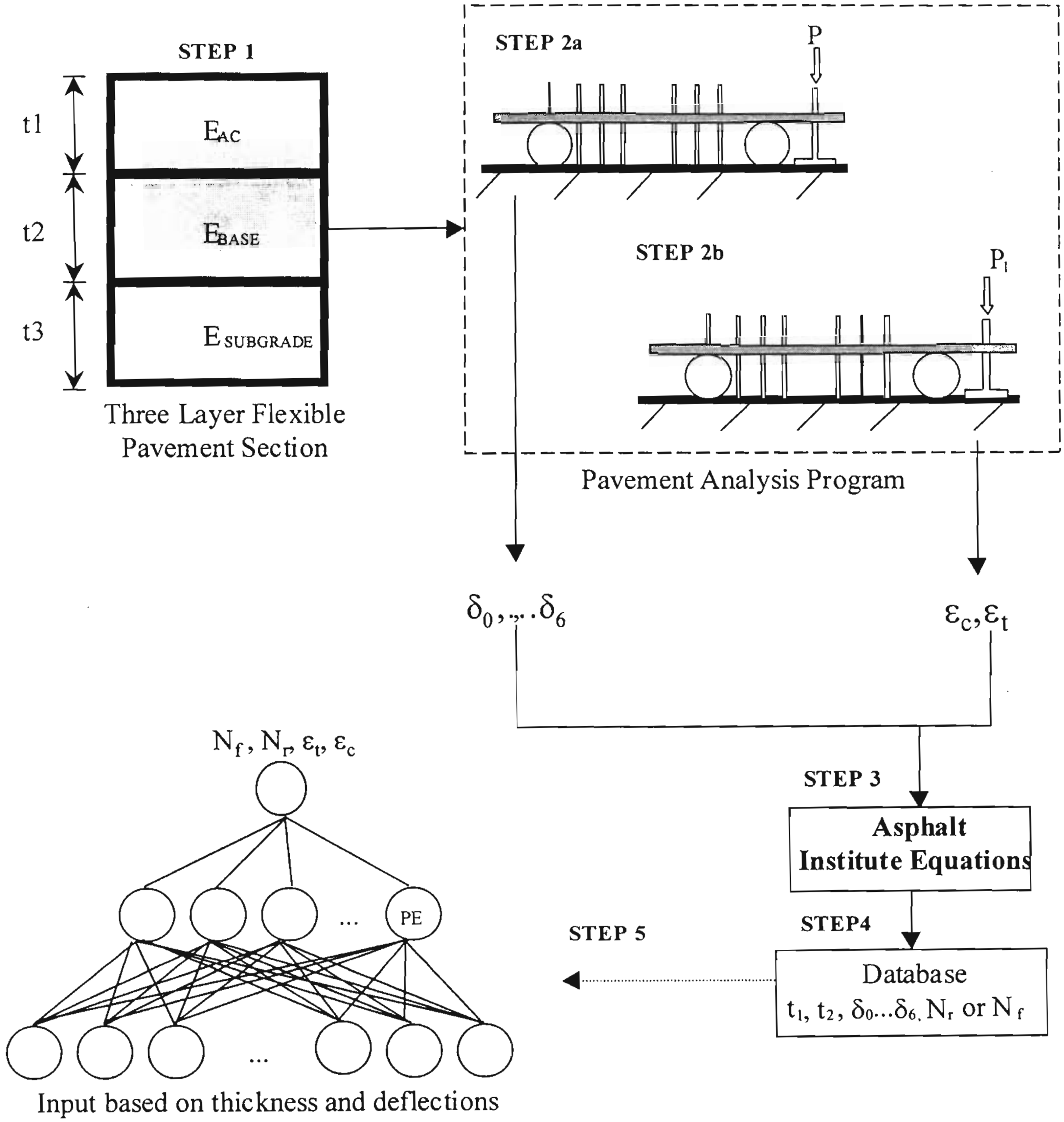


Figure 3.1 - Synthetic Database Generation Process

Once a section was defined, a FWD test on the section was simulated using the five-layer linear elastic program WESLEA [STEP 2a]. The seven FWD readings were computed under a static load of 40 KN (9000 lb) acting over a 152 mm (6 in.) radius and with a uniform 305 mm (12 in.) spacing for the seven sensors. The thickness and seven deflections constituted the input vector for the ANNs.

As stated earlier, the variables that define the output vector could be the critical strains or the remaining life associated with each failure mode. Using WESLEA, the critical strains, for each of the sections generated, were evaluated under a simulated dual tandem loading (DTL) of 80 KN (18000 lb) [STEP 2b]. These computed strains were then used in Equations 2.1 and 2.2 to determine the rutting or fatigue cracking remaining life of the pavement section [STEP 3]. This process was repeated for every pavement section until a comprehensive database was built [STEP 4]. Finally, training and testing files were selected from this comprehensive database to develop the ANN models [STEP 5]. Through this process a synthetic database with 360,000 examples was produced. Training and testing files were extracted using random sampling.

Data Processing

A very important step in developing ANN models is data pre-processing. In many engineering applications, raw data should be preprocessed to ensure that the ANN learning process is not inhibited. Thus, the data extracted from the database was subjected to mathematical transformations before being used in the training of ANN models.

A combinatorial analysis was conducted to select a suitable set of transformations for each of the input and output variables. The analysis involved replacing each of the raw input and output variables with one or more transformed variables, during the ANN training process. The final transformations were selected from a pool of candidate transformation chosen *priori*. A genetic algorithm was implemented to choose the best set of transformations. The criteria used to select the transformations, was the minimization of the root mean square (RMS) error of the output. Table 3.1 shows the pool of candidate transformations and those selected by our algorithm for training the ANN model that predicts the rutting remaining life. A different set of transformations was used for each of the ANN models developed.

Results of two Artificial Neural Network models, one trained with the raw data and the other trained with pre-processed data are shown in Figure 3.2. The accuracy gained by pre-processing of the data is evident.

Table 3.1 - Candidate Transformations

Name	Function
Identity function *	x
Natural logarithm function *	ln(x)
Log of Log	log(log(x))
Exponential function	exp(x)
Exp of Exp	exp(exp(x))
Square function	x^2
Fourth Power function	x^4
Square root function *	$x^{0.5}$
Fourth root function	$x^{0.25}$
Inverse function (1/x)	x^{-1}
1 / (Square function) *	x^{-2}
1 / (Fourth Power function)	x^{-4}
1 / (Square root function)	$x^{-0.5}$
1 / (Fourth root function)	$x^{-0.25}$
Hyperbolic tangent function *	tanh(x)
Log (x/(1-x)) *	ln(x/(1-x))

*** Transformations applied to data used for developing the ANN model that predicts the rutting remaining life**

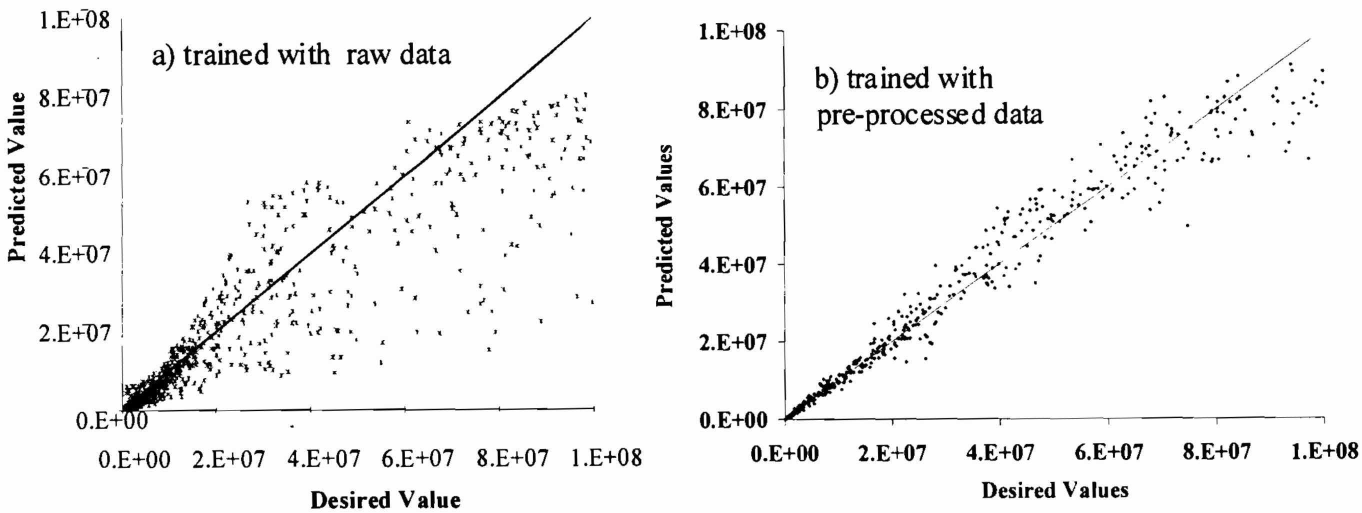


Figure 3.2 - Results of Two ANN Models

Chapter 4

Artificial Neural Networks Models

ANN Development

All the ANN models developed during this project have been based on a multi-layer feed-forward backpropagation algorithm. A Kalman filter (Puskorius and Feldkamp, 1991) was selected as the learning rule, to estimate the weights for the links that join the processing elements between two adjacent layers. The sigmoid function was selected as the transfer function of the processing elements. The sigmoid transfer function is used in the output layer to transfer the weighted sum, as shown in Figure 2.2, to fit within certain specified bounds (Smith, 1993). The architecture (number of hidden layers and their corresponding number of PEs in each of them) was chosen based on the RMS error of the output. The model with the best architecture was then tested and validated with a testing data file. The architectures for the final models consisted of three layers. However, the number of PE's in the input and hidden layers were different for each model. The number of PE's in the input layer depended on the data transformations used for the model. Likewise, the number of PE's in the hidden layer depended on the model's performance. In the development of the ANN architecture, it is always desirable to keep the number of PE's to a minimum. The smaller the architecture is, the more robust the ANN model will be (NeuralWare, 1993).

ANN Models

Four ANN models were developed for a three-layer flexible pavement. Two of the models predict the rutting and fatigue cracking remaining lives according to the Asphalt Institute Equations (see Table 2.1). The other two models predict the maximum tensile and compressive strains at the layer interfaces. As mentioned earlier, the result from these two ANN models can be used with any of the failure models in Table 2.1 to estimate remaining life. All four models are based on the ranges of pavement sections shown in Table 4.1. These ranges were based on surveys conducted by TXDOT Personnel.

Table 4.1 - Ranges of Pavement Section Variables Used in ANN Model Development

Pavement Variables		Units	Value	
			Minimum	Maximum
Asphalt Thickness	(t_1)	mm (in.)	25.4 (1)	254 (10)
Base Thickness	(t_2)	mm (in.)	102 (4)	457 (18)
Asphalt Modulus	(E_{AC})	MPa (ksi)	2067 (300)	6900 (1000)
Base Modulus	(E_{BASE})	MPa (ksi)	207 (30)	759 (150)
Subgrade Modulus	($E_{SUBGRADE}$)	MPa (ksi)	35 (5)	167 (25)

The ANN models developed during this project are summarized in Table 4.2. The table contains the best and final architecture, the limitation or bounds of the prediction range, and the performance of each model. These models are valid for pavement sections listed in Table 4.1, and should not be used to predict values outside those ranges.

Table 4.2 - Specifications and Architectures of the Three-Layer ANN Models

ANN Model	Number of PEs (input /hidden /output)	Prediction Bounds		Performance (% error)
		Upper	Lower	
Fatigue Cracking	9 / 30 / 1	25 million ESALS	2000 ESALS	+/- 20%
Rutting	13 / 28 / 1	25 million ESALS	2000 ESALS	+/- 10%
Tensile Strain	11 / 18 / 1	350E-6	75E-6	+/- 10%
Vertical Strain	7 / 24 / 1	950E-6	225E-6	+/- 10%

Remaining Life for Fatigue Cracking

Figure 4.1 shows the results for the ANN model that predicts the remaining life associated with fatigue cracking of a pavement. The figure shows 500 cases. The upper limit for valid predictions of this model is twenty-five million ESALS. The range of pavement properties covered by this model is listed in Table 4.1 except for the minimum AC thickness, is 75 mm (3 in.) instead of 25 mm (1 in.). The model's architecture is comprised of 9 PE's in the input layer and 30 PE's in the hidden layer. The fatigue cracking ANN model predicts 86% of the desired values within a +/- 20% error.

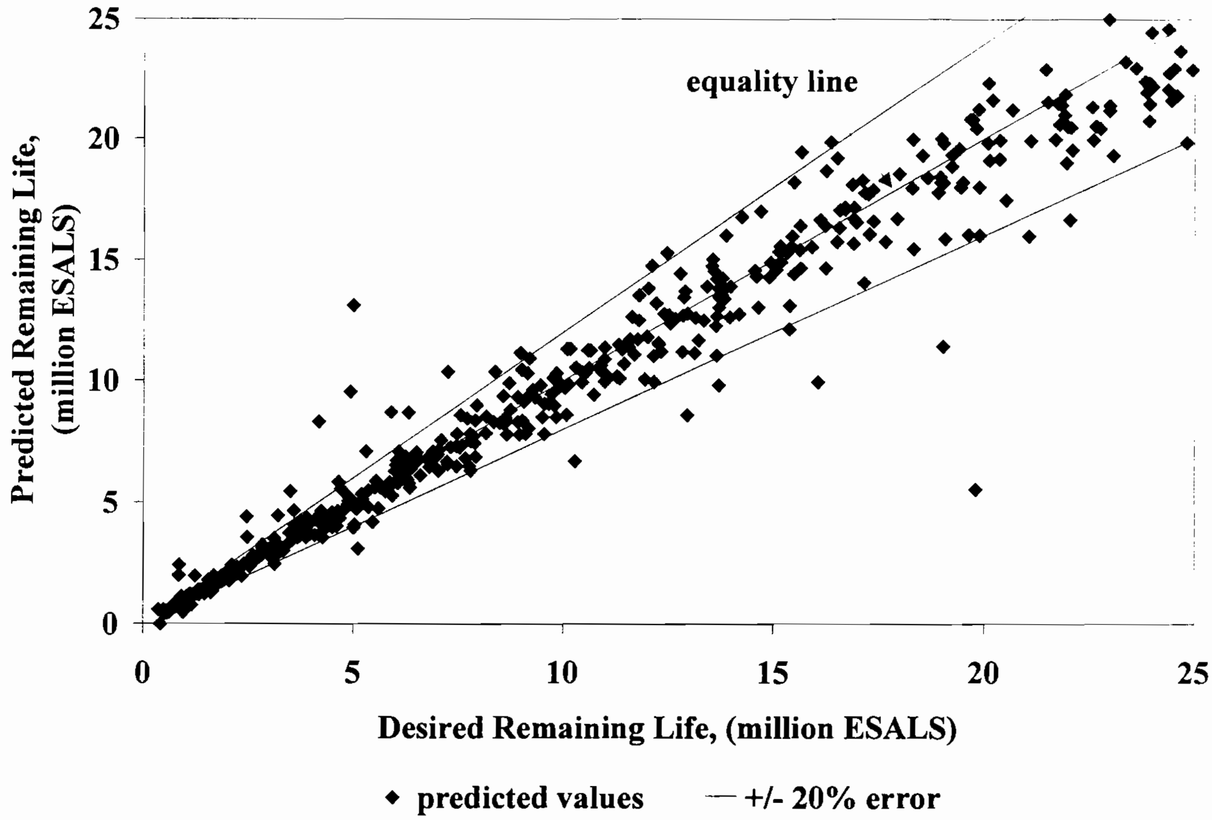


Figure 4.1 - Results of the Fatigue Cracking (N_f) ANN Model

Remaining Life for Rutting

Figure 4.2 shows the results for the ANN model that predicts the remaining life associated with rutting of a pavement. The model is applicable to the entire range listed in Table 4.1. Results for 500 cases are plotted. The maximum number of ESALS is limited to twenty-five million. The model predicts a remaining life of about twenty-five million ESALS for any section that has a remaining life beyond this value. The model's architecture is comprised of 13 PE's in the input layer and 28 PE's in the hidden layer. This ANN model was trained with a database consisting of 5000 examples. The trained model predicts 95% of the desired values within a 20% margin of error.

