Artificial Neural Network Models For Assessing Remaining Life of Flexible Pavements

by

Imad Abdallah, MSCE
Octavio Melchor-Lucero, MSCE
Carlos Ferregut, Ph.D.
and
Soheil Nazarian, Ph.D., P.E.

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Development of a Comprehensive, Rational Method for Determination of Remaining Life of an Existing Pavement

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16. Abstract

Most mechanistic-empirical methods for determining the integrity of an existing pavement rely on the use of deflection-based nondestructive evaluation devices to determine the integrity of a pavement section. To estimate the remaining life associated with two types of distress in a flexible pavement, namely fatigue cracking and rutting, the critical strains and stresses at the interfaces of the layers of the pavement should be known. After the critical strains are calculated, a number of models can be used to estimate the remaining life. This report presents a case study that shows the feasibility of using an algorithm based on artificial neural network technology (ANN) to estimate the remaining life of flexible pavements. The report includes, in detail, the development and results of a system of ANN models that have been developed to predict the critical strains for a wide range of three and four layer flexible pavement sections with variable depth to bedrock. The inputs to these ANN models are only the best estimates of the thickness of each layer and the surface deflections obtained from a Falling Weight Deflectometer (FWD).

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Imad Abdallah, M.S.
Octavio Melchor-Lucero M.S.
Carlos Ferregut, Ph.D.
Soheil Nazarian, Ph.D., P.E. (69263)

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Abstract

Most mechanistic-empirical methods for determining the integrity of an existing pavement rely on the use of deflection-based, nondestructive evaluation devices to determine the integrity of a pavement section. To estimate the remaining life associated with two types of distress in a flexible pavement, namely fatigue cracking and rutting, the critical strains and stresses at the interfaces of the layers of the pavement should be known. After the critical strains are calculated, a number of models can be used to estimate the remaining life. This report presents a case study that shows the feasibility of using an algorithm based on artificial neural network technology (ANN) to estimate the remaining life of flexible pavements. The report includes, in detail, the development and results of a system of ANN models that have been developed to predict the critical strains for a wide range of three- and four-layer flexible pavement sections with variable depth to bedrock. The inputs to these ANN models are only the best estimates of the thickness of each layer and the surface deflections obtained from a Falling Weight Deflectometer (FWD).

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 collectively referred to 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.

Unfortunately, a model that can universally predict the remaining life of a pavement does not exist. The success of the existing models in predicting the remaining life seems to depend on the pavement structure. To compensate for this shortcoming, the tendency has been towards developing more complicated models that require sophisticated parameters that are not readily available to the pavement designers. The researchers have taken an alternative approach.

An algorithm has been developed that combines the functional condition of a pavement (i.e., percent cracking and depth of rut) at the time of FWD testing with simple remaining life algorithms to predict the remaining life of pavements. In addition, a series of artificial neural network (ANN) models have been developed to predict the critical strains. The inputs to these ANN models are only the best estimates of the thickness of each layer and the surface deflections obtained from a falling weight deflectometer. As such, the backcalculation process is eliminated.

The objectives of this project were 1) to form a system of neural network models which will reliably predict the remaining lives of three-layer and four-layer flexible pavements with variable depth to bedrock--the system of networks consists of: a) neural network models that predict the thickness of the subgrade-layer and b) neural network models that predict the critical strains and the modulus of the asphalt-concrete layer, which are then used in existing remaining lives models; 2) to integrate an algorithm for estimating the uncertainty in the predicted remaining life of pavement section from the uncertainty in the geometric and material properties of the section; 3) to develop a Pavement Performance Curve (PPC), which incorporates the results of the ANN models, condition survey and traffic; and 4) to develop a state-of-the-art modular software that incorporates items 1 through 3 and provides results manifested with sophisticated graphical user interface (GUI), designed, specifically, to complement TxDOT decision-making practices.

The first report of this project focused on presenting the methodology. It discussed the theory of artificial neural networks, the feasibility of using neural network technology to predict the pavement distresses based on the pavement layers' thicknesses and the seven FWD readings, and the development of a PPC based on the widely accepted Weibull-type curve. That report also contained the development and results of four ANN models for a three-layer flexible pavement. Two of the models predicted the rutting and fatigue cracking remaining lives according to the Asphalt Institute (AI) equations. The other two models predicted the maximum tensile and compressive strains at the layer interfaces. The models seem to be reasonable in their predictions.

In this report, the validation of the methodology is presented, in a case study, using actual data collected from the Texas Mobile Load Simulator (TxMLS) site. The study compares the predictions of the ANN models to those of a backcalculation process. Results of the ANN models matched those of the backcalculation process fairly well. The study also illustrated the use of the PPC using actual field data. The results of the PPCs showed that the measured and predicted degradation of the section match closely. The case study also illustrated the strength of combining both the structural and functional aspects of a pavement from the PPC.

Based on the results of the case study, several ANN models were developed to predict the critical strains of three-layer and four-layer flexible pavement systems with varying bedrock depths. The models covered a wide range of sections common in the state of Texas. To develop models that account for different bedrock depths', the thickness of the subgrade was required. Therefore, an ANN model that predicted the thickness of the subgrade was developed. Another model to predict the modulus of the AC-layer was needed in order to use existing remaining life models such as the Asphalt Institute equation. A series of ANN models was developed and validated using a comprehensive synthetic database. The development and results of these models are documented in this report.

The artificial neural network technology has proved to be a feasible and practical technology to develop models to assess the integrity of pavements using data that is readily available to pavement engineers. This is particularly advantageous because other approaches require information from laboratory tests, making the assessment more tedious and time-consuming. Another advantage of ANN models 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 contains a set of artificial neural networks (ANN) that predicts the critical strains of pavement sections with variable depths to bedrock. The development of the software is at its final stages. A reporting tool is being added to allow the automation to print a summary and the results of a project file.

A training seminar was conducted for several members of the TxDOT personnel. Based on their recommendations, modifications to the interface of the software are also being made. Upon completion, both UTEP and TxDOT staff members will use the software to evaluate the methodology using existing flexible pavement sections.

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Chapter 1

Introduction

The main purpose of this report is to discuss, in detail, the development and results of the system of artificial neural networks developed as a part of Project 0-1711. The project is currently in its fourth year. The information presented in this report encompasses the work efforts of the past year (third year of the project). The first report of Project 0-1711 (Ferregut et al. 1999) details the purpose and overall methodology proposed for this project.

The project focuses on the development of a procedure to assess the performance of a flexible pavement using data collected from a FWD device. The FWD measures the deflection profile at the surface of the pavement using seven seismic transducers (geophones). The procedure to determine the pavement performance is intended to provide a more simplified alternative to the backcalculation procedure commonly used. The existing backcalculation process requires judgment from the user because of the non-uniqueness of the backcalculated set of moduli.

The proposed methodology was developed with extensive use of artificial neural network (ANN) models to predict pavement distress. The use of neural network models in pavement engineering has increased in recent years. Appendix A in Ferregut et al. (1999) provides a summary of publications about the various applications in pavement engineering for this type of model. The increase in popularity of ANN models to solve engineering problems is largely due to their ability to handle complex nonlinear mathematical relations such as the relation between the FWD deflections and the distress conditions of a pavement.

Objectives

The objectives of this project are:

1) to form a system of neural network models which will reliably predict the remaining lives of three-layer and four-layer flexible pavements with variable depth to bedrock. The system of networks consists of:

a) models that predict the thickness of the subgrade-layer, and

b) models that predict the critical strains and the modulus of the asphalt-concrete layer, which are then used in existing models that compute the remaining life of the pavement;

2) to integrate an algorithm for estimating the uncertainty in the predicted remaining life of pavement section from the uncertainty in the geometric and material properties of the section;

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

4) to develop a state of the art modular software that incorporates items 1 through 3 and provides results manifested with sophisticated graphical user interface (GUI), designed specifically to complement TxDOT decision-making practices.

The research objectives of this project can be categorized in three phases: 1) feasibility, 2) development, and 3) implementation. The main focus in the feasibility phase was to determine the viability of developing ANN models that can be used to compute the remaining life of a flexible pavement. In the development phase, the objective was: a) to develop a system of ANN models that can be used to assess the performance of most flexible pavement sections in the state of Texas and b) to incorporate the models into a software. The third phase, the implementation phase, focused mainly on the validation and use of the software tool with actual field data. The feasibility of the overall methodology was presented in the previous report. This report presents, in more detail, the development and results of the system of ANN models.

Organization

Chapter 2 of this report summarizes the feasibility phase. That chapter also contains a case study, which focuses on the comparison of ANN outcomes with actual field data from a site trafficked with the Texas Mobile Load Simulator. Chapter 3 details the process of developing a system of ANN models for three- and four-layer flexible pavements and the results of the ANN models. The last chapter contains the conclusions of the research effort thus far.

Chapter 2

Summary of Previous Efforts in the Project

The feasibility phase consisted of two activities. ANN models were first developed and used to predict failure properties of a pavement, and, second, a methodology was worked out to illustrate the pavement performance with time. The methodology incorporated the results from the ANN models and the uncertainty in the remaining life results attained from the uncertainty that exists in the properties of the pavement. The development of an ANN model required a comprehensive database that can be used in training and in validating the model. A recent report by Ferregut et al. (1999) explained the process of generating such a comprehensive database and the process of training an ANN model. The authors also reported on four ANN models that were developed to predict pavement distress. The four models predicted fatigue cracking, rutting, tensile strain, and compressive strain. All four models were developed based on a three-layer pavement system with a constant depth to bedrock. The ANN models developed were based on the mathematical equations used to calculate the remaining lives associated with fatigue cracking, N_f, and rutting, N_r, as defined in Huang (1993). For the fatigue cracking failure mode, the model takes the following general form

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

and for the rutting failure mode the general form is

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

where ε_t is the tensile strain at the bottom of the asphalt concrete (AC) layer and ε_c is the compressive strain on top of the subgrade. Parameter E_{AC} is the modulus of elasticity of the AC layer. The constants in Equations 2.1 and 2.2 are usually determined from field performance data, road tests, or laboratory tests. The two models developed to directly predict fatigue cracking and rutting were based on the Asphalt Institute equation. The constants proposed by the Asphalt Institute (AI) are frequently specified (Huang, 1993). Those values, based on the U.S. Customary Units, are $f_1 = 0.0796$, $f_2 = 3.291$, $f_3 = 0.854$, $f_4 = 1.365\text{E-}9$, and $f_5 = 4.477$. The other two models developed to predict the critical strains could be used to determine the remaining life of a flexible pavement using any number of equations that follow the mathematical format specified in Equations 2.1 and 2.2. Figure 2.1 portrays the two distresses, fatigue cracking and rutting. It also

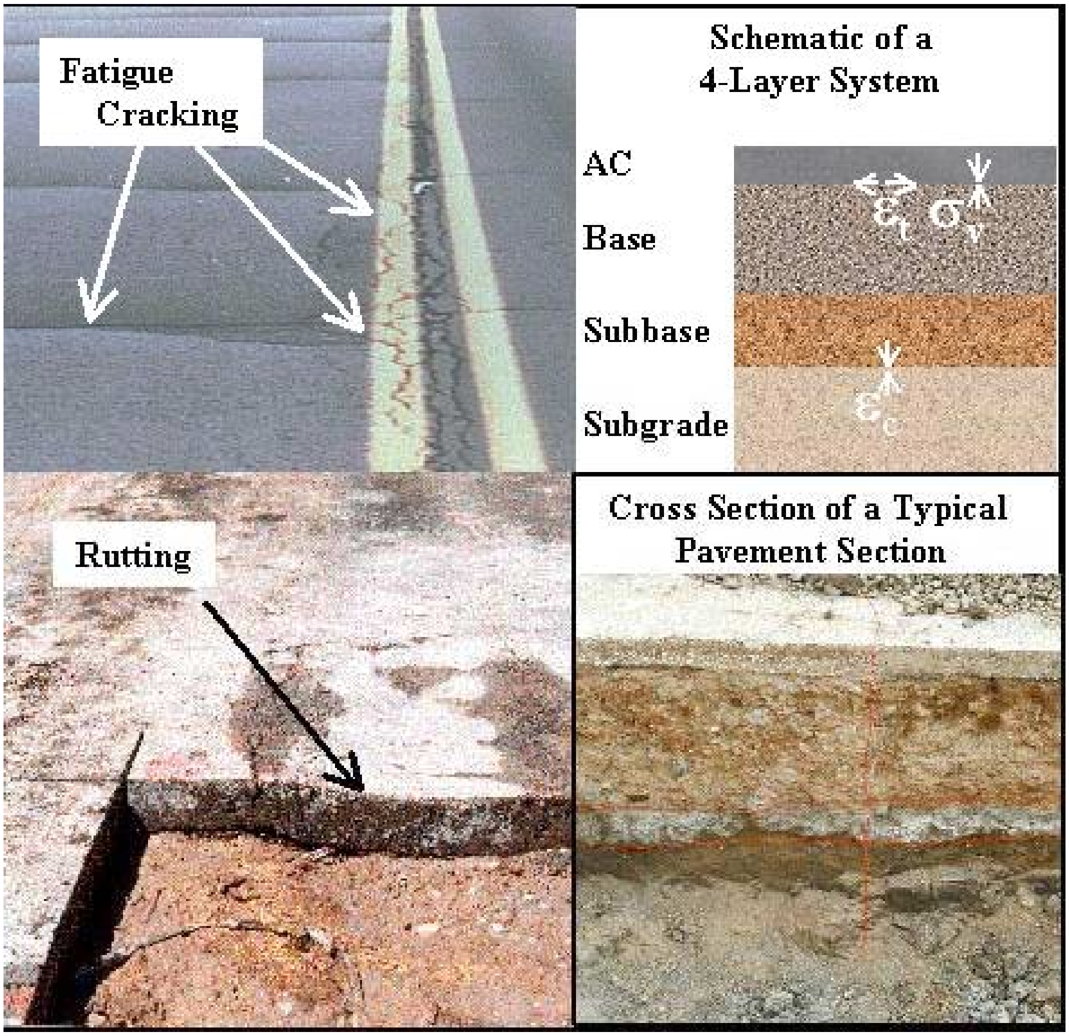

FIGURE 2.1 - Example of Pavement Distresses and Schematic of Location of Critical Strains

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shows a schematic of a pavement system identifying the locations of the critical stresses and strains and a cross-section of an actual pavement section

Typically, once a model has been trained and validated, the development process ends, and the model is ready for implementation. However, that is not the case in this project. Since each ANN model was trained and validated using a synthetic database, a validation of the model with actual data was necessary. Another crucial step was the verification of the proposed methodology with actual field data. To check the feasibility of the entire process, a case study was carried out using a database provided by TxDOT. The database contained data collected during the loading of a site with the Texas Mobile Load Simulator (TxMLS). The next five sections detail the case study that was carried out. First, a description of the TxMLS is presented. This is followed by a brief explanation of the site and test plan. Then, a discussion of the ANN models and the process of developing a pavement performance curve (PPC) is offered. Finally, the validation process and results based on the study are discussed.

Texas Mobile Load Simulator (TxMLS)

A detailed description of the Texas Mobile Load Simulator (TxMLS) system, shown in Figure 2.2, can be found in Hugo and Fults (1999). This device is equipped with six full sets of tandem axles operating up to 20 km/hr in a closed loop system. The characteristics of the system are summarized in Table 2.1. The tandem axle loads are set statically to about 150 kN, the maximum legal tandem axle load in Texas. The TxMLS is approximately 26 m long, 6 m tall and 4 m wide, with a test area of 3 m by 12 m. Loads are simultaneously applied along two wheel paths about 3 m apart.

FIGURE 2.2 - Texas Mobile Load Simulator

TABLE 2.1 - Characteristics of Texas Mobile Load Simulator (from Hugo and Fults, 1999)

FEATURE	TECHNICAL DATA
No. of bogies	6
No. of axles/bogie	2 (dual tandems)
Total no. of full axles	12
Drive axles	2
Towed axles	10
No. of wheels	24 duals
Tires/axle	4
Tire type	295X75R22.5 Low profile radial
Tire pressure (kPa)	690
Nominal tire tread width (mm)	230
Nominal distance between tire centerlines (mm)	330
Nominal wheel diameter (mm)	1000
Nominal load per axle (kN)	75.6
Nominal load per wheel (kN)	18.9
Load mechanism	Conventional highway truck springs
Load setting	Electro-mechanical
Suspension	Steel springs
Nominal speed (kph)	18
Duration of load pulse at operational speed (sec)	0.05
Nominal rest periods between load applications	Rest periods vary between 0.2s, 0.74s and 1.74s
Nominal time per cycle (sec)	8
Power	2x120 kVA DC motors
Maximum production rate/12 h shift (No. of axles)	>50 000
Lateral wander (mm)	435 (left/right)
Mobility	Tractor towed supported on special bogies
Overall operational machine dimensions (m):	
Length	26.2
Width	3.9
Height	6.4
Total nominal mass (metric ton)	120
Test section size (m)	12 x 3
Temp control during tests	None-except for cover by structural shell

Description of Site and Test Plan

The site, which was located in Victoria, TX, was a four-layer flexible pavement section. The pavement profile nominally consisted of about 75 mm (3 in.) of ACP, over 300 mm (12 in.) of base, underlain by 150 mm (6 in.) of lime-treated subbase and a clayey subgrade. The TxMLS personnel performed the FWD tests and condition survey at predetermined load applications with load repetitions of 0, 2500, 5000, 10,000, 20,000, 40,000, 80,000, 160,000, 320,000 and about 632,000. After the site was considered as failed, two trenches were installed in the transverse direction. The major finding from the trenching operation was that almost all of the rutting occurred below the AC-layer and that the thickness and quality of the lime-treated subbase was somewhat variable.

Figure 2.3 illustrates the test grid along which data was collected. The FWD deflections were measured along three longitudinal lines. The two longitudinal lines, denoted as b and d in the figure, were along the wheelpath. Line c corresponded to the centerline and was not trafficked throughout the test. Along each longitudinal line, the FWD tests were performed at 1.5 m intervals at 9 points marked as 0 m through 12 m. Accordingly, 27 data points were available for consideration in this study. The condition survey was typically done in a 1.5 m by 1 m grid along the wheel paths.

