Stiffness Properties of Composite Pavements Using Artificial Neural Network-Based Methodologies

Center for Highway Materials Research

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Stiffness Properties of Composite Pavements Using Artificial Neural Network-Based Methodologies

by

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Research Project 0-1711

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

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Abstract

Most mechanistic-empirical methods for determining the remaining life of an existing pavement rely on the use of deflection-based nondestructive evaluation (NDE) devices. This report describes a methodology based on Artificial Neural Networks (ANN) techniques to estimate moduli of different layers in a composite 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. The outcome of the study is a computer program that estimates the moduli of different pavement layers in a more robust manner.

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 layers' moduli of a given composite pavement section. The methodology is based on Artificial Neural Networks (ANN) techniques and statistical concepts. In the proposed approach, the traditional backcalculation process is omitted. In addition, it only uses data readily available to pavement engineers, such as the measured deflection bowls and the section layers' thickness.

The objectives of this project were modified due to the lack of mechanistic models for a composite pavement sections. The new objectives were 1) to develop ANN models to compute the modulus of each of the layers of a composite section and 2) to create a software tool that can integrate the future models as they become available.

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 is one of the three-layer moduli.

In the absence of a comprehensive database containing the required properties of actual pavements, a synthetic database was generated to simulate and cover a wide range of possible pavement sections. FWD tests on the pavement were simulated to obtain the deflection basin in a number of composite pavement sections. At the end, a database with 10,000 exemplars was compiled. The data sets for training, testing and validating the ANN models developed were sampled from this database.

Four ANN models were developed for a three-layer composite pavement. One model predicts the modulus of the AC layer, the second the modulus of the base layer, and the last two models the modulus of the subgrade layer, one when the depth to rigid layer is known and one when the location of rigid layer is not known. When the depth to bedrock is introduced to the model, the modulus of the subgrade is predicted more accurately.

All the models and algorithms developed have been integrated into a software tool. The latest version of the software, developed using C^{++} development-programming language, works in Windows 95/98/00/NT environment.

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 the traditional backcalculation approach is that the moduli can be calculated for a large number of pavement sections at one time.

Implementation Statement

The software developed is ready for limited implementation. We recommend that staff members of the Pavement Section utilize this program along with the existing methodologies for evaluation purposes and for providing recommendations for future improvements.

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Chapter 1

Introduction

One of the most common nondestructive evaluation (NDE) methods to estimate pavement performance data is the falling weight deflectometer (FWD). The seven peak deflections, 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 will be then possible to estimate the pavement's remaining life using any available model (Huang, 1993). Despite the straightforwardness of this approach, several concerns still exist over its rationality. One of those concerns is the weakness in the existing backcalculation procedures. 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 at the bottom of the AC. These critical strains are typically calculated using layered theory and backcalculated moduli.

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 moduli of a given composite section. In our methodology, which is based on artificial neural networks (ANN), the traditional backcalculation process is omitted. The input data are parameters readily available to pavement engineers, such as the measured deflection bowls, and the section layers thickness.

Objectives

One of the objectives of the last year of Project 0-1711 was to extend the capabilities of Program REPP 2000 (Rational Estimation of Pavement Performance) to estimate the remaining life of composite sections. As a reference, REPP 2000 is a software that combines artificial neural network (ANN) technology with uncertainty analysis to determine the performance of a flexible pavement using measurements from the FWD. The software integrates a series of artificial neural network models developed for a wide range of three- and four-layer flexible pavement sections with variable depth to rigid layer. The ANN models compute the following items:

- Depth to rigid layer (if not input)
- Compressive strain at the top of the subgrade
- Tensile strain at the bottom of the AC layer
- Modulus of the AC layer for sections with AC layers thicker than 3 in. (75 mm)

The software provides the following capabilities:

- Provide data input from a FWD file automatically
- Process ANN models developed for estimating modulus, strains, and depth to rigid layer
- Predicted remaining life using the Asphalt Institute, Shell or any user defined models under rutting and fatigue cracking failure modes
- Account for uncertainty in the input parameters and determine a range of remaining life
- Incorporate information from traffic reports and condition surveys to develop and graphically display a pavement performance curve (PPC)
- Provide an automatic and real time report
- Provide graphical presentation of the variation in remaining life along the pavement section with relevant statistics
- Establish confidence bounds for the PPC's and the profile of the test section.

For composite pavements, an extensive literature search and personal interviews either yielded performance models that were not mechanistic, required a large number of laboratory-derived parameters as opposed to using the FWD, or were proprietary. As such, it was decided to limit the scope of the project to estimating moduli of different layers instead of estimating the remaining lives. These ANN models were not incorporated into the software for flexible pavements REPP 2000, rather they were incorporated into a separate program to facilitate their execution. As soon as suitable models are developed, they can be incorporated in the REPP 2000 program. In this report, the results from such effort 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 as related to composite pavements. In Chapter 3, the process of generating databases for training, testing and validating the ANN models is described. Chapter 4 provides an overview of the process of creating artificial neural networks models that estimate the modulus of each layer. This chapter also presents the results of the ANN models developed. Chapter 5 describes the software developed to estimate the modulus. The last chapter contains the conclusions of the research effort in this project. Appendix A contains an overview of the software, which contains a detailed description of the windows in the software and their features. This appendix is equivalent to the online help of the software.

Chapter 2

Background

Falling Weight Deflectometer

The Falling Weight Deflectometer, as shown in Figure 2.1, is an evaluation instrument designed to monitor structural pavement condition. 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 within the FWD, measure the time histories of deflections. Extracted from the time histories are seven peak deflections that define the deflection basin. These deflections provide part of the input to the methodology developed under this project.

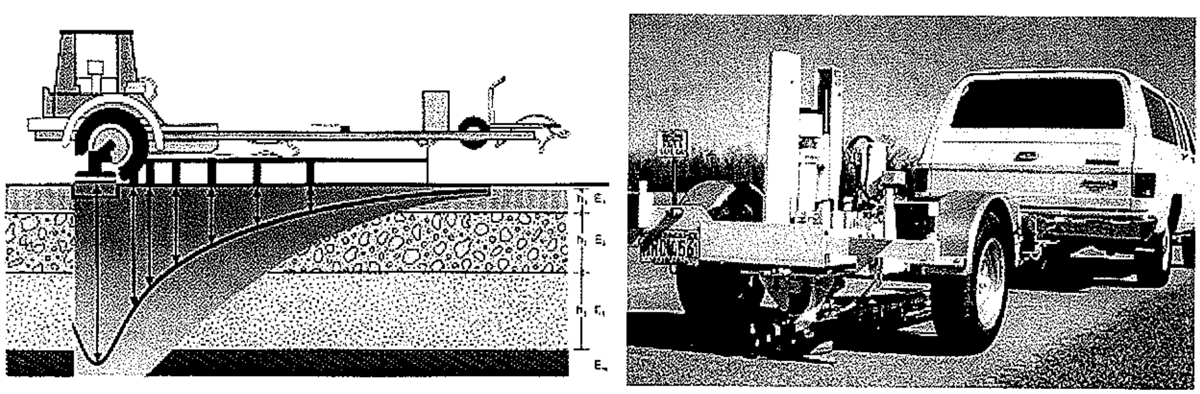


Figure 2.1 - Schematic of Falling Weight Deflectometer

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.

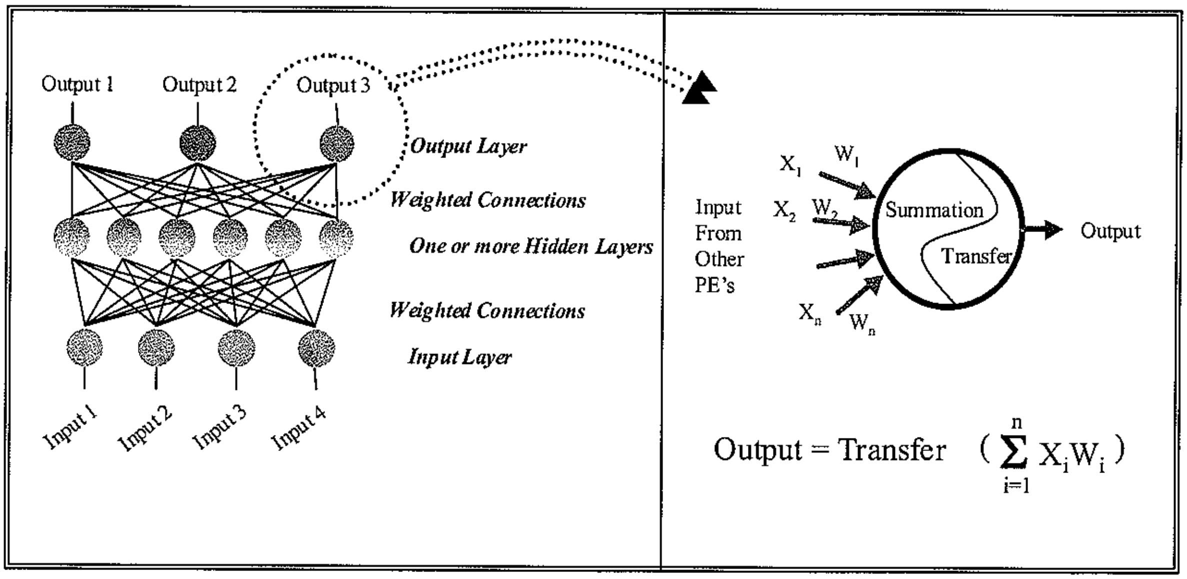


Figure 2.2 - Components of an Artificial Neural Network

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) Meier and Rix (1994) and Gucunski et al. (2000 and 1995) for parameter determination, such as the pavement section moduli; 2) Garrick et al. (1994) and Eldin and Senouci (1995a and 1995b) for assessment of the condition of the pavement and 3) Alsugair and Sharaf (1994) and Taha and Awad (1995) for selection of maintenance strategies.

Remaining Life Models in Composite Pavements

The most important failure mode that composite pavements can develop is reflection cracking. The primary mechanisms that lead to the development of reflection cracks are (a) the horizontal movement due to temperature and (b) moisture changes and the differential vertical movement due to traffic loadings. Both failure modes occur at the joints and cracks, with the horizontal movement being considered more critical.

According to Huang (1993), hot mix asphalt (HMA) overlays on PCC pavements are most difficult to analyze mechanistically because it involves two different types of materials. Finite element programs can model HMA as the top layer and PCC as the bottom layer. However, the bottom slab is difficult to model if cracks are present. Elastic layer programs may also be used to analyze this type of composite pavements if stress adjustment factors for edge and corner loads are known.

Usually the procedure for overlay design is similar to that of new pavements, except that the condition or remaining life of the existing pavement at the time of the overlay is taken into consideration. The thickness of the overlay is determined so that the damages in either the existing pavement or the new overlay will be within allowable limits. This mechanistic procedure has been used by Portland Cement Association (PCA) for the design of PCC overlays on PCC pavements.

Huang states that certain distresses particular to rigid pavements should also be considered in the design of composite sections, such as pumping, cracking, spalling, and faulting. However, no remaining life models or equations for the failure modes mentioned above are presented.

A thorough literature review was performed in search of remaining life or performance models for composite pavements. The following is a brief summary of the most relevant papers found, presented in chronological order.

Fernando et al. (1986) present a simplified pavement evaluation and AC overlay flexible pavement design procedure. The procedure models the pavement as a three-layer structure (typical in Pennsylvania) and requires FWD deflections for estimating remaining life and appropriate overlay thickness. Linear elastic program BISAR was used to develop strain vs. deflection relationships for asphalt tensile and compressive strains from measured FWD deflections taken at a load level of 9000 lbs (44 kN). This approach was believed to be a simpler and more straightforward approach than backcalculation of layer moduli and subsequent calculation of stresses and strains. Pavement performance predictions that were calculated using strains from the deflection relationships were compared with those from deflection basin-fitting algorithms. Results from field data indicated that the performance predictions based on tensile strain using laboratory-determined moduli are more realistic than those obtained from backcalculation and asphalt strain – deflection relationships. Also, they concluded that performance estimates based on subgrade strain were more stable and less sensitive to the procedure used to analyze the pavement. Relationships for designing overlay thickness were developed by evaluating the variation in pavement strains due to the addition of an overlay.

