USDOT Region V Regional University Transportation Center Final Report

NEXTRANS Project No 010IY01

Nondestructive Pavement Evaluation Using Finite Element Analysis Based Soft Computing Models

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DISCLAIMER

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TECHNICAL SUMMARY

NEXTRANS Project No 010IY01 Final Report, October 2009

Nondestructive Pavement Evaluation Using Finite Element Analysis Based Soft Computing Models

Introduction

Evaluating structural condition of existing, in-service pavements constitutes annually a major part of the maintenance and rehabilitation activities undertaken by State Highway Agencies (SHAs). Accurate estimation of pavement geometry and layer material properties through the use of proper nondestructive testing and sensor technologies is very important for evaluating pavement's structural condition, its remaining life for maintenance and rehabilitation purposes, and for properly incorporating life cycle cost considerations into an up to date, improved Pavement Management System. For this purpose, pavement deflection basins gathered from the nondestructive Falling Weight Deflectometer (FWD) test data are commonly used to evaluate pavement structural conditions. Development of an innovative methodology, called SOFTSYS, Soft Computing Based Pavement and Geomaterial System Analyzer, is proposed here as an original way of interpreting the results of FWD tests for full-depth and conventional flexible pavements with the purpose of determining pavement layer properties as well as the layer thicknesses from FWD data without the need for pavement coring. Since the layer thickness information plays a crucial role in FWD data back calculation and remaining pavement life estimation, the outstanding contribution of SOFTSYS will be in the reliable estimation of pavement layer thicknesses in addition to their stiffness properties. Using only FWD test results (i.e. deflections) as inputs, SOFTSYS will calculate all the necessary properties for pavement evaluation.

Findings

This study focused first on the use of ANN pavement structural models developed with the results of the ILLI-PAVE finite element (FE) program to predict pavement deflections under FWD loading. Then an innovative soft computing application, referred to herein as SOFTSYS, was introduced for the hybrid use of Genetic Algorithms (GAs) and artificial neural networks (ANNs) to estimate pavement layer properties including the hot mix asphalt concrete (HMA) thickness from only the FWD test data collected on full-depth asphalt pavements built on both natural and lime modified subgrades.

The performances of the developed surrogate ANN structural models (forward models) were well above satisfactory; i.e., these ANN models could be used in lieu of finite element analyses for the quick and accurate predictions of the surface deflections and the critical responses of all types of full-depth flexible pavements found/constructed in Illinois, Indiana and Ohio. The results of pavement structural modeling with the ILLI-PAVE FE program proved that improvements due to the constructed lime stabilized subgrade soil layer had to be captured separately in the analyses since significant differences were found between the critical pavement responses of full-depth pavements on unmodified subgrade and lime stabilized subgrade. Therefore, for correctly modeling the pavement response and behavior with the lime stabilized subgrade soil layer, separate forward analysis approaches were developed to accurately predict pavement deflection profiles and pavement critical responses under FWD loading.

Thickness variability was a real issue in the field, and destructive pavement coring was not always a viable option to determine layer thickness. The SOFTSYS, Soft Computing Based Pavement and Geomaterial System Analyzer, framework developed as a software tool was used successfully to backcalculate the layer moduli and the HMA thicknesses of the full-depth asphalt pavements analyzed. SOFTSYS was shown to work effectively with the synthetic data obtained from ILLI-PAVE FE solutions. The very promising SOFTSYS results obtained indicated average absolute errors (AAEs) on the order of 6% and 9% for the HMA thickness estimation for full depth pavements and full depth pavements built on lime stabilized soil layers.

The field validations of SOFTSYS with Staley Road FWD data in Illinois and LTPP data in Indiana also produced meaningful results. Higher deflection values correlated well with the thinner backcalculated HMA thicknesses. In addition, the thickness data obtained from GPR testing matched reasonably well with the SOFTSYS results although in some locations the maximum difference between the two results was up to 3 in. The variations of HMA thickness observed were attributed to variations in the FWD data. The data obtained from GPR also indicated that the constructed HMA thicknesses were generally greater than the design thickness (by approximately 1 in.) although there were sections that were even thinner than the design thickness. The thickness data from the field were deemed to be essential to calibrate the GPR test results. In addition, the validations of SOFTSYS with LTPP design data proved that proper calibration of parameters is a must to obtain reliable results from the SOFTSYS methodology.