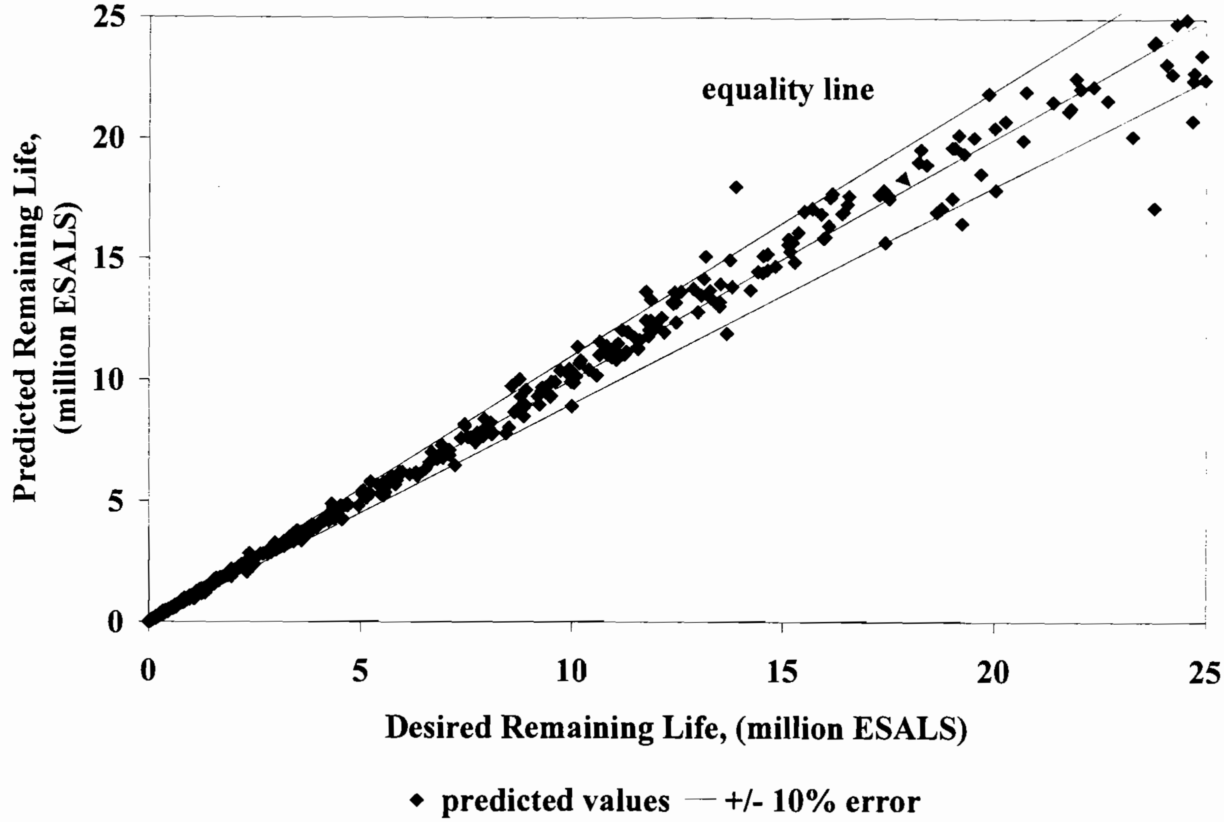


Figure 4.2 - Results of the Rutting (N_r) ANN Model

Tensile and Compressive Strains

Figures 4.3 and 4.4 show the results for the ANN models that predict the tensile and compressive strains at the layer interfaces of a pavement, respectively. These ANN models were developed primarily because various institutions such as the Asphalt Institute, Shell, Illinois Department of Transportation, Transport Research Laboratory, and Belgian Road Research Center assign different values to the coefficients of Equations 2.1 and 2.2. Figure 4.3 compares the predicted tensile strain with the desired strain. The model's architecture is comprised of 11 PE's in the input layer and 18 PE's in the hidden layer. For the 500 cases shown, this ANN model predicts 90% of the desired values with +/- 10% error.

Figure 4.4 illustrate the performance of the ANN model that predicts the compressive strain. The model's architecture is comprised of 7 PE's in the input layer and 24 PE's in the hidden layer. The performance of this ANN model indicates that 96% of the desired values are predicted with +/- 10% error.

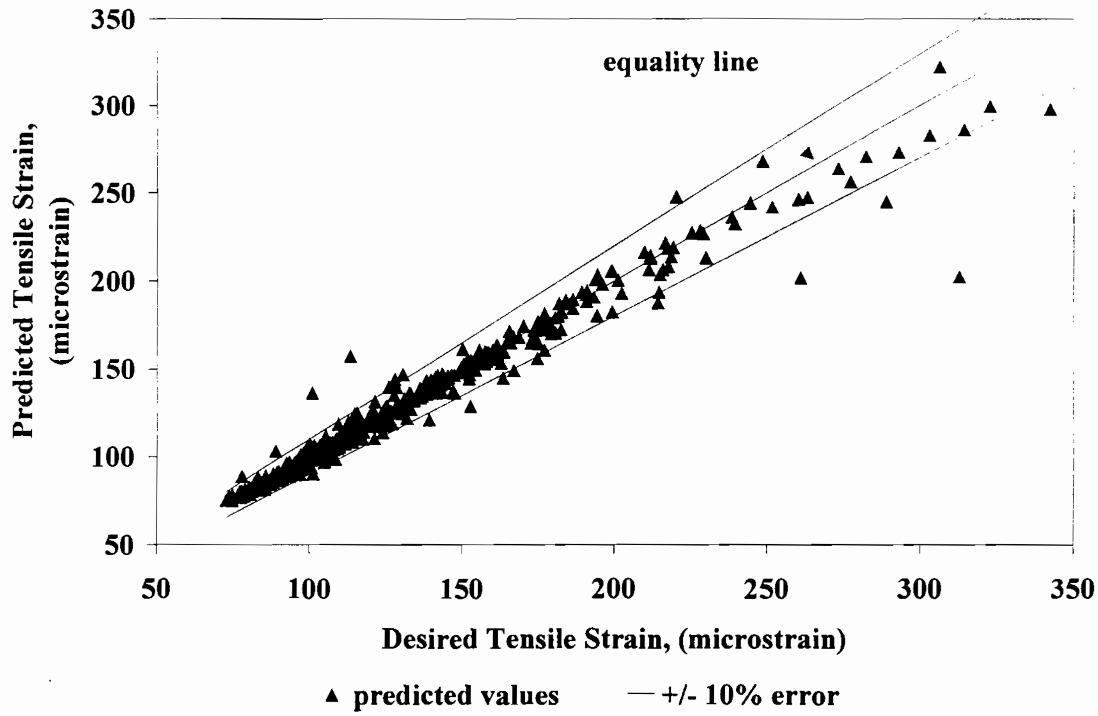


Figure 4.3 - Results of the Tensile Strain (ε_t) ANN Model

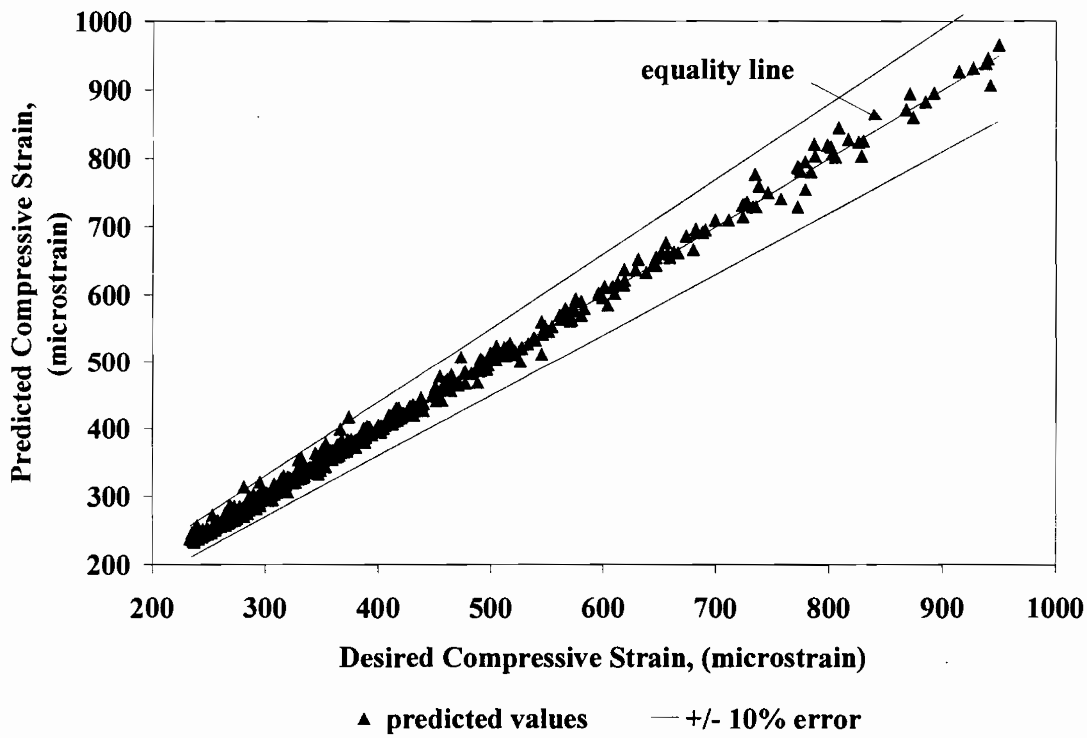


Figure 4.4 - Results of the Compressive Strain (ε_c) ANN Model

Pavement Performance Curves

To describe the continuous performance of a pavement with time or alternatively with passing traffic, the pavement performance curve (PPC) has been proposed (Garcia-Diaz et. al., 1984 ; Vepa et. al., 1996). In general, a PPC is a monotonically non-decreasing curve. A popular model used for this curve is the Weibull function. The Weibull function is a two-parameter curve that is commonly used to describe the "life" of a system. Mathematically, the Weibull function is expressed as:

$$D = 1 - \exp\left(-\left(\frac{T}{\beta}\right)^{\alpha}\right) \tag{4.1}$$

where:

D = level of damage

T = number of accumulated traffic to reach D in ESALS,

α , β = site dependent parameters.

A PPC can be generated for failure mode of the pavement. Figure 4.5 graphically shows a pavement performance curve that is based on Equation 4.1. The graph represents the damage accumulation in the pavement plotted against traffic or time. The actual shape of the curve is a function of the parameters used in the equation. The figure also shows the concept of remaining life used in this project: *the extra time/traffic (from the day the NDT was performed) that it will take for a section to reach a failure limit.* The failure limit shown in the figure represents the maximum damage level that can be tolerated before the pavement is repaired. This limit is different for each failure mode of the pavement. For example, in this project the failure limits considered were: for rutting 12.7mm (0.5 in.) and for fatigue cracking 45% of the wheel path.

To obtain the parameters of a PPC, it is necessary to know at least two points on the curve. The first point may be obtained from the results of an ANN remaining life model, or from one of the remaining life regression models in Table 2.1, and the corresponding failure limit. The second required point is obtained from available information about the past performance of the pavement. The following two cases present two scenarios in which different amount of information is used to generate the PPC.

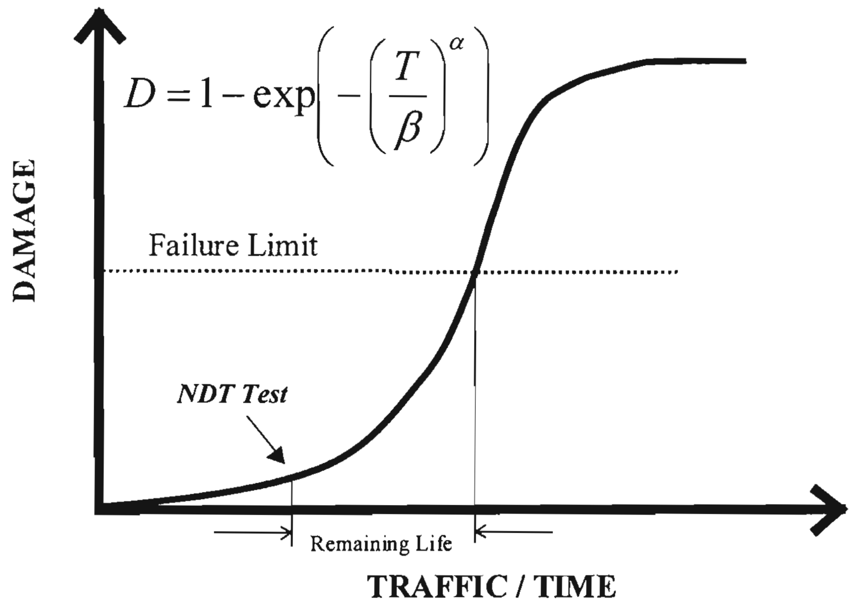


Figure 4.5 - Pavement Performance Curve

Case 1: This scenario assumes that: 1) no damage existed when the pavement section was new, 2) the accumulated traffic of the pavement section at the time of the NDE is known, and 3) at the time of the NDE no record of the level of distress is available. Based on this assumption, the PPC of a pavement section can be generated using two points. One point is when the pavement was constructed (no traffic, no damage). The other point is obtained by adding the predicted remaining life to the traffic at the NDE test time. The result is the time/cumulative traffic at which the pavement reaches the failure limit.

Case 2: The second scenario is similar to the first with the exception of the third assumption. In this case, a condition survey is carried out during the field test. Based on this new assumption, the PPC of the pavement section can be generated using three points. The first point is when the pavement was constructed (no traffic, no damage). The second point is obtained from the damage measured and the accumulated traffic at the time of the test. The third point is obtained from the results of the ANN model.

The parameters in equation 4.1 can be obtained with a closed form solution for Case 1 and using linear regression for Case 2.