The development of mathematical models for the performance prediction of asphalt concrete overlays of flexible pavements in Ontario is addressed by Hajek et al. (1987). The objective was to develop reliable empirical performance prediction models using the long-term pavement performance (LTPP) data from an existing pavement management system.Their models could (a) estimate the immediate effect of an overlay on pavement serviceability and (b) estimate its life cycle period. Because the pavement information databank was not yet fully functional, additional data were obtained from a variety of sources including pavement performance records, contract drawings, and traffic files. The duration of overlay life cycle for a predetermined terminal serviceability (PCR of 55 years) was estimated as a function of overlay thickness, traffic, maintenance patching, and life cycle duration of the initial pavement. The latter variable was included in the model to capture the influence of local field conditions and to characterize the strength of the underlying support structure. The overall conclusion was that the proposed models were preliminary and should be updated when more data became available.

Foxworthy and Darter (1989) presented a concept for the backcalculation of layer moduli from FWD data as part of the overall process of NDT and NDE of rigid airfield pavements. The ILLI-SLAB finite-element model was used to backcalculate the dynamic Young's modulus (E) of the PCC surface and a composite dynamic modulus of subgrade reaction (k) for the supporting layers of the system from FWD-generated deflections. FWD field-testing was conducted at three Air Force installations in Texas, New York, and North Carolina to provide representative cross-sections and environmental conditions. The deflection basin is described in terms of the maximum deflection under the FWD loading plate (D0) and the cross sectional "area" of the basin. These two variables found critical to the uniqueness of the backcalculated parameters. The "area" concept combines all the measured deflections in the basin into a single number to minimize the effect of an erroneous geophone reading. In addition, to eliminate the effect of variable loads and to restrict the maximum and minimum values of the area, each deflection reading is normalized with respect to the maximum deflection (D_0). A correlation is presented that relates dynamic *k* values to traditional static *k* values determined from plate-bearing tests. A similar model is suggested to correlate dynamic E with static E to use in static analysis of pavement structures where a dynamic analysis is not appropriate.

Pierce et al. (1993) reported on a mechanistic, empirically based flexible pavement overlay design method developed by Washington DOT using the information contained in their pavement management system and deflection data obtained from FWD. The design criterion for overlay design was primarily based on Monismith's fatigue cracking (Monismith and Epps, 1969) and Chevron's rutting models. EVERCALC (based on CHEVRON N-LAYER) was used for the backcalculation of layer moduli using FWD measurements. EVERPAVE a mechanistic, empirically based overlay design program was used to calculate overlay thickness by comparing the pavement performance lives for fatigue cracking and rutting, using projected design traffic volume (ESALs). The solution converges when the maximum distress performance period exceeds the design traffic volume.

Huang (1993) has a chapter that presents several overlay design methodologies that depend on the type of overlay and existing pavement. The chapter concludes that layer elastic programs can be used as mechanistic design models if both the overlay and the existing pavements are flexible. However, for HMA overlays on PCC pavements, stress adjustment factors for edge and corner loadings should be applied. According to Huang, three general methods can be used for overlay design: the effective thickness approach, the deflection approach, and the mechanistic-empirical approach. The Asphalt Institute employs both the effective thickness and the deflection methods for the design of HMA overlays on both flexible and rigid pavements. The AASHTO Design Guide provides the most comprehensive overlay design procedure based on the effective thickness approach. For flexible overlays on rigid pavements, the design methods can be divided into two categories: (a) the normal structural overlay method and (b) the break and seat overlay method. The overlay thickness obtained by the normal structural overlay method must be checked against a minimum thickness to minimize reflection cracking.

Hall and Darter (1994) presented a procedure that has been developed for backcalculation of a concrete slab and foundation moduli from deflections measured on composite pavements. The AREA method advocated by Hoffman and Thompson (1981) was used to backcalculate the PCC slab elastic modulus and the subgrade k-value. According to Hall and Darter, the most difficult aspect of the structural evaluation of composite pavements is the assessment of the overall condition of the PCC slab in its current state, which requires the most experienced and expert judgment. In the backcalculation process, the PCC moduli should be considered in conjunction with the type, quantity, and severity of visible distress. One possible option to relate PCC moduli to distress is to conduct FWD testing in both cracked and intact areas. Testing in cracked areas poses several practical difficulties since no guidelines are available for how to conduct deflection testing in cracked areas. The second approach is to test intact areas only. The disadvantage of this approach is that the engineer must consider the backcalculation results and distress survey results separately in assessing the condition of the slab.

McPeak and Khazanovich (1997) presented a procedure for backcalculating strength parameters of the PCC, AC and underlying layers from deflections collected by a FWD. They also describe the advantages and disadvantages of using elastic layers and Winkler foundations in the backcalculation process. As a rule of thumb, backcalculation programs based on elastic layer theory are used for AC pavements and Winkler foundation for PCC pavements. According to this paper, the major drawback of elastic layered based backcalculation is that it may be influenced by the chosen seed moduli and the experience of the engineer performing the backcalculation. Another drawback is that in the analysis and design of PCC and composite pavements, the subgrade layer is modeled with the Winkler (springs) model, which is not directly correlated to the elastic layer model parameters. On the other hand, plate theory has been used in the analysis of PCC slab-on-grade pavement systems assuming that there is no compression on the upper layer. All deflections are attributed to compression of the subgrade and bending of the plate. This assumption is particularly poor for composite pavements. In addition, the AC and PCC have to be modeled as one layer. These two limitations render regular plate theory unusable for AC/PCC pavement structures.

McPeak abnd Khazanovich evaluated three backcalculation procedures to determine their applicability and accuracy for asphalt-overlaid composite pavements. The three procedures consisted of program DIPLOBACK (Khazanovich, 1994) that is based on elastic layered theory and procedures based on AREA (Hoffman and Thompson, 1981) and Best Fit (Smith et al., 1995) that are based on Winkler foundation. The last two programs are not applicable to the deflection measured directly under the load. When that deflection was ignored in the analysis, the structural properties of the pavement system were more closely predicted. DIPLOBACK, which treats the overlay as an elastic layer rather than a plate, predicted the moduli of the composite layers better than the other two programs for thin and thick AC layers.

A number of empirical models have been developed for predicting reflective cracking in AC overlaid pavements. Some models relate several pavement, environmental, and traffic loading variables to the amount of reflective cracking. Examples of some of the variables include cumulative 18 kip ESALS, overlay thickness, age of overlay, freezing index, and some measure of condition of the PCC pavement prior to overlay with an AC layer.

Owusu-Antwi et al. (1998) developed a model for predicting the "real-life" behavior of composite (AC/PCC) pavements using the principles of fracture mechanics. The model estimates the amount of reflective cracking using data that is routinely available. The proposed model relates the damage caused by temperature and traffic loads to the total amount of reflective cracking in AC/PCC pavements, using Miner's cumulative damage approach and distress data from the LTPP database for calibration. For 33 LTPP AC overlaid PCC pavement sections, the number of load applications to failure and the total damage caused by traffic and temperature loading were determined. After a sensitivity analysis was performed on the model, it was concluded that the approach could be used to obtain a model that reasonably predicts reflective cracking. However, the model can be expanded for use in pavement management applications and as design checks. The drawback of this model is that the FWD deflections are not used to determine any of the input parameters.

Asphalt Institute (2000) provides the state-of-the-practice for evaluating and designing asphalt overlays for concrete pavements. Two procedures for evaluating the structural capacity of existing rigid pavements and for computing the thickness of the overlay are suggested. The primary method used by the Asphalt Institute is the effective thickness procedure, in which the actual thickness of each layer is converted to an equivalent thickness based on the condition of the layer. The conversion factors are based on a visual description of the material. As such this method cannot be considered as a mechanistic approach. The manual briefly discusses the different factors involved in the design of overlays. However, performance models are not addressed.

In general, as indicated before, at this time suitable models for predicting the remaining life of composite pavements that use FWD as a direct input do not exist. However, several models that utilize backcalculated moduli, amongst other parameters do exist. Therefore, the focus of the project was shifted from estimating remaining life to estimating the moduli of different layers.

Chapter 3

Database of Pavement Section Parameters

The main ingredients for developing an ANN model are a set of examples that show specific values of the independent variables and the corresponding values of the dependent variable(s). These examples are necessary to create an ANN model by training and testing. Specific to the work presented in this report, each example consists of an input vector with ten elements that represent the thickness of the AC, and base layers (t_1, t_2), depth to rigid layer, and the seven FWD readings (d_0...d_6), and an output vector, whose only element defines the quantity that the model will predict. In this case, that quantity is the modulus value of any of the three layers. An overview of the ANN development process is discussed in Chapter 4.

Ideally, a database of examples is 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 comprehensive synthetic database was generated to simulate and cover a wide range of possible three-layer pavement systems.

Database Generation

The overall process employed to generate a synthetic database is similar to previous work presented for this project. Chapter 3 of Report 1711-1 (Ferregut et al., 1999) and Report 1711-2 (Abdallah et al., 2000) illustrate graphically the database generation process. Basically, the feasible range for each pavement parameter was established. Table 3.1 shows the minimum and maximum values for the thickness and moduli that were used. The table also shows the increment used for each of the parameters. To randomly simulate pavement within these ranges, a Monte Carlo simulation was conducted (Ang and Tang, 1984) using the following assumptions: 1) the variables were not correlated and 2) the pavement section variables were simulated using a discrete uniform distribution. A total of 10,000 pavement sections were generated. For each pavement section defined, a FWD test on the section was simulated using the five-layer linear elastic program WESLEA. The seven FWD readings were computed under a static load of 9000 lb (40 KN) acting over a 6 in. (152 mm) radius and with a uniform 12 in. (305 mm) spacing for the seven sensors. This completed the number of variables required for a comprehensive database. The thickness and seven deflections constituted the input vector for the ANNs. And as stated earlier, the variables that define the output vector were each of the three layer moduli.

Table 3.1 - Ranges of Pavement Section Variables Used in ANN Model Development

Pavement Variables		Units	Value	
			Minimum	Maximum
Asphalt Thickness	(t_1)	in. (mm)	0.5 (12)	10 (250)
Stabilized Base Thickness	(t_2)	in. (mm)	4 (100)	24 (600)
SubgradeThickness	(t_3)	in. (mm)	60 (1500)	200 (5100)
Asphalt Modulus	(E_{AC})	ksi (GPa)	200 (1.4)	1000 (7)
Base Modulus	(E_{BASE})	ksi (GPa)	1000 (7)	8000 (55)
Subgrade Modulus	($E_{SUBGRADE}$)	ksi (GPa)	5 (34)	45 (300)

Data Processing

A very important step in developing ANN models is data pre-processing. In many engineering applications, raw data should be pre-processed 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 a *priori*. A genetic algorithm was implemented to choose the best set of transformations. The criteria used to select the transformation, was the minimization of the root mean square (RMS) error of the output. Table 3.1 in the Report 1771-1 includes the pool of candidate transformations that were also used for improving the quality of data in the ANN development process. A different set of transformations was used depending on the performance of each model developed.

Report 1711-1 showed the importance of pre-processing before training a neural network model. The figure from that report is reproduced in Figure 3.1. The results of two Artificial Neural Network models, one trained with the raw data and the other trained with pre-processed data are shown. The improvements in model gained by pre-processing of the data is evident.