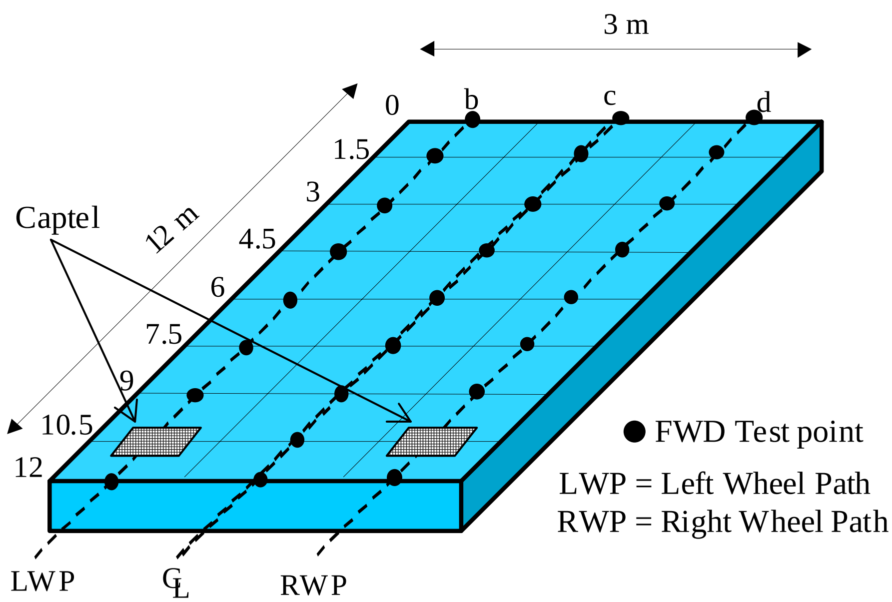


FIGURE 2.3 - Schematic of Testing Area with TxMLS

ANN Models

Since this was a four-layer system, two new ANN models to predict fatigue cracking and rutting of the pavement were developed. The models were based on the Asphalt Institute equations. An additional model, a third model, to predict the rate of rut was also developed. Chen and Lin (1999) demonstrated that the following rutting model based on calculating the rate of rut is reasonable for estimating the remaining life at the validation site used in this study:

$$\log(RR) = C_1 + C_2 \log(\delta_0) + C_3 \log(N_{18}) + C_4 \log(\sigma_c), \tag{2.3}$$

RR is the rate of rutting in microinches per axle load repetition, δ_0 is the surface deflection under the load plate in mils (obtained from the FWD test), N_{18} is the equivalent 18-kip (80-KN) single-axle load, and σ_c is the 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.) thick, are appropriate for this site. The values, based on the U.S. Customary Units, 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. The equation is:

$$R_T = 302.2 - 26.33(S_T) - 14.12(B_T), \tag{2.4}$$

where S_T and B_T are the AC thickness and base thickness in inches, respectively. Equation 2.4 was proposed by Finn et al. (1986) as a calibration or a shift factor to adjust the estimated rutting based on field observations.

Pavement Performance Curve

The steps involved in predicting the performance of a pavement with time, in this study, are summarized in Figure 2.4. The first step in the process of estimating the remaining life was to measure the FWD deflections and to obtain the best estimate of the pavement layer thickness. This set of data, as a part of Step 2, was then preprocessed to determine the input used in the ANN model. The processed data were used as input into the “trained” ANN models. These models instantaneously estimated the remaining life based on the failure model selected (Step 3). Smith (1993) provides a readable explanation of the ANN theory and describes the mathematics involved, and Ferregut et al. (1999) contains the specific approach followed for training the ANN models to estimate remaining lives.

The predicted remaining life using the ANN models was combined with the functional condition of the pavement to develop a pavement performance curve (PPC) (Garcia-Diaz et. al., 1984). A popular model used for this curve is the Weibull function. The Weibull function, which is commonly used to describe the “life” of a system, can be mathematically expressed as:

$$D = 1 - \exp\left(-\left(\frac{T}{\beta}\right)^{\alpha}\right), \tag{2.5}$$

where *D* is the level of damage and T is the number of accumulated traffic to reach *D*. Parameters α and β are statistically determined site-dependent parameters.

Step 4 of the figure schematically shows a pavement performance curve based on Equation 2.5. 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 a pavement 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. In this study, the failure was defined as 13 mm (0.5 in.) of rutting, or 45% area of the wheel path for fatigue cracking, as recommended by the Asphalt Institute.

To obtain the parameters of a PPC in Figure 2.4, it was necessary to know at least two points on the curve. The first point may be obtained from the results of an ANN model used to determine the remaining life in ESALs and the corresponding failure limit (P1). For the second point, it was assumed that the pavement is defect free at the end of construction (no traffic, no damage; P2).

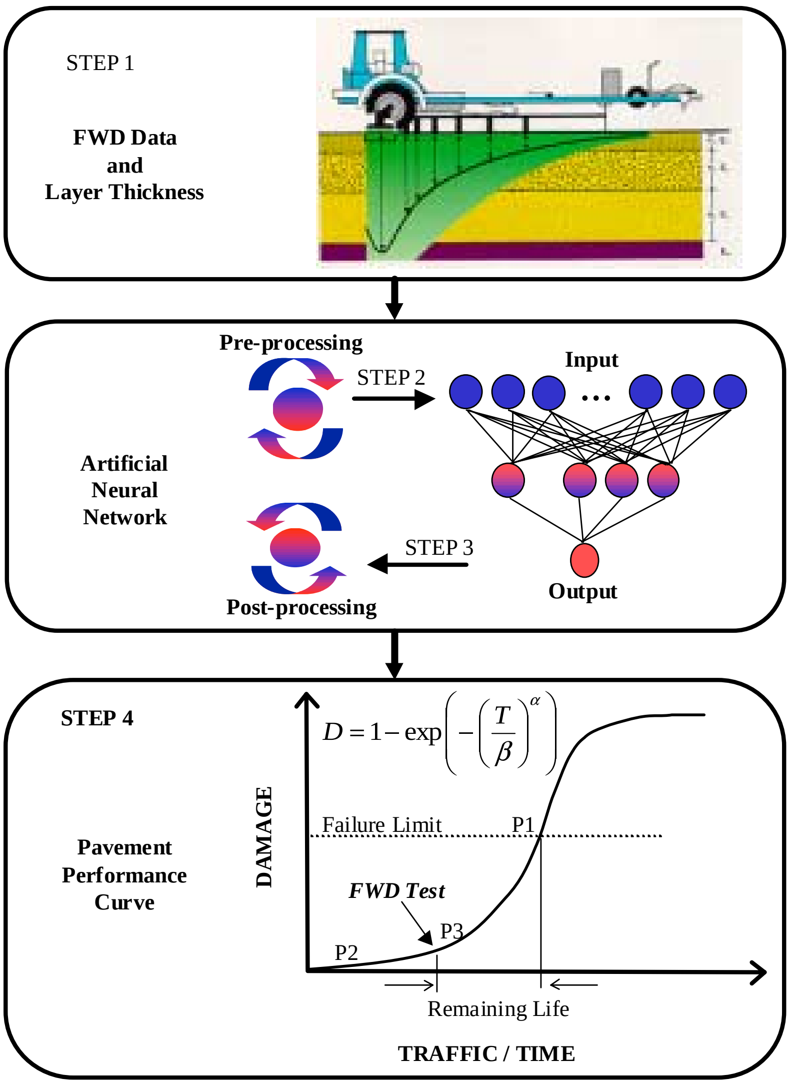


FIGURE 2.4 - Summary of Methodology Used to Describe Service Life of a Pavement

In addition, if the condition of the pavement was measured at the time that the FWD test was performed, that point can also be considered to constrain the shape of the PPC (P3). If all three points are available, a regression was used to develop the curve. The results from the case study include pavement performance curves with both two and three points.

Validation Process

The validation process was carried out in two stages. The first stage verified that the theoretical remaining lives reported by the ANN models and those calculated by the conventional method (backcalculation) were reasonably similar. The results from this stage gave the researchers an indication of how the research would progress. The second stage consisted of comparing the predicted remaining lives and performance curve with those observed at the site. In this step, the impacts of site-related and material-related variability were also considered.

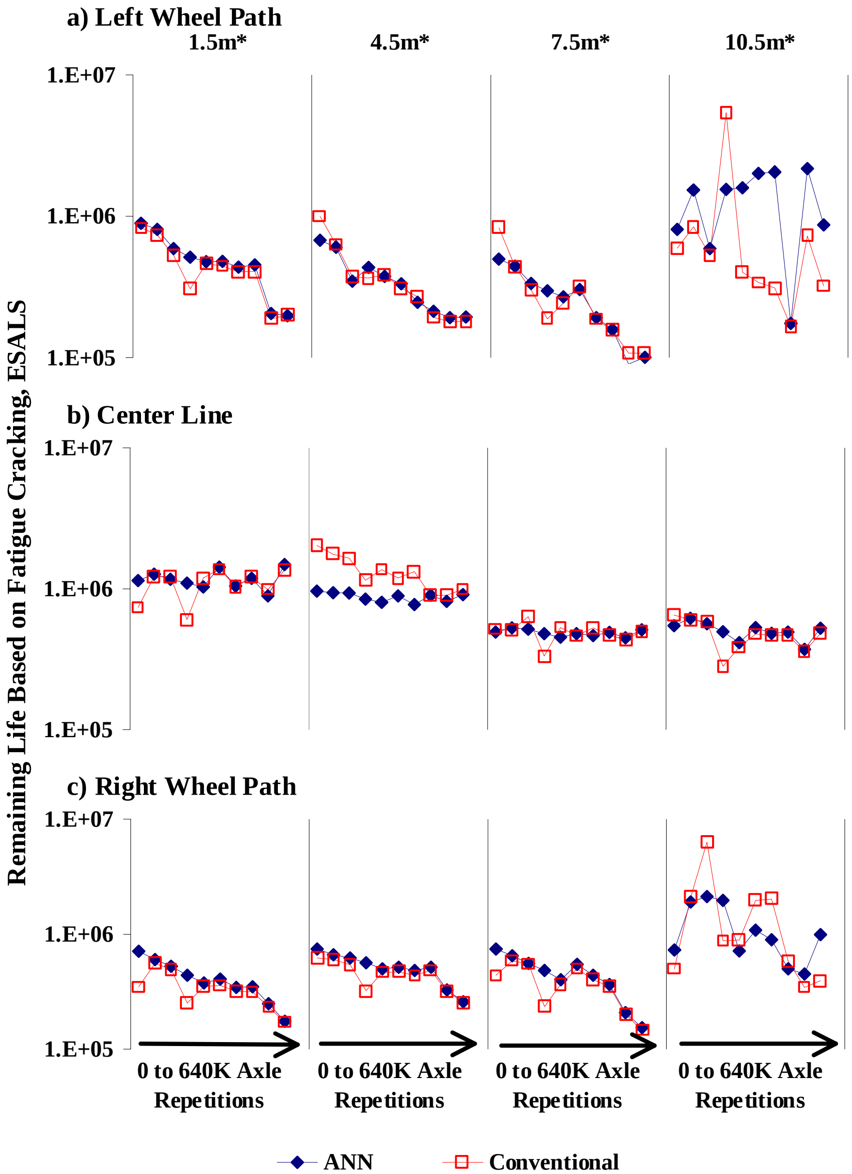
Comparison of ANN Results with Conventional Methods

The remaining lives due to fatigue cracking that were computed using the conventional approach and using the ANN model, after the application of predetermined number of axles, are included in Figure 2.5. This figure shows results along four transverse lines (1.5 m, 4.5 m, 7.5 m and, 10.5 m as marked in Figure 2.3). An expert in pavement design carried out the prediction of the remaining lives with the conventional method using the program MODULUS 5. The 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. As for the remaining life results from the ANN models, they were obtained instantaneously since the ANN models were already developed.

From Figure 2.5, 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. For three of the four transverse lines, the predicted remaining lives are practically the same, except for occasional differences. The exact reasons for the occasional variations are not known. However, they seem to coincide with occasions when the modulus of the AC layer could not be backcalculated with much certainty and the backcalculation misfits were rather high. Even though the results from the ANN model fit the overall trends, this does not guarantee that the ANN model is a better predictor. This matter will be discussed in the next section.

The remaining lives from the conventional and ANN models along the centerline of the pad seem to be independent of loading. This was a desirable outcome, which indicated that the constant decrease in the remaining lives along the two wheelpaths was primarily due to damage to the pavement during loading and was not as much related to the environmental condition during the MLS loading. The differences observed between the results from the ANN models and the conventional methods at a transverse distance of 4.5 m along the centerline cannot be explained at this time.

The results from the lateral cross-section of 10.5 m are quite interesting. Neither the ANN models nor the conventional methods predict the remaining life in a consistent pattern along the two wheelpaths. Captel, a weigh in motion (WIM) device, was installed at the cross-section to monitor the load applied from MLS. Figure 2.3 shows the location where two AC blocks were cut to install the captel. This explains the inconsistency in the results at this cross-section.



*** Corresponds to transverse lines shown in Figure 2.3**

FIGURE 2.5 - Comparison of Fatigue Cracking Remaining Lives from ANN Models and Conventional Method

Remaining lives due to rutting followed a rather different pattern. The Asphalt Institute model (Equation 2.2), using the conventional approach, yielded 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 test points. This value is slightly greater than the upper limit of the remaining life that was used during training of the ANN model. Since ANN models cannot extrapolate outside the range of outputs used in training, the models return a value slightly greater than the upper limit. Therefore, from the results of the ANN models, one can only deduce that the remaining life is in excess of 2.8 million

ESALs. One thing is clear from the results of both approaches; the fundamental model (Equation 2.2) is not appropriate for describing the rutting behavior of this site. These results suggest that the strain level in the subgrade layer did not reflect the rutting that occurred at the site.

Remaining life results from the ANN models and from the conventional method, which is based on the Finn model, are compared in Figure 2.6. The two methods yield fairly close results for the amount of approximation involved in the ANN model and for the weakness in backcalculating moduli.

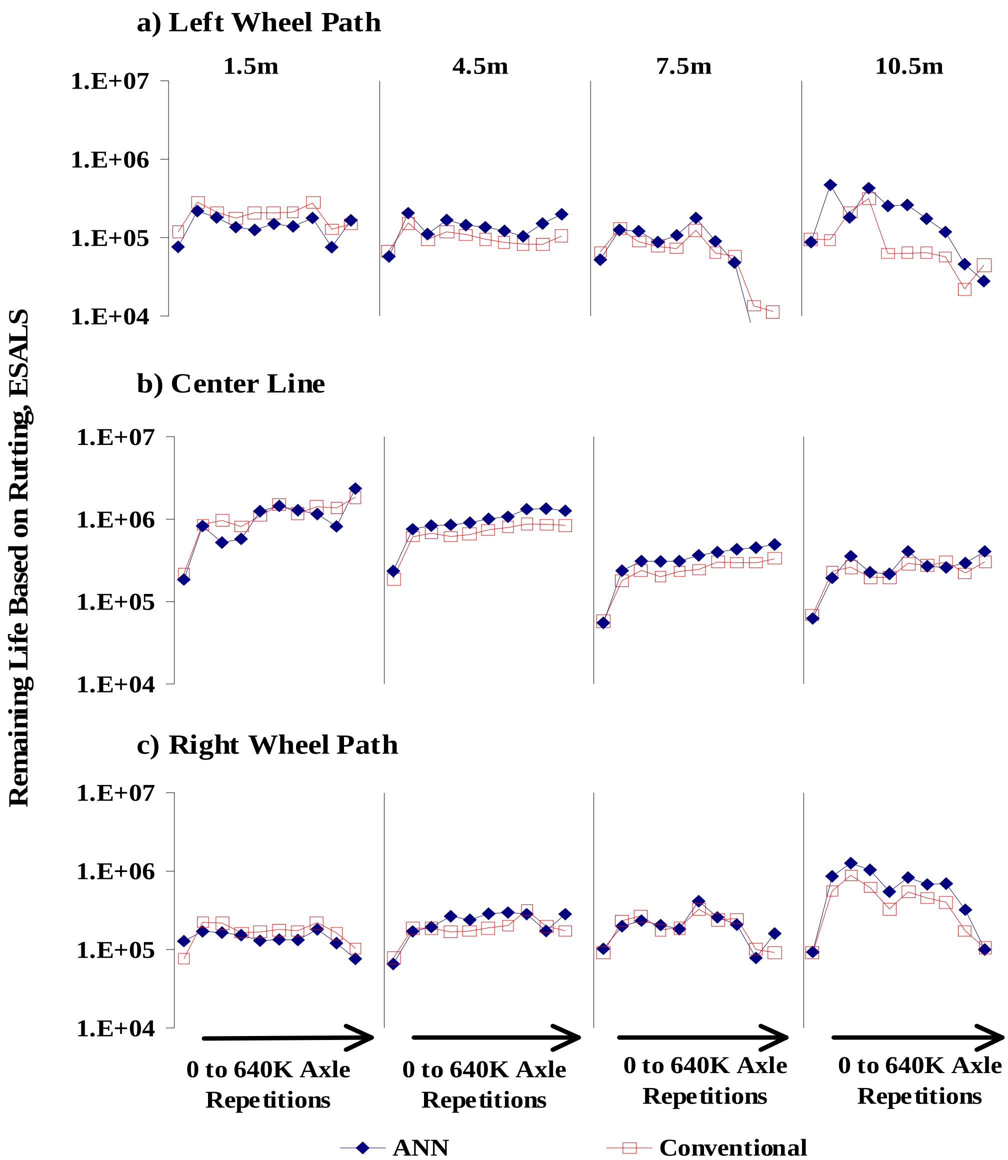


FIGURE 2.6 - Comparison of Rutting Remaining Lives from ANN Models and Conventional Method

Once again, the remaining lives along the centerline (see Figure 2.6b) are independent of the MLS loading, except for the FWD results from just before loading (first point). The estimated remaining lives from the FWD tests before MLS loading were systematically lower. This occurs when the "load term" in Equation 2.3 is zero. Surprisingly, the estimated remaining lives, due to rutting, along the wheelpaths from the FWD tests (see Figure 2.6a and 2.6c) seem to be independent of both the amount of load applied and the intensity of the rutting at the site.

In general, results from this part of the study indicated that, in most cases, the ANN models can estimate the remaining lives at least as well as a trained design engineer. Since the ANN models yield results almost instantaneously and without requiring any engineering judgment, it seems reasonable to use the ANN models with confidence.

Comparison of Estimated and Observed Remaining Lives

Typical observed progression of pavement cracking from regular condition survey during MLS loading is shown in Figure 2.7. Up to 40,000 repetitions, the section did not exhibit any cracking. At about 80,000 repetitions, the section could be considered as failed. As such, this case may not be as typical as those encountered under actual traffic. For the sake of brevity, most of the discussion is limited to results obtained after 20,000 repetitions (no visible damage) and 80,000 repetitions (extensive damage). The results associated with other load repetitions can be found in Ferregut et al. (1999).

Figure 2.7a shows three calculated pavement performance curves for the case in which visible cracking was negligible. Figure 2.7b shows the curves for the case in which the section was extensively cracked. In each figure, one performance curve was obtained using only the condition survey. At 20,000 axle repetitions, the 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 actual pavement condition, but still underestimates the behavior of the pavement.

The second PPC considers only the structural condition. For results from 20,000 repetitions, the PPC is more representative of the behavior of the pavement as compared to the previous case, except that the performance is over-estimated. When 80,000 axle repetitions are considered, the PPC is more or less similar to the case in which only the condition survey was used. However, the remaining life is over-estimated.

The third PPC corresponds to the situation in which both the condition survey at the time of the FWD data collection and the remaining life from the ANN model were considered. In this circumstance, when the percent cracking is more than zero, the Weibull curve was fitted to three points (consisting of the 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 were evident at the site, the Weibull curve was 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 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.