From FWD Test to PPC

Figure 4.6 summarizes the steps required to construct a pavement performance curve. Step 1 illustrates how the thickness and FWD data is collected and used as input to the ANN model. Step 2 indicates how the ANN model uses the pre-processed data to estimate the output. Step 3 shows that the output of the ANN model is post-processed. Finally, the performance curve is obtained in Step 4. Once the FWD data is collected the rest of the process is almost instantaneous.

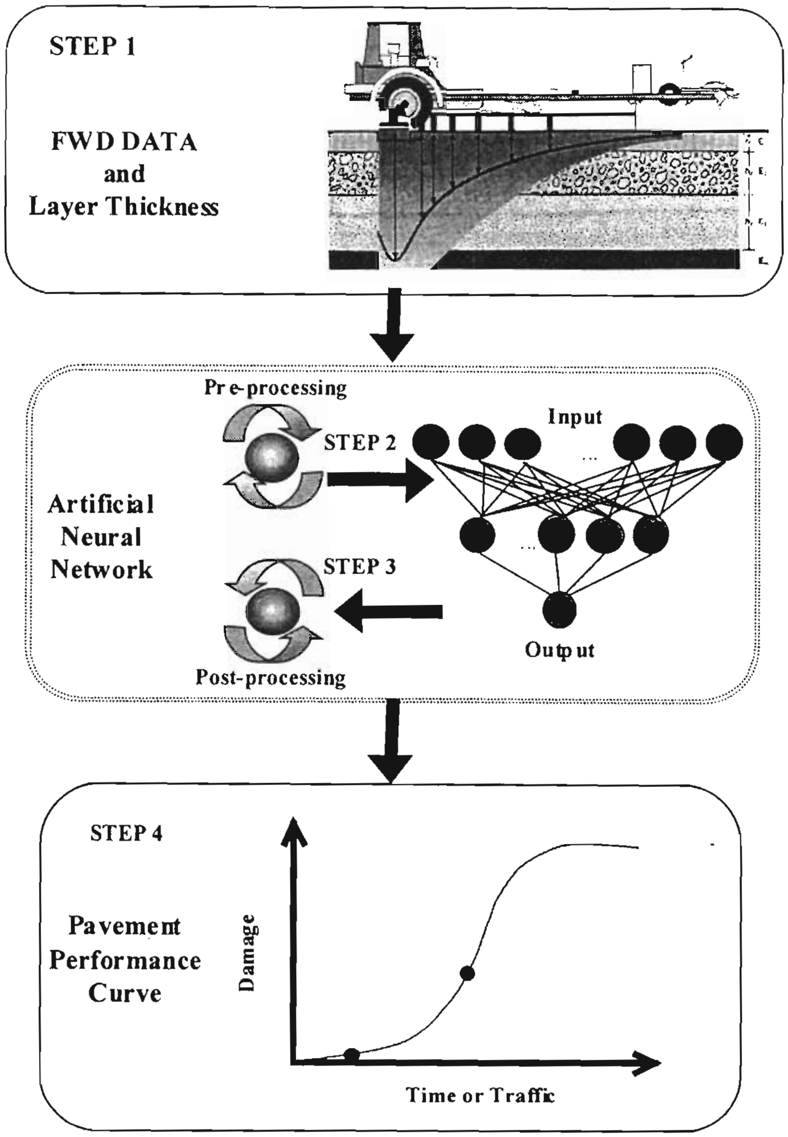
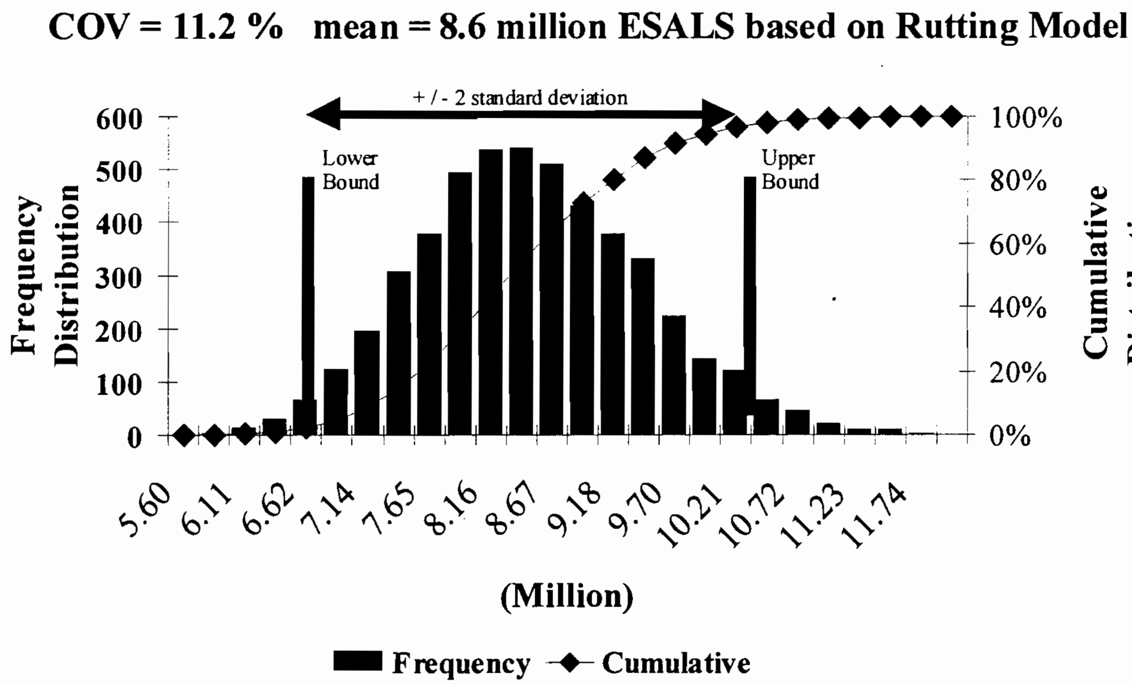


Figure 4.6 - Overall Process of Estimating the Integrity of a Pavement

Confidence Bounds for Remaining Life and Pavement Performance Curve

The approaches to predict the remaining life of a pavement and to produce its PPC, described in the foregoing sections, assume that all the required input variables are known with certainty. However, it is well acknowledged that the actual thicknesses of the layers of a given section may not correspond to those specified, and that there are experimental errors in the FWD tests. In addition, the cumulative traffic passing through a section can only be known with a given level of confidence. The impact of uncertainty in the layer thicknesses and in the deflection basin on the predicted remaining life of a pavement is shown in Figure 4.7. If the input variables are accepted as random variables with given probability density functions, then the output variable (remaining life) is also a random variable defined by a probability density function. Once this distribution is known, upper and lower confidence bounds for the predicted remaining life can be established as shown in the figure. Due to the highly nonlinear relationship, between the pavement section variables and the predicted remaining life variable, finding the probability density function of the remaining life can only be practically done through a Monte Carlo simulation (Ang and Tang, 1984).



Variable	C.O.V.	Correlation	Distribution
Thickness	10%	None	Tnormal*
Deflections	2%	Correlated	Normal

* Truncated Normal

Figure 4.7 - Uncertainty in the Remaining Life of a Pavement

To conduct the simulation, the statistics and the type of distribution of each of the input variables should be known. In our approach we assume that the mean values of the variables are: for the section parameters, the specified values; and for the deflections, the measured values. The variability of each parameter is a function of construction practices and the conditions under which the NDT is performed. The level of variability is commonly quantified by the coefficient of variation (ratio of standard deviation and the mean value of a variable). Some data on suitable coefficients of variation for the variables used by the ANN models have been reported in the literature and summarized by Vennalaganti et al (1994b). In our simulation, all input variables are assumed to have normal or truncated normal distribution.

After analyzing the deflection data in the synthetic data base, it was determined that the FWD deflections are correlated. Tables 4.3 and 4.4 show the correlation matrixes used for simulating deflections. The matrices are different because they were obtained using separate samples. However the trend in the correlation coefficients is basically the same.

Table 4.3 - Correlation Matrix of the Deflections Used in Developing Fatigue Cracking ANN Models

	d0	*d1*	*d2*	*d3*	*d4*	*d5*	*d6*
d0	1	0.90	0.75	0.68	0.64	0.63	0.64
d1		1	0.95	0.89	0.86	0.85	0.85
d2			1	0.99	0.97	0.96	0.95
d3				1	0.99	0.99	0.99
d4		Symmetric			1	0.99	0.99
d5						1	0.99
d6							1

Table 4.4 - Correlation Matrix of the Deflections Used in Developing Rutting ANN Models

	d0	*d1*	*d2*	*d3*	*d4*	*d5*	*d6*
d0	1	0.85	0.62	0.51	0.48	0.48	0.49
d1		1	0.92	0.85	0.82	0.81	0.81
d2			1	0.99	0.97	0.96	0.96
d3				1	0.99	0.99	0.99
d4		Symmetric			1	0.99	0.99
d5						1	0.99
d6							1

Once the Monte Carlo simulation is performed, the results can be used to define confidence bounds for the predicted remaining life. Figure 4.7 shows a histogram built with the results of one such a simulation and the upper and lower bounds defined by plus/minus two standard deviations from the mean value. A pavement performance curve can be obtained using each of the bounds thus defined. These curves in turn define a region for the possible location of the PPC. Figure 4.8 shows a schematic representation of these concepts. It also shows a pavement performance curve generated using the mean value of the predicted remaining life.

A numerical example of the methodology described in this chapter is given in Chapter 6.

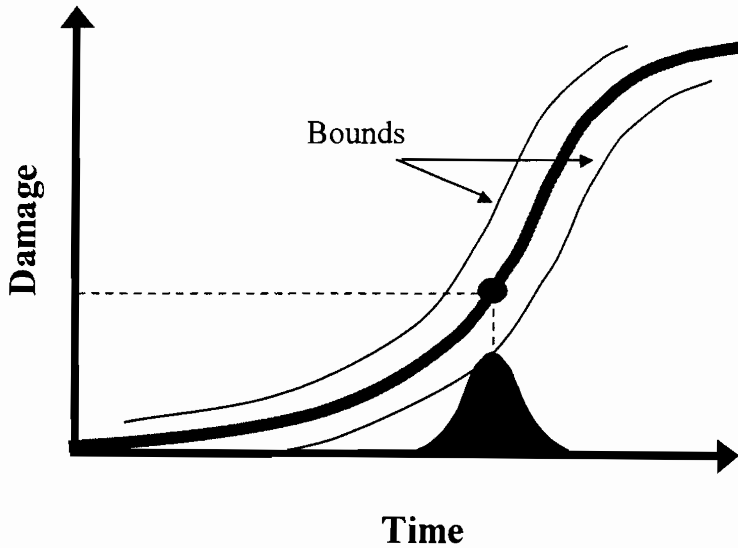


Figure 4.8 - PCC with the Upper and Lower Confidence Bounds

Chapter 5

Description of Software

This chapter contains a description of the prototype software developed to predict the remaining life of flexible pavements. The software is the product of integrating the various methodologies described in the previous chapters.

Presently, the software contains two ANN models that predict the remaining life of a three-layer pavement section for both the rutting and fatigue cracking failure modes. The ANN models are based on the Asphalt Institute equations. The software also contains the uncertainty-processing algorithm based on the Monte Carlo simulation methods. An option to obtain the pavement performance curve based on the cumulative Weibull distribution has also been incorporated. Efforts are being made to develop a stand-alone end product that will be user-friendly and complimentary to procedures used by TXDOT pavement engineers.

Software Architecture: Main Modules and Sub-Modules.

The beta version of the software to compute the remaining life of pavements, hereinafter the software, is being developed under Windows 95, using C++ development-programming language, which allows object oriented programming. The major benefit of object oriented programming is the capability of developing programs with a modular architecture.

The software was designed to have three main modules: a) *Input and Project Information* module; b) the *Artificial Neural Network (ANN) and Uncertainty processing* module; and c) the *Reliability and Results* module (see Figure 5.1).

Each module is comprised of additional sub-modules organized in three levels. The first level sub-modules are classified according to the "*pavement types*" to be analyzed. Two pavement types were originally considered, a) Flexible and b) Rigid. Currently, the software only handles flexible pavements (see Figure 5.2).

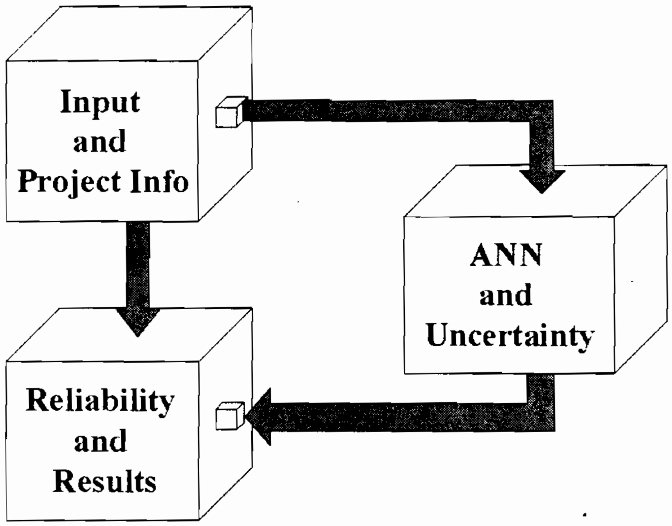


Figure 5.1 - Software Architecture: Main Modules

Each first level sub-module is comprised of a second level of sub-modules that are classified under the "*performance models*" criteria. Any available performance model can be incorporated at this level. So far, the models that predict the remaining life according to the Asphalt Institute are the only ones incorporated.

The third and final level consists of the "*failure mode*" for which the remaining life is to be determined. Two failure modes are currently incorporated for flexible pavements: rutting and fatigue cracking.

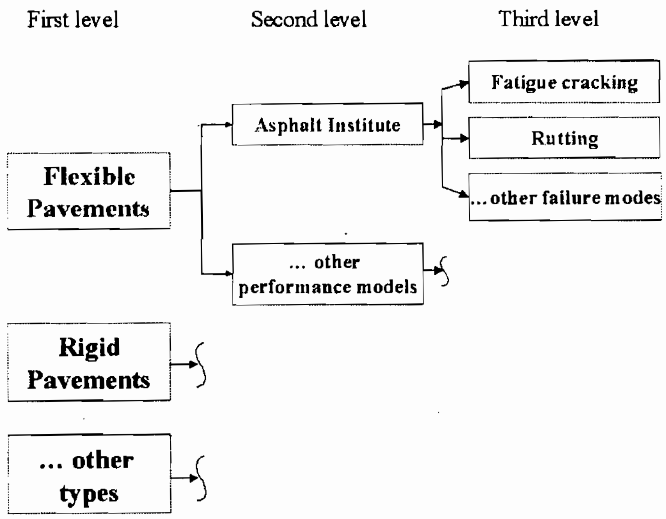


Figure 5.2 - Software Architecture: Three-Level Sub-Modules

The failure mode sub-modules that contain the ANN models are further comprised of three sections that perform specific data processing tasks. An ANN per pavement type per performance model per failure mode is integrated into the software to determine the corresponding remaining life (see Figure 5.3).