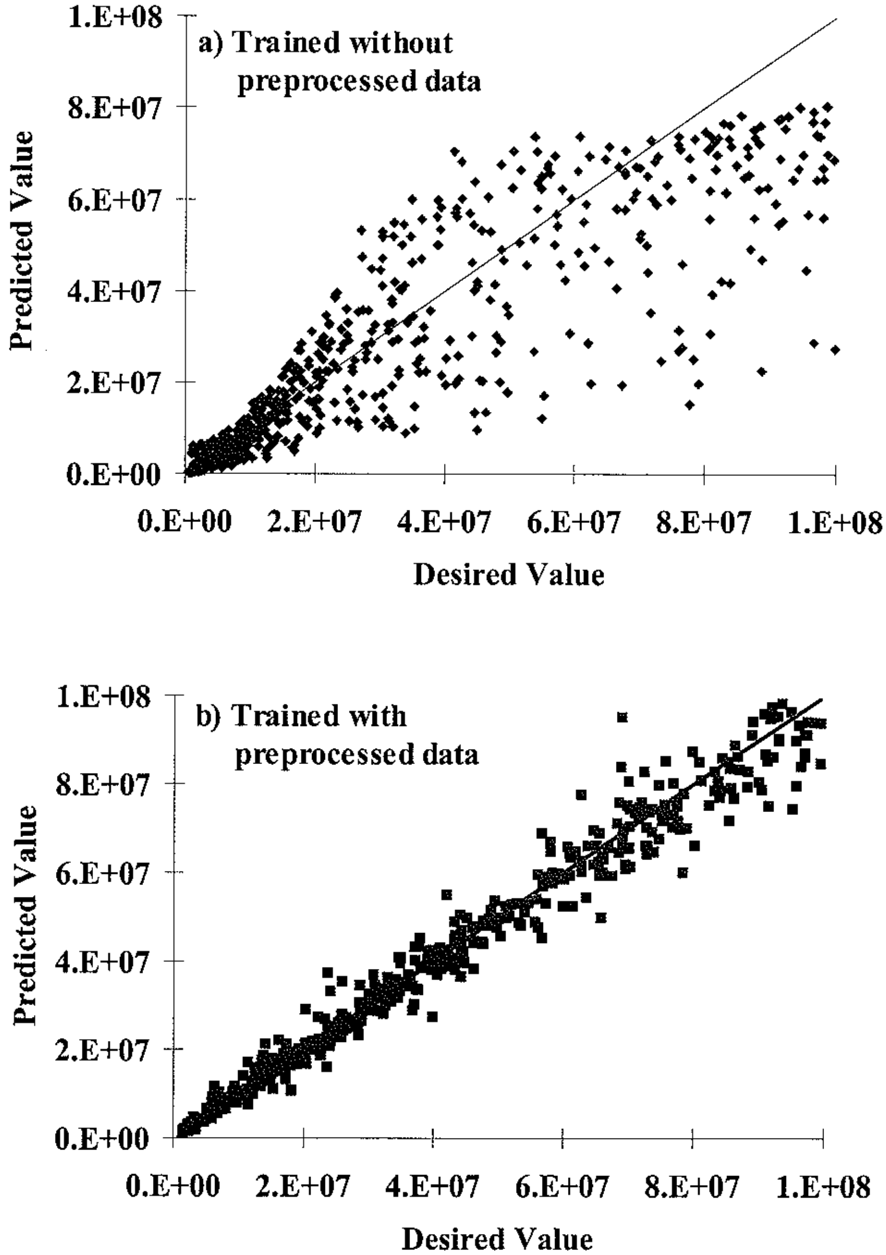


Figure 3.1 - Results of Two ANN Models

Chapter 4

Artificial Neural Network 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 evaluated with a validating data file (file was sampled randomly from the comprehensive database). 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 PEs 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 composite pavement. Three of the models predict the modulus of each of the three layers of the pavement section. The three models use as input the thickness of the AC and the stabilized base layers and the FWD deflection readings. Predictions of the AC and base moduli were reasonably accurate; however the modulus of the subgrade was predicted with more variability. To improve on the prediction of this modulus, a fourth ANN model that uses the depth to bedrock as an additional variable was developed. This model predicts the modulus of the subgrade with greater accuracy than the previous model. All four models are based on the ranges of pavement sections shown in Table 3.1. These ranges were based on surveys conducted by TxDOT personnel.

The ANN models developed during this phase of the project are summarized in Table 4.1. The table contains the best and final architecture, the bounds of the prediction range, and the root mean square (RMS) error of each model. These models are valid for pavement sections listed in Table 3.1, and should not be used for pavement sections with values outside those ranges.

Table 4.1 - Specifications and Architectures of the Three-Layer ANN Models

ANN Model	Number of PEs (Input/Hidden/Output)	Prediction Bounds		RMS Error
		Upper	Lower	
Modulus of AC	36-29-1	1000 ksi (7 GPa)	200 ksi (1.4 GPa)	0.031
Modulus of Stabilized Base	37-30-1	8000 ksi (55 GPa)	1000 ksi (7 GPa)	0.054
Modulus of Subgrade	37-29-1	45 ksi (300 MPa)	5 ksi (35 MPa)	0.06
Modulus of Subgrade with depth to rigid layer input	40-16-1	45 ksi (300 MPa)	5 ksi (35 MPa)	0.01

Modulus of AC

Figure 4.1a compares the AC moduli results from the ANN model with the expected values. A total of 350 data points are presented. The bounds for the ±10% absolute error are also shown. 95% of the predicted values are contained within these limits. Figure 4.1b is a chart that shows the frequency with which predictions were made within a given error. The chart contains three separate sets of data: training, testing and validation sets. Each set contained 1000, 350, and 350 cases, respectively. This figure also shows the cumulative frequency plots for each data set. According to the plot corresponding to the validation set, the model predicts 95% of the desired values with a margin of error of 10% or less. Similar levels of accuracy were obtained for the other two data sets.

Modulus of Stabilized Base

Results for the modulus of the stabilized base layer are shown in Figure 4.2. Predictions of base moduli may also be considered accurate for engineering purposes. Figure 4.2b shows that, unlike the previous case, only 82% of the base moduli in the validation set wer7e predicted within a margin of error of 10% or less. Results for the other two sets also experienced a drop in accuracy with respect to the previous case.

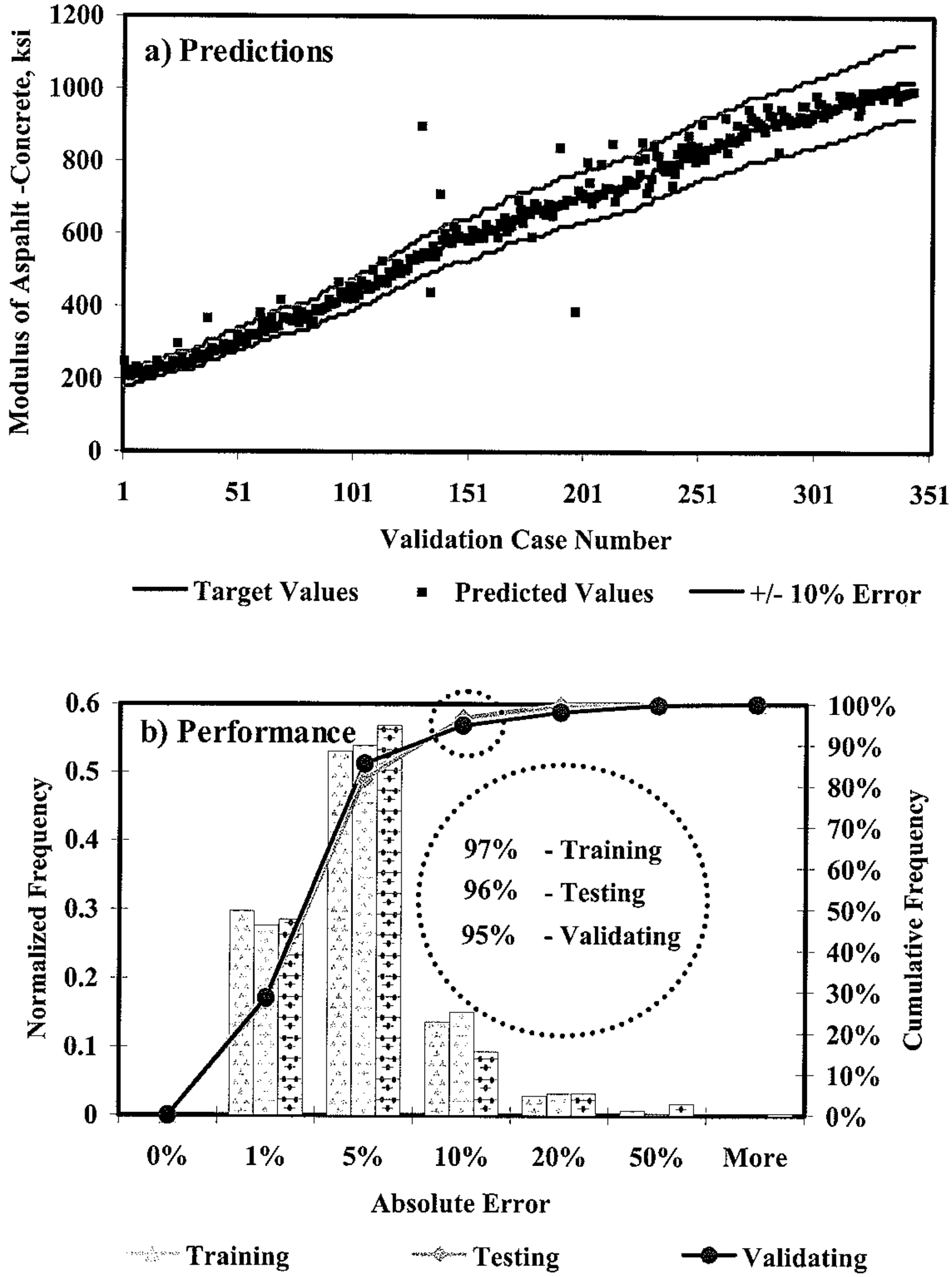


Figure 4.1 - Quality of ANN Models Developed for Predicting Modulus of AC Layer

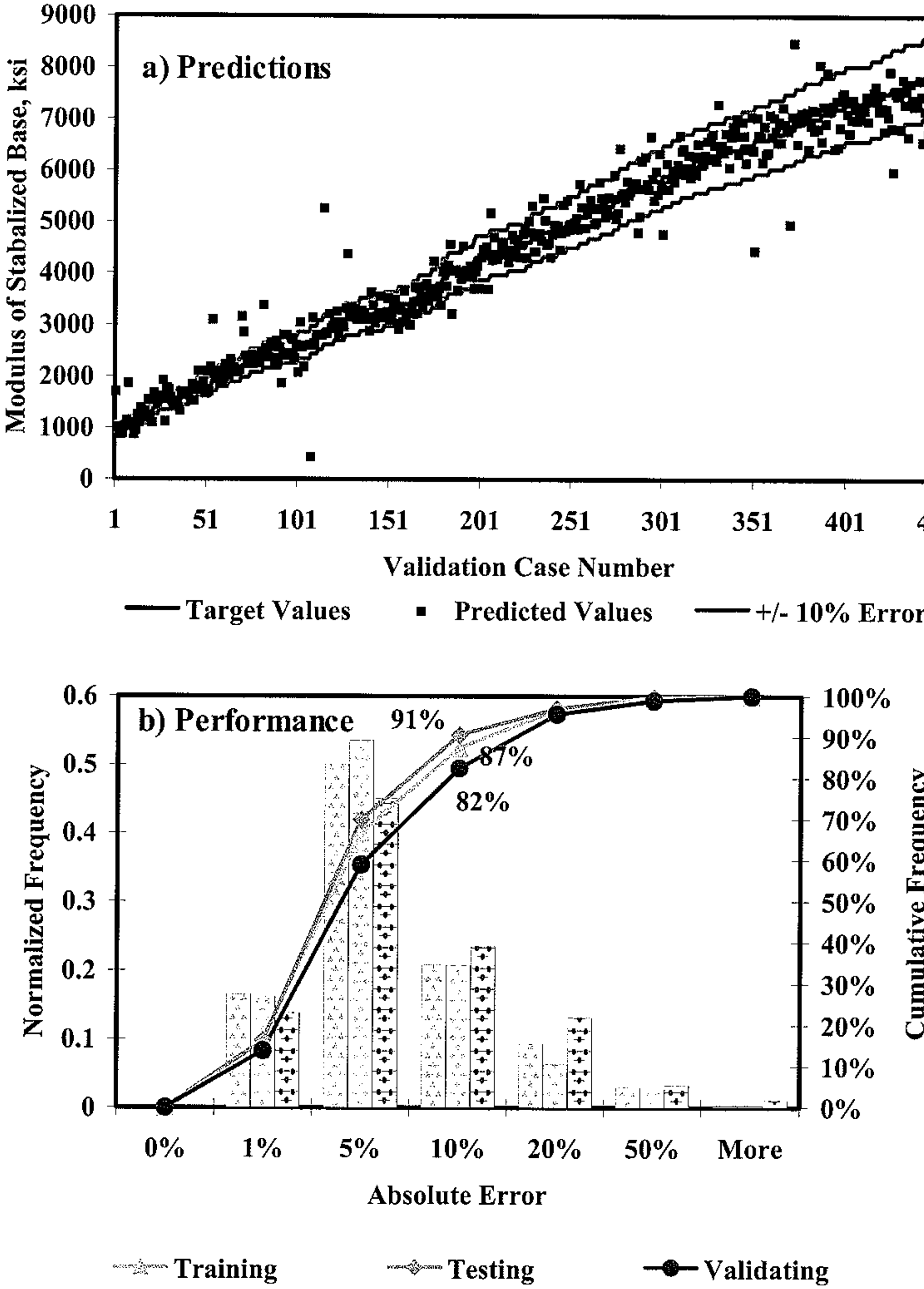


Figure 4.2 - Quality of ANN Models Developed for Predicting Modulus of Base Layer

Modulus of Subgrade

Unlike the previous two cases, the results of the original ANN model that predicts the subgrade modulus without regards to the depth to rigid layer were less accurate. Figure 4.3 shows the corresponding plots. Figure 4.3a shows that a large number of cases that fall outside the 10% error bounds. Also, from Figure 4.3b, the results from the validation set shows the percentage of subgrade moduli predicted within an error of 10% is a low 63%.