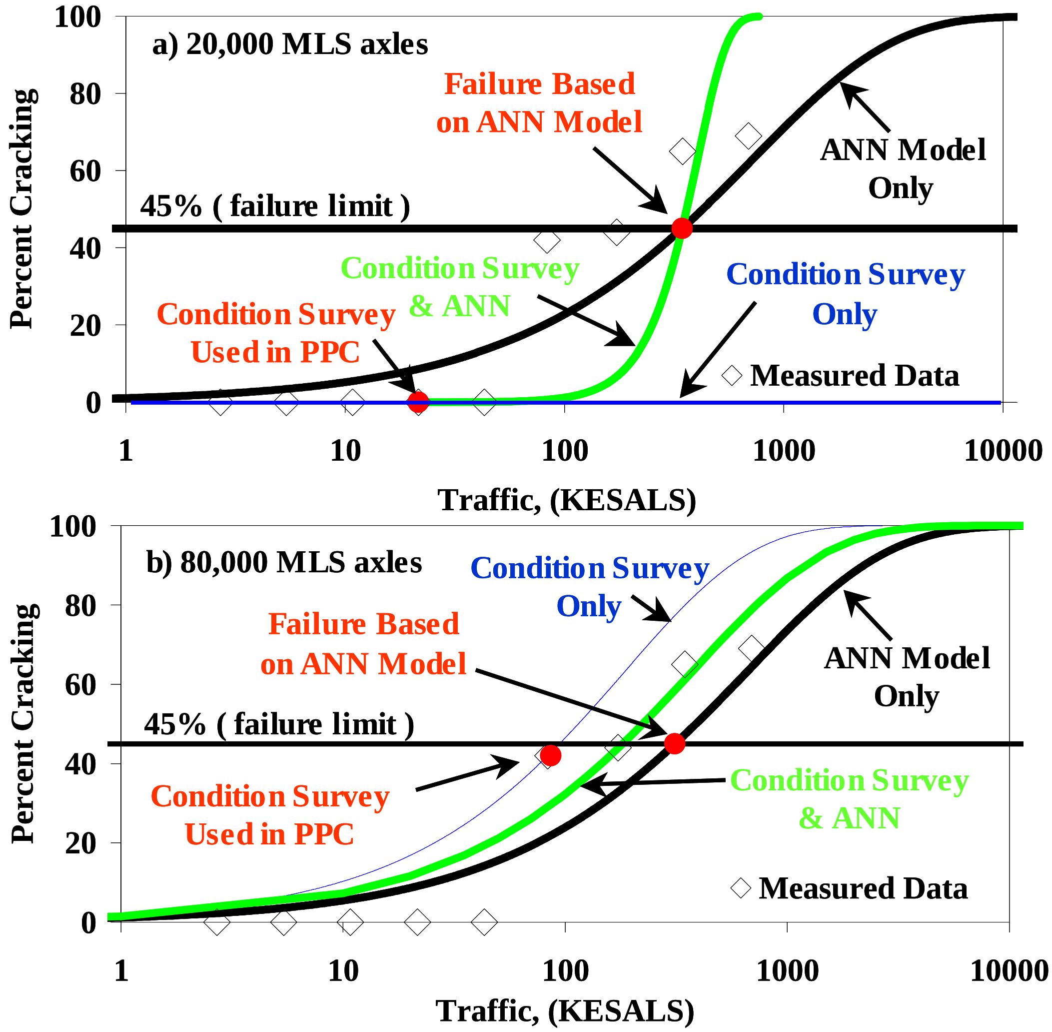
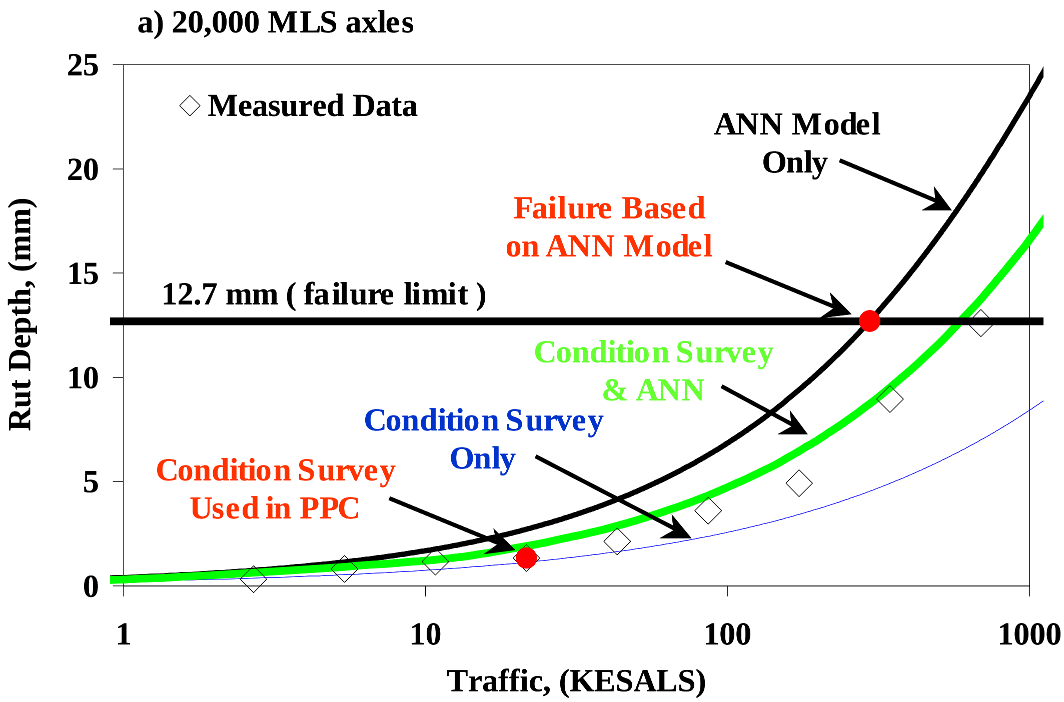


FIGURE 2.7 - Comparison of Actual Fatigue Cracking Performance Curves with Calculated Ones Using Several Strategies

As mentioned previously, the predictions of the Asphalt Institute model for rutting were unrealistically high. This occurred because the AI model was not appropriate for this site. Based on the trenching operation, most of the rutting occurred above the subgrade-layer. However, the Finn model seems to be appropriate for the site.

The actual variations in rut depth with the number of ESALs, as well as estimated PPC from the three strategies mentioned above, are compared in Figure 2.8. 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.



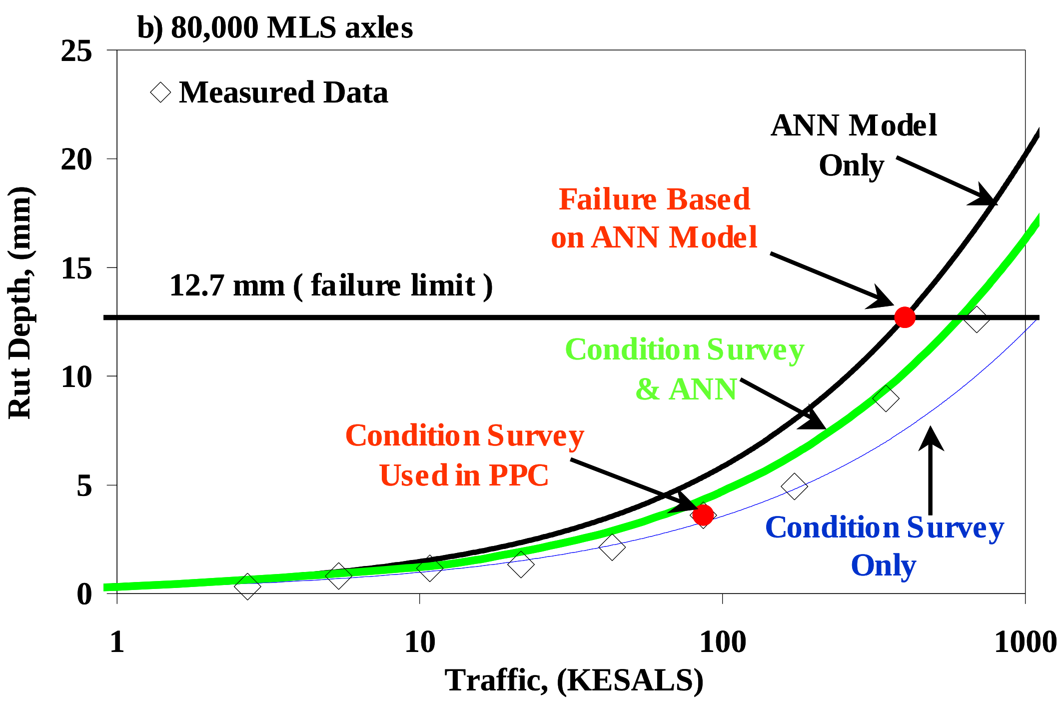


FIGURE 2.8 - Comparison of Actual Rutting Performance Curves with Calculated Ones at 20,000 and 80,000 Repetitions Using Several Strategies

So far the validation process has been related to point-by-point comparisons. In a typical pavement design, one hardly relies on the results from one test point. To further study the overall validity of the results over the area of the tested pad, the material- and geometry-related variability were also considered. The results of this activity are summarized in Table 2.2 below.

The variations in the FWD deflections under the load (Sensor 1) and at distances of about 0.6 m (Sensor 3) and 1.8 m (Sensor 7) from the source within the test pad area are shown in Figure 2.9 as contour plots, for measurements made after 20,000 and 80,000 load repetitions. The overall mean values and the coefficients of variation (COV) of readings of the seven sensors are given in Table 2.2. After 20,000 repetitions, the deflection of Sensor 1 varies between 350 and 600 microns (see Figure 2.9a). Similarly, the deflections of the other two sensors depicted vary by a factor 2 within the tested area. This may represent a reasonable variability to be found along a section of the road. In general, the upper parts of the graphs exhibit smaller deflections relative to the lower parts.

After 80,000 repetitions, the trends in the deflections observed for Sensor 1 and Sensor 3 are more or less similar to those measured after 20,000 repetitions. However, the deflections reported for Sensor 7 seem to be greater for the lower half of the section.

The variations in the backcalculated moduli of different layers computed from the FWD deflections are shown in Figure 2.10. Because of the variability in the deflection basins, the reported moduli are quite variable as well. The moduli of the AC and the base from the 20,000 and 80,000 repetitions are fairly similar. Conversely, the moduli of the subbase and subgrade are somewhat different for the two load repetitions. The mean and the coefficient of variation of the modulus for each layer after each load repetition are also summarized in Table 2.2.

TABLE 2.2 - Summary of Results Obtained at Test Pad

Parameter		**20,000 MLS Axles**		**80,000 MLS Axles**	
		Mean	**COV**	**Mean**	**COV**
FWD Deflection (mm)	**Sensor 1**	0.474	0.12	0.486	0.16
	Sensor 2	0.209	0.17	0.219	0.20
	Sensor 3	0.098	0.19	0.101	0.21
	Sensor 4	0.060	0.14	0.061	0.15
	Sensor 5	0.041	0.13	0.042	0.13
	Sensor 6	0.029	0.13	0.030	0.13
	Sensor 7	0.022	0.15	0.022	0.14
Modulus (MPa)	**AC**	3133	0.39	3340	0.37
	Base	179	0.33	173	0.39
	Subbase	1021	0.86	1463	0.78
	Subgrade	131	0.12	124	0.13
Remaining Life (KESALs)	**Fatigue Cracking**	440	0.23	390	0.37
	Rutting	470	0.35	500	0.29

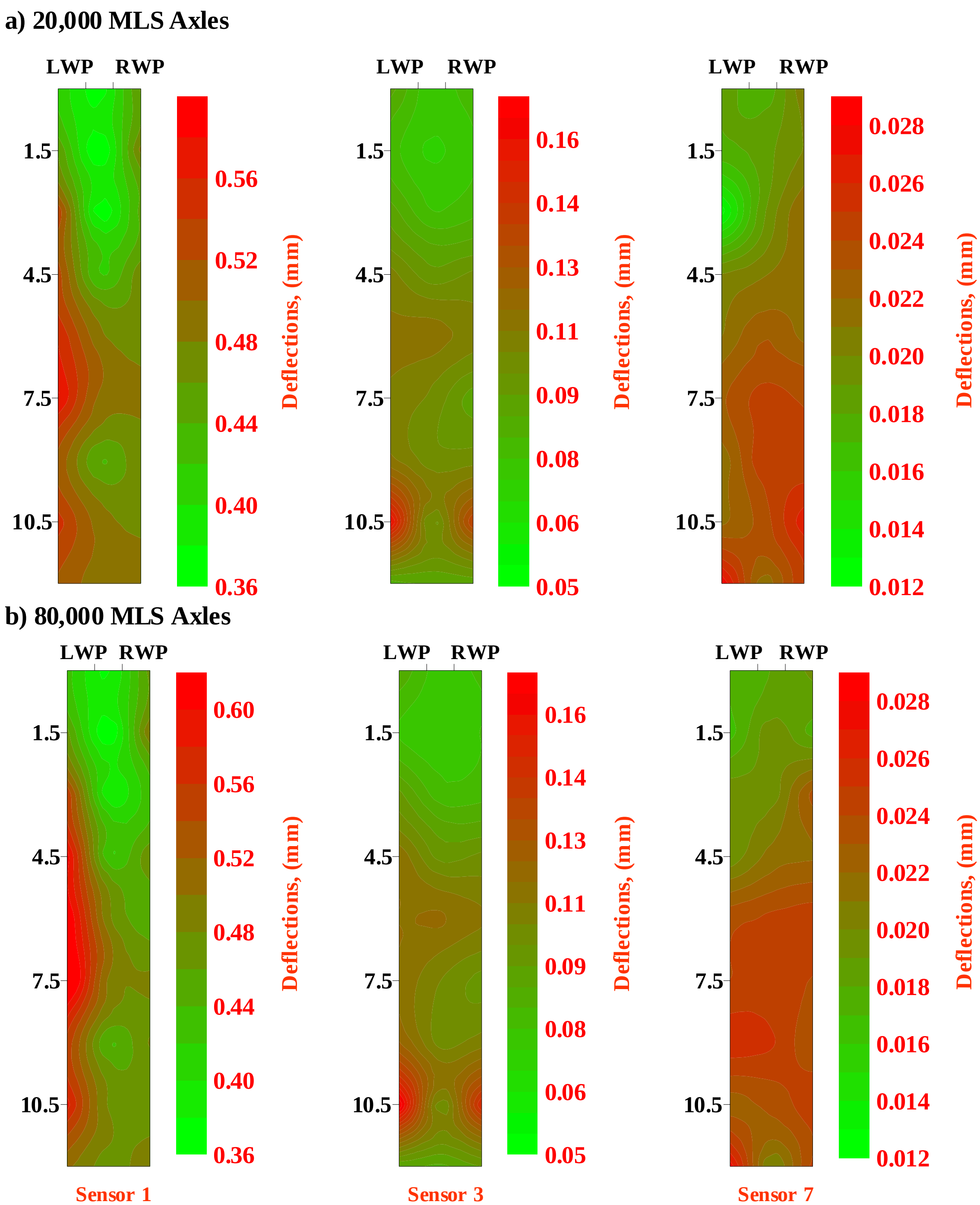


FIGURE 2.9 - Variation in Deflection Values with Location within the Test Pad

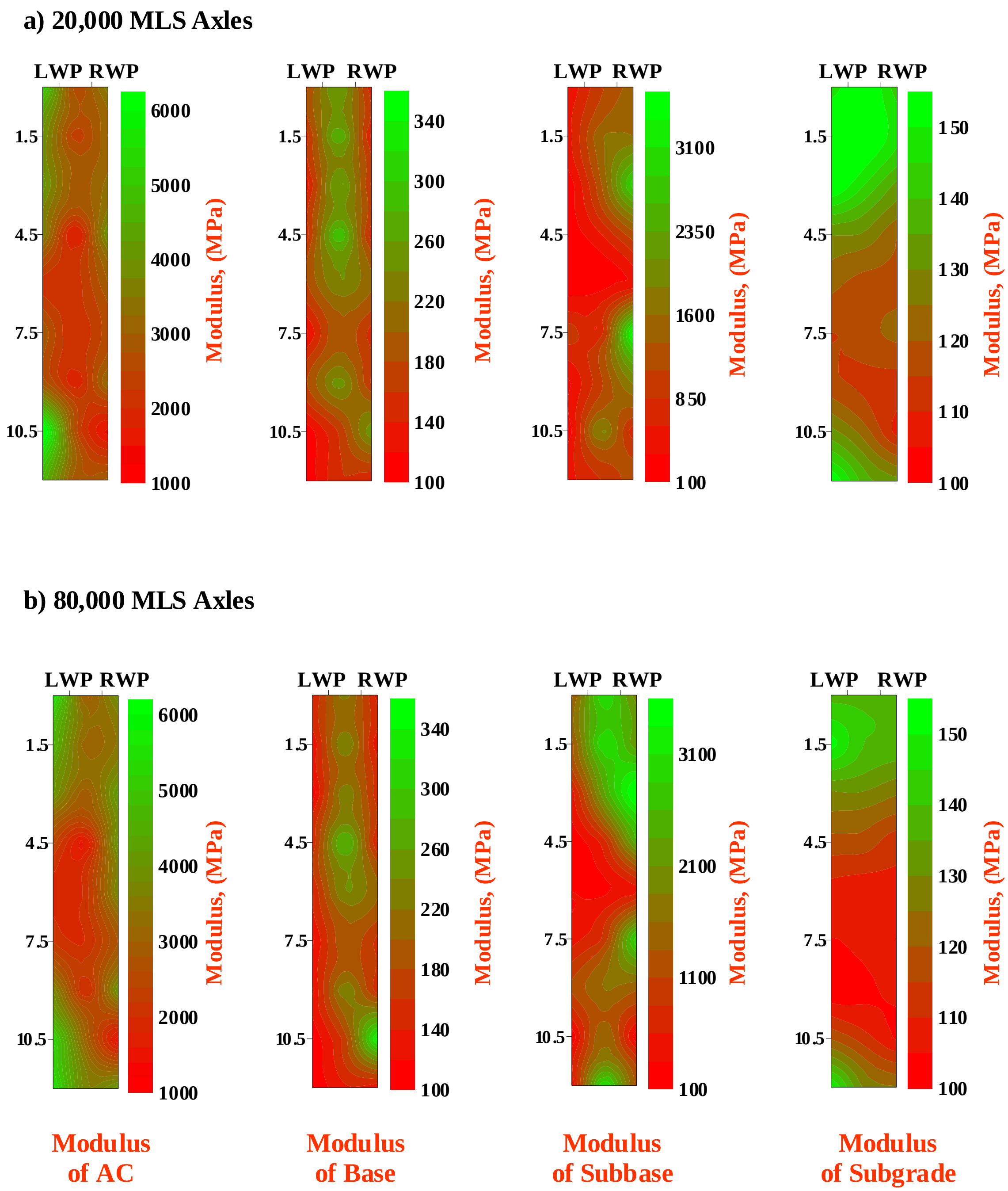


FIGURE 2.10 - Variations in Backcalculated Moduli with Location within the Test Pad

Based on the mean and the coefficient of variation reported for each FWD sensor after each load repetition, a Monte Carlo simulation was carried out to determine the variability of the remaining lives associated with the variability of deflections. One of the advantages of ANN models is that the Monte Carlo simulation is almost instantaneous and, as such, can be incorporated in day-to-day pavement analysis. During the simulation, an uncertainty of 10% was also assigned to the thickness of each layer. In this exercise about 1000 cases were simulated. The results are shown in Figure 2.11, and the means and the coefficients of variation are reported in Table 2.2.