For each ANN, the input data (comprised of pavement thickness and FWD deflections) is read from a file and passed to the pre-processing section, where a set of mathematical functions transform the data before it is processed by the corresponding ANN. Immediately after, the transformed inputs are passed through the ANN and the corresponding remaining life is determined in a transformed space. To be able to interpret the results in real space, the transformed ANN output is passed through the post-processing section where another set of mathematical functions are used.

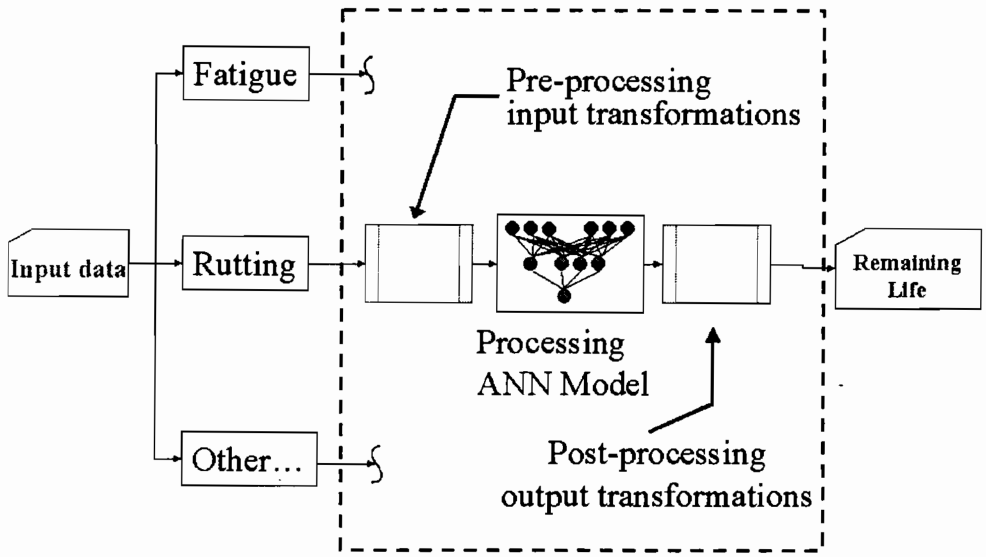


Figure 5.3 - Software Architecture: ANN Processing Sections

In the uncertainty analysis module, 250 Monte Carlo simulations per pavement case are conducted to determine the statistical parameters of the predicted remaining life. These parameters are later used to determine the remaining life's confidence intervals, and to establish confidence bounds on the PPC.

The C++ programming language proved to be suitable for the integration of the different methodologies used to determine the remaining life of a pavement, providing the framework to develop a modular and windows based application, without sacrificing user-friendliness. A typical program execution is described in Appendix B.

Chapter 6

Case Study

A case study is included in this chapter to demonstrate how the ANN-based methodology to predict the remaining life of pavements is applied. Information collected from one of the Texas Mobile Load Simulator (TxMLS) test sites is used to illustrate the process.

Description of Site

The site, located in Victoria, TX, is designated as Pad F5. The section is a four-layer asphalt-concrete pavement with the following nominal features:

- Asphalt layer of 75 mm (3 in.)
- Lime-treated base of 300 mm (12 in.)
- Lime-treated subbase of 150 mm (6 in.)
- Clayey subgrade

The test section was 3m (10 ft) wide by 12m (40 ft) long. To facilitate data collection, the test area was divided into a grid, as shown in Figure 6.1. FWD deflections were measured at each point on the grid. Only data from the middle of the section, shaded in the figure, were used in this case study.

Testing and Data Collection

The TxMLS personnel performed condition survey at predetermined load applications. The progression of rutting and fatigue are documented in Tables 6.1. This table contains the average rut, and percent fatigue cracking about the 6-m mark in the longitudinal direction (see Figure 6.1). The results from the FWD tests are included in Table 6.2.

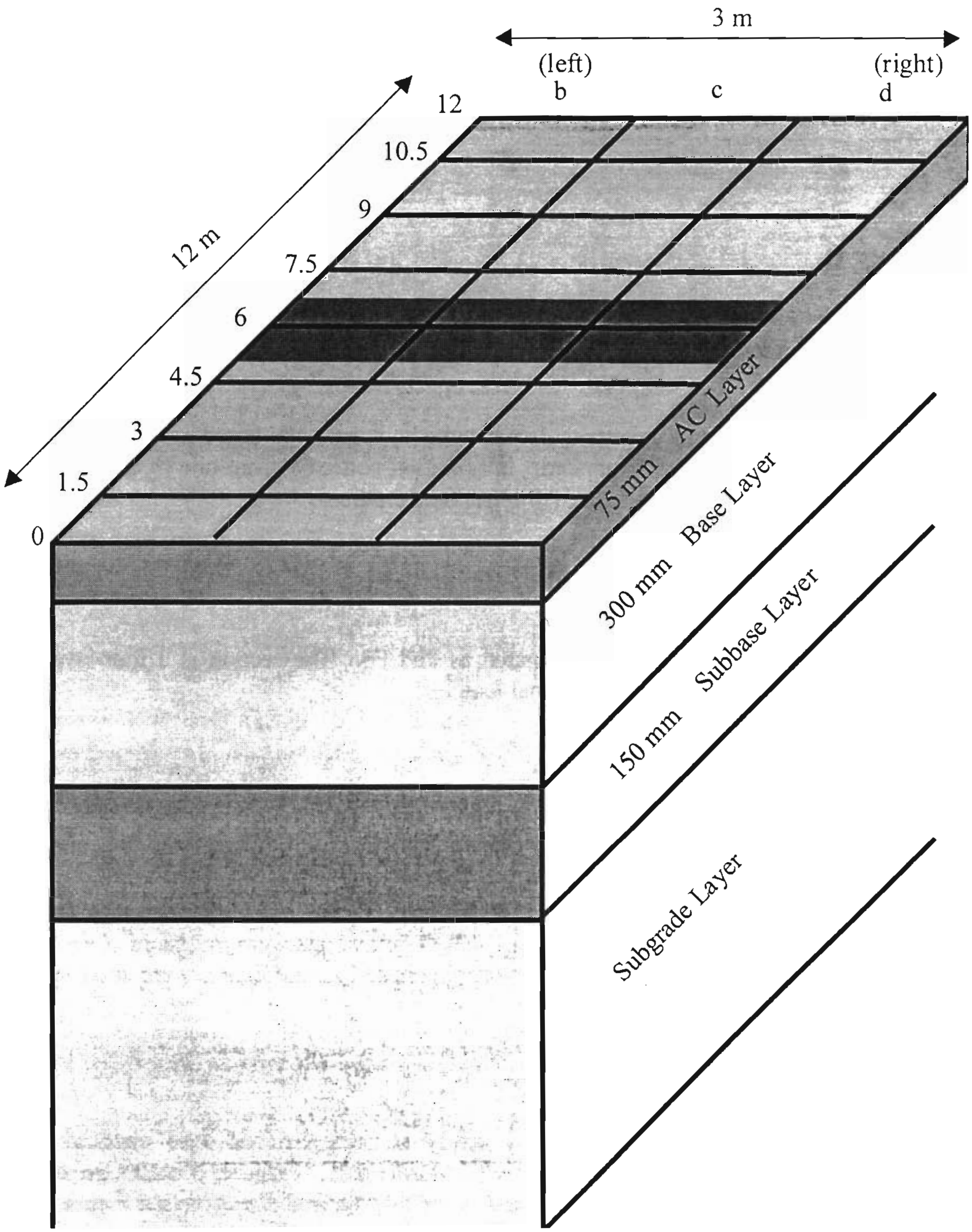


Figure 6.1 - MLS Pad F5 Test Section

Table 6.1 - Percent Cracking and Rutting Measured for Pad F5 at the 6-m Mark

MLS Axles	Percent Cracking		Rutting, (mm)
	Left	Right	Average
0	0	0	0.0
2500	0	0	0.5
5000	0	0	0.7
10000	0	0	1.0
20000	0	0	1.3
40000	0	0	1.9
80000	42	16	3.7
160000	43	16	4.7
320000	66	50	7.5
640000	69	60	9.8

Table 6.2 - FWD Data Collected for Pad F5

MLS Axles	Location	d0 (mm)	d1 (mm)	d2 (mm)	d3 (mm)	d4 (mm)	d5 (mm)	d6 (mm)
0	b	0.473	0.196	0.098	0.062	0.044	0.033	0.025
	c	0.448	0.201	0.101	0.064	0.043	0.031	0.022
	d	0.389	0.182	0.095	0.061	0.044	0.032	0.024
2500	b	0.471	0.209	0.103	0.064	0.044	0.031	0.023
	c	0.449	0.208	0.108	0.068	0.044	0.031	0.022
	d	0.404	0.196	0.102	0.064	0.045	0.033	0.024
5000	b	0.544	0.238	0.106	0.065	0.044	0.031	0.023
	c	0.457	0.211	0.108	0.068	0.044	0.029	0.023
	d	0.408	0.198	0.099	0.063	0.043	0.032	0.023
10000	b	0.533	0.227	0.108	0.066	0.044	0.032	0.023
	c	0.463	0.213	0.109	0.070	0.044	0.030	0.021
	d	0.430	0.207	0.105	0.064	0.043	0.031	0.021
20000	b	0.559	0.242	0.111	0.068	0.043	0.031	0.021
	c	0.484	0.222	0.114	0.070	0.047	0.032	0.023
	d	0.468	0.218	0.108	0.066	0.045	0.032	0.022
40000	b	0.561	0.250	0.111	0.067	0.043	0.031	0.020
	c	0.474	0.221	0.113	0.071	0.047	0.033	0.024
	d	0.460	0.227	0.109	0.065	0.044	0.033	0.023
80000	b	0.626	0.256	0.115	0.068	0.046	0.033	0.024
	c	0.480	0.220	0.117	0.073	0.048	0.033	0.024
	d	0.445	0.219	0.111	0.068	0.047	0.034	0.025
160000	b	0.610	0.259	0.103	0.062	0.043	0.032	0.023
	c	0.477	0.220	0.106	0.065	0.044	0.032	0.023
	d	0.446	0.209	0.097	0.059	0.043	0.031	0.022
320000	b	0.814	0.303	0.113	0.064	0.040	0.028	0.019
	c	0.503	0.230	0.118	0.072	0.045	0.031	0.021
	d	0.549	0.259	0.112	0.069	0.046	0.033	0.023
640000	b	0.769	0.284	0.128	0.073	0.046	0.034	0.025
	c	0.506	0.247	0.124	0.076	0.049	0.035	0.025
	d	0.570	0.251	0.122	0.072	0.050	0.037	0.027

ANN Models

Since pad F5 was a four-layer system, and the ANN models developed up to this phase of the project were for a three-layer system, three new ANN models had to be developed. These models consisted of: 1) an ANN to estimate the remaining life associated with rutting using the Asphalt Institute criterion, 2) an ANN to estimate remaining life associated with fatigue cracking using the Asphalt Institute criterion, and 3) an ANN to predict vertical compressive stress under the asphalt layer.

Chen et al. (1999) demonstrated that the rutting model that is based on calculating the rate of rut is reasonable for estimating the remaining life at the validation site used in this study. The general form of the equation is:

$$\log(RR) = C_1 + C_2 \log(d_0) + C_3 \log(N_{18}) + C_4 \log(\sigma_c) , \tag{6.1}$$

where RR = rate of rutting in microinches per axle load repetition, d_0 = surface deflection under the load plate in mils (obtained from the FWD test), N_{18} = equivalent 18-kip (80-KN) single-axle load, and σ_c = vertical compressive stress under the asphalt layer in psi.

The constants proposed by Finn et al. (1986), specifically for conventional construction with hot mix asphalt (HMA) less than 150 mm (6in.), are appropriate for this site. The constants are C_1 = Log (R_T) – 5.617, C_2 = 4.343, C_3 = -0.167 and C_4 = -1.118. Parameter R_T is the ratio of the observed rutting to the estimated rutting, and can be determined from:

$$R_T = 302.2 - 26.33(t_1) - 14.12(t_2) , \tag{6.2}$$

where t_1 and t_2 are the AC thickness and base thickness in inches, respectively. Equation 6.2 was proposed by Finn et al. (1986) as a calibration or a shift factor to adjust the estimated rutting based on field observations. Therefore, the ANN model that predicts the compressive stress was used in conjunction with the Finn et al. model.

To develop the ANN model, a database containing the thickness, modulus and remaining lives was created following the methodology explained in Chapter 3. The ranges of pavement properties considered in generating the database are reflected in Table 6.3. The values reported in the table were selected based on the available information from a trenching operation at the site and backcalculated moduli reported by Chen et al. (1998). As before, to execute any of the three ANN models, the only information needed is the thickness of the layers and the deflections from the FWD tests.

The remaining lives due to fatigue cracking from the conventional approach and the ANN models are included in Table 6.4. The conventional approach corresponds to backcalculating moduli from the deflection basin, calculating the tensile strain at the bottom of the AC layer, and using Equation 2.1 to estimate the remaining life. From Table 6.4, the conventional method and the ANN models provide reasonably close results given the shortcomings of the conventional method and the approximations involved in the ANN model. This statement is true for all FWD measurements reported in the table. The advantage of the ANN model, as indicated before, is that the results are provided instantaneously, without any need for backcalculation.

Table 6.3 - Pavement Sections used in ANN Model Development for this Case Study

Pavement Designs			Value	
			Minimum	**Maximum**
Asphalt Thickness	mm (in.)	(t_1)	51 (2)	102 (4)
Base Thickness	mm (in.)	(t_2)	254 (10)	356 (14)
Subbase Thickness	mm (in.)	(t_3)	76 (3)	229 (9)
Asphalt Modulus	MPa (ksi)	(E_{AC})	690 (100)	6900 (1000)
Base Modulus	MPa (ksi)	(E_{BASE})	69 (10)	690 (100)
Subbase Modulus	MPa (ksi)	($E_{SUBBASE}$)	69 (10)	2067 (300)
Subgrade Modulus	MPa (ksi)	($E_{SUBGRADE}$)	69 (10)	345 (50)

Table 6.4 - Remaining Life due to Fatigue Cracking

Methods	Location	Axles				
		0	**5000**	**20000**	**80000**	**320000**
ANN (million ESALS)	**Left**	498	336	332	228	109
	Right	1,008	889	600	750	344
Conventional* (million ESALS)	**Left**	661	405	378	256	192
	Right	1,276	986	758	859	406

* Asphalt Institute Equation

Similar results for the remaining life due to rutting are given in Table 6.5. The Asphalt Institute model (Equation 2.2) using the conventional approach yields remaining lives in the ranges of 4 million to 12 million ESALS. The ANN model reports a value of 2.8 million ESALS for all FWD test results. This value is the upper limit of the remaining life introduced to the ANN model. Since ANN models cannot extrapolate results outside the range of outputs that they are trained for, they return the upper limit as the response. Therefore, from the ANN models one can only deduce that the remaining life is in the excess of 2.8 million ESALS. One thing is clear from the results of both methods: Equation 2.2 is not appropriate for this site. These results clearly show that if the fundamental model is not accurately describing a phenomenon, the ANN models will not yield reasonable results.