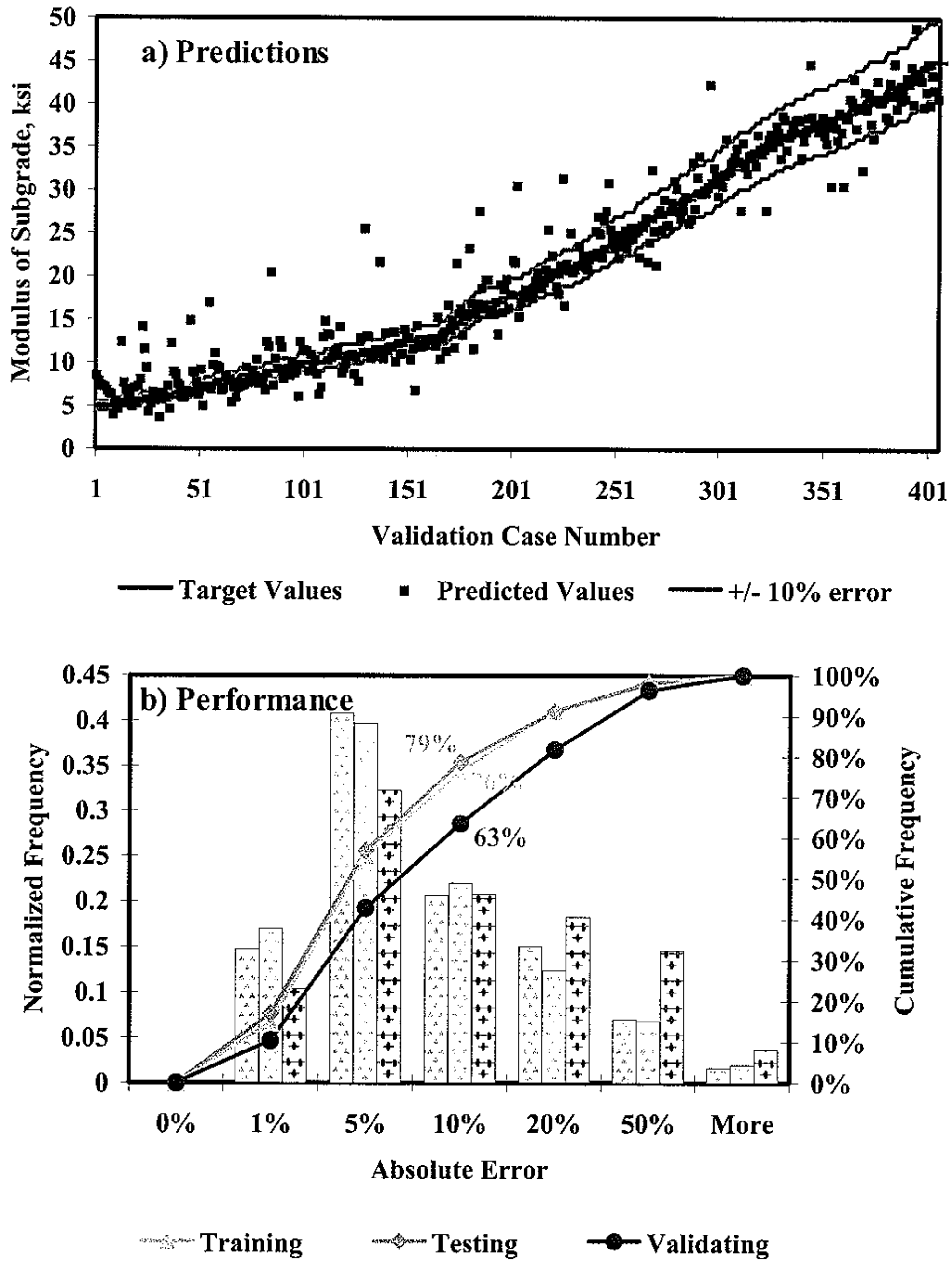


Figure 4.3 - Quality of ANN Models Developed for Predicting Modulus of Subgrade Layer

To improve on these results, a modified ANN model was developed. In addtion to the thickness of the layers and the FWD deflections, the thickness of subgrade layer was included in the model's input. Prediction of the subgrade modulus was improved significantly when this variable was considered. Results are shown in Figure 4.4. The frequency of the predictions within a 10% error improved from 63% to 98% for the validation set. The training and testing sets experienced similar improvements. To use the modified model, the user needs to input the thickness of subgrade in additional to the nine input parameters of thickness and deflections.

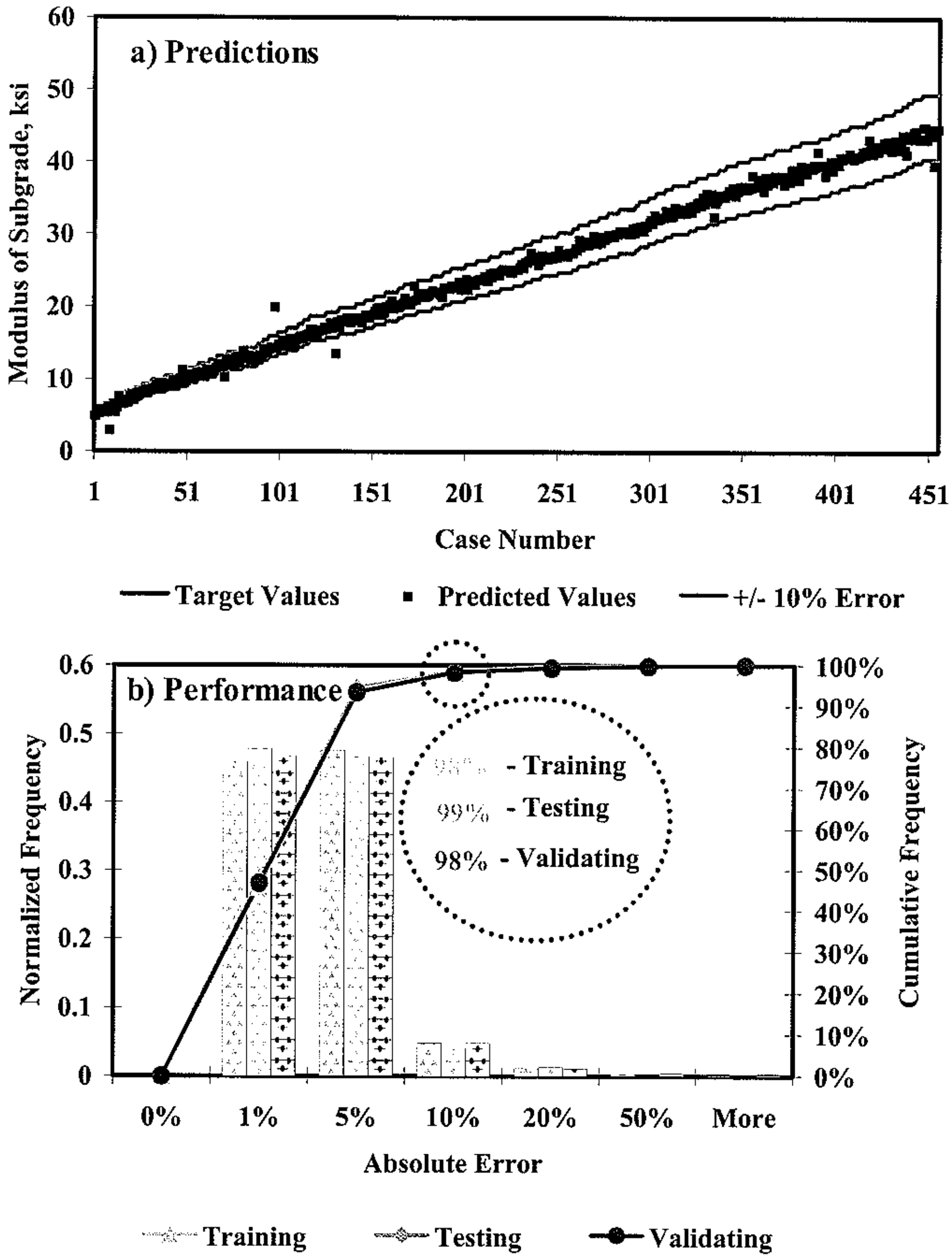


Figure 4.4 - Quality of ANN Models Developed for Predicting Modulus of Subgrade Layer (Including Thickness of Subgrade in Input)

Chapter 5

Description of Software

This chapter contains a description of the software developed to predict the layer moduli of composite sections. The software is named "M.E. Program" which stands for Modulus Estimation. The M.E. Program uses artificial neural network technology to determine the layer moduli using layer thickness and measurements of deflections from the Falling Weight Deflectometer.

The software integrates a series of neural network models developed for a wide range of three-layer composite pavement sections with variable subgrade thickness. The ANN models compute:

1. the modulus of asphalt-concrete
2. the modulus of stabilized base
3. the modulus of subgrade

The software includes algorithms:

- to read deflections automatically from an FWD file
- to apply temperature correction to FWD deflections
- to read from a text file prepared as input to ANN models
- to process ANN models and obtain layer moduli
- to save all information in a database file
- and to plot the profile of an entire test section for modulus of each layer

The major benefit of this software tool is that the estimation of the moduli is instantaneous; therefore a large amount of data can be processed at once.

The software was developed under the assumption that thickness and FWD readings are precise measures, no uncertainty in the input is considered.

Software Architecture

This is the first version of the software and is developed under Windows 95/98/00/NT operating systems. The development environment is based on C++ 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 around three main routines: a) *Processing of FWD data,* b) *Execution of Artificial Neural Networks* and c) *Viewing of the results graphically and numerically.* The three routines are organized in three levels. Figure 5.1 shows the main architecture of the software. The first level contains the processes used to prepare the input file from the FWD data and section thicknesses. The second level is estimating the layer moduli using the ANN models. The third level is to extract the results and display the information numerically and graphically. The later two levels are self-explanatory; however, the first level is further detailed in Figure 5.2. The figure illustrates two choices that are available for the user. They are a) to automatically extract data from FWD file and generate a text file as input to the ANN model and b) to use a text file directly as input to the ANN models. The first option allows for deflection normalization with temperature based on a study by Scullion (1987). After extracting FWD data from files generated by the FWD operating program version 20, the program normalizes the deflections based on load and temperature as indicated in the figure. The advantage of this option is that the user's interaction with the FWD file is minimized. The second option allows the user to produce any number of thicknesses and deflection sets in the input file.