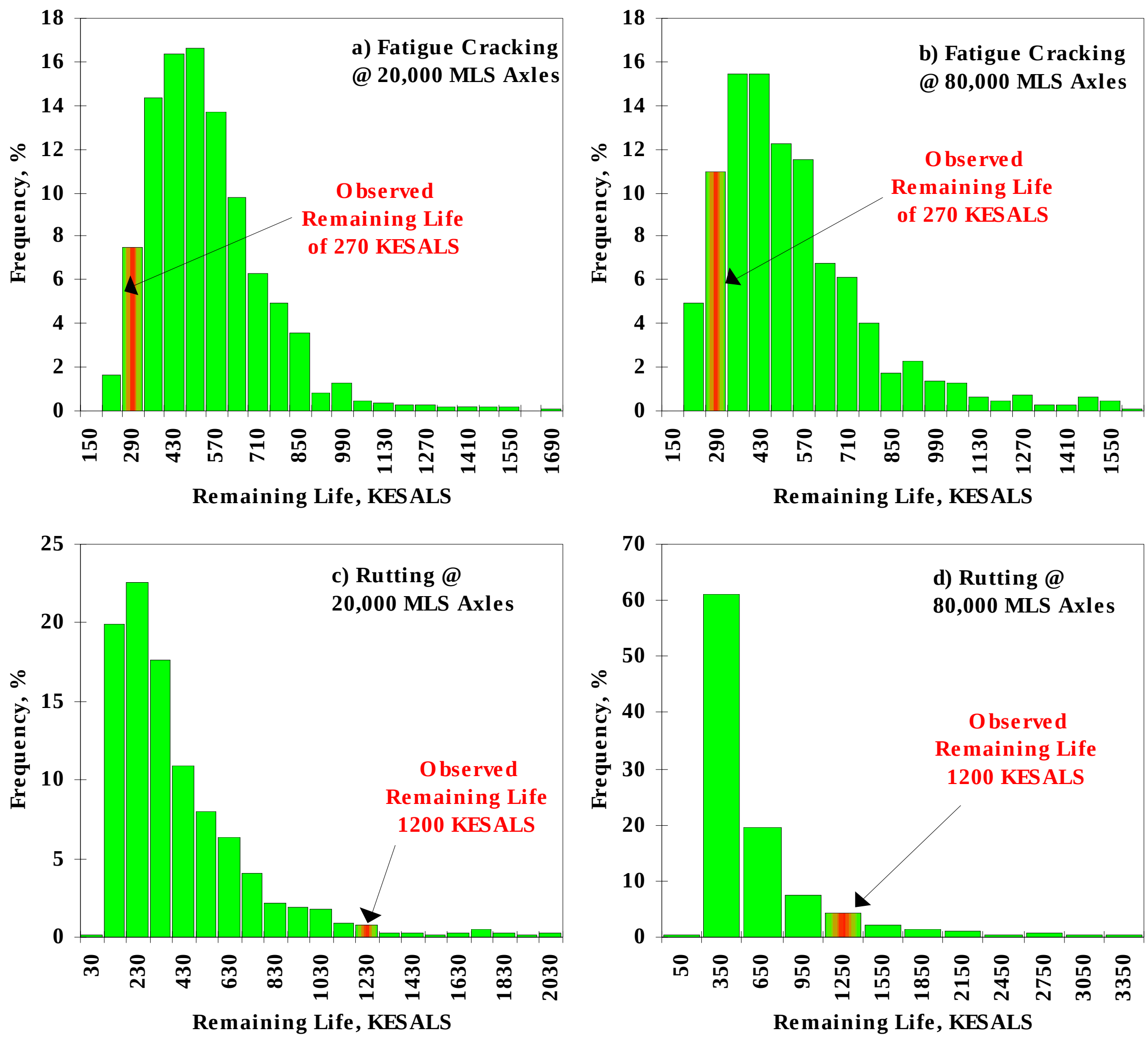


FIGURE 2.11 - Simulated Distribution of Remaining Life Based on ANN Models vs. Observed Remaining Life of Entire Test Slab

As shown in Figures 2.11a and 2.11b, the distribution of the remaining life due to fatigue is slightly biased to the right for each of the load repetitions studied, despite the fact that all the variables for the simulation were considered to have a normal distribution. The variability in the results increased with the number of load repetitions considered. From the figure, it is possible to consider the remaining life with the highest frequency of occurrence as the most likely computed value. The most likely observed remaining life for the test pad is also shown in these figures. This value clearly falls in the range of possible values for the remaining life when uncertainties are taken into account. The figures clearly show that for this example, the most likely remaining life is closer to the observed value when the 80,000 repetitions are considered.

Similar trends are observed for the rutting mode. In this case, as shown in Figure 2.11c and 2.11d, the observed remaining life falls in the tails of the histogram for both cases. This suggests that the models used to predict the rutting remaining life, when uncertainty is taken into account, give fairly conservative values.

To provide some light about the variability computed for the remaining life versus the variability of the remaining life observed in the field, a remaining life for both fatigue cracking and rutting were computed using the deflections at each test site in the pad. The two analyses to estimate remaining life described in the foregoing were applied to these results. This process generated two sets of pavement life values, with fatigue cracking set containing 8 points and rutting containing 18 points. The cumulative distribution functions (CDF) for each set of values are shown in Figure 2.12. The figures also show the cumulative distribution function of the authors' best estimates for the remaining life of the pavement using the condition survey. This exercise was performed at both 20,000 and the 80, 000 MLS load repetitions.

Figures 2.12a and 2.12b correspond to the fatigue cracking. In general, the variability of the predicted results and the observed values is about the same, which is indicated by the slope of the CDFs; however, for any given level of probability the predicted results are larger than the observed ones. These differences become smaller as the probability level increases. The conclusion from this analysis is that the models used to predict remaining life are statistically nonconservative in this particular example. The results for the rutting case, shown in Figures 2.12c and 2.12d, show the opposite trend. The predicted results are more conservative from a statistical point of view for this particular site. As in the previous case, as the probability level increases, the corresponding remaining life values for the three curves get closer.

As indicated before, all observed damages reported in Figure 2.12 were measured using a 1.5-m by 1-m grid. Therefore, the systematic differences, shown in the figure, are related to that case. When the result of the overall damage to the pad is compared with the most likely value of the remaining lives of the section (see Figure 2.11), the observed and calculated values are in closer agreement. The differences, observed in Figures 2.11 and 2.12, confirm that the size of the grid and the method used to measure defects significantly impact the final conclusion drawn. Therefore, for the future use of the APT data for activities such as the one described here, it may be beneficial to harmonize the definition and the methodology that should be used to measure defects.

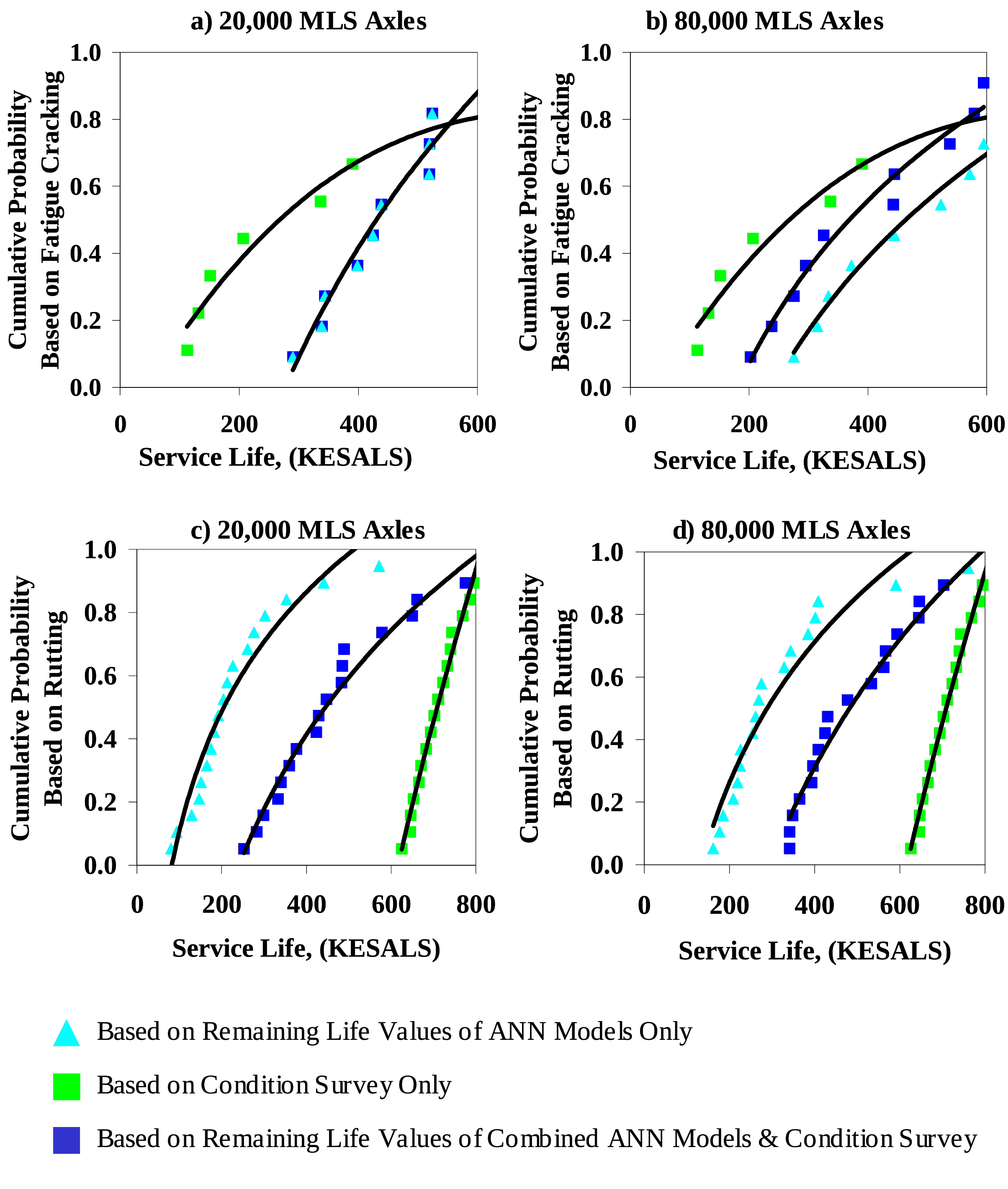


FIGURE 2.12 - Comparison of the Pavements Service Life Based on Observed Data, Results of ANN Models, and PPC

Conclusions of the Case Study

In this case study, researchers analyzed the process of validating the appropriateness of a new methodology for predicting the remaining life based on the APT data. The deflections measured with the FWD are used as part of the input to artificial neural network models that compute the rutting and cracking remaining lives of the pavement. Even though the proper development of the ANN models requires expertise and is time-consuming, estimating the remaining lives with these models is almost instantaneous and does not require any judgment by a skilled engineer. The calculated remaining lives are then combined with the condition of the pavement to forecast the pavement performance.

The results from this study indicated that, in general, the degree of the reasonableness of any new algorithm can be readily and economically determined using an APT facility. Several specific conclusions can also be drawn. For the proposed model, the most reasonable predicted remaining lives were obtained when the condition survey, at the time of the FWD testing, was combined with the deflection measurement.

When a point-by-point comparison between the predicted and observed remaining lives was carried out, mixed results were obtained. In some locations, the predicted and observed values were fairly close, while in others large differences were observed. Typically, the proposed model under-estimated the remaining life based on rutting and over-predicted due to fatigue cracking. The differences can be mainly attributed to two parameters: 1) approximations involved in the proposed models and 2) the way localized damage is defined.

When the geometrical and material-related variability of the site was considered, the remaining lives seem to fall between a 95% confidence interval for both rutting and fatigue. Therefore, for network level assessments or most project-level design, the methodology may be adequate.

Based on the success of the results in this case study, the researchers proceeded to implement the development of a system of neural network models to predict the critical strains for three and four layer pavement systems with variable depth of bedrock. The development and results of these models are detailed in the next chapter. The case study also provided the researchers with insight on how to modify the modeling aspect of the software. The software is currently in the final stage of development (for flexible pavements). Although a brief description of the software was provided in Research Report 1711-1, a detailed report will be produced at the conclusion of the software development phase.

Chapter 3

Development and Results of ANN Models

Database Generation

In Report 1711-1, ANN models that predicted the critical strains and ANN models that predicted the remaining life of a flexible pavement based on the Asphalt Institute equation were developed. Both sets of models were based on constant depth to bedrock of 6 m (240 in.). Based on the success of developing those models and the results of the case study, two modifications were made. The first modification was to have ANN models that predict distress of pavement sections with variable depths to bedrock. This required developing a neural network model to predict the thickness of the subgrade. The second adjustment was to develop models for predicting the critical strains. The two strains that were predicted were ε_c and ε_t and were based on Equations 2.1 and 2.2. No models were developed to predict the critical stress (based on the Finn model) as was the case in this study, which was mainly due to time constraints of the project. Also, the compressive strain at the top of the subgrade can be used in a variety of distress models to determine the rutting of a flexible pavement. Based on these modifications, a system of artificial neural network models for three- and four-layer flexible pavement systems with variable depth to bedrock was developed. This system of models covered a wide range of pavement sections. The ranges of pavement thickness and modulus of each layer are shown in Table 3.1. These ranges cover most types of flexible pavements that exist in Texas.

Using the parameters and ranges in Table 3.1, a Monte-Carlo simulation algorithm (Ang and Tang, 1984) generated 50,000 pavement sections. The randomly generated sections were based on a discrete uniform distribution.

In order to obtain the FWD deflections and critical strains for each section, a linear elastic program, WESLEA (Chou, 1981), was employed. Chapter 3 in Ferregut et al. (1999) provides an explanation of the process. To generate such a comprehensive database was very time-consuming but nevertheless necessary. The large database was studied thoroughly, and statistical conclusions were drawn about the relationship between all the parameters.

TABLE 3.1 - Ranges of Pavement Parameters for Three- and Four-Layer Systems

Pavement Parameters		Units		Value			
				Minimum		Maximum	
Asphalt-Concrete Thickness	(t_{AC})	mm	(in.)	13	(0.5)	254	(10)
Base Thickness	(t_{BASE})			102	(4)	457	(18)
*Subbase Thickness	($t_{SUBBASE}$)			102	(4)	305	(12)
Subgrade Thickness	($t_{SUBGRADE}$)			1524	(60)	6350	(250)
Asphalt-Concrete Modulus	(E_{AC})	MPa	(ksi)	1380	(200)	6900	(1000)
Base Modulus	(E_{BASE})			276	(40)	3450	(500)
*Subbase Modulus	($E_{SUBBASE}$)			276	(40)	1380	(200)
Subgrade Modulus	($E_{SUBGRADE}$)			28	(4)	311	(45)

* this range only applies to four-layer system

Data Processing

Data processing or data mining has been recognized as the most important aspect of developing ANN models. Based on the researchers' experience, data mining consumes up to 70% of the time used to develop a neural network model. Theoretically, one of the advantages of using an ANN model is their ability to handle complex problems and eliminate the hassle of any data processing. This ability is based on the fact that as the relationship between the input and output becomes more nonlinear the ANN model will compensate by increasing the learning-time (slower learning rate) and increasing the PEs in the hidden layer to achieve a more complex architecture. Therefore, the ANN is able to map any relationship between the input and output variables. However, this was not the experience in the modeling of the ANN models in this project. The input and output data required intensive processing techniques to produce meaningful results. Meaningful-data represents a set of variables having strong relationships between the input and output. Because of the high non-linearity of this problem, obtaining a set of meaningful-data was very time-consuming and required some expert judgment.

Inputs and Outputs

Before manipulating the data for modeling, the inputs (independent values) and the outputs (dependent values) were identified. The inputs consisted of the seven deflections (d_0,d_1,…,and d_6) and the pavement section properties such as: a) thickness of the AC layer (t_{AC}), b) thickness of the base layer (t_{BASE}), c) thickness of subbase ($t_{SUBBASE}$) (for a four-layer system), and d) the thickness of the subgrade ($t_{SUBGRADE}$). The outputs consisted of the critical strains. Table 3.2 shows the variety of remaining life models produced by various institutions to determine fatigue cracking and rutting. It can be observed that both the Asphalt Institute model and the Shell model require the modulus of the AC-layer to calculate the remaining life values. An ANN model was developed to predict the modulus of the AC-layer to enable the use of these two remaining life models.

TABLE 3.2 - Fatigue Cracking Model and Rutting Model Parameters Used to Determine Remaining Life of a Flexible Pavement (from Huang, 1993)

Institution	$N_f = f_1 (\varepsilon_t)^{-f2} (E_{AC})^{-f3}$			$N_r = f_4 (\varepsilon_c)^{-f5}$	
	f_1	f_2	f_3	f_4	f_5
Asphalt Institute	0.0796	3.291	0.854	1.365E-9	4.477
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

Figure 3.1 shows all the ANN models that were developed. One ANN model was used to predict the thickness of the subgrade for each pavement system. The results of these models were made part of the input to the ANN models that predicted the critical strains and the modulus of the AC-layer. Two sets of ANN models, based on the thickness of the AC-layer, were used to predict the critical strains. For thin AC-layers, the range of thickness was less than or equal to 76 mm (3 in.). The range of thick AC-layers was 76 mm (3 in.) to 254 mm (10 in.). From past modeling experience, the ANN models produced better results when this classification was conducted. Data generated for models with thin AC-layers had a fixed value of 500 ksi for the modulus of the AC layer. Therefore, only one model was required to predict the modulus of thick AC-layers for each layer system. Another point illustrated in the figure is that each network predicted only one parameter. This guarantees that the architecture of the model will not be influenced by more than one output, and, in turn, leads to more accurate results and simpler models.

The input and output ranges of the pavement thickness and modulus for the “Thin” and “Thick” models are indicated in Table 3.3. This table indicates which variables were used as inputs and outputs in developing the ANN models. An ANN model predicted the thickness of the subgrade from the thickness of the AC, base, subbase (for a four layer system), and deflections. Once the thickness of the subgrade was known, it was used as part of the input to the other ANN models. Also included in the table are the ranges of the deflections and critical strains, which were calculated using a linear elastic program.