As indicated before, the Finn et al. (1986) model for predicting the remaining life based on rutting is appropriate for this site. The rate of rut from the Finn model using the ANN and conventional methods are also compared in Table 6.5. The two methods yield fairly close results for the amount of approximation involved in the ANN model and the FWD backcalculated moduli.

Table 6.5 - Remaining Life due to Rutting

Model	Methods	Axles				
		0	5000	20000	80000	320000
Asphalt Institute (million ESALS)	ANN	2.8*	2.8*	2.8*	2.8*	2.8*
	Conventional	12.9	10.0	6.70	5.6	4.1
Finn et al. (log (RR))	ANN	4.09	1.69	1.34	0.99	0.70
	Conventional	4.32	1.84	1.49	1.11	0.80

* Upper bound of the trained ANN model

From the results shown in both Tables 6.4 and 6.5, it can be concluded that the ANN models are quite satisfactory, and can readily replace the conventional methods within the limitations they are trained for.

To demonstrate the strengths and the weaknesses of the pavement performance curves developed by the algorithm described in Chapter 5, the case study is expanded one more step. The observed pavement performance from condition survey is shown in Figure 6.2. Up to 40,000 repetitions, the section does not exhibit any cracking. At about 80,000 repetitions, the section can be considered as failed. As such, this case may not be as typical as those encountered under actual traffic.

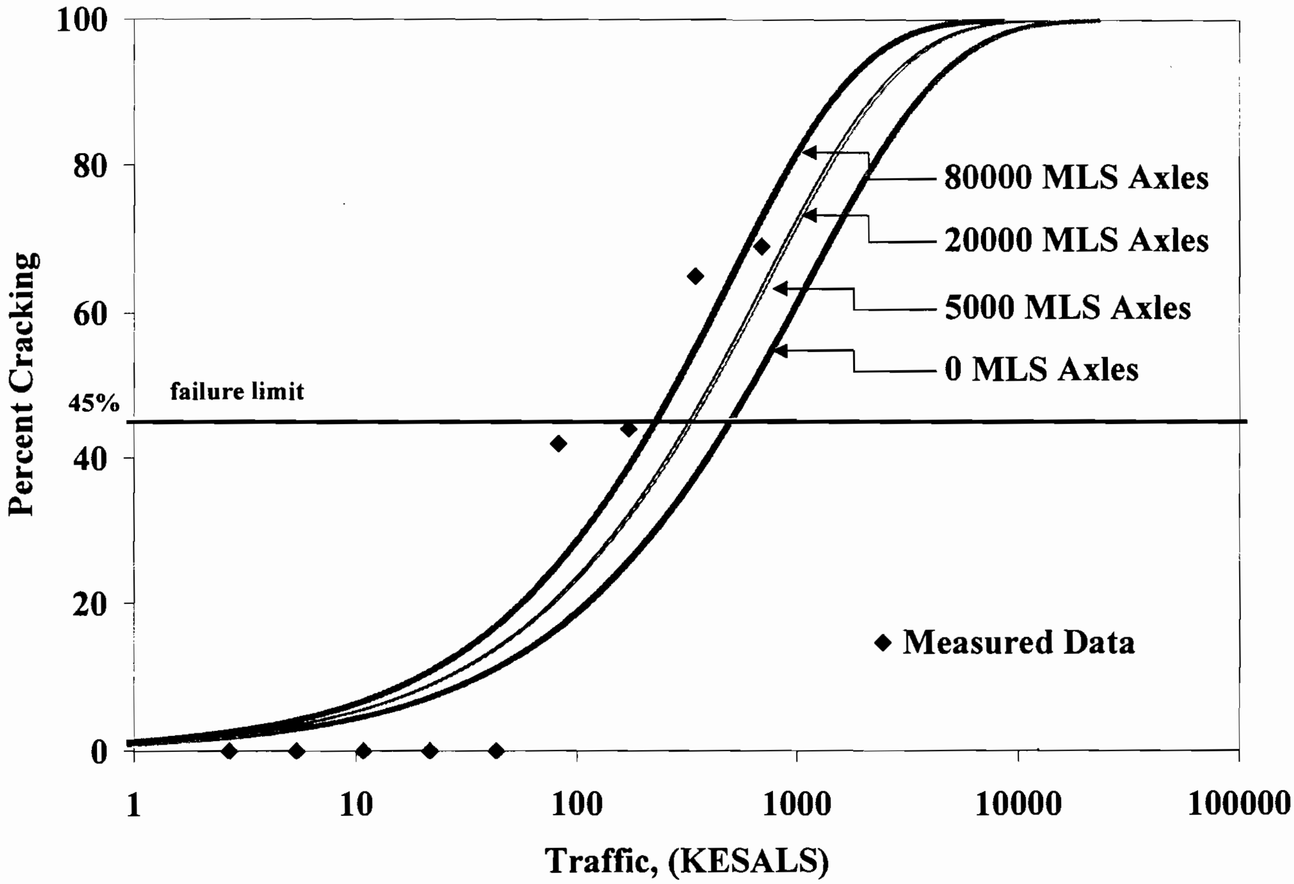


Figure 6.2 - Comparison of Percent Cracking for Pavement Performance Curves from ANN Models and InSitu Condition Survey (Condition Survey not Considered)

The pavement performance curves related to fatigue cracking from FWD tests at several load repetitions are also included in the figure. The procedure defined in Chapter 4 (Case 1) was used; that is only the data corresponding to remaining life from the ANN and the origin were used to develop the Weibull curves. From the figure, when the FWD deflection basin is used along with the Asphalt Institute failure model before the application of load, the PPC curve does not follow the observed results well. However, as the FWD data from greater load repetitions are used, the PPC becomes more representative of the observed progression of failure. The FWD results past 160,000 repetitions are not used because, by definition, the section can be considered as failed.

The same case study is repeated again with one difference. The condition of the pavement, in terms of cracking or rutting at the time of FWD test, is also considered. When the percent cracking is more than zero, the Weibull curve is fitted to three points (consisting of origin, the result from the ANN model, and a point corresponding to the condition of the pavement at the time of FWD test). On the other hand, when no cracks are evident at the site, the Weibull curve is fitted to two points (the results from the ANN model and the point corresponding to the condition of the pavement at the time of FWD test). The results are included in Figure 6.3. The PPC from the FWD tests before applying the load is identical to that shown in Figure 6.2. The PPC's from FWD data and condition surveys after 5,000 and 20,000 load repetitions predict final failure better. However, the pattern to final failure is not very accurate. Finally, from NDT and condition survey at 80,000 repetitions, the performance curve is quite realistic.

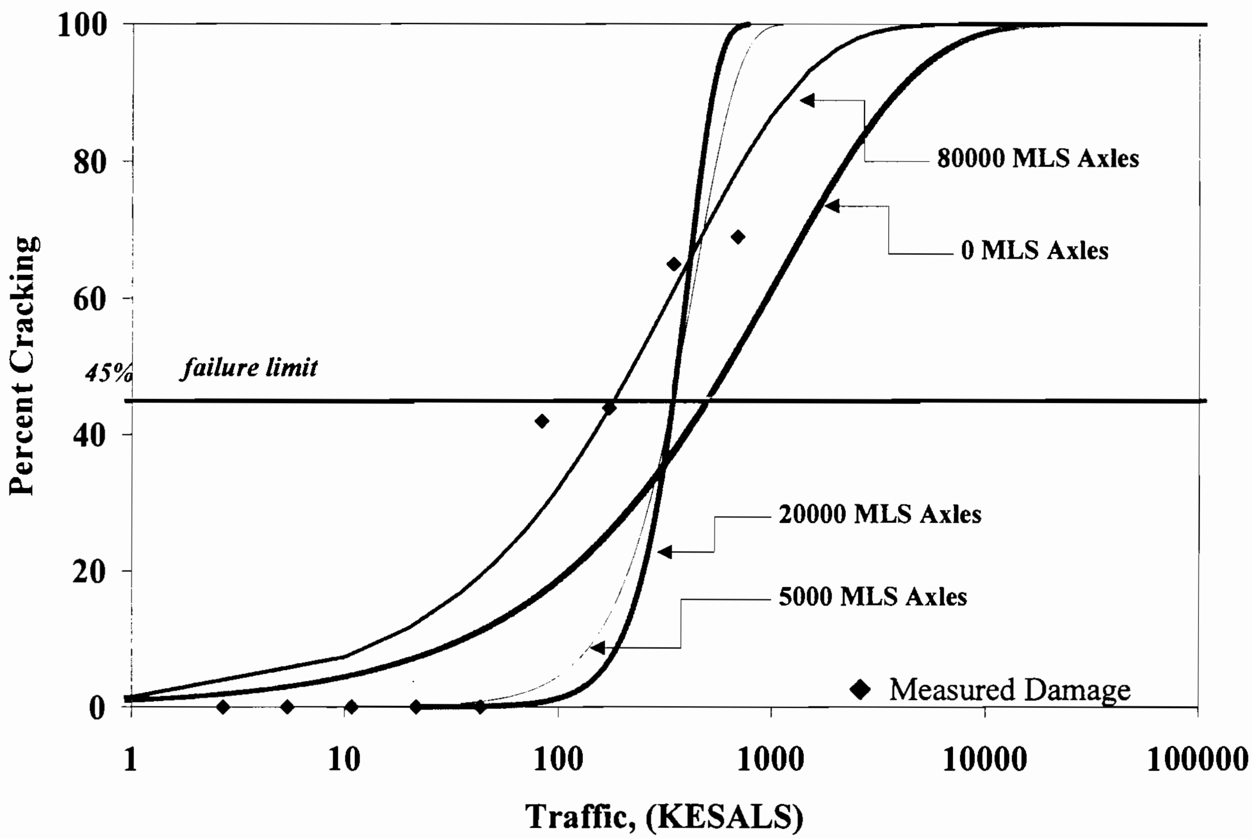


Figure 6.3 - Comparison of Percent Cracking for Pavement Performance Curves from ANN Models and InSitu Condition Survey (Condition Survey Considered)

The impact of combining the structural and functional results in determining the remaining life is reflected in Figure 6.4. Three performance curves are shown in Figures 6.4a and 6.4b. One performance curve corresponds to when only the condition survey is used to predict the remaining life. At 20,000 axle repetitions, that PPC is not representative of the behavior of the pavement (the curve is superimposed on the x-axis); whereas for 80,000 repetitions, the performance curve is more representative of the in situ condition, but still underestimates the behavior of the pavement. The same trend is also applicable when only structural condition is considered, except that the performance is over-estimated. When both the condition survey and FWD data are considered, the performance curves for both 20,000 and 80,000 repetitions are more representative of the actual pavement condition. However, for 20,000 repetitions, the intermediate cracking is not predicted well because the actual field condition resembles a step function.

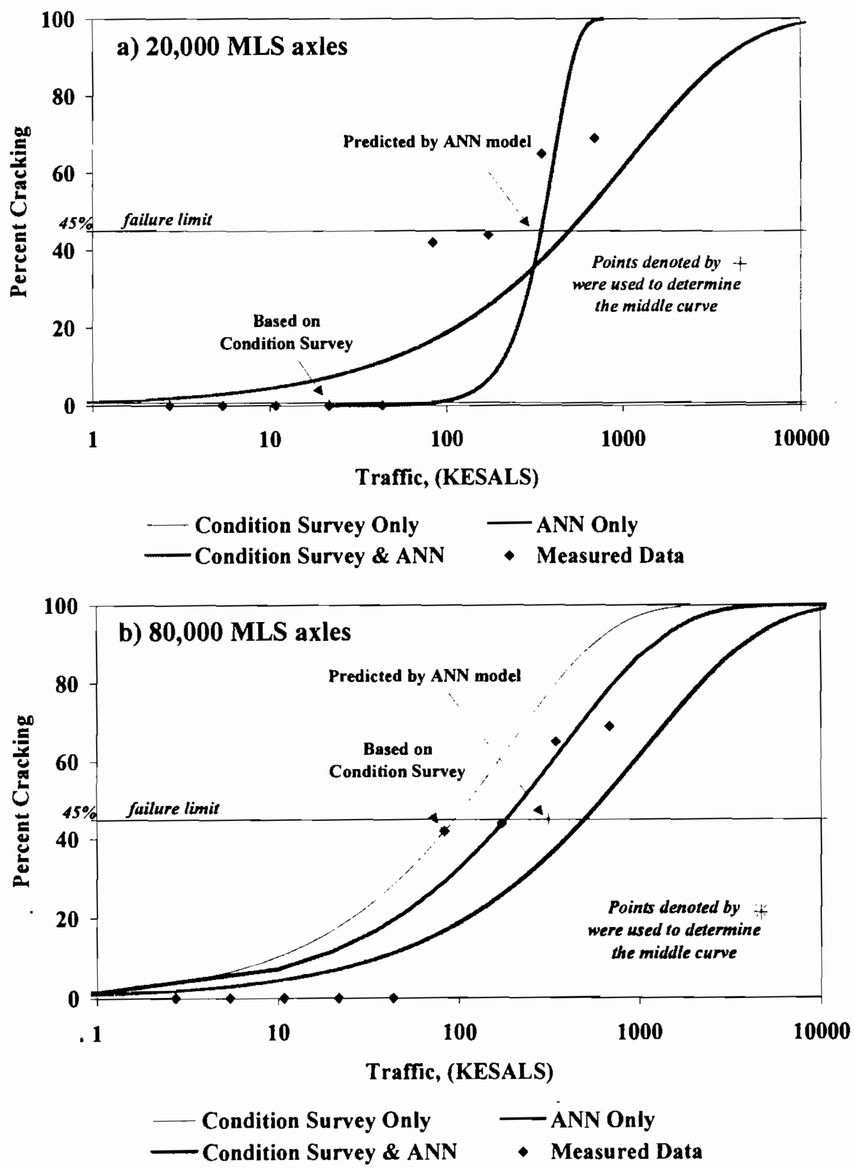


Figure 6.4 - Comparison of Different Models used in Predicting Pavement Performance due to Fatigue Cracking

This case study shows that in order to better predict the future behavior of a pavement section, the structural and functional conditions of the pavement should be combined.

As indicated before, the predictions of the Asphalt Institute model for rutting was unrealistically high. This occurred because the AI model is not appropriate for this site. It is impossible to obtain realistic results from an inappropriate model, independent of the method used. However, the Finn model seems to be appropriate for the site.

The same process used to illustrate the PPC for fatigue cracking is used for rutting. Figure 6.5 compares variations in rut depth based on results of the Finn et al. model with measured rutting. The pavement performance curves were constructed by fitting a Weibull curve using Case 1 and Case 2 as defined in Chapter 4. Figure 6.5a shows the PPC based on two points (Case 1). Figure 2 shows the PPC when the condition survey is used to develop the curve (Case 2). Since the Finn model is based on the rate of rutting, the FWD data from before the application of the load cannot be used. Figure 6.5, the short-term rutting of the pavement is reasonably accurately predicted in all cases. However, as expected, the final rut depth is more accurately estimated when the condition survey is considered and for FWD data at higher axle repetitions.