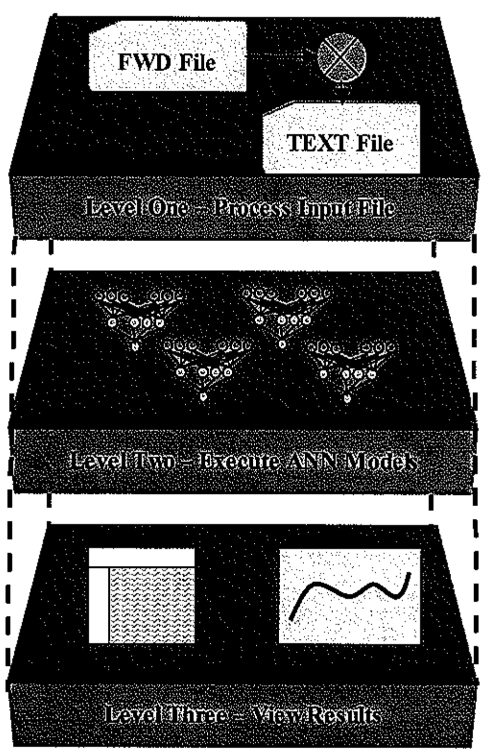


Figure 5.1 - Software Architecture: Main Modules

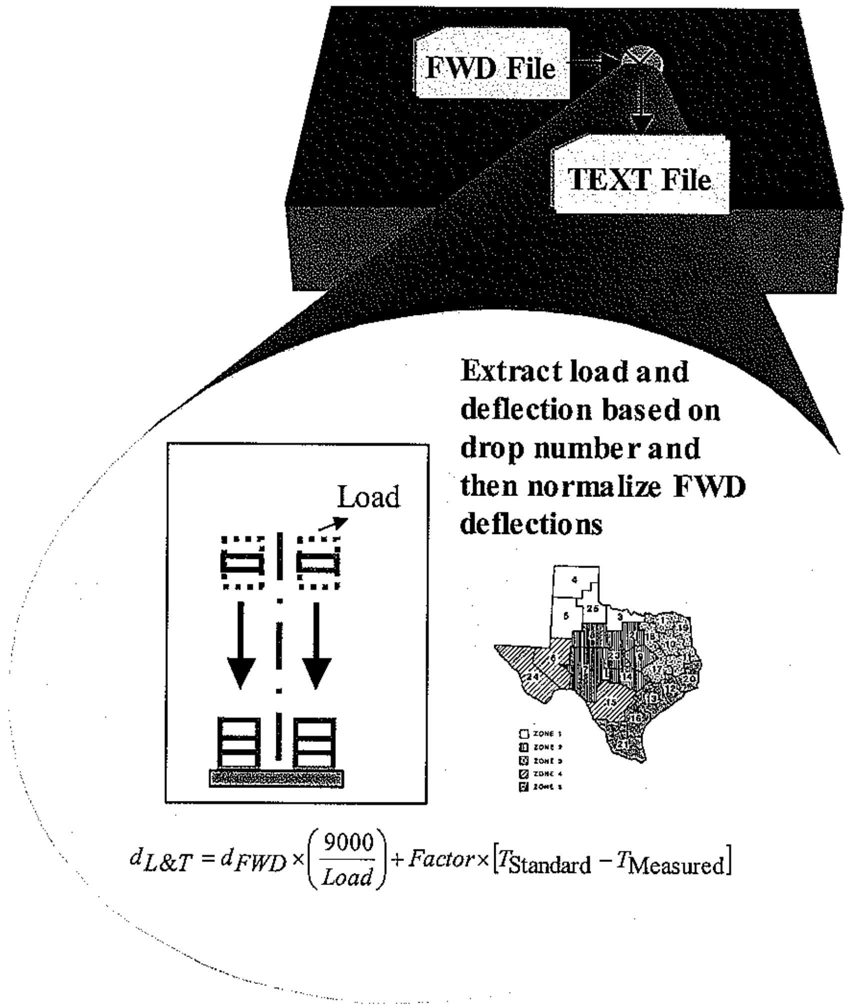


Figure 5.2 – Selecting and Processing of Input File

Software Preview

The main features of the M.E. Program are illustrated in the next three figures. Figure 5.3 shows the *main menu* window of the software. This form, which is the core of the software, allows the user to select the file type and to view the results. Figure 5.4 shows the window that appears if the user selects to process an FWD file. In this form, the user inputs the section properties and selects an FWD file to extract the deflection information. The window that displays the results is shown in Figure 5.5. In this window, the results can be viewed either numerically in a data grid or graphically depicting the section profile. A detailed description of the features in each window is provided in Appendix A (Software Overview), which is equivalent to the online help of the software.

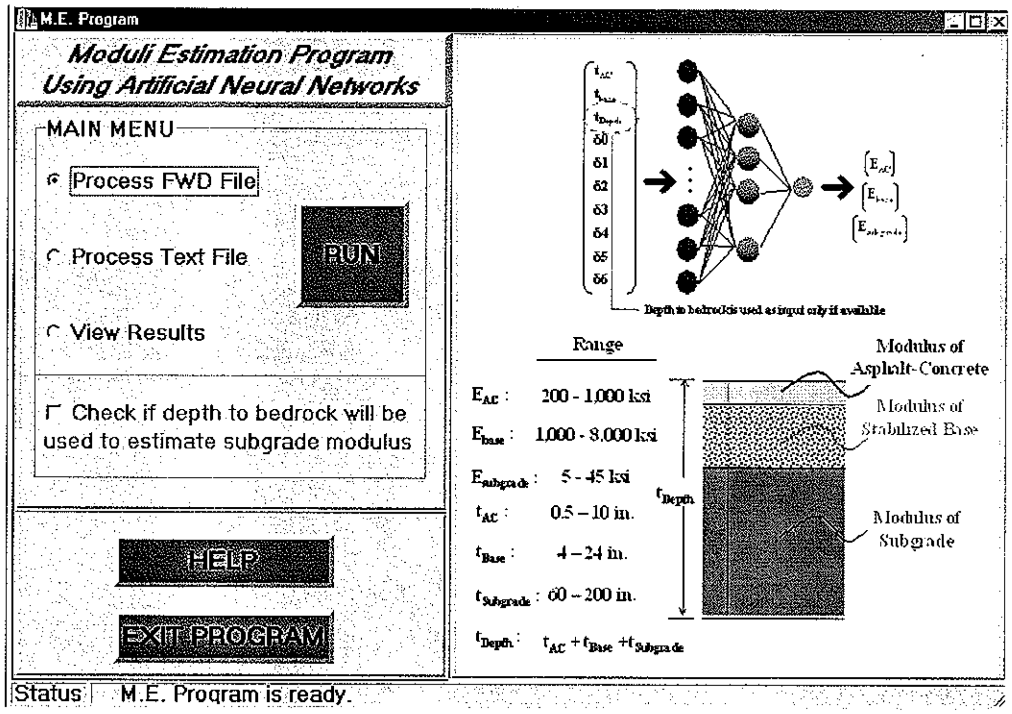
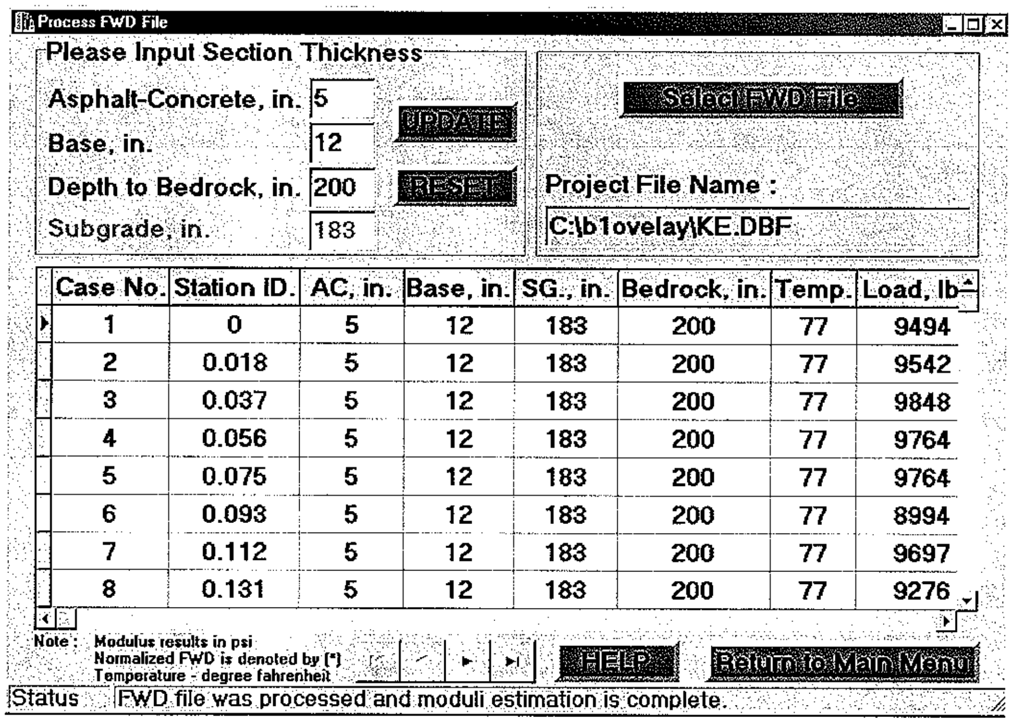


Figure 5.3 – Software Windows: Main Menu



Case No.	Station ID.	AC, in.	Base, in.	SG., in.	Bedrock, in.	Temp.	Load, lb
1	0	5	12	183	200	77	9494
2	0.018	5	12	183	200	77	9542
3	0.037	5	12	183	200	77	9848
4	0.056	5	12	183	200	77	9764
5	0.075	5	12	183	200	77	9764
6	0.093	5	12	183	200	77	8994
7	0.112	5	12	183	200	77	9697
8	0.131	5	12	183	200	77	9276

Figure 5.4 - Software Window: Process FWD File

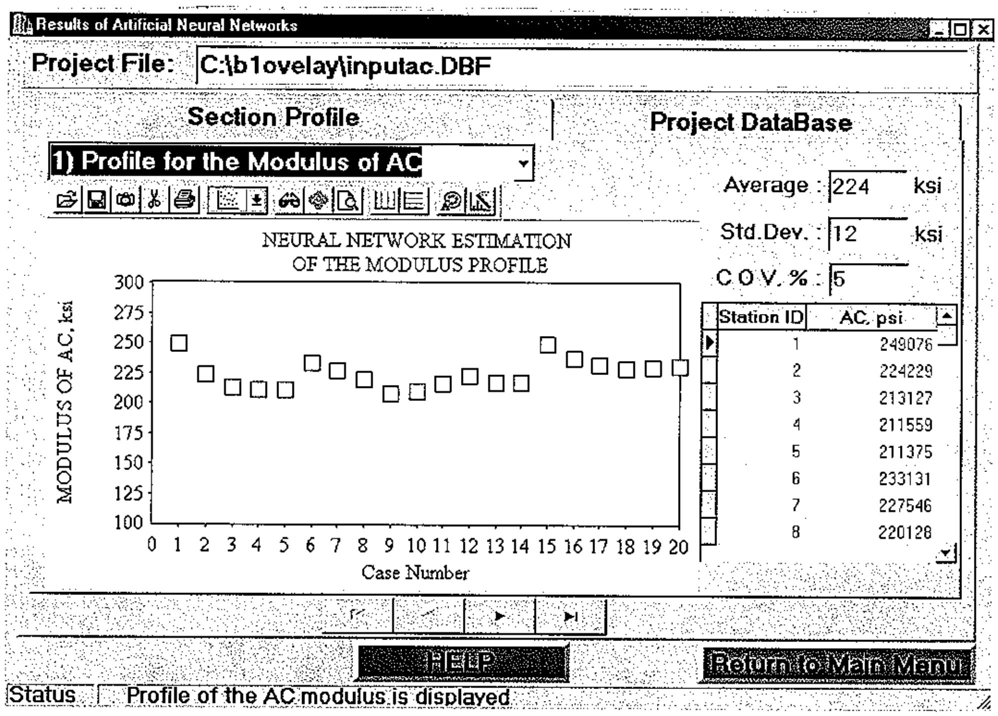


Figure 5.5 - Software Window: Results of Artificial Neural Networks

Chapter 6

Summary and Conclusions

This report summarizes the efforts to develop a methodology based on the Artificial Neural Networks to process data from the Falling Weight Deflectometer to estimate the layer moduli of a pavement. The project is completed with close cooperation between TxDOT and UTEP.