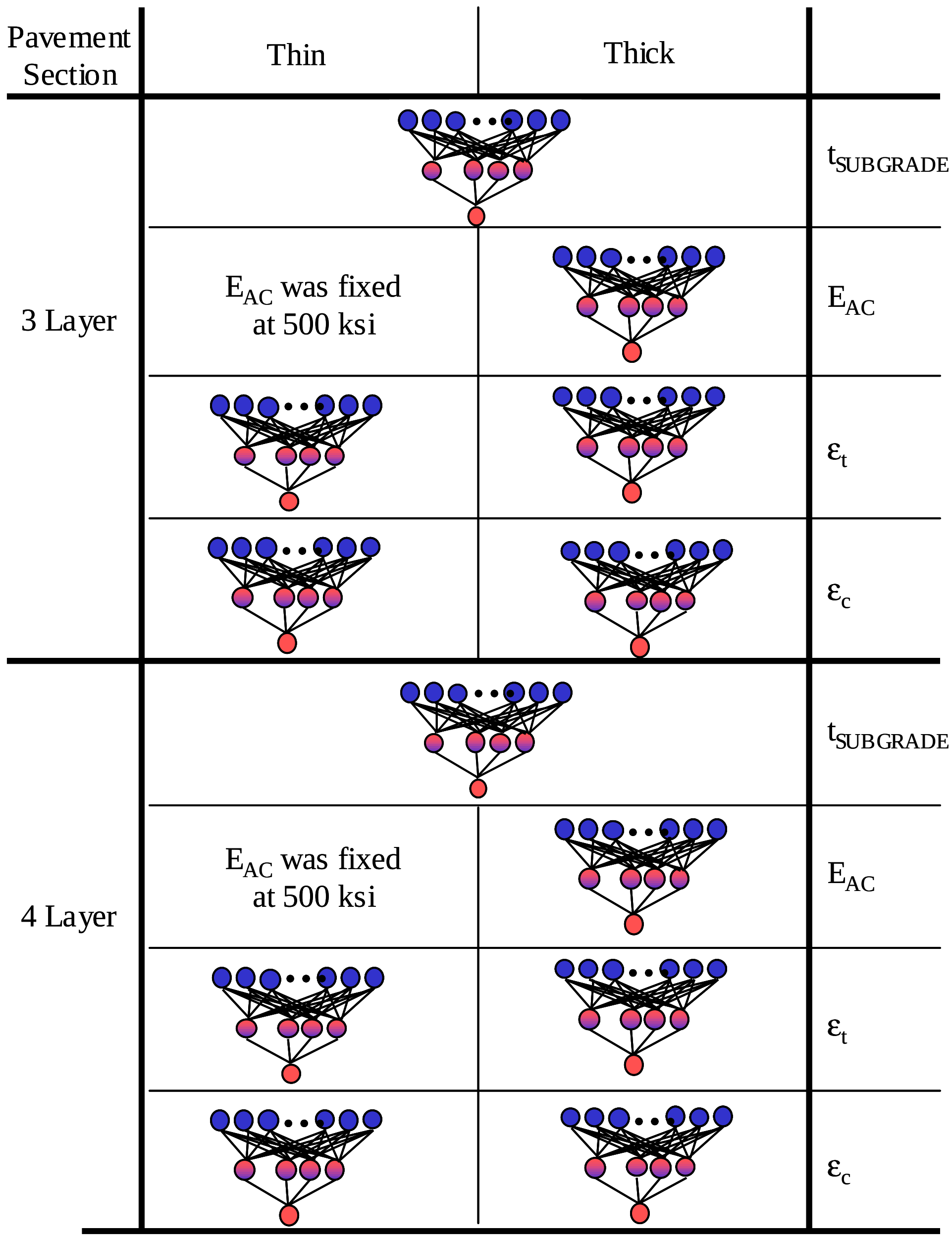


FIGURE 3.1 - System of Artificial Neural Network Models for Three- and Four-Layer Flexible Pavements

TABLE 3.3 - Ranges of the Inputs and Outputs Data for Developing the ANN Models

<table>
<tr><th colspan="3" rowspan="2">Network Variables</th><th rowspan="2">Units</th><th colspan="2">Minimum and Maximum Values</th></tr>
<tr><th>Thin</th><th>Thick</th></tr>
<tr><td rowspan="5">Input</td><td>Asphalt-Concrete Thickness</td><td>(t_{AC})</td><td rowspan="3">mm (in.)</td><td>12.7 (0.5) / 89 (3.5)</td><td>89 (3.5) / 254 (10)</td></tr>
<tr><td>Base Thickness</td><td>(t_{BASE})</td><td colspan="2">102 (4) / 457 (18)</td></tr>
<tr><td>*Subbase Thickness</td><td>$(t_{SUBBASE})$</td><td colspan="2">102 (4) / 305 (12)</td></tr>
<tr><td>Deflections</td><td>$(d_0 - d_6)$</td><td>mm (mils)</td><td colspan="2">Up to 2 (up to 80)</td></tr>
<tr><td>Subgrade Thickness</td><td>$(t_{SUBGRADE})$</td><td>mm (in.)</td><td colspan="2">1524 (60) / 6350 (250)</td></tr>
<tr><td rowspan="5">Output</td><td rowspan="2">Tensile Strain</td><td rowspan="2">(ε_t)</td><td rowspan="2">absolute microstrain</td><td colspan="2">50 - 400 for three-layer system</td></tr>
<tr><td colspan="2">50 - 250 for four-layer system</td></tr>
<tr><td rowspan="2">Compressive Strain</td><td rowspan="2">(ε_c)</td><td rowspan="2">microstrain</td><td colspan="2">50 – 1200 for three layer system</td></tr>
<tr><td>50-1250 4-Layers</td><td>250-650 4-Layers</td></tr>
<tr><td>Asphalt-Concrete Modulus</td><td>(E_{AC})</td><td>MPa (ksi)</td><td>Fixed at 3450 (500)</td><td>1380 (200) / 6900 (1000)</td></tr>
</table>

* this range only applies to four-layer system

Data Sampling

Once the inputs and outputs were selected and the variable ranges defined, the next step was to sample the data to obtain a meaningful relationship between the input and output for each neural network model. Typically, the first step in data sampling is to perform a correlation analysis between the inputs and outputs. A correlation analysis provides a good feel for the relation between two values. Based on the correlation analysis, inputs that do not have any relation to the output can be eliminated. For this project, the correlation analysis showed that all inputs were correlated to each of the outputs. Therefore, all the input variables were used in the training process.

To increase the correlation between the inputs and outputs, a transformation algorithm was utilized. The transformation algorithm generated hybrid or offspring variables based on the original variables. This transformation was performed for both the input and output variables. These offspring variables are intended to exhibit more linear and smoother characteristics than the original variables. The algorithm transformed and prioritized the new variables based on these linear characteristics. The new variables are then used in the training of the neural network models, as illustrated in Figure 3.2. Once the model was trained, the output was back-transformed to the original or "real" output, as depicted in the figure. The candidate transformations used in this process are summarized in Table 3.4. The table summarizes the transformations selected for both the three- and four-layer systems. The transformations were selected using a genetic algorithm.

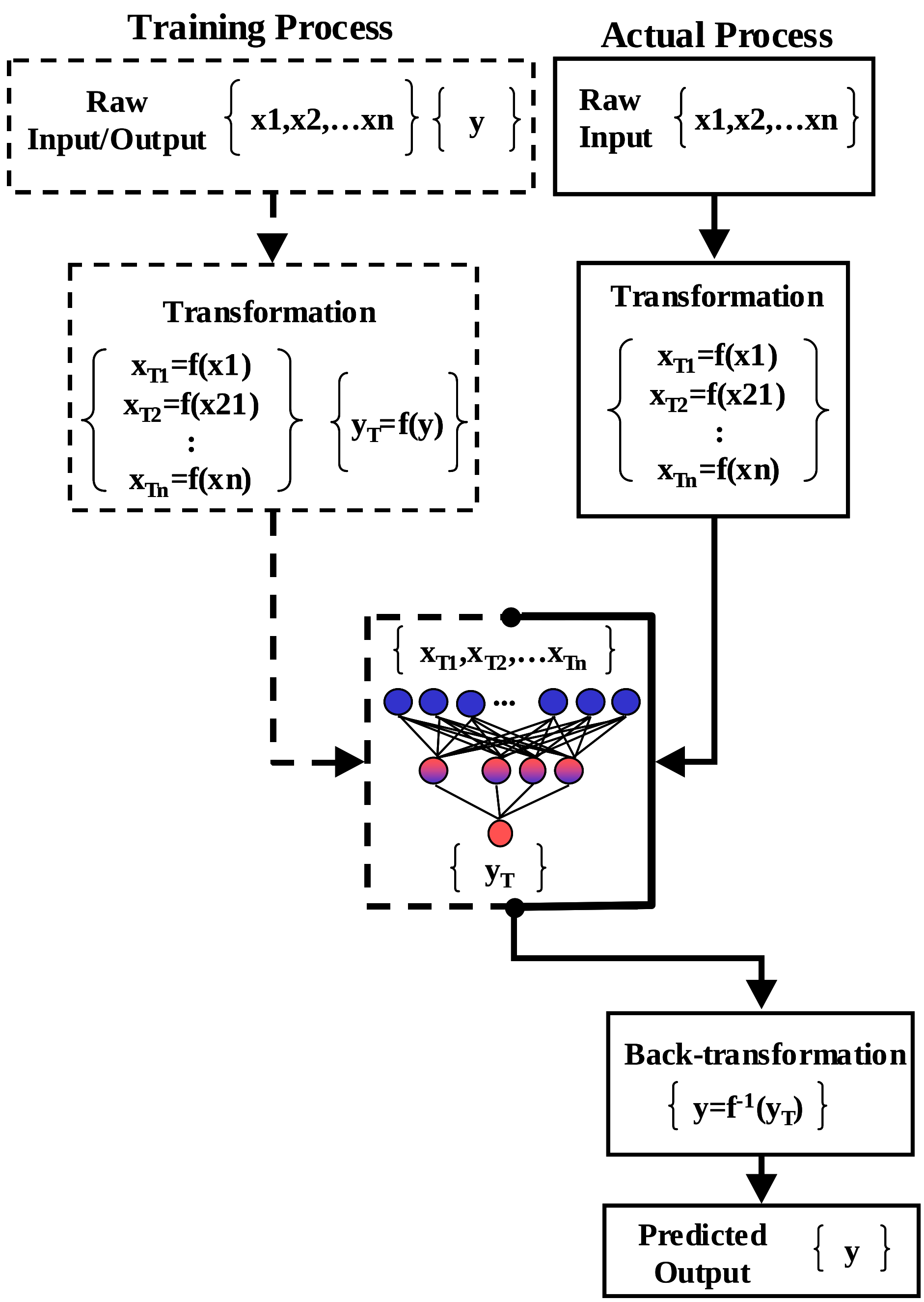


FIGURE 3.2 - Flow of Variable Transformation Process for Determining Inputs and Outputs to ANN Models

TABLE 3.4 - Selected Transformations Used for Training Each ANN Model

ANN Models / Transformations Used for the Input and Output Variables	Three-Layers						Four-Layers					
	Thin		Thick				Thin		Thick			
	Tensile Strain	Compressive Strain	Tensile Strain	Compressive Strain	Modulus of AC	Depth of Subgrade	Tensile Strain	Compressive Strain	Tensile Strain	Compressive Strain	Modulus of AC	Depth of Subgrade
Identity function	I	I	I	I	I	I	I	I	I	I	I	I
Natural logarithm function					I		I	I			I	I
Double Log			I			I	I			I		
Exponential function	I	I	I	I	I			I	I		I	I
Double Exp		I	I	I	I					I		
Square function	I	O	I	O	O	I	I	I	O	I		O
Fourth Power function	I	I	I	I	I	O	I	I	I	I	I	I
Square root function					I			I			I	
Fourth root function								I	I		I	I
Inverse function (1/x)		I		I				I	I			
1 / (Square function)	I	I		I				I	I			
1 / (Fourth Power function)	I	I	I							I	I	I
1 / (Square root function)												
1 / (Fourth root function)						I						
Hyperbolic tangent function	I	I	I	I	I	I	I	I	I	I	I	I
Log (x/(1-x))	O		O	I			O	O		O	O	I

Note: I - selected input transformation, O - selected output transformation

Artificial Neural Network Parameters

An important step during the training of the ANN models was choosing the appropriate learning algorithm. Part of the learning process was to generate data sets for training, testing and validating. Having a large database made it easy to set up three data sets for each of the networks. The parameters necessary for the training algorithm were 1) the learning rule, 2) the noise level, 3) the transfer function, and 4) the evaluation function. The learning rule used for all the networks was the

Kalman-Filter (Puskorius and Feldkamp, 1991). Two noise levels were selected for the networks: a) no noise and b) moderate noise. The sigmoid function was selected as the transfer function. All the neural network models were generated and evaluated based on two evaluation functions: a) the root mean square (RMS) error and b) the correlation function. This meant that four networks for each of the twelve models, depicted in Figure 3.2, were developed. The training process began once these parameters were set. Once each network was developed and tested, it was validated using the validation data set. Four competing ANN models were developed for computing each parameter. To choose the best model, a systematic procedure was designed using the absolute error criteria. The absolute error was defined as:

$$\%\ Absolute\ Error = \frac{|actual - predicted|}{actual} * 100 \qquad (3.1)$$

The predicted values were the values obtained from the neural network model, and the actual values were the values from the validation data set. The absolute error was calculated for each record of the validation file. The ANN model that produced the lowest overall absolute error was selected. The performance of each of the selected ANN models is presented in the next section.

Results of the ANN Models

Twelve artificial neural network models were developed for the three- and four-layer flexible pavements. To facilitate the explanation of the results of each model, two graphs are presented. The first graph compares the model's predicted results with the desired values. A ±10% error band, based on the values from the validation data, is also plotted to illustrate the accuracy of the model. The second graph is a combination of plots. One is a histogram showing the frequency of model predictions within a certain absolute error. The other one is the cumulative frequency plot that shows the total number of model predictions that are less than or equal to a certain absolute error.

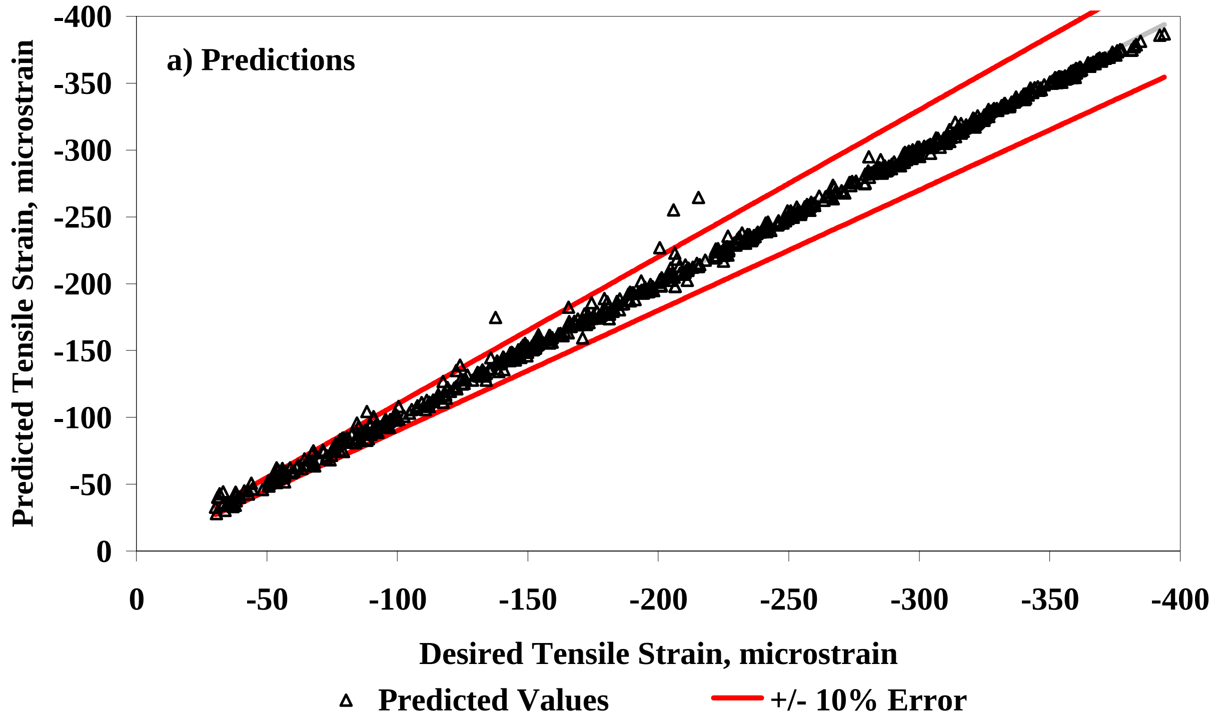
Figure 3.3 contains the results for the model developed to predict the critical tensile strain for a three-layer pavement system with variable depth to bedrock. This model predicts the tensile strain for thin AC layers. In Figure 3.3a, the predicted results of the ANN model are compared to the desired values of the validation set. The ±10% error band plotted in this graph visually demonstrates the performance model. The predicted values cluster around the line of equality. Furthermore, the histogram in Figure 3.3b shows that the critical strains in about 450 pavement sections were predicted with an error of ±1%. Based on the cumulative plot, 97% of the predictions were at less than a 10% absolute error. These results clearly show that this model was well trained since it predicted the critical tensile strain with a high accuracy level.

As mentioned previously, the ANN models originally developed in this project were based on a fixed depth to bedrock. Since the proposed system of ANN models was based on variable depth to bedrock, a model to predict the thickness of the subgrade was needed. Figure 3.4 shows the results of the model that predicts the thickness of the subgrade for a three-layer system. The first graph in the figure shows the predicted thickness of the subgrade layer for all the pavement sections cases that were used to validate the model. The plot compares the predicted results and the values from the validation data. This graph shows a step function of the different thickness used in the development of the ANN model. The step function is not represented well in the graph because of the number of cases used to validate this model. However, most of the predicted values cluster around the step function indicating a high accuracy level in the predictions. The graph also illustrates that very few of the predicted thicknesses fall outside the ±10% error band. The results of the performance graph reinforce the model's predictive ability. The graph shows an accuracy of 96% with less than 10% absolute error. This percentage would be higher if pavement sections with subgrade thicknesses of 6.4 m (250 in.) were eliminated from the validation set. Even though the ANN model was trained and able to predict subgrade thicknesses up to 6.4 m (250 in.), common practice in engineering design and analysis usually limits the thickness to about 5 m (200 in.) or less.

The rest of the figures showing the results of the other ten ANN models are included in Appendix A. All the figures present the results of their respective models in a format similar to Figures 3.3 and 3.4. Table 3.5 includes a result summary of all the ANN models developed that shows the resulting architecture, the evaluation functions, the number of pavement sections used to validate the ANN models, and the cumulative percentage of the predicted results that had an absolute error of 1%, 5%, 10%, and 20% for all twelve ANN models.

Table 3.5 shows that the architecture of all the models seems to follow a certain trend. Except for one model, all the ANN models seem to have a smaller number of PEs in the hidden layer compared to the input layer. This suggests that the information in the input layer was sufficient and a higher order of mapping was not necessary. Also, the number of PEs in the input layer was almost the same for all the models and was influenced by the variable transformation algorithm discussed in the early part of the chapter. The reason for having a similar number of PEs in the input layer, with the exception of the two models used to predict the thickness of the subgrade, could be that the ANN models had the same original number of input variables. A closer look at the architectures reveals another trend. It can be seen that overall the models developed to predict the compressive strain have the lowest number of PEs in their hidden layer. This suggests that the relationship between the inputs and the outputs for these models were less complex, resulting in more robust architecture. Only one model out of the twelve shows that the number of PEs in the hidden layer is larger than the PEs in the input layer. It should be noted that this same model has the highest level of accuracy with almost 100% of the results being predicted at a ±10% error.