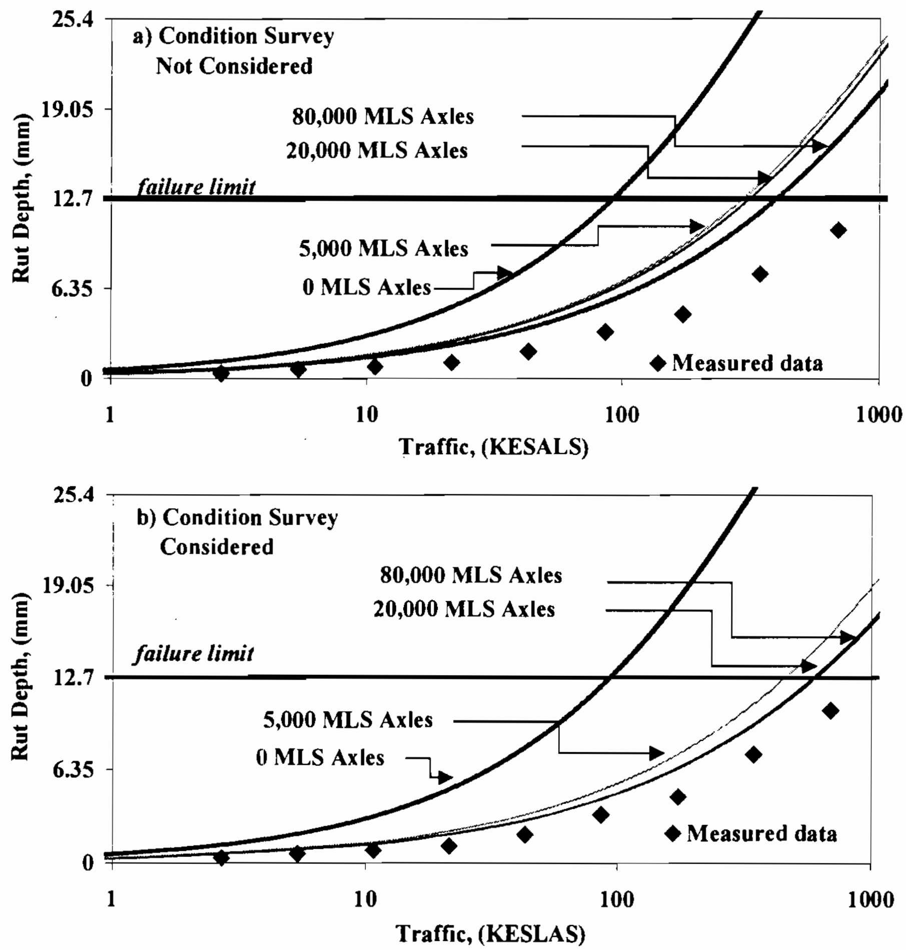


Figure 6.5 - Comparison of Rut Depth for Pavement Performance Curves from ANN Models and InSitu Condition Survey

Figure 6.6 shows the actual variations in rut depth with the number of ESALs as well as estimated PPC from the three strategies: 1) only the condition survey considered, 2) only ANN results considered, and 3) both condition survey and ANN results are considered. Once again, the results show that the most realistic PPCs are determined when the structural and functional conditions of the pavement are combined.

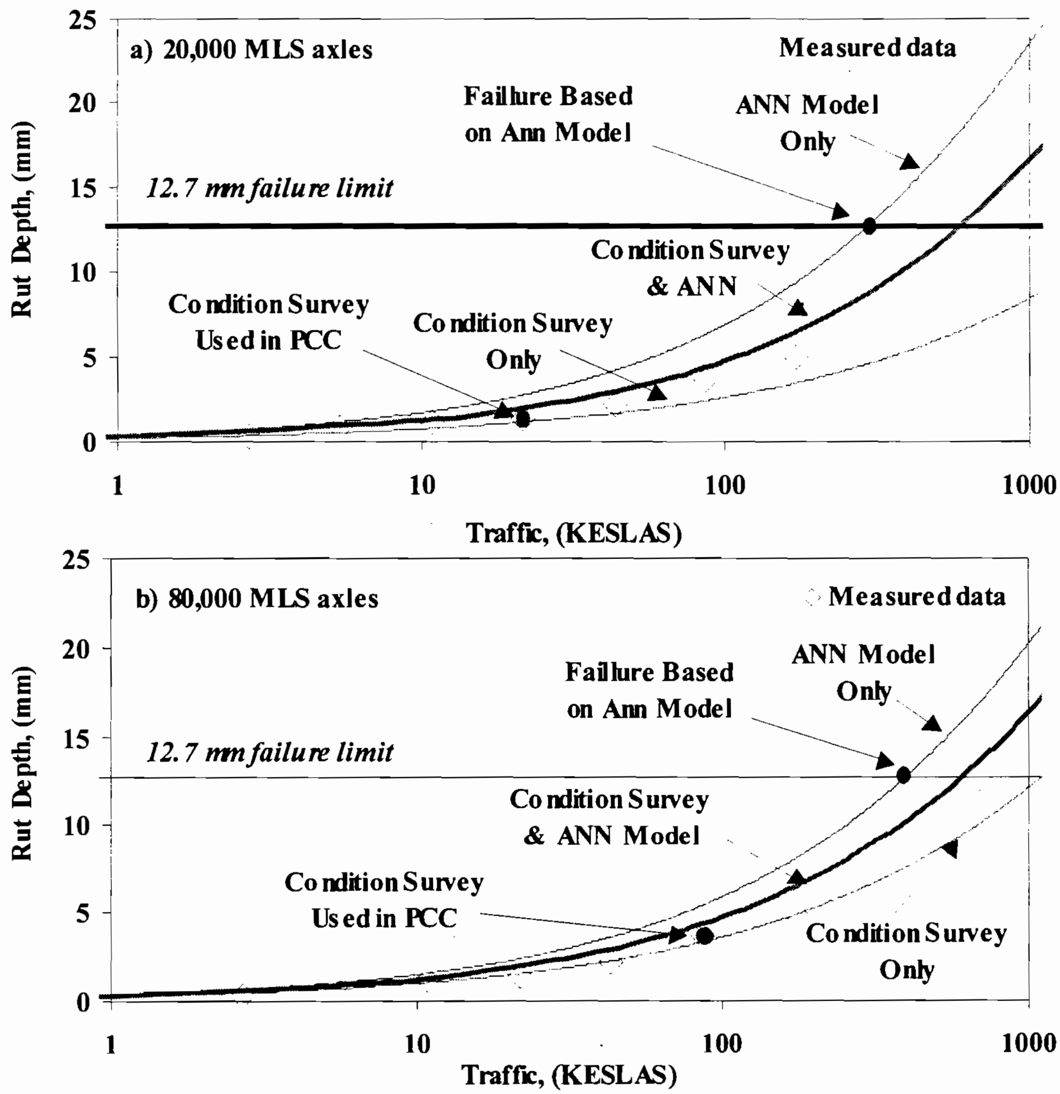


Figure 6.6 - Comparison of Actual Rutting Performance Curve with Calculated Ones Using Several Strategies

Chapter 7

Summary and Conclusions

This report summarizes the efforts to develop a methodology based on the Artificial Neural Networks to process data from NDE tests, such as the Falling Weight Deflectometer, to estimate the remaining life of a pavement. The project has progressed with close cooperation between TxDOT and UTEP.

The following items summarize the achievements during the period covered by this report.

1. Artificial neural network models were developed which rapidly and reliably predict the remaining lives of flexible pavements. Other models were developed to predict the critical strains at the interfaces of the layers.

2. An algorithm has been developed to assess the influence that uncertainty (variability) in the input variables has on the predicted remaining life and critical strains.

3. An algorithm to produce a pavement performance curve that incorporates the results of the ANN models, condition survey and traffic has been developed.

4. A modular software that incorporates all methodologies and algorithms described in this report, is being developed.

The following is a detailed assessment of the status of this project:

1. Four general ANN models have been developed, two models to predict the remaining life of flexible pavements, based on two possible failure modes of the pavement; and two models to predict the critical strains which can be used in existing remaining life models. The models are based on a three-layer system and a constant depth to bedrock. Based on discussions between TXDOT and UTEP, and on the success of the ANN models, a set of ANN models is being developed to predict critical stresses, critical strains, and remaining lives of pavements for three-layer and four-layer systems with varying depth to bedrock.

2. The software includes
   - ANN models,
   - algorithms for estimating the uncertainty in the predicted remaining life and critical strains,
   - methodology to establish upper and lower bounds for the pavement performance curve, and
   - graphical results module.

3. A case study has been conducted on an MLS site. This allowed for both UTEP researchers and TXDOT personnel to initially verify the methodology, proposed in this report, using real data. Although the output for this case study shows promising results, further studies will be conducted when new data become available.

Artificial Neural Network technology has proven to be a feasible and practical approach in the development of models to assess the integrity of pavements using data that is readily available to the pavement engineer. This is particularly advantageous because other approaches require information from laboratory tests, making the assessment more tedious and time consuming. Another advantage of an ANN model over traditional approaches is that the remaining life can be calculated without having to backcalculate the elastic moduli of each pavement layer.

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Appendix A

Summary of Available Literature on ANN Applications in Pavement Engineering

Table A1 - Neural Network Applications to Pavements

APPLICATION	NETWORK TYPE/ (TRANSFER FUNCTION)	SOFT WARE	INPUT	OUTPUT	No. OF HIDDEN LAYERS	No. OF NODES PER HIDDEN LAYER.	No. OF TRAINING EXAMPLES	No. OF TESTING EXAMPLES	COMMENTS
Classification of types of cracks from video images [Chou et.al. 1995] [Chou et.al. 1994]	B	Neural Ware	(17) Moment invariants 4 Bamiek 7 Hu 6 Zernike	(7) Different types of cracks.	(1)	(17)	(36-135) (2000 epochs)	(6-27)	Data provided by NCHRP 1-27; Neural network classified 100% of the cases. The largest output value determines type of distress.
Determination of condition rating (CR) of : R/C pavements. [Eldin and Senouci 1995]	B (Sigmoid)	N/A	(15) Distress severity levels and density.	(1) CR	(1)	(6)	298 w/ 60% of noise	3902 w/60% of noise	Data provided by ODOT; Neural Networks were able to identify CR even with high noise levels with a 95% confidence level.
Jointed concrete pavements. [Eldin and Senouci 1995a]			22 (a)				1202 (a)	6812 (a)	
Flexible pavements [Eldin and Senouci 1995b]			17 (b)				774 (b)	1736 (b)	
Automated inversion of SASW test data to evaluate elastic moduli and layer thickness [Gucunski et.al. 1995]	B	Neuro Shell 2 Window s ver.	(6 ?) Dispersion curve and associated profile with 5 parameters based on shearwave velocity and thickness of AC layer	(6) 3 layer thicknesses and 3 shearwave velocities	(1)	(70)	152 patterns	36 patterns	Data collected from state of New Jersey roads; Training was over when both neural networks showed the same mean squarred error; The 5 layer neural network was the best of both, it predicted everything except the thickness of the subbase layer.
	B				(3)	(total of 66)			

* B: Backpropagation; F-F: Feed-forward; GA: Genetic Algorithm; GANNT: Genetic Adaptive Neural Network Training; N/A: Not available; η:learning coefficient

Table A1 - Neural Network Applications to Pavements Cont.....

APPLICATION	NETWORK TYPE/ (TRANSFER FUNCTION)	SOFT WARE	INPUT	OUTPUT	No. OF HIDDEN LAYERS	No. OF NODES PER HIDDEN LAYER.	No. OF TRAINING EXAMPLES	No. OF TESTING EXAMPLES	COMMENTS
Interpretation of raw data from ultrasonic pulse echo (UPE) for NDT of concrete structures [Haskins and Alexander 1995]	B	Neural Network Toolbox for Matlab	(N/A) UPE signals	(N/A) Ultrasonic Pulse Velocity signals as target values	N/A	N/A	186 UPE signals	30 UPE signals	Data provided by USACE; Neural network was able to rank concrete specimens in correct order of deterioration.
Select maintenance strategy for pavements. [Taha and Hana, 1995]	B with GA using mutation and crossover = 1.0	Brain Maker with genetic training option	(16) [binary] Distress type, density, severity, riding comfort index, traffic vol.,climate, crack type.	(7) [binary] Mainte-nance strategy	(1)	(16)	235 (100 epochs)	100	Data previously used (?); Ten networks are created over 50 generations; The best network is selected after training; Six out of 100 cases were misclassified.
Recommended M & R actions based on pavement condition [Alsugair and Sharaf 1994]	B	N/A	(57) 19 distress types with 3 severity levels.	(13) Different M & R actions.	(1)	(40)	55	30	Data collected by visual observation of Egyptian road network; Some sets were obtained with PAVER; Accuracy of network was 66 %; No examples are given.
Automated pavement condition evaluation system [Garrick et.al. 1994]	MLF-F (SQP algorithm)	N/A	(3-12) features of distress (3 pixel densities and angle of inclination	(1) Type of distress recognized	(1)	(6)	60 images	23 images	Data collected from ConnDOT; Neural network had a success rate of over 90 %

* B: Backpropagation; N/A: Not available

Table A1 - Neural Network Applications to Pavements Cont...

APPLICATION	NETWORK TYPE/ (TRANSFER FUNCTION)	SOFT WARE	INPUT	OUTPUT	No. OF HIDDEN LAYERS	No. OF NODES PER HIDDEN LAYER.	No. OF TRAINING EXAMPLES	No. OF TESTING EXAMPLES	COMMENTS
Backcalculate pavement moduli [Meier and Rix 1994]	B	N/A	(9) 2 thicknesses 7 deflections	(3) Layer Moduli	(2)	(11-8)	9750	250	Data generated; Both networks give robust estimates of moduli w/noise and are faster than other searching techniques.
						(5-15)	9750 w/noise	250	
Priority assessment of Highway pavements maintenance needs [Fwa and Chan, 1993]	B (Sigmoid)	Neural Works	(6) Indices for highway functional class, skid resistance, crack width, crack length, pavement serviceability, rut depth.	(1) Priority rating score.	(1)	(1)	(128-12500) SET I: linear and non-linear data - structured - random	300	Data generated; Network can learn regardless of data generation methodology and with up to a 50% level of noise.
							SET II: data w/several noise levels		
							SET III: empirical data		
Automatic process and analysis of moire fringes of pavement surface [Guralnick et.al. 1993]	B ML	Neural Ware	(N/A) Binarized pattern of pavement image	(N/A) Reproduced image of the surface	(1)	(10)	500 and 3000	N/A	Sensitivity accuracy and efficiency of the NN was compared to results from other fringe thinning algorithms; Reproduced surface resembles actual surface with 2% error.
Conditions assessment of utility cuts [Pant et. al. 1993]	B (Sigmoid)	Neural Works Profess. II Plus	(30) Type and severity of distress (data preprocessed).	(1) Utility Cut Condition Index	(1)	(10)	721	311	Data collected in Cincinnati; Utility Cut Condition Index determined w/ Delphi method; Network accurately predicted 92 % of the outputs.