Artificial neural network models were developed, which rapidly and reliably predict the layer moduli of AC, base and subgrade of composite sections. Four ANN models were developed. Three of the models require only the thicknesses of the AC and stabilized base and normalized FWD deflections. The fourth model was developed for predicting the modulus of the subgrade using the thickness of subgrade as additional input. A modular software that incorporates all algorithms described in this report was also developed.

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.

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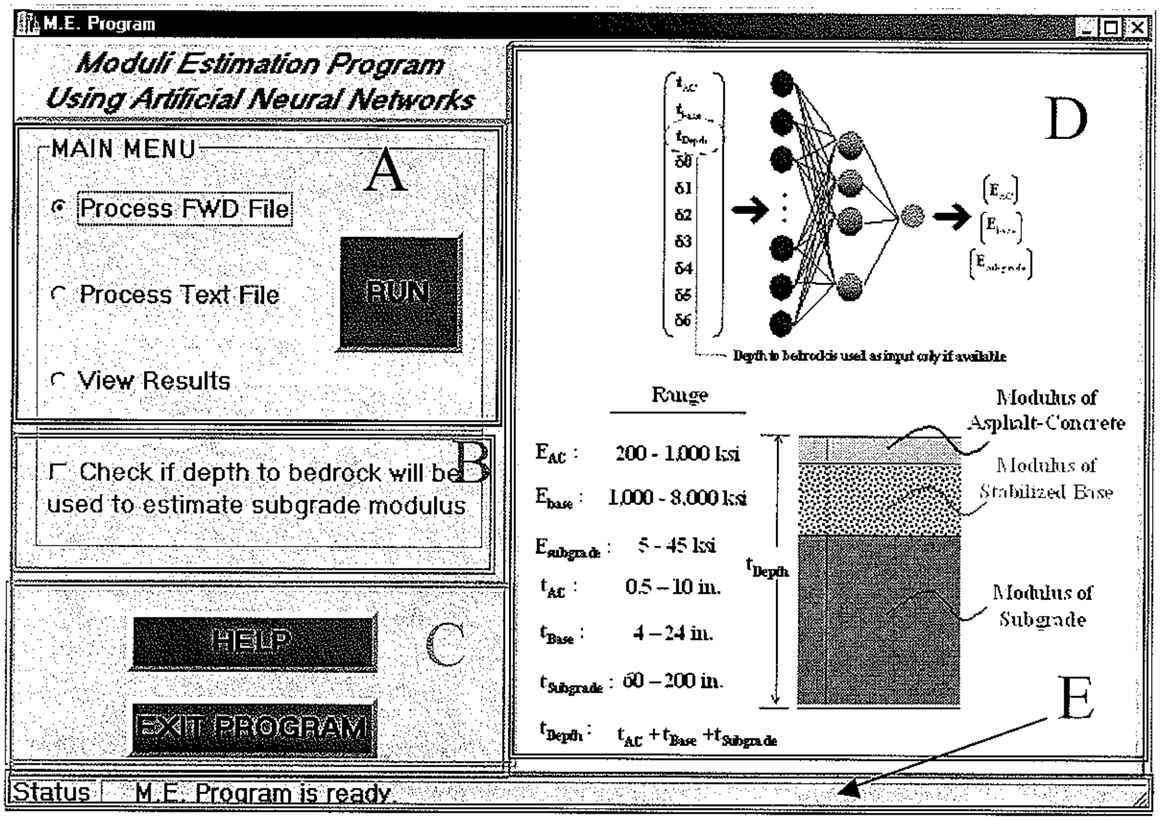
Appendix A

Software Overview

This section provides a detailed illustration of the forms used in the program. Each window that appears in the software is demonstrated followed by a description of that window.

Main Window



MODULI ESTIMATION PROGRAM USING ARTIFICIAL NEURAL NETWORKS -- This software uses artificial neural network (ANN) technology to determine the layer moduli using layer thickness and measurements of deflections from the Falling Weight Deflectometer. The software integrates a series of artificial neural network models developed for a wide range of three-layer composite pavement sections with variable subgrade thicknesses.

A) MAIN MENU – From the Main Menu section three options are available:
   a. Process FWD File – guides the user through a set of procedures that uses data from the FWD file to estimate layer moduli.
   b. Process Text File – guides the user through a set of procedures that uses data from a text file(s) the user prepares to estimate layer moduli.
   c. View Results – guides the user to view results generated by the ANN for either of the two previous options.

   After selecting any of these options press the [*RUN*] button to carry out the process.

B) CHECK IF DEPTH TO BEDROCK WILL BE USED TO ESTIMATE SUBGRADE MODULUS CHECKBOX – When processing an FWD file, if this option is checked, a space is provided in the next window that prompts to input the depth to bedrock. When processing a text file, if this option is checked, two warning messages will appear. The first message informs the user that the first input file that will be selected will be used to estimate the AC and base moduli. The second message informs the user that a second input file will be required to estimate the modulus of the subgrade. The reason for two input files is that the ANN models that estimate the AC and base moduli, do not require the thickness of the subgrade as input, therefore, the file needs to be prepared without that parameter. The second file however, will contain the thickness of the subgrade as an input.

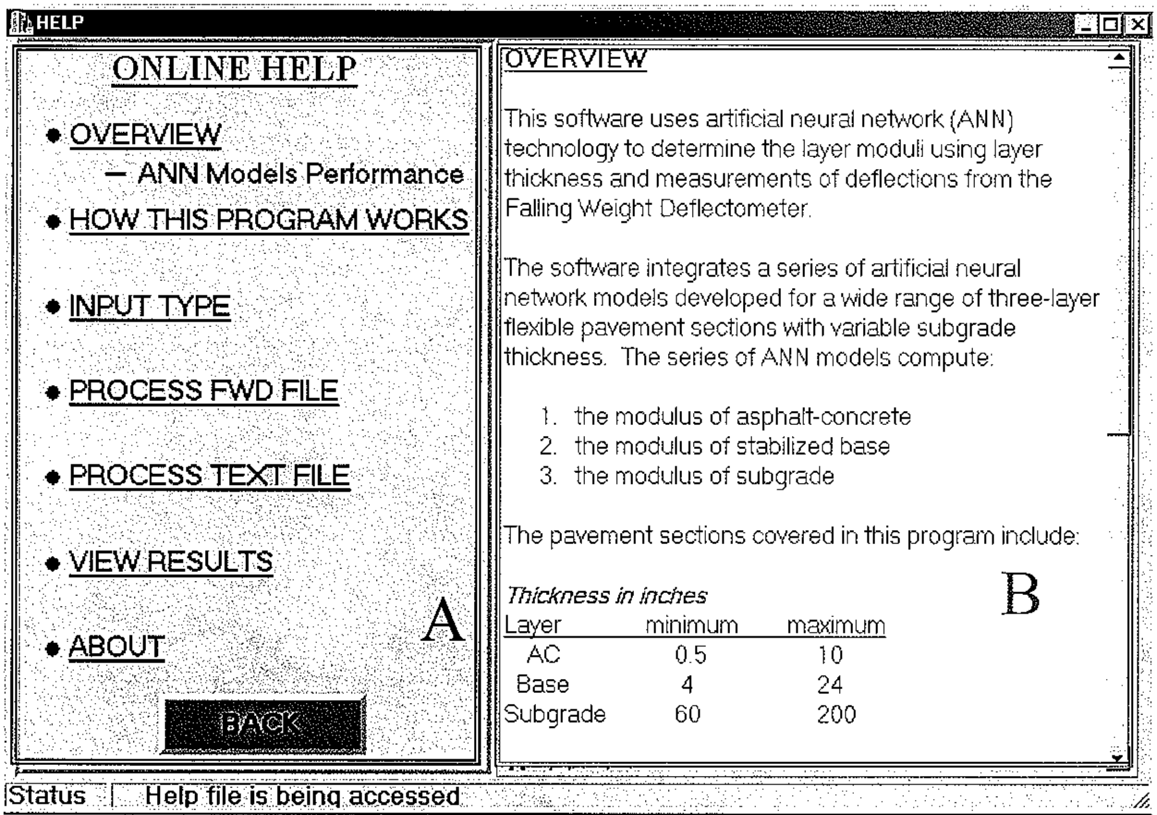
C) HELP BUTTON AND EXIT PROGRAM BUTTON –

a. Help Button – Clicking on the [*HELP*] button in any window will access the "*Online Help*" window. The "*Online Help*" window is used to access information that assist in understanding how this program works. More detailed information is provided in the next section.
   The Online Help feature works simply by clicking on any of the topics. This will hyperlink to a detailed explanation that pops up on the right hand side of the window.
b. Exit Program Button – Clicking on the [*EXIT PROGRAM*] button simply terminates the process.

D) IMAGE -- The image to the right of the window graphically represents an abstract of this program. On the top half of the image a symbol of the ANN models is represented showing the inputs and the outputs used by each model. The bottom half of the image shows the range of section properties used when developing the ANN models.

E) STATUS BAR – The status bar is located at the bottom of each window in the program, displaying the current status.

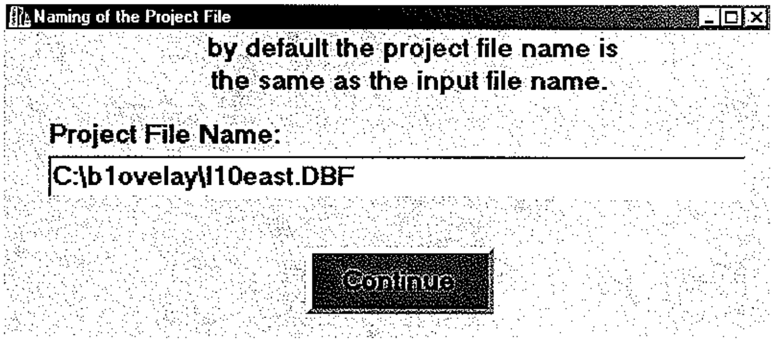
Help Window



A) "ONLINE HELP" MENU – This menu appears when the [HELP] button is clicked. It lists seven topics that explain in detail how the program works. Clicking on each topic will display the explanation on the right hand side of the window thus having the topics menu always available.
Clicking on the [BACK] button will terminate the help window and return to the previous window where the online help was accessed.

B) "ONLINE HELP" DISPLAY – This space displays the contents of each topic explaining in detail about how the program works. If the same topic is clicked twice, the main window image appears hiding the contents of the topic.

Naming of the Project File Dialog Box



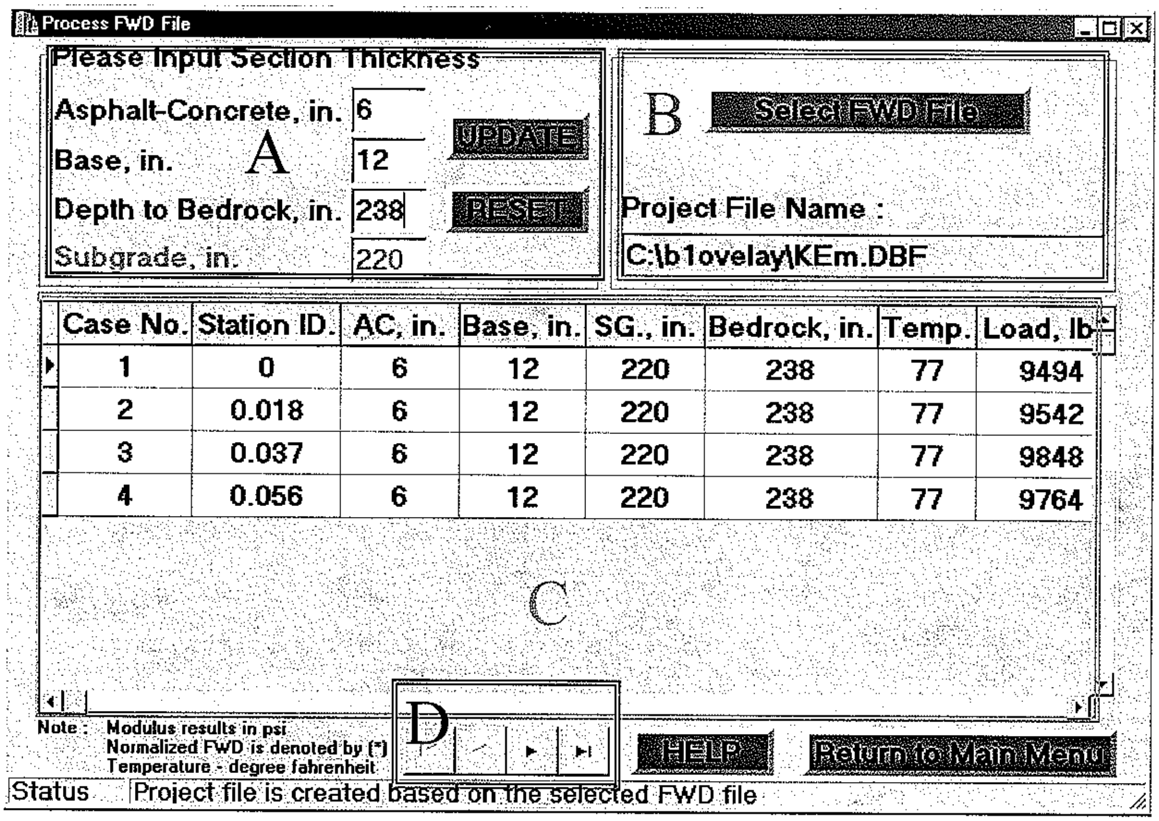
This dialog box appears:

- after clicking the [Select FWD File] button under the process FWD file window,
- after selecting the input text file(s) when selecting the "Process Text file" option,

prompting the user to enter and save the project filename.