Table 3.5 also shows that the model selection criterion was not biased to either of the evaluation functions. However, it seems like the models selected using the correlation function to evaluate the training progress have a simpler architecture than those that were selected using the RMS error to evaluate the training progress. These trends need to be looked at and investigated by the ANN model development team. The only model that does not show as high a level of accuracy as the rest is the model that predicts the thickness of the subgrade for a four-layer system. Based on the values in Table 3.5, the model achieves an accuracy level of 89% within a ±10% error. A closer look at Figure A.10 in Appendix A reveals that most of the error was contributed at the higher thickness values. The contributed errors from sections with subgrade thickness of 6.4 m (250 in.) skew the models accuracy level. Figure A.10 clearly shows that at thicknesses of 5m (200 in.) and less the majority of the predicted values form clusters around the validation data or step function. Without the thickness of 6.4 m (250 in.), this model could achieve a much higher level of accuracy.



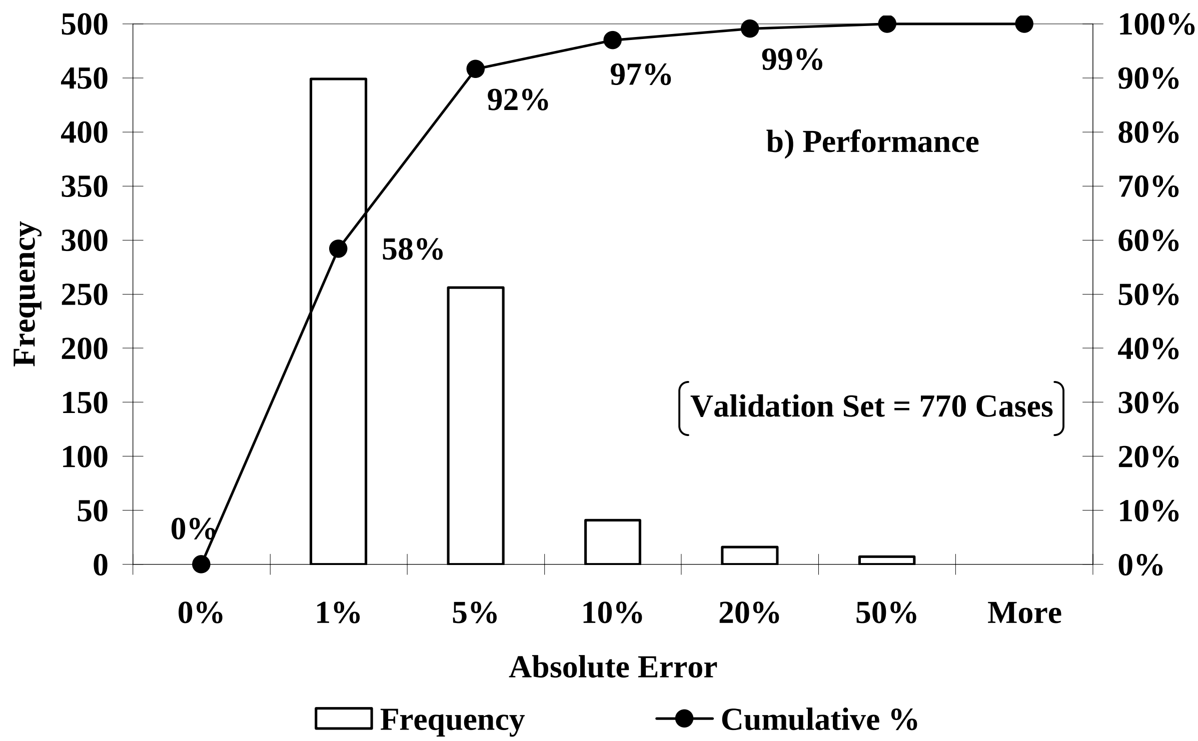
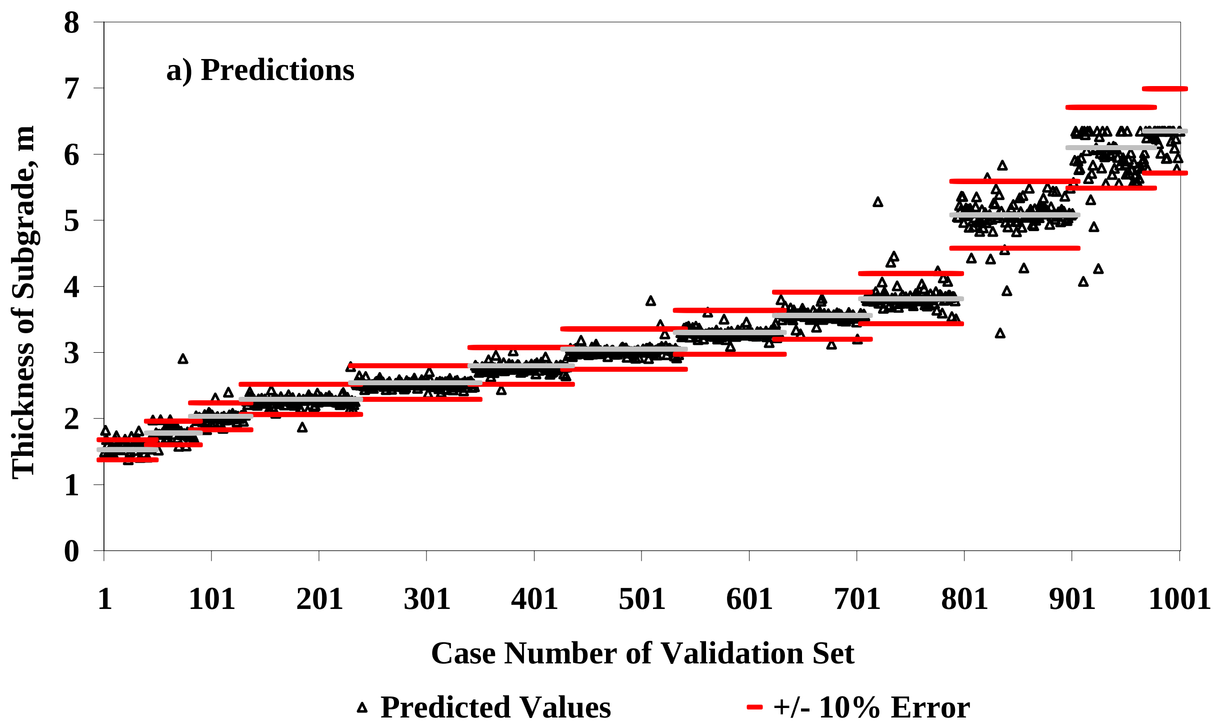


FIGURE 3.3 - ANN Model's Prediction and Performance Based on the Validation Data for the Tensile Strain Parameter of a Three-Layer Pavement System with a Thin AC-Layer



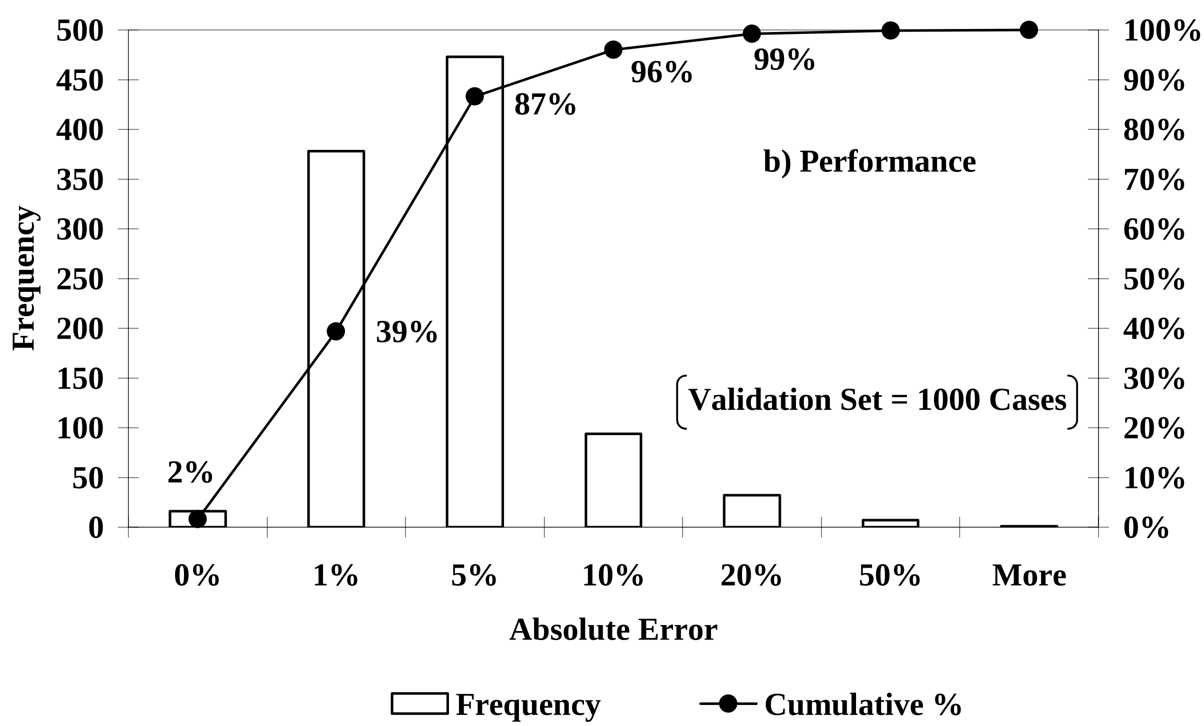


FIGURE 3.4 - ANN Model's Prediction and Performance Based on the Validation Data for the Thickness of the Subgrade for a Three-Layer Pavement System

TABLE 3.5 - Summary and Performance of the ANN Models For Three-Layer and Four-Layer Flexible Pavement Systems

ANN Models			Sections in Validation Set	Architecture	Evaluation Function	Cumulative % of Results Based on Absolute Error			
						1%	5%	10%	20%
3-Layers	Thin	ε_t	770	40-25-1	Correlation	58	92	97	99
		ε_c	875	40-24-1	Correlation	49	89	95	98
	Thick	ε_t	1500	42-50-1	RMS	66	99	-	-
		ε_c	900	42-42-1	RMS	67	98	-	-
		E_{AC}	5000	42-30-1	RMS	28	82	95	99
	$T_{Subgrade}$		1000	39-31-1	RMS	39	87	96	99
4-Layers	Thin	ε_t	1270	45-12-1	Correlation	23	83	95	99
		ε_c	574	41-7-1	Correlation	25	66	81	91
	Thick	ε_t	808	40-30-1	RMS	66	95	98	-
		ε_c	500	43-10-1	Correlation	62	99	-	-
		E_{AC}	1000	45-30-1	RMS	25	79	93	99
	$T_{Subgrade}$		1000	43-30-1	RMS	21	68	89	97

Chapter 4

Summary and Conclusions

This report summarizes the efforts to develop a system of Artificial Neural Network (ANN) models that use data from NDE tests, such as the Falling Weight Deflectometer, to ultimately estimate the remaining life of a pavement. The project has progressed with close cooperation between TxDOT and UTEP.

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

1) A case study was conducted to validate the methodology of using ANN models to predict the remaining life of flexible pavements.

2) A series of artificial neural network models were developed for three- and four-layer flexible pavements systems with variable bedrock depths. The series of models included six pairs of models, one for each layer system:

    a) one pair predicted the thickness of the subgrade layer,
    b) one pair predicted the compressive strain at the top of the subgrade-layer for sections with thin AC layers,
    c) one pair predicted the compressive strain at the top of the subgrade-layer for sections with thick AC layers,
    d) one pair predicted the tensile strain at the bottom of the AC-layer for sections with thin AC layers,
    e) one pair predicted the tensile strain at the bottom of the AC-layer for sections with thick AC layers, and
    f) one pair predicted the modulus of the AC-layer for sections with thick AC layers.

3) The above models have been incorporated into the software.

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

1) The development of the artificial neural network models is completed.

2) The software is at its final stage of development. Thus far, the software includes algorithms:

   a) to automatically read an FWD file,
   b) to process all twelve of the ANN models presented in this report,
   c) for estimating the uncertainty in the predicted remaining life,
   d) to use the Asphalt Institute equation, the Shell model, or any user defined model and calculate the remaining life based on the results of the ANN models,
   e) to incorporate information from traffic report and develop the pavement performance curve,
   f) to plot the profile of an entire test section, and
   g) to establish upper and lower bounds for the pavement performance curve and the profile of the test section.

3) Code is being incorporated to the software to generate a project report automatically.

4) A comprehensive users guide and a Help file are currently under development.

5) The software is also being tested to identify any “bugs” in the program.

The last phase of this project will be to test the software with actual data collected from existing flexible pavement sections. This process will validate the entire methodology as a whole using actual field data. This process will be a combined effort with both the researchers at The University of Texas at El Paso and selected personnel from the Texas Department of Transportation. This is the most important step in the project because it will provide insight into how TxDOT pavement engineers would use the software tool.

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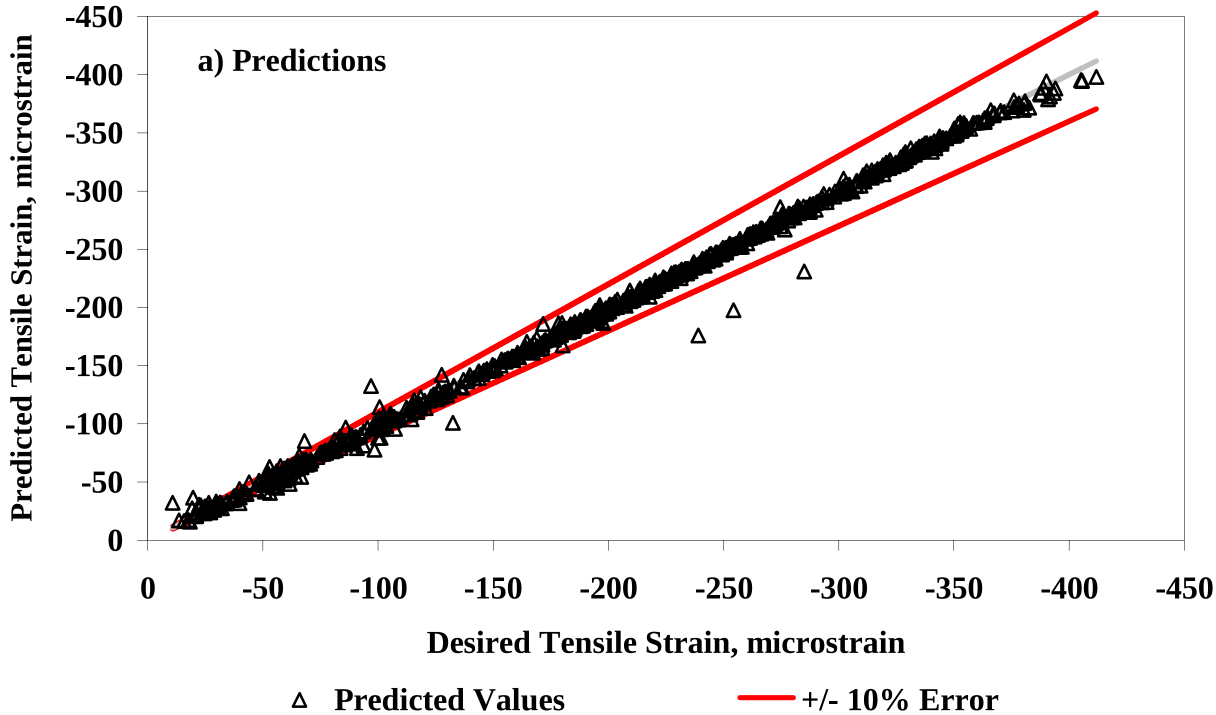
Appendix A

ANN Models' Predictions and Performance Based Validation Data Sets for Three-Layer and Four-Layer Systems



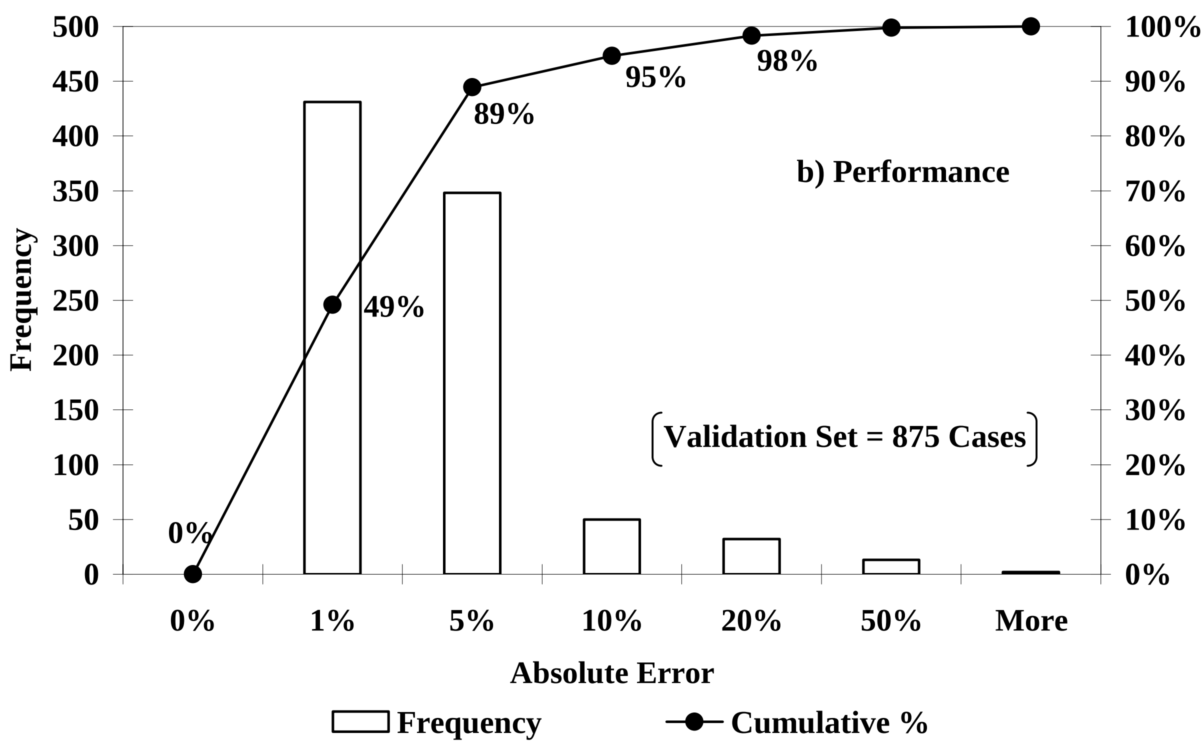


FIGURE A.1 - ANN Model's Prediction and Performance Based on the Validation Data for the Tensile Strain Parameter of a Three-Layer Pavement System with a Thick AC-Layer