* F-F: Feed-forward; ML: Multi-layered; N/A: Not available

Table A2 - Neural Network Applications to Pavements: Comparison Studies

APPLICATION	NETWORK TYPE/ (TRANSFER FUNCTION)	SOFT WARE	INPUT	OUTPUT	No. OF HIDDEN LAYERS	No. OF NODES PER HIDDEN LAYER.	No. OF TRAINING EXAMPLES	No. OF TESTING EXAMPLES	COMMENTS
Prediction of pavement condition rating (PCR) [Shekharan and George 1997]	Modular GANNT F-F	N/A	(?) Pavement structure, age, traffic, route classification.	(1) PCR	(1)	(8)	N/A	N/A	Data provided by ODOT; Results compared to those of regression models are similar; Network is a viable alternative.
Predict skid resistance to assess future rehabilitation needs on flexible pavements. [Owusu-Ababio 1995]	Adaptive modeling procedure (quadratic function)	Auto Net	(4) Pavement age, AADT, speed limits, pavement regional location.	(1) Skid number.	(2)	(total of 5)	45	15	Data provided by ConnDOT; Compared to Linear Regression LR model using the mean error (E) and the coeff. of determination (R^2); Network gives lower (E) and higher (R^2); Network fits better than LR.
Crack type pattern classification from pavement images. [Kaseko et.al.1994]	B MLF-F (sigmoid ?) α=0.7 η=0.1	"C" progrm .lang.	(5) Parameters extracted from histogram of distressed pixels in binary image, such as: distressed pixel density, variances of distressed pixels in several orientations.	(5) Crack types.	(1)	(5)	230	230	Data provided by NCHRP 1-27; Both neural networks perform slightly better than Baye's classifiers and k-NN classifiers on the test data set.
	2PWL i)competitive learning ii) Kohonen LVQ2 rule (η=decaying function)				No. of modules (?)	No.of nodes per module (3)			

* AADT: Annual average daily traffic; B: Backpropagation; F-F: Feed-forward; GANNT: Genetic Adaptive Neural Network Training; LVQ2: Learning vector quantization 2; ML: Multi-layered; N/A: Not available; 2PWL: two-stage piecewise linear; α:momentum gain; η:learning coefficient

Table A2 - Neural Network Applications to Pavements: Comparison Studies Cont...

APPLICATION	NETWORK TYPE/ (TRANSFER FUNCTION)	SOFT WARE	INPUT	OUTPUT	No. OF HIDDEN LAYERS	No. OF NODES PER HIDDEN LAYER.	No. OF TRAINING EXAMPLES	No. OF TESTING EXAMPLES	COMMENTS
Selection of pavement sections for routing and sealing (R&S) maintenance treatment. [Hajek and Hurdal 1993]	B (sigmoid) learning rate=1 to guarantee convergence if possible	Brain Maker Profess II Plus	(40) 15 pavement surface defects 30 severity and density of defects	(1) Desirability of R&S (scale from 0-10)	N/A	N/A Set to automatic neuron selection	148 pavement sections Provided b MTO	20 pavement sections	Neural network is compared against a rule-based expert system ROSE; Input-output training sets were determined by ROSE; Network yields comparable results to ROSE's for higher desirabilities (range from 6-10); Network is faster and easier to develop, has greater generalization ability and can include uncertainty implicitly as part of training; Network does not explain reasoning.
Automated thresholding of 255 asphalt concrete pavement images. [Kaseko et.al. 1993]	MLF-F	N/A	(3) Mean and std. dev. of gray level histogram and co-occurrence parameter	(1) Threshold value	(1)	(3)	130 image vectors	125 image vectors	Data provided by NCHRP 1-27; Neural network compared to linear regression model; Neural network unnecessary due to strong linear relationship between input and output.
Prediction of a pavement condition index (PCI). [Schwartz 1993]	N/A	N/A	(?) Pavement age, traffic, subgrade strength and other variables	(1) PCI	N/A	N/A	N/A	N/A	None

* B: Backpropagation; F-F: Feed-forward; ML: Multi-layered; N/A: Not available

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Appendix B

Software Overview

Opening and Running the Program

Once the software has been completely installed and run, the main menu appears on the screen.

Four menu items show in the menu bar: 1) *Project Information*, 2) *Life & Uncertainty*, 3*) Results and Reliability* and 4) *Help*. The first three correspond to the main modules integrated in the software. In addition to the main menu items, a Help menu item is included, for later incorporation of a Help file.

Under each menu item a list of submenus are "nested" or associated to the main menu items. These submenus correspond to the different levels of sub-modules described in Chapter 6 (Figure B.1). The general flow of execution is from left to right, starting with the project information definition.

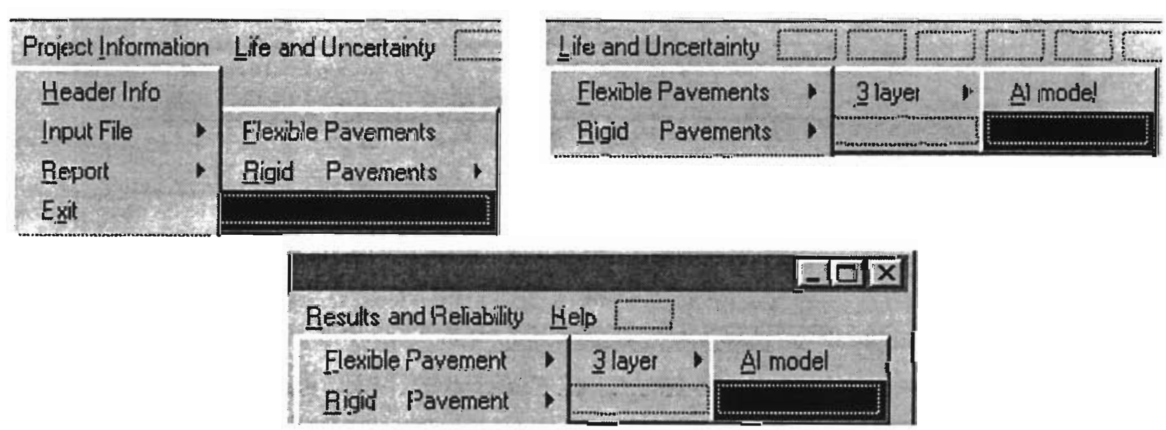

Figure B.1 - Typical Menu Items and Nested Menus

Project Information

The first main menu item to choose is the *Project Information/ Header Info*. A window frame will appear on the screen with several edit boxes prompting for executive information that describes the project under analysis (see Figure B.2).

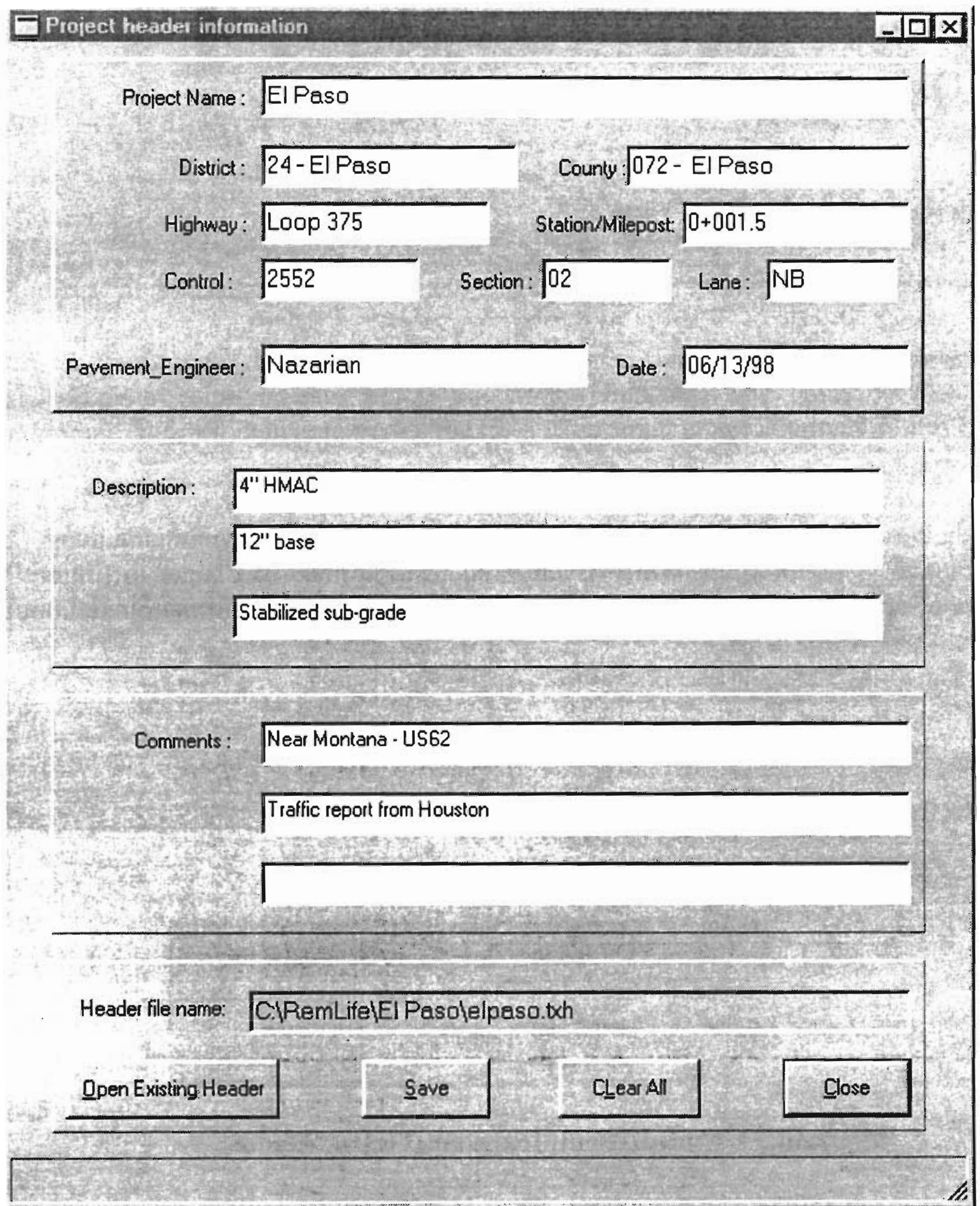

Figure B.2 - Project Header Information Window

The information may be entered and then saved into a text file, or an existing file can be opened and modified for ease of use. Typical information entered includes project location, test date, pavement description, and a section for additional comments and other pertinent information.

The above information is not required to process the remaining life, yet it will be used to customize the final report.

Data Management within the Software

The program requires that all the project data including the input and output data be stored in a dBase table, hereinafter the "project file", throughout the execution of the program. This particular feature of the program is justified under the following reasons:

1. dBase is a universal format, allowing portability among software programs,
2. data management, data manipulation and program maintenance is easier and faster,
3. allows faster and safer access to the data,
4. the C++ developer software has several built-in functions to access and manipulate database tables allowing easier programming, as opposed to accessing and manipulating text files,
5. all of the above comply with the initial criteria of developing a modular architecture program.

When using the software, the user does not require to be experienced in using or programming databases. The manipulation of the dBase table is "invisible" to the user, since it is an internal process within the program. The user only sees a grid displaying the data values.
The "project file" is generated using the corresponding template file (e.g. F3AI.dbf). This file is chosen when the user selects the pavement type, layer system and analysis model under the *Project Information/ Input file* menu items (see Figure B.3).

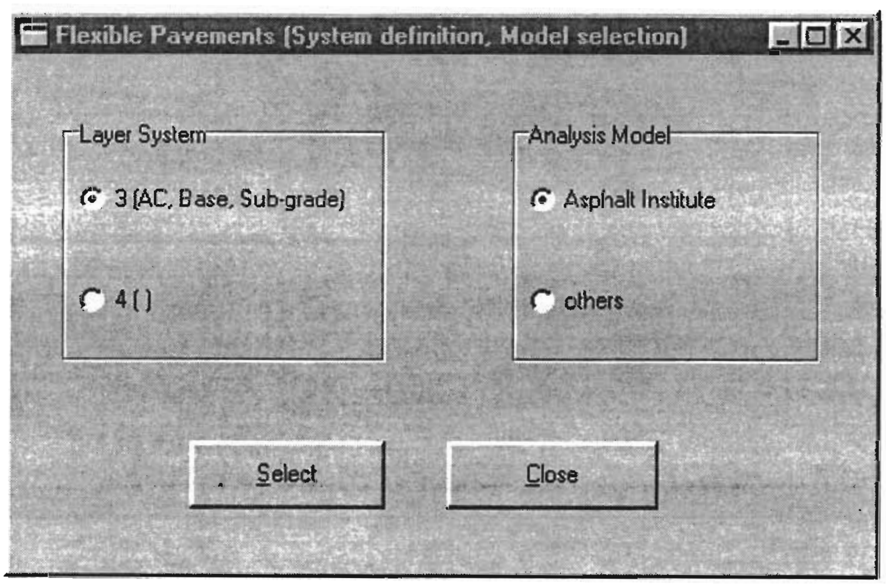

Figure B.3 - Layer System/Analysis Model Window for Flexible Pavements

Currently, the software defaults to a three-layer system and the Asphalt Institute model. As different layer systems and performance models become available, they will be incorporated in the software and this window will be updated accordingly.

Once the pavement type and layer system options are defined and the performance model is chosen, the Create/Edit Project File window shows on the screen. This window might be slightly different for other pavement types. The window shown in Figure B.4 corresponds to the typical input format for a three-layer flexible pavement.