NOTE: By default the project file name is the same as the input file name. However the user can change the name of the project file. After the project file name is selected the user presses the [*CONTINUE*] button to proceed.

Process FWD File Window



A) <u>SECTION THICKNESS</u> – This section allows the user to enter the thickness of the following layers:
   a. Asphalt-Concrete (AC),
   b. Stabilized Base,
   c. Depth to bedrock (if necessary).

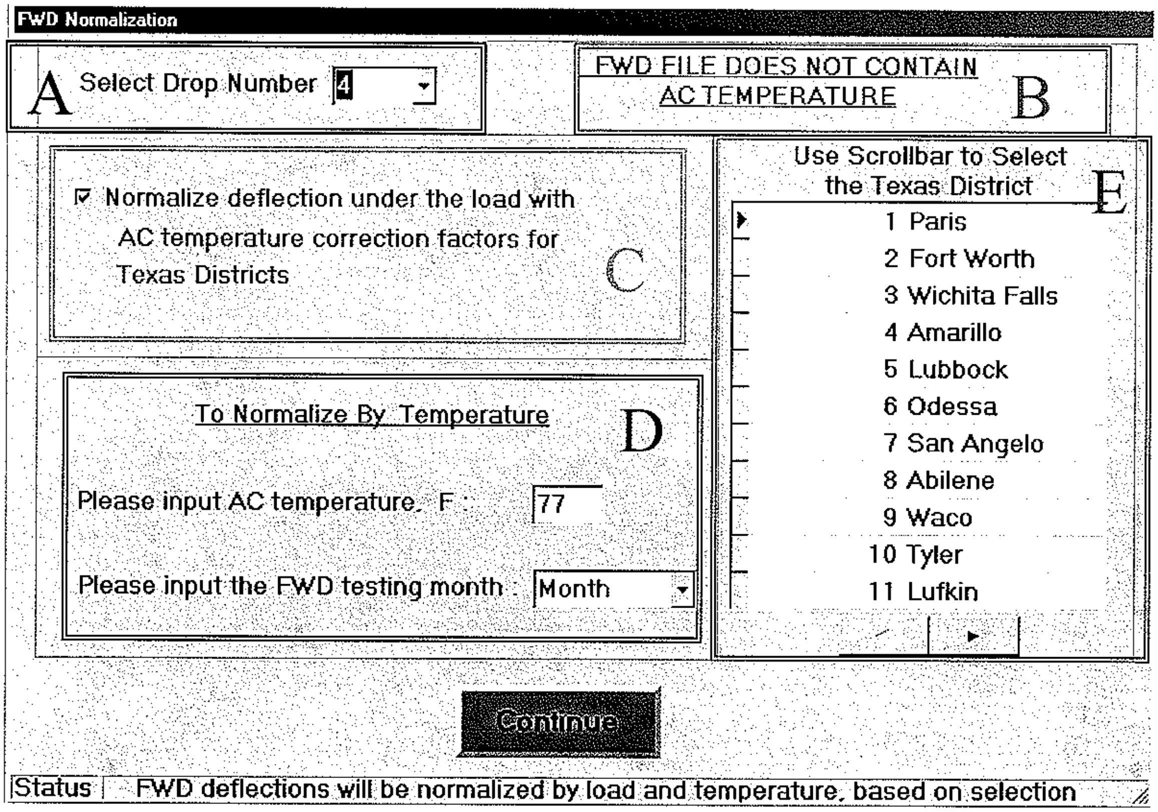
   Also included are two buttons: [*UPDATE*] and [*RESET*]. The [*UPDATE*] button is used to accept the information after the user enters the thickness values. The [*RESET*] button is used to clear the values if the user wishes to replace them with the previous set of values.
   NOTE : Since this model requires the thickness of subgrade layer as input and pavement engineers are more familiar dealing with depth to bedrock or depth to rigid layer, the software requires the user to input the depth to bedrock and then calculates the thickness of the subgrade and uses that value as input to the fourth ANN model.

B) <u>FWD FILE AND PROJECT FILE NAME</u> – This section contains:
   a. a button which allows the user to select an FWD file,
   b. and a textbox display of the project file path.

C) <u>DATABASE GRID</u> – This database grid displays all data from the input file and the results generated by the program. The database is displayed after the FWD file is processed. This database can also be accessed from the Project Database tab when the "*View Results*" option in the main menu is selected.

D) NAVIGATION TOOL – This four-button tool allows the user to scroll the different cases reported in the database table.

FWD Normalization Window



A) SELECT DROP NUMBER – This section contains a drop-list that allows the user to choose a specific drop height from which the corresponding FWD readings will be used.

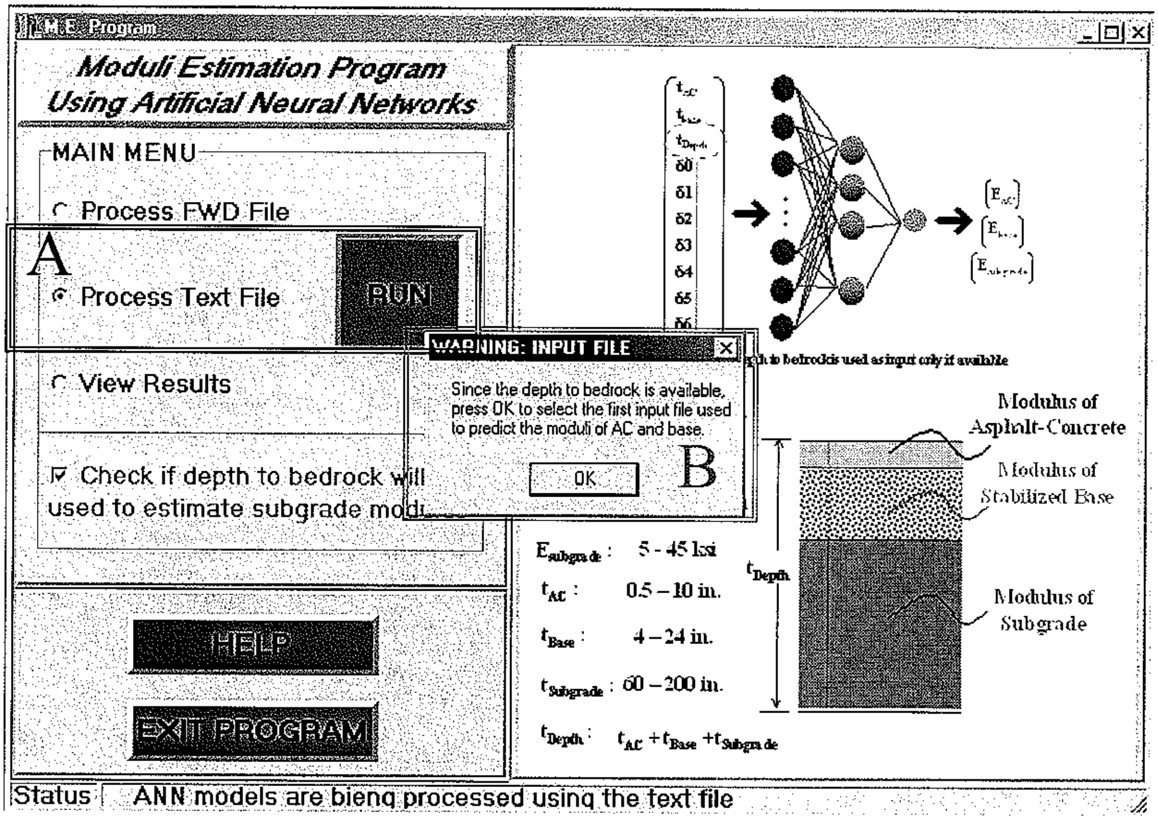
B) FWD FILE DOES/ DOES NOT CONTAIN AC TEMPERATURE – This section displays a message that informs the user when the selected FWD file does not contain the temperature of the AC layer.

C) NORMALIZE DEFLECTION UNDER THE LOAD WITH AC TEMPERATURE CORRECTION FACTORS FOR TEXAS DISTRICTS – Checking this box allows the user to define temperature normalization options. This displays section D (To Normalize By Temperature) and section E (the Texas Districts).

D) TO NORMALIZE BY TEMPERATURE – In this section, the user enters the AC temperature in degrees Fahrenheit and selects the FWD testing month from the drop down list.

E) TEXAS DISTRICT SELECTION – In this section, the user selects the Texas District where the FWD test was performed using the navigation tools at the bottom of the list.

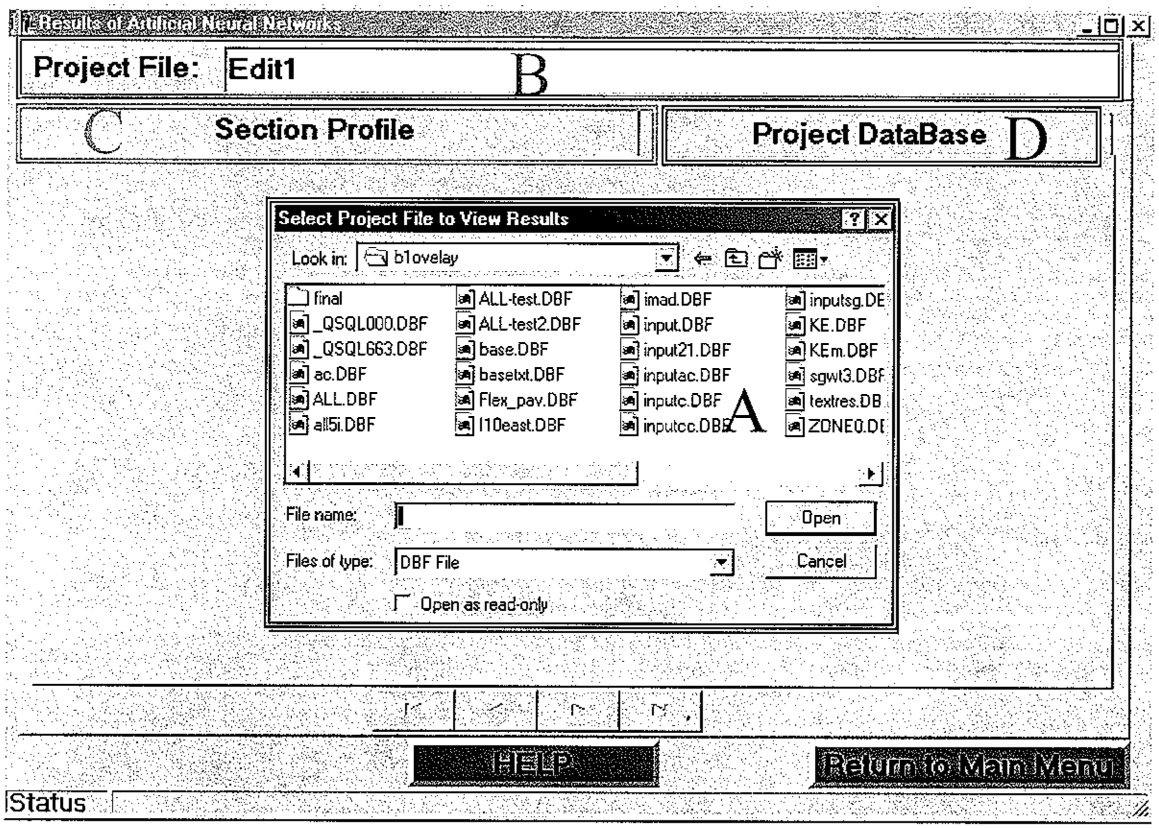
Main Menu Window (For Selecting Text File)



A) PROCESS TEXT FILE – Before choosing this option, the user should be aware that the text file must be prepared before using this program in the proper format for the ANN models to process them. After selecting this option in the main menu, click the [*RUN*] button to continue. The user should also check/ uncheck the depth to bedrock option.