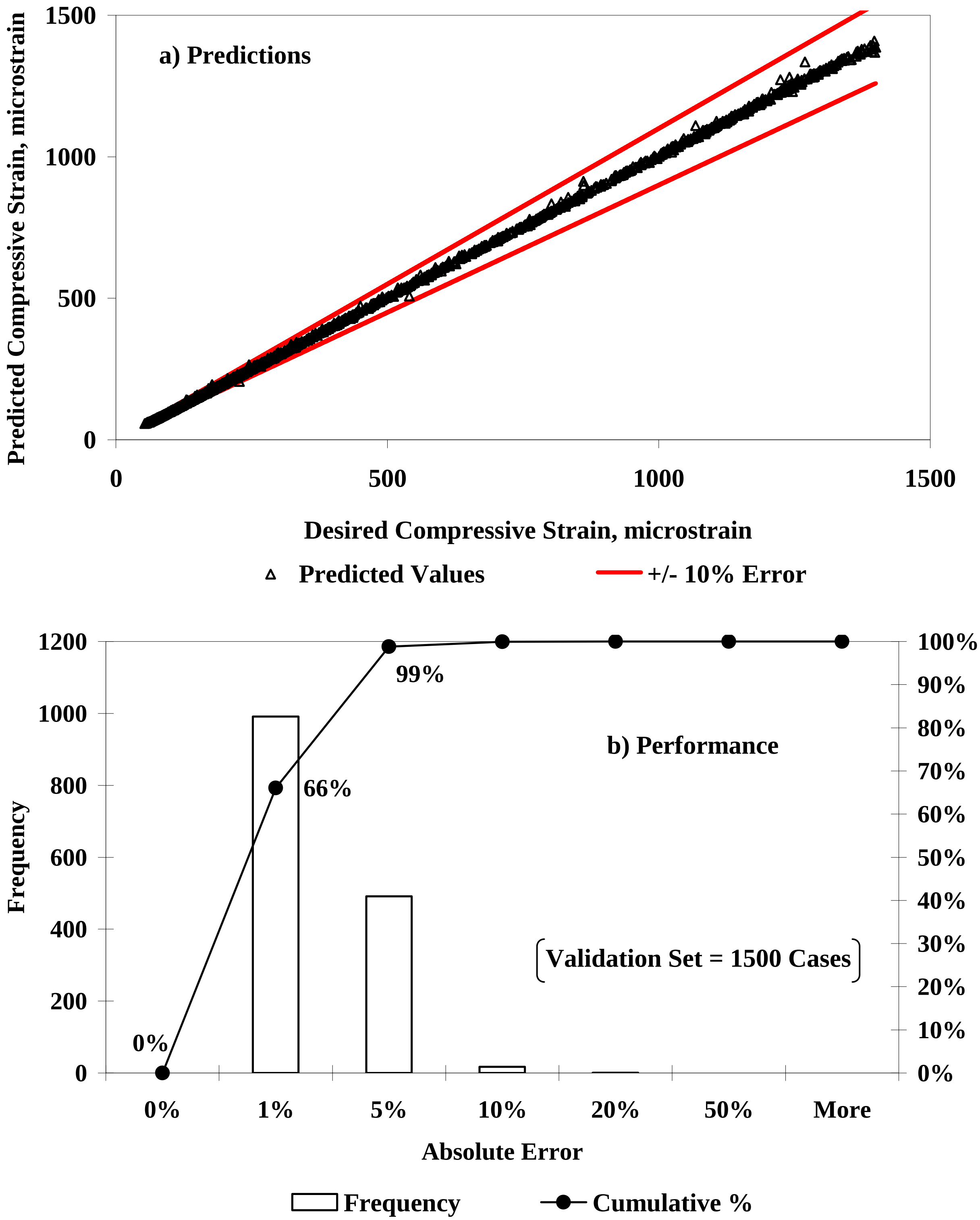


FIGURE A.2 - ANN Model's Prediction and Performance Based on the Validation Data for the Compressive Strain Parameter of a Three-Layer Pavement System with a Thin AC-Layer

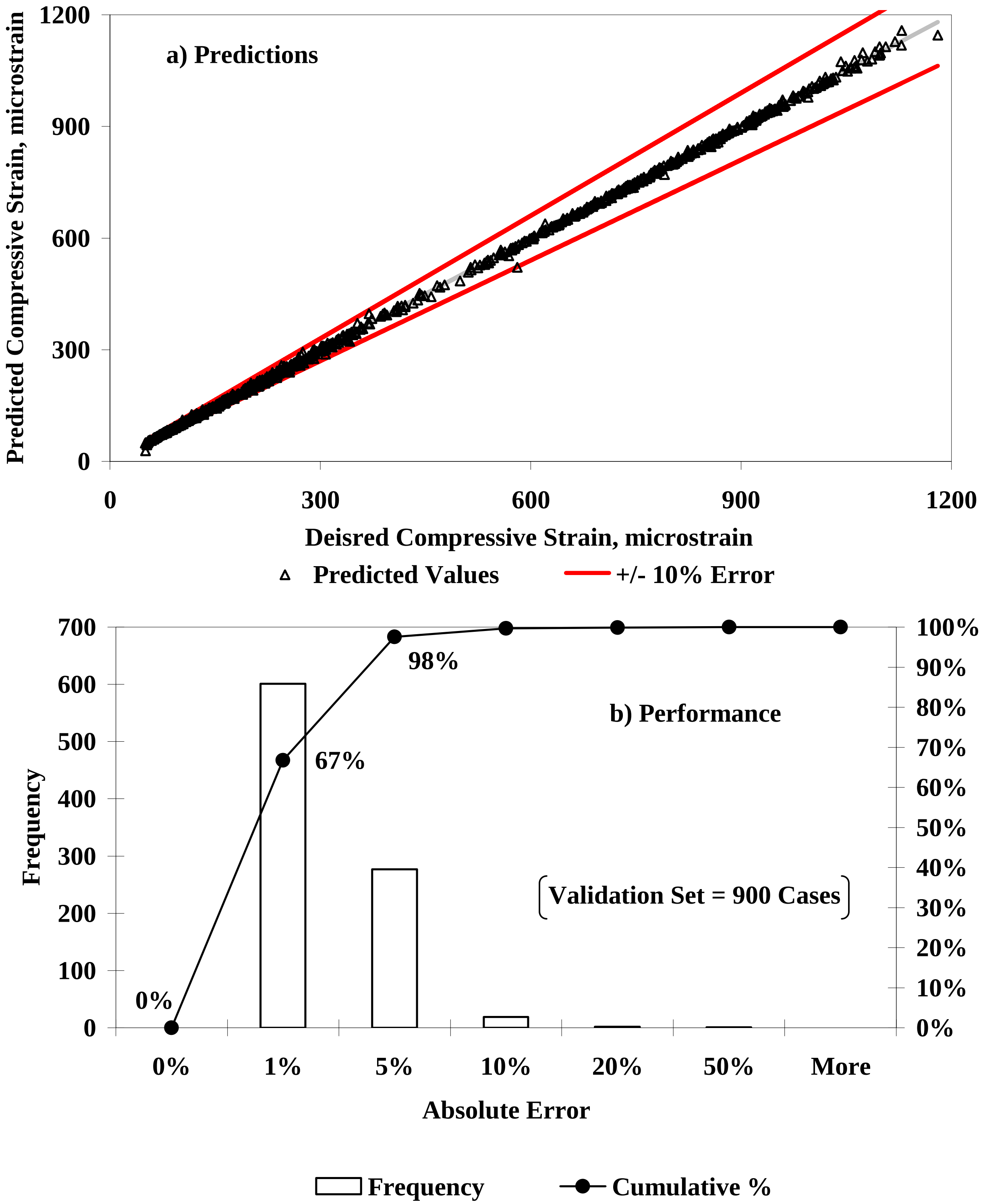


FIGURE A.3 - ANN Model's Prediction and Performance Based on the Validation Data for the Compressive Strain Parameter of a Three-Layer Pavement System with a Thick AC-Layer

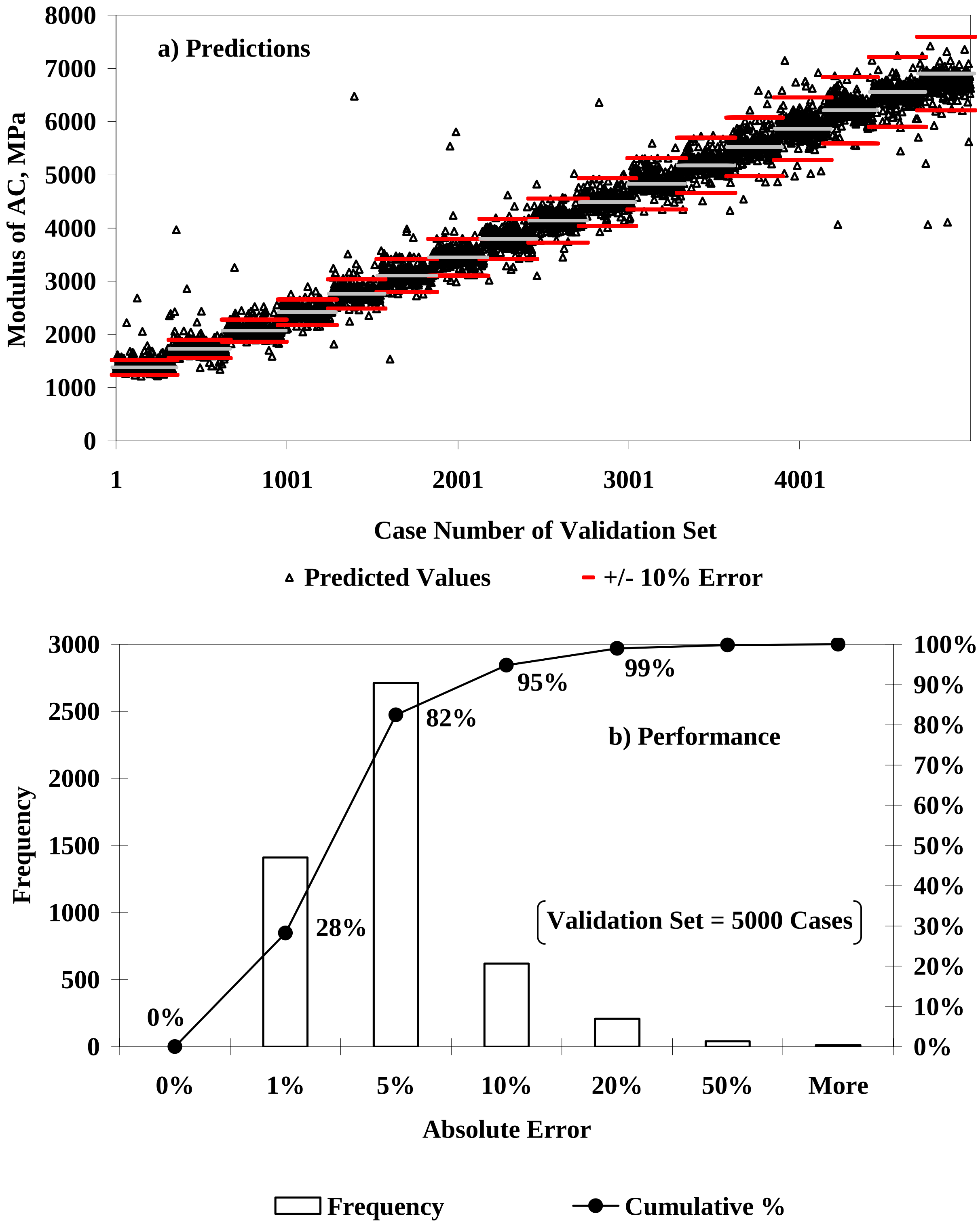


FIGURE A.4 - ANN Model's Prediction and Performance Based on the Validation Data for the AC Modulus Parameter of a Three-Layer Pavement System with a Thick AC-Layer

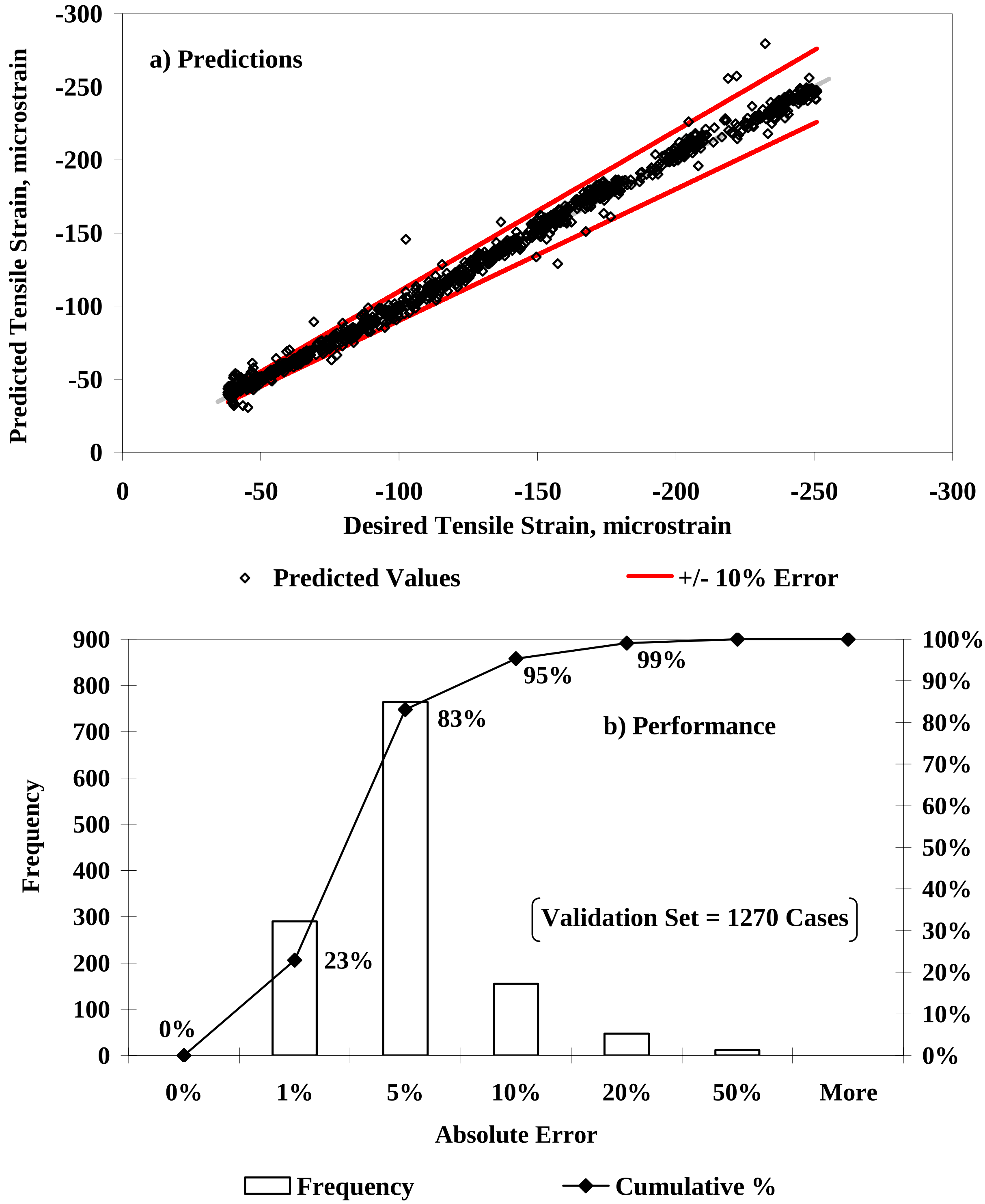


FIGURE A.5 - ANN Model's Prediction and Performance Based on the Validation Data for the Tensile Strain Parameter of a Four-Layer Pavement System with a Thin AC-Layer

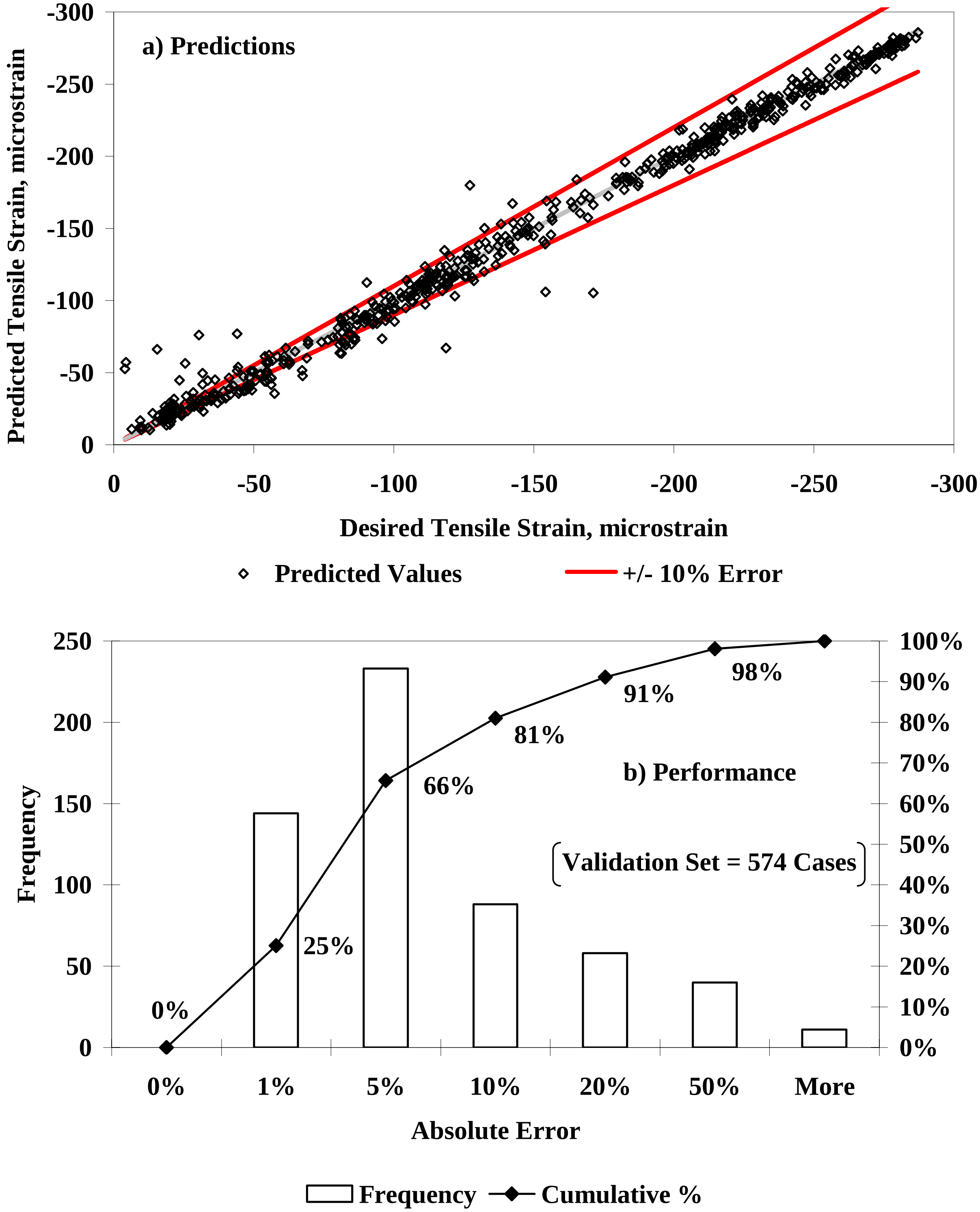


FIGURE A.6 - ANN Model's Prediction and Performance Based on the Validation Data for the Tensile Strain Parameter of a Four-Layer Pavement System with a Thick AC-Layer