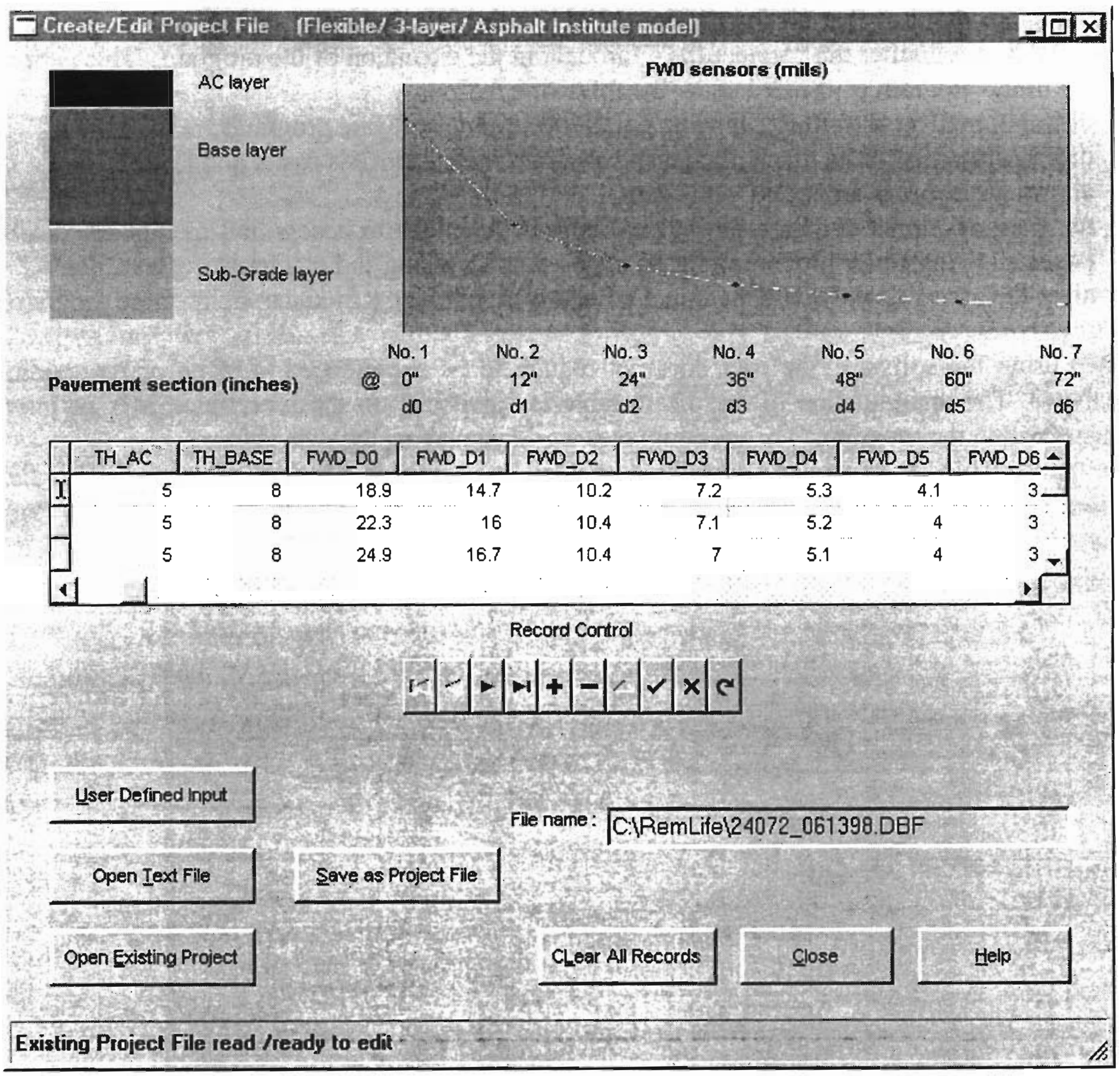

Figure B.4 - Create/Edit Project File Window for a 3-Layer Flexible Pavement

The user has three options to generate the "project file", listed as follows:

a) *User Defined Input*: by clicking on this button, the user creates a new project file. First a new file name must be entered in the Open dialog box shown in Figure B.5. Currently, the user must choose the "system folder" and type the name of the new file. The user must type a file name that is not currently existent in the selected folder. The dialog box displays the existing database table files in the current folder for this purpose.

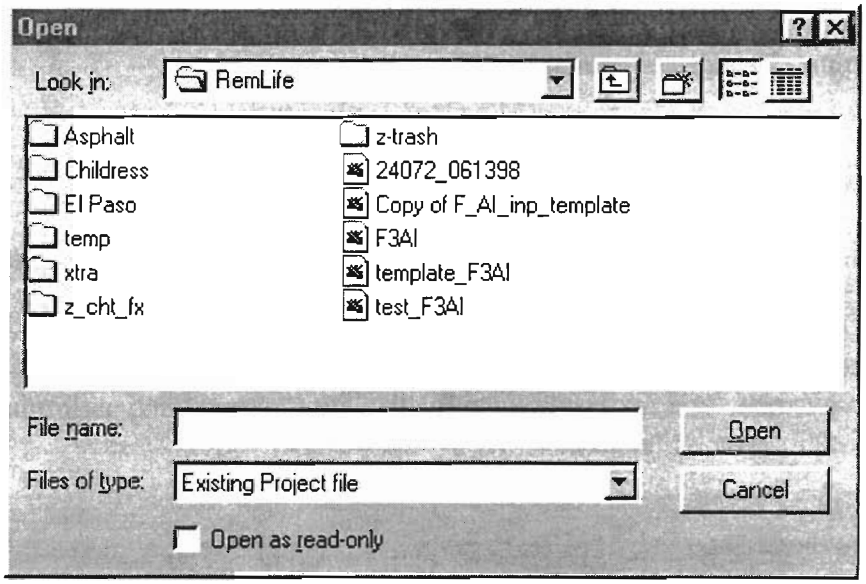

Figure B.5 - Typical Open Dialog Box to Choose a New Project File or Open an Existing One

b) *Open Text File*: By clicking on this button the user is allowed to open a text file (*.txt) from a similar open dialog box as in Figure B.5 and edit the data if necessary.

c) *Open Existing Project*: The user can also open an existing project file in dBase format (*.dbf) if desired. Figure B.4 shows the data retrieved from an existing project file and displayed in the datagrid.

The dBase and Text formats are commonly used file formats, and are also compliant with TxDOT standards. Therefore, the reason for having only these formats incorporated.

Once the new file name is entered or an existing one is chosen, the template file is used to generate the new database table. The control is returned to the Create/Input File window to start entering or editing the input parameters in the data grid.

The user must always click on the "Save as Project File" button to insure that the database table is generated. When saving the project file, a suffix is appended to the file name (*_F3AI.dbf) with the name of the template that generated the project file. This feature allows easy identification of project files since it contains the minimum information regarding pavement type, number of layers and analysis model.

In this window the user is allowed to scroll over the data, by use of the record control buttons and scroll bars. The buttons can scroll the database and position the cursor on a certain record (e.g. the first record, the next, the previous or the last record), and allow the user to add entire new records, delete or edit existing ones and refresh and update the database. Help hints are available under each control button for easy identification. Likewise, the scroll bars allow similar tasks except for database editing.

Once the project file has been saved, the following task is to process the inputs through the ANN models to determine the expected remaining life.

Remaining Life Processing with Uncertainty Analysis

At this point the "project file" should contain the necessary input parameters, namely the pavement' layer thickness and the FWD deflections.
To process the remaining life through the corresponding ANN models, the second main module must be accessed by choosing under the second main menu item *Life and Uncertainty* the corresponding pavement type and subsequently the layer system and performance model (e.g. *Flexible Pavement/ 3 layer/ AI model*).

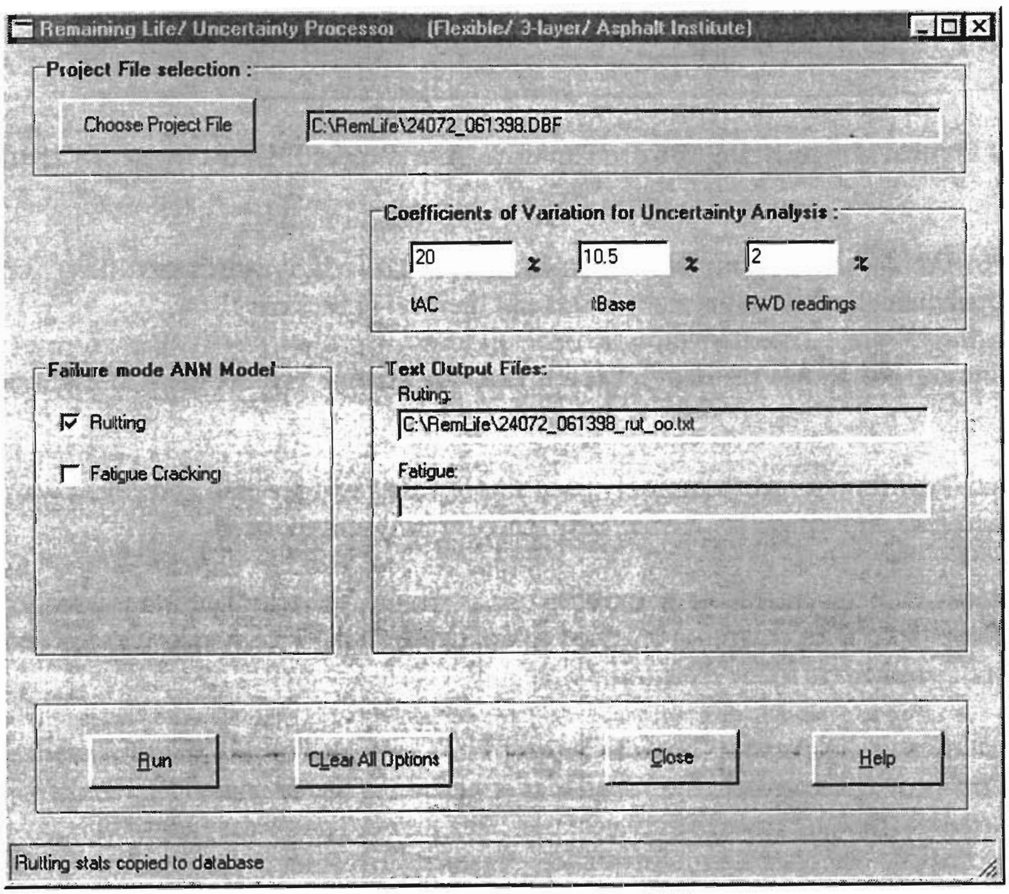

Figure B.6 - ANN Model Selection and Uncertainty Analysis Parameters

When accessing this module, the window depicted in Figure B.6 is displayed on the screen. In this window the user must do the following:

a) first select the ANN model(s) under which the remaining life is to be determined. For a flexible pavement, rutting and fatigue cracking are currently available;
b) choose the project file that contains the input data;
c) enter coefficients of variation for each input parameter. These values are assigned empirically or can be obtained from published references.

Once these options are set, the processing starts after clicking the "Run" button. The processing will take anywhere from several seconds to several minutes, depending on the number of cases to be analyzed. During the run, the status of the processing is displayed at the bar located at the bottom of the window.

Both the deterministic remaining life values and the corresponding statistical parameters are determined. These values are stored in the "project file" and for practical purposes, separate text files are also created containing the input and output values.

When the processing is finished, the output text filenames are displayed in the edit boxes located in the middle portion of the window. The window may then be closed to continue with the next step is to view the results and inspect the performance of the pavement with the presence of traffic and conduct the reliability study for final analysis. This is accomplished in the third main module of the software described in the following section.

Pavement Remaining Life/ Expected Performance and Reliability Analysis

Once the remaining life values and the corresponding uncertainty parameters have been determined in the ANN/Uncertainty module, the results are combined with traffic data to build a Pavement Performance Curve (PPC) and conduct a Reliability Analysis.

To access the *Reliability and Results* module, the user selects from the main window the menu item with the same title, and in addition selects the typical options (pavement type, layer system and performance model). The corresponding window will appear on the screen.

To see the PPC displayed, the user must follow the next steps (see figure B.7):

a) first choose the "project file" that contains the determined remaining life values;
b) choose a failure mode for which the remaining life has been determined. If the remaining life values are available for the failure mode selected, the corresponding PPC will appear on the window based on default traffic and damage data;
c) set or change the traffic and damage data such as pavement age, cumulative traffic after the first year the pavement was built, traffic growth, amount of damage at the time the NDT was performed among others, to see the effects on the pavement' life.

The PPC chart also highlights the failure limit criteria boundary set for the corresponding performance model. Moreover, the remaining life in years is computed and displayed.

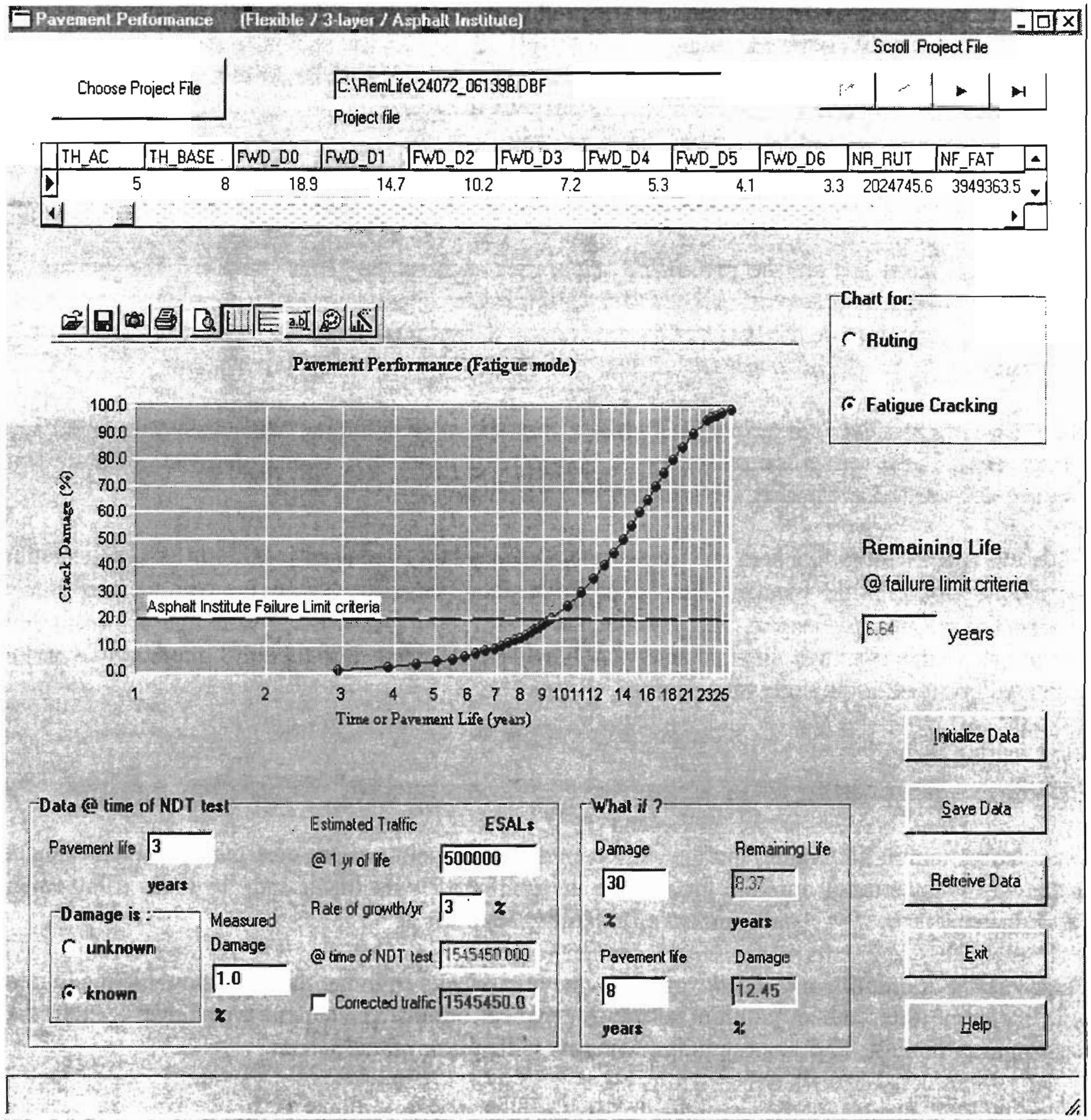

Figure B.7 - Pavement Performance Curve, Traffic and Damage Data

Some of the features integrated in this window allow the user to: a) toggle between failure modes to compare the corresponding PPC's; b) scroll over the "project file" to compare the different PPC's for each pavement case; c) perform What if? analyses by changing the parameters; d) save and retrieve from a text file traffic and damage data, and e) customize the PPC chart.