Recommendations

SOFTSYS was presented to be reliable, accurate and quick evaluation tool for both pavements and geomaterials. Although it has many capabilities, it needs to be used with caution since SOFTSYS requires many parameters to be tuned and selected carefully. In addition, its full potential needs to be further investigated and developed in future research projects.

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CHAPTER 1. INTRODUCTION

1.1 Background and motivation

Evaluating structural condition of existing, in-service pavements constitutes annually a major part of the maintenance and rehabilitation activities undertaken by State Highway Agencies (SHAs). Accurate estimation of pavement geometry and layer material properties through the use of proper nondestructive testing and sensor technologies is very important for evaluating pavement's structural condition and determining options for maintenance and rehabilitation. For this purpose, pavement deflection basins gathered from the nondestructive Falling Weight Deflectometer (FWD) test data are commonly used to evaluate pavement structural conditions. Often these interpretations of FWD test data also require the layer thicknesses of the tested pavements for backcalculation of the pavement layer properties. With the recent AASHTO move towards adopting mechanistic based pavement analysis and design concepts and procedures nationwide, interpretations of FWD data from routine nondestructive testing currently demands the use of advanced multi-layered and finite element (FE) solutions for proper analyses of pavement structural conditions. Often these interpretations of FWD test data also require the layer thicknesses of the tested pavements for backcalculation of the pavement layer properties.

Soft computing is an umbrella of computational intelligence techniques that handle subjective and numerical (even ambiguous) information and include the principal components as artificial neural networks (ANNs), fuzzy mathematical programming, and evolutionary computing such as genetic algorithms (GAs). These techniques are powerful and versatile computational tools for organizing and correlating information in ways that have proved useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more-traditional computational methods. The use of soft computing techniques also allows creating analysis tools that tolerate imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution cost, and better rapport with reality. These nontraditional computational intelligence techniques have already proven to outperform traditional modeling counterparts in solving various complex engineering problems including pavement analysis. The recent adoption and use of ANN modeling techniques in the new NCHRP 1-37A Mechanistic-Empirical Pavement Design Guide for AASHTO has especially put the emphasis on the successful use of ANNs in pavement systems. Further, a current Transportation Research Board subcommittee was focused on "Applications of Nontraditional Computing Tools Including Neural Networks" with the primary mission to provide practitioners a better understanding on and at the same time foster the use of the ANNs and other nontraditional computational intelligence techniques in pavement engineering applications related to transportation facilities.

In recent successful applications at the University of Illinois, the use of ANNs was introduced for backcalculating the pavement layer moduli and predicting the critical pavement responses directly from the FWD deflection basins (Ceylan et al. 2004; Pekcan et al. 2006). ILLI-PAVE finite element program (Elliott and Thompson 1985; Gomez-Ramirez and Thompson 2001; Thompson 1987; Thompson 1989; Thompson 1992; Thompson 1994; Thompson and Elliott 1985), extensively tested and validated for over three decades, has been used as the primary analysis tool for the solution of full-depth and conventional flexible pavement responses under the standard 9-kip FWD loading. ANN models then trained with the results of the ILLI-PAVE solutions have been found to be viable alternatives to backcalculate the pavement layer moduli and predict the critical pavement responses based on the FWD deflection data (Ceylan et al. 2005; Pekcan et al. 2006; Pekcan et al. 2007; Pekcan et al. 2008). The trained ANN models are capable of backcalculating the pavement layer moduli and predicting critical pavement responses, such as tensile strain in the asphalt concrete linked to fatigue cracking and vertical stress/strain linked to subgrade rutting, with very low average absolute errors of those obtained directly from nonlinear ILLI-PAVE FE analyses. These error magnitudes are commonly much smaller than the ILLI-PAVE algorithms currently in use by Illinois DOT. However, it was also shown that these models were developed with the assumption that the layer thicknesses information is known in advance or needs to be taken from design thickness data, which is generally not available or erroneous when available. In addition to this, ANN models are not capable of estimating layer thicknesses using only FWD deflections since they implement direct inversion methodology. In order to estimate the pavement layer parameters completely and more reliably, there is a need to replace the existing backcalculation technique with a better one.