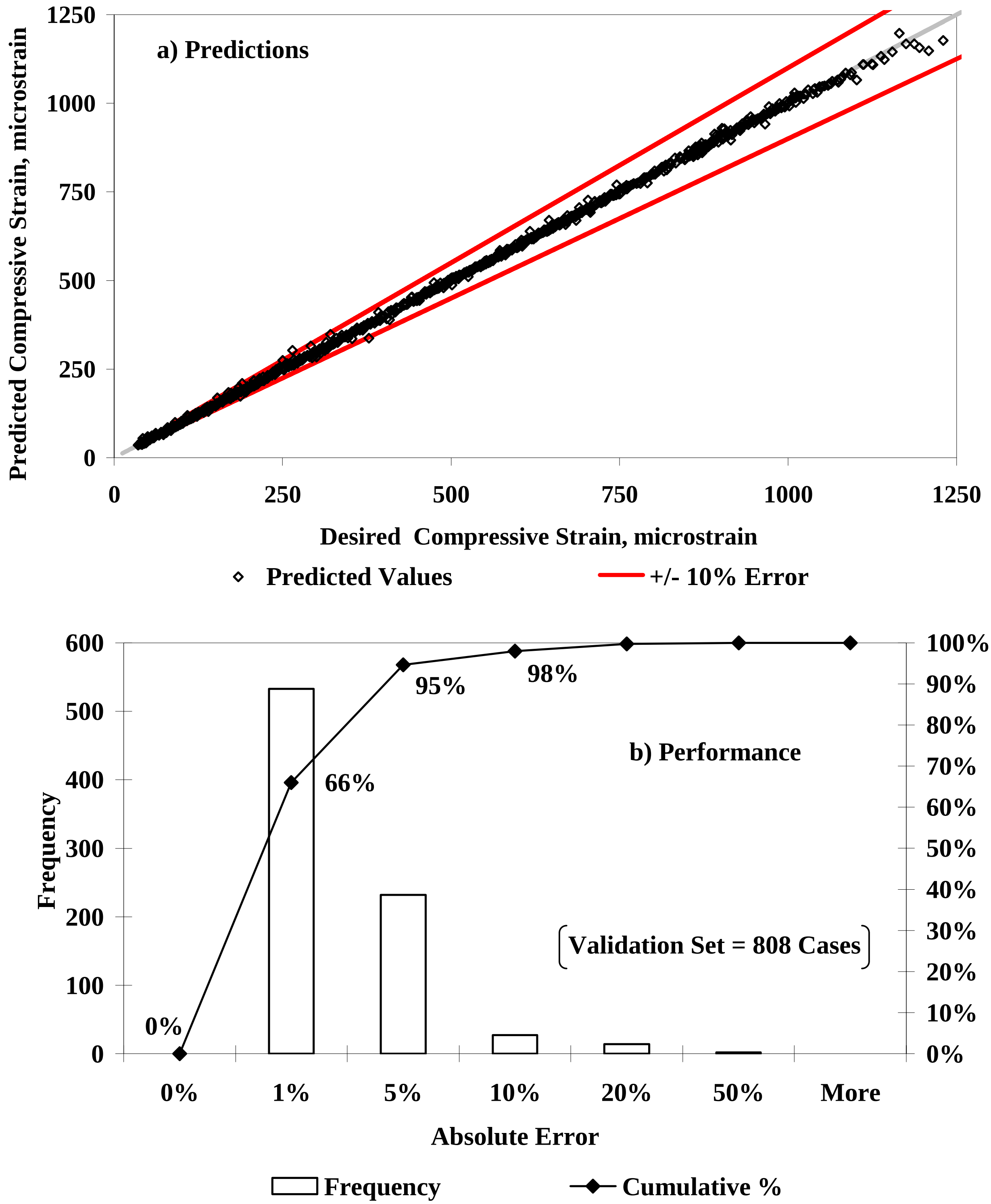


FIGURE A.7 - ANN Model's Prediction and Performance Based on the Validation Data for the Compressive Strain Parameter of a Four-Layer Pavement System with a Thin AC-Layer

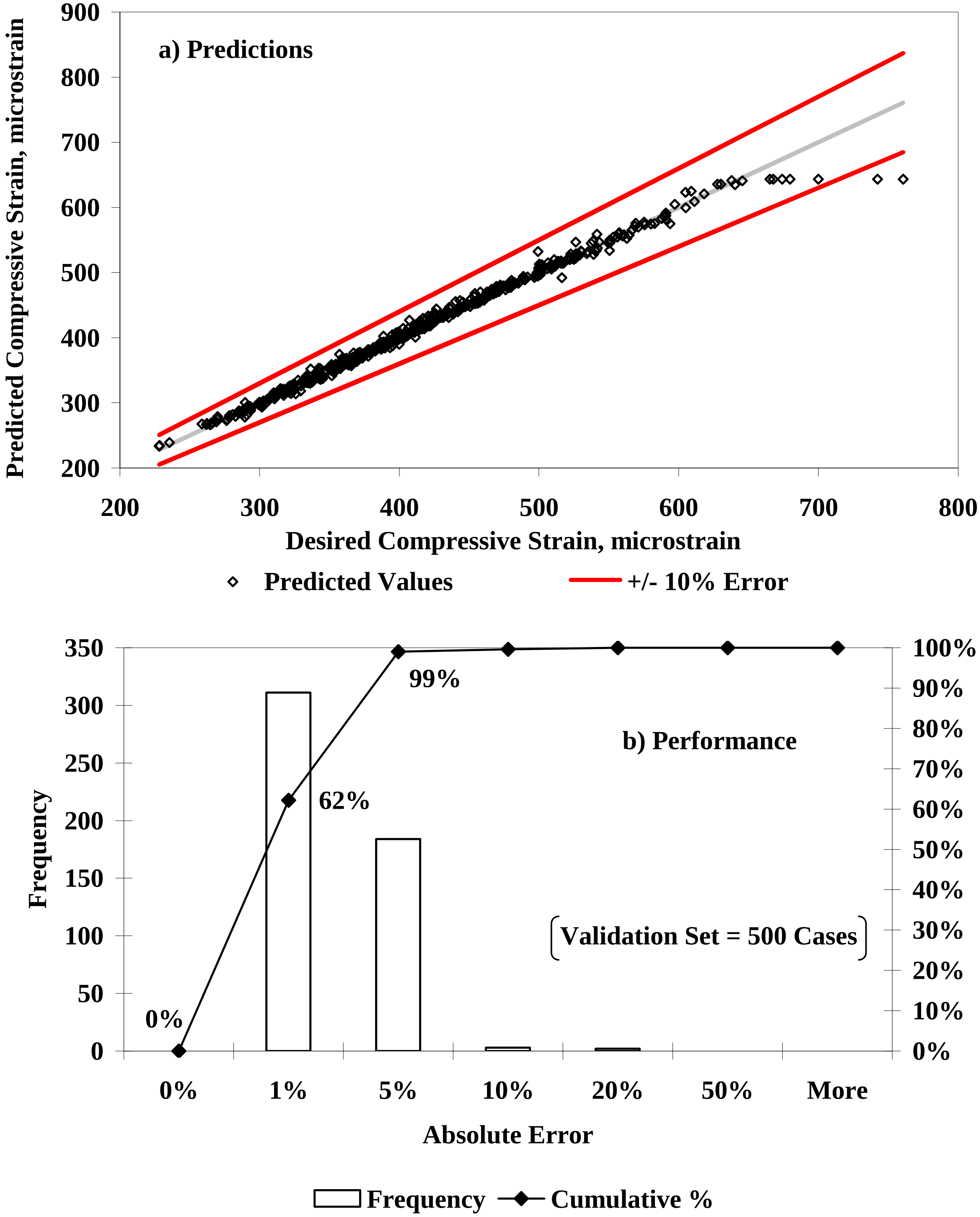
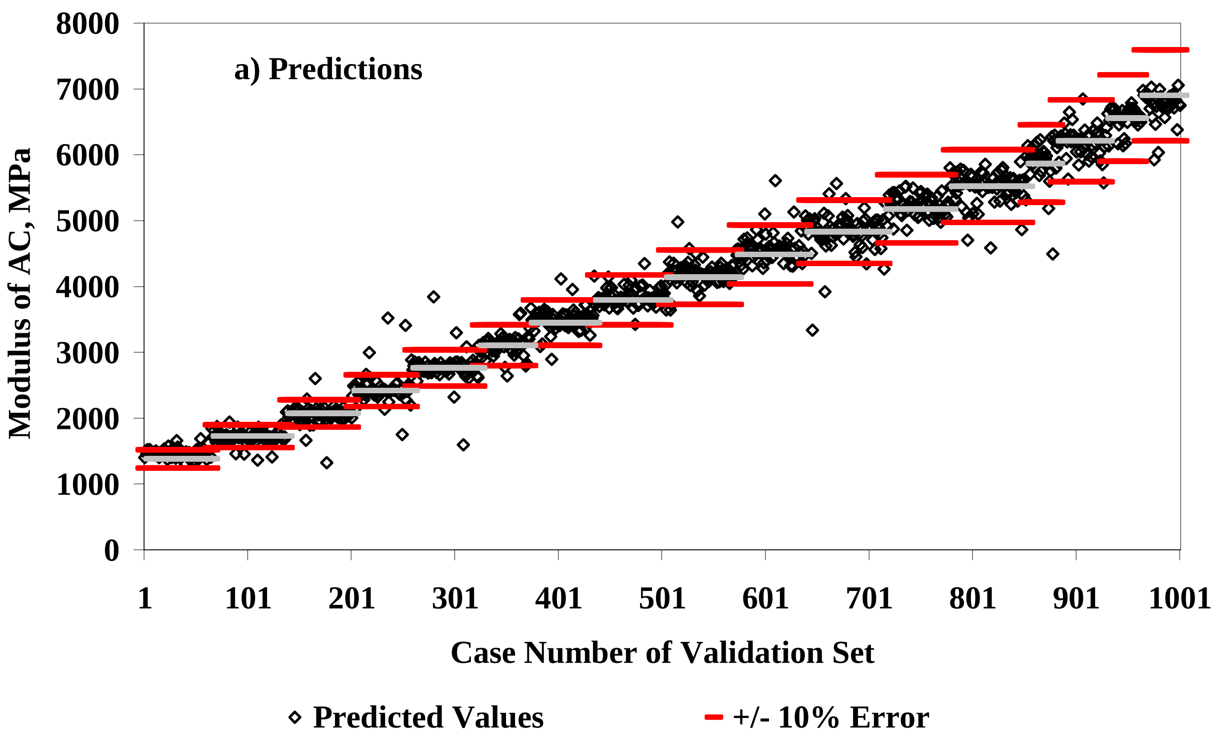


FIGURE A.8 - ANN Model's Prediction and Performance Based on the Validation Data for the Compressive Strain Parameter of a Four-Layer Pavement System with a Thick AC-Layer



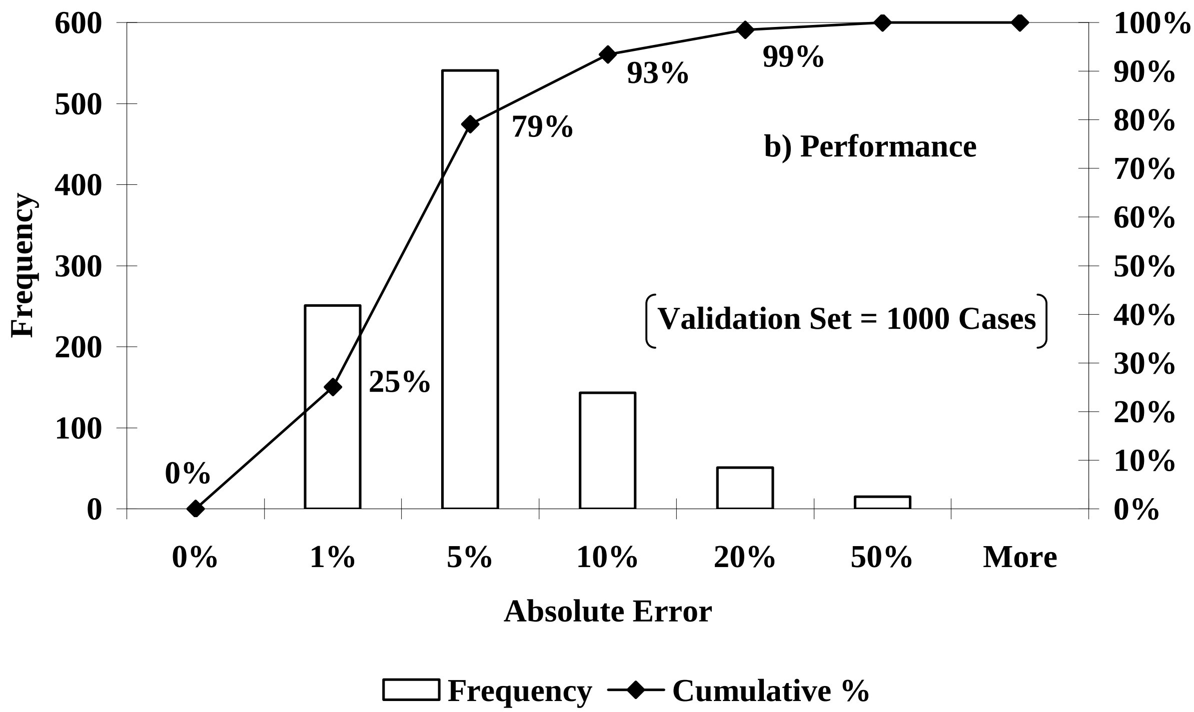
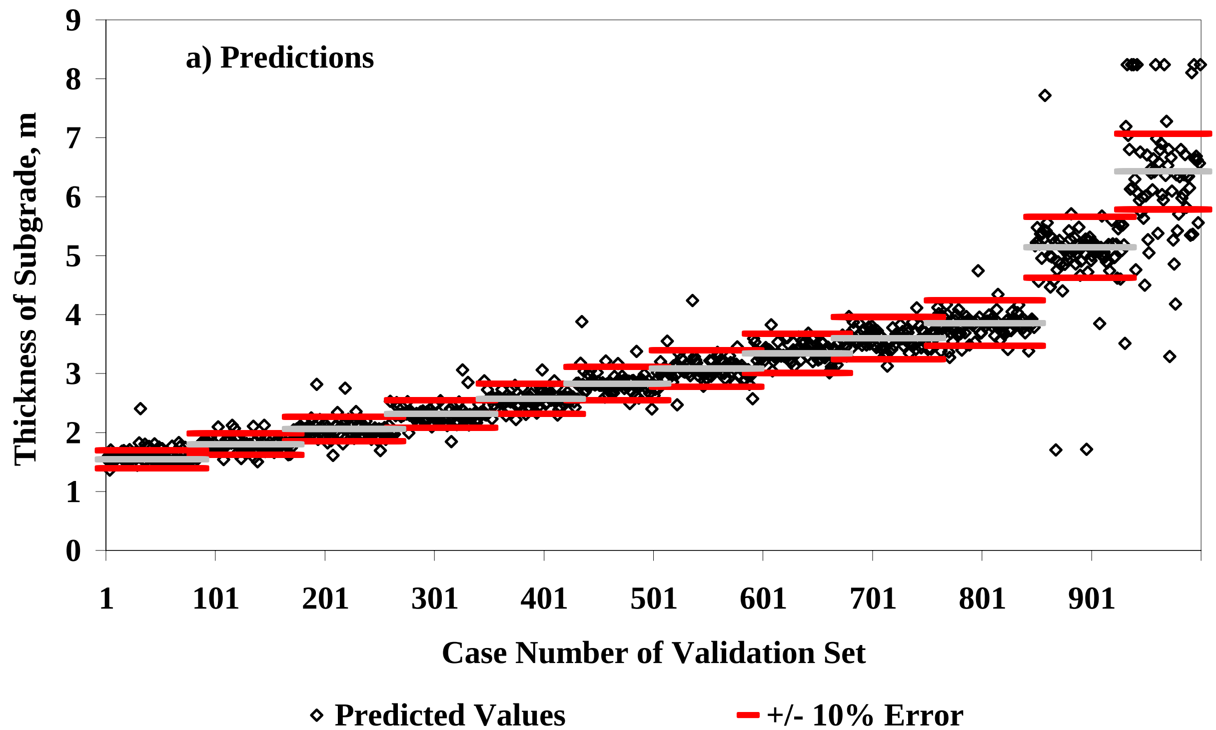


FIGURE A.9 - ANN Model's Prediction and Performance Based on the Validation Data for the AC Modulus Parameter of a Four-Layer Pavement System with a Thick AC-Layer



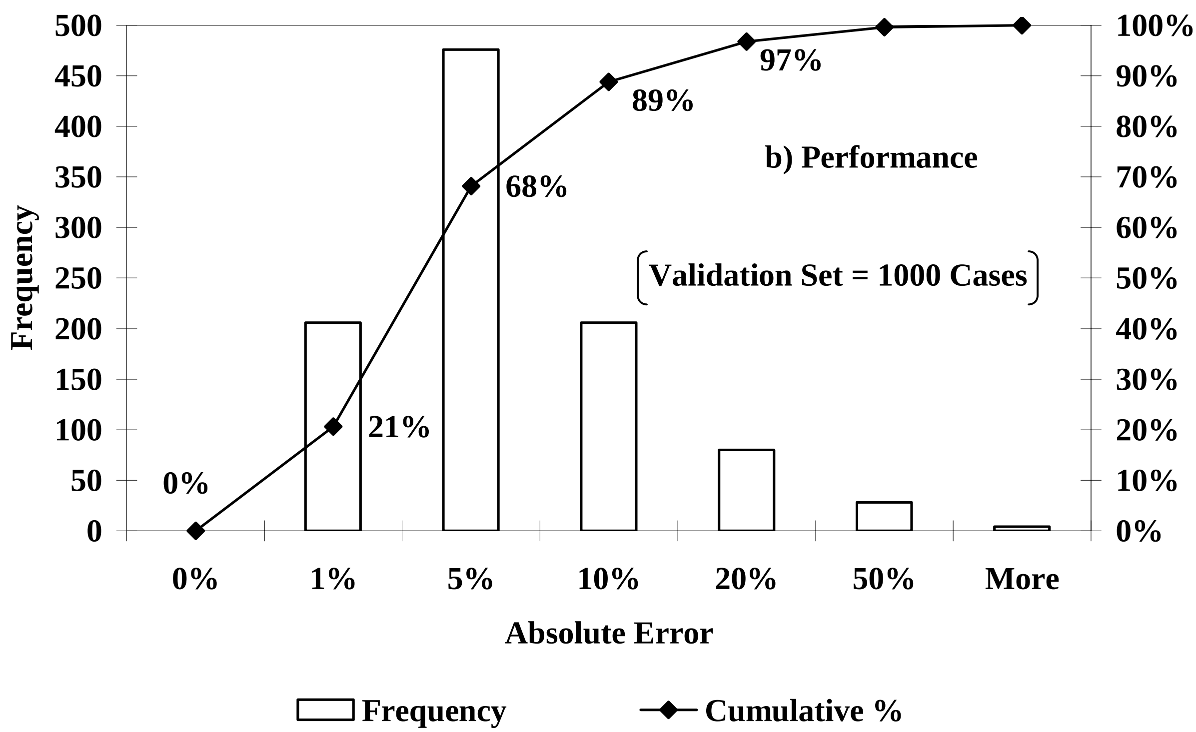


FIGURE A.10 - ANN Model's Prediction and Performance Based on the Validation Data for the Thickness of the Subgrade for a Four-Layer Pavement System