B) INPUT FILE WARNING – When the depth to bedrock option is checked a warning message appears informing the user that the first input text file that will be selected will be used to estimate the AC and base moduli. A second input file will be asked for to estimate the modulus of the subgrade. After pressing the [*OK*] button on each message box, the user is prompted to provide the name of the project file.

Results of Artificial Neural Network Model Window (Part I)



A) SELECT PROJECT FILE TO VIEW RESULTS – After selecting the View results option and the [*RUN*] button in the main window, the Results of Artificial Neural Networks window appears in the background and an open file dialog box in the foreground where the user is prompted to select and open a project file.

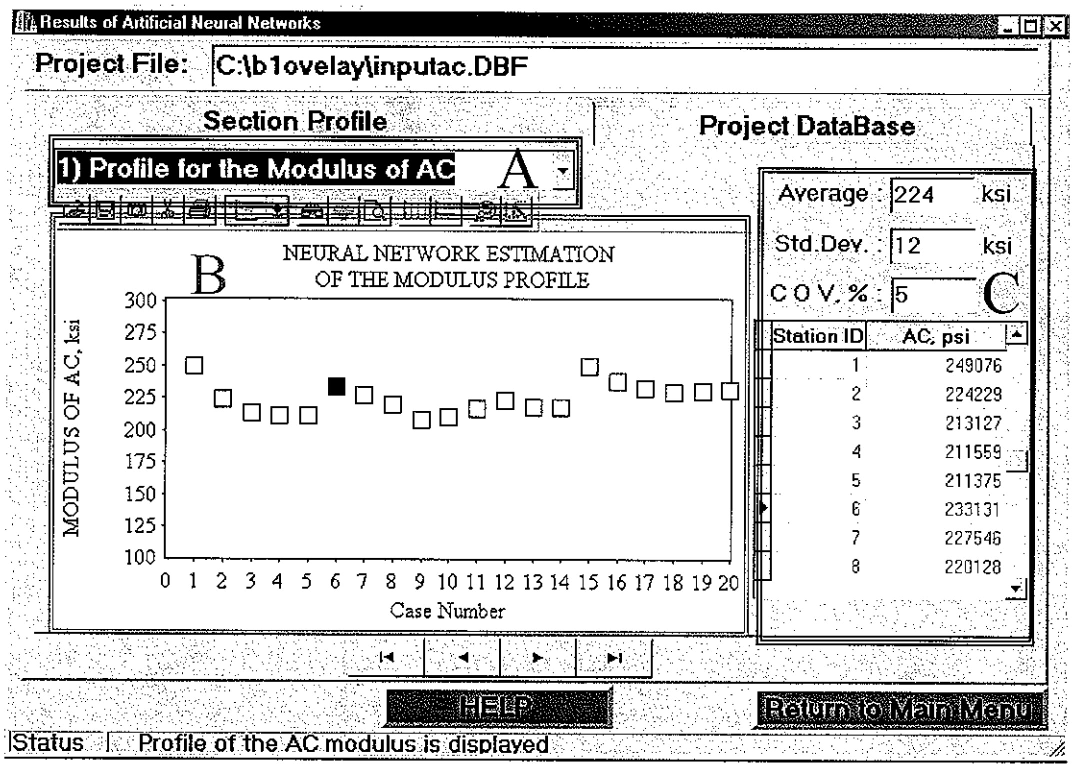
B) PROJECT FILE – The Project File textbox displays the name of the project file selected for viewing.

C) SECTION PROFILE – The Section Profile tab shows a graph that presents the neural network estimation of the modulus profile

D) PROJECT DATABASE – Under this tab, the project database table displays data read from the input file as well as the computed results in numerical format.

NOTE: Navigation buttons allow the user to scroll through the database.

Results of Artificial Neural Networks Window (Part II)



A) SELECT MODULUS PROFILE – Use the drop-list to select the desired modulus profile among the following layers:
   a. Asphalt-Concrete,
   b. Stabilized Base, or
   c. Subgrade.

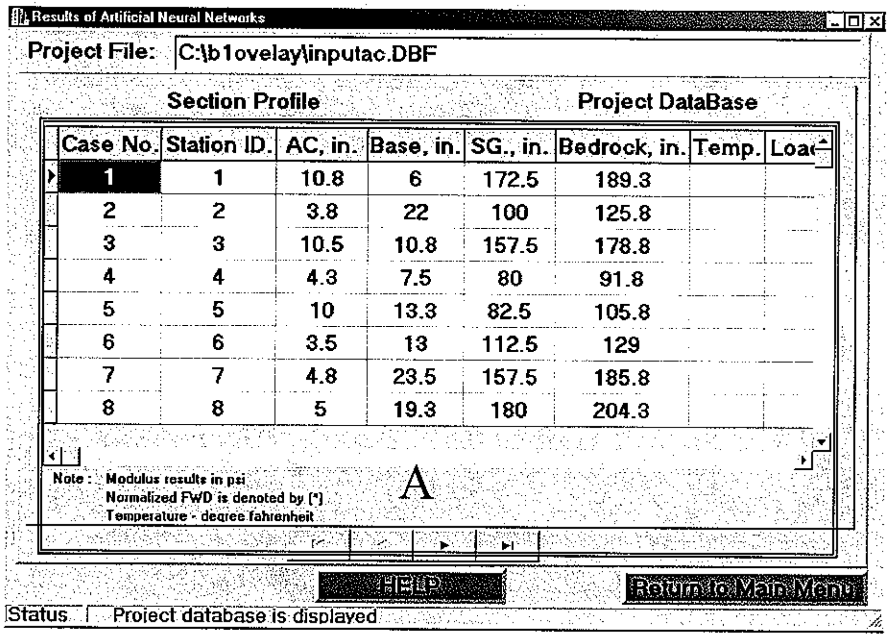
   The user can switch back and forth between layer profiles.

B) GRAPH – This graph presents the neural network estimation of the modulus profile. The vertical axis shows the layer modulus, and the horizontal axis show the case number. The graphical view of the modulus profile also contains a toolbar that allows the user to:
   - save the graph,
   - take a snap shot of the graph,
   - print the graph, and
   - manipulate the graph's appearance.

C) VALUES -- This section shows the statistical parameters (average, standard deviation, and coefficient of variation) of the set of computed moduli for the selected layer. A scroll down-list shows the estimations of the layer modulus per case.

NOTE: The Navigation buttons allow the user to scroll the database through each case back and forth, pointing out the selected case in the scroll down-list and highlighting in "black" the corresponding point in the graph.

Results of Artificial Neural Networks Window (Part III)

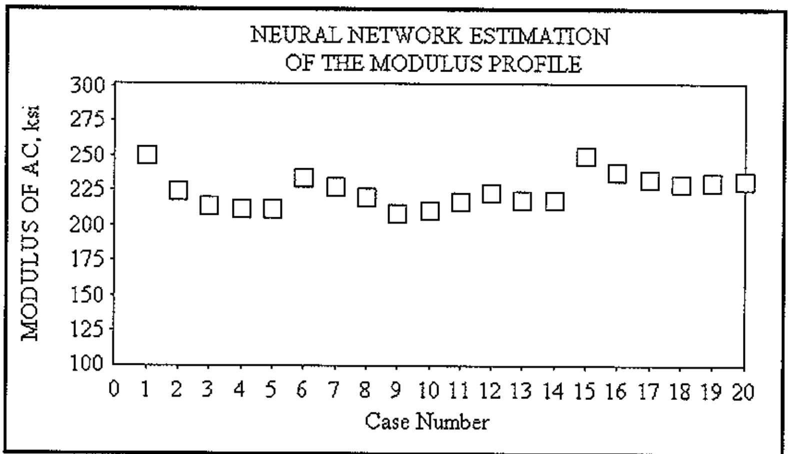


Case No.	Station ID.	AC, in.	Base, in.	SG., in.	Bedrock, in.	Temp.	Loa
1	1	10.8	6	172.5	189.3		
2	2	3.8	22	100	125.8		
3	3	10.5	10.8	157.5	178.8		
4	4	4.3	7.5	80	91.8		
5	5	10	13.3	82.5	105.8		
6	6	3.5	13	112.5	129		
7	7	4.8	23.5	157.5	185.8		
8	8	5	19.3	180	204.3		

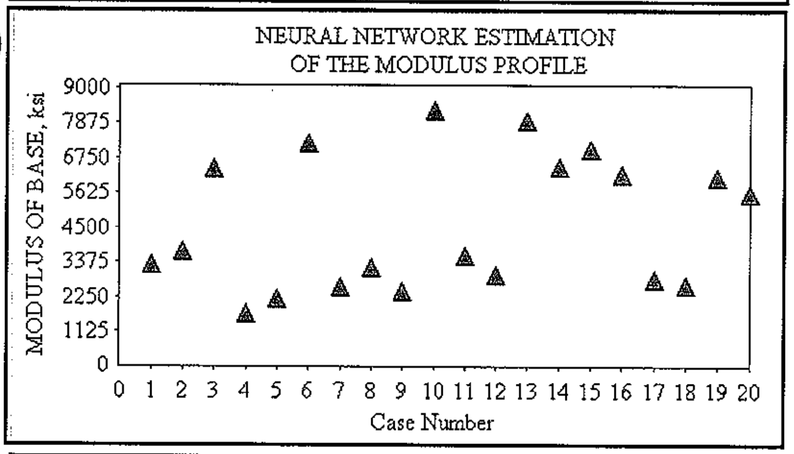
A) <u>DATABASE GRID</u> – The grid under the "Project Database" tab shows the results of the selected project file. If the project file is based on a FWD file, the table will contain all the information from that process. However, if the project file is based on a text file, the table will only contain the inputs and outputs of the ANN models

Typical Graphs of Results (Section Profile)

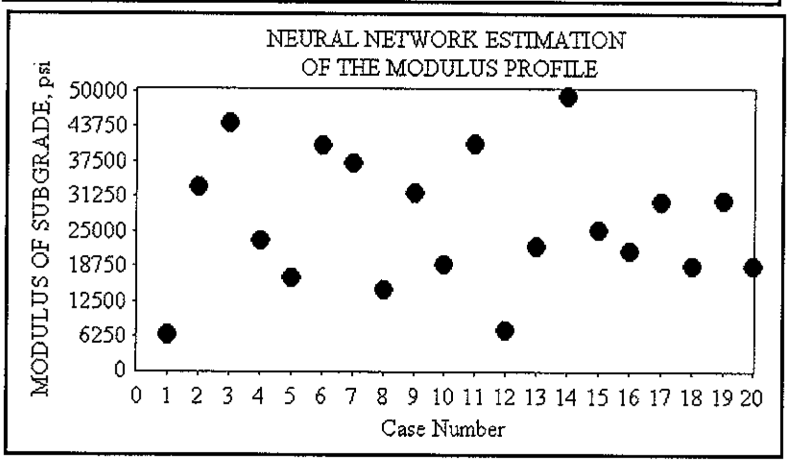
A)



B)



C)



A) PROFILE FOR THE MODULUS OF AC – This graph depicts the profile of the modulus of asphalt-concrete (in ksi units) versus the corresponding case number.

B) PROFILE FOR THE MODULUS OF BASE – This graph depicts the profile of the modulus of the stabilized base (in ksi units) versus the corresponding case number.

C) PROFILE FOR THE MODULUS OF SUBGRADE – This graph depicts the profile of the modulus of the subgrade (in psi units) versus the corresponding case number.