Development of an innovative methodology, called SOFTSYS, Soft Computing Based Pavement & Geomaterial System Analyzer, has been implemented here as an original way of interpreting the results of FWD tests for full-depth pavements with the purpose of determining pavement layer properties as well as the layer thicknesses from FWD data without the need for pavement coring. Since the layer thickness information plays a crucial role in FWD data backcalculation and remaining pavement life estimation, the outstanding contribution of SOFTSYS is that it is able to estimate the pavement layer thicknesses reliably in addition to their stiffness properties. Using only FWD test results (i.e. deflections) as inputs, SOFTSYS calculates all the necessary properties for pavement evaluation. For this purpose, it uses a combination of two soft computing techniques, ANNs and Genetic Algorithms (GAs). The SOFTSYS approach, being so quick and robust, has been utilized for real time evaluation of pavements to also facilitate as-constructed pavement layer thickness quality control and the verification of in-service pavement overlay design parameters.

1.2 Research Objectives

The overall objectives in this NEXTRANS research are to:

(1) support the development of the framework SOFTSYS for evaluating in-service flexible pavements with the purpose of determining pavement layer thicknesses as well as the layer properties from FWD data without the need for pavement coring,

(2) compare and verify SOFTSYS results with those of the nonlinear ILLI-PAVE based FE solutions, and,

(3) validate SOFTSYS performance for determining pavement thicknesses and layer properties with actual field data where Ground Penetrating Radar (GPR) tests can be performed for layer interface locations and/or cores can be collected from existing highway pavements in coordination with the nondestructive FWD testing and pavement evaluation activities of SHAs.

By successful completion of this study, the intent has been to provide field engineers with a field validated nondestructive pavement evaluation tool called SOFTSYS, to assess pavement condition and to provide solutions when there is no thickness data available for the pavement section, where FWD testing is performed and eventually help assess pavement rehabilitation strategies.

1.3 Research Methodology

The NEXTRANS research was performed using the following detailed project tasks and integration aspects:

Task 1 – Characteristics of Flexible Pavements: Participation and collaboration by the SHAs in Illinois, Indiana, and Ohio were essential in identifying typical flexible pavement types, including those with lime stabilized subgrades, and geometries in their State, establishing a database of these in-service pavements, and collecting field FWD data. For this purpose, an extensive Long Term Pavement Performance (LTPP) database was also utilized.

Task 2 – Generating ILLI-PAVE FE Solutions: A comprehensive ILLI-PAVE FE analysis database was established to cover ranges of all pavement types, layer thicknesses and material properties identified. The nonlinear ILLI-PAVE mechanistic solutions are equivalent to the most sophisticated LEVEL 1 analysis results of the newly released 1.0 version of the Mechanistic Empirical Pavement Design Guide software.

Task 3 – Development of the SOFTSYS Methodology: The SOFTSYS approach was developed by integrating IT based data mining and soft computing techniques for the determining reliably pavement layer thicknesses by nondestructive means. Integrating and implementing findings of the previously mentioned UIUC researchers has been a key component of success under this task. Both the ILLI-PAVE mechanistic pavement solution database and field collected FWD data have essentially been used in the training and development. In addition, SOFTSYS methodology primarily used more accurate forward calculation results when compared to the backcalculation ANN models developed in a recent Illinois DOT project by the authors. The role of GAs has been primarily in the area of optimization and search with its parameters inspired by the natural evolution.

Task 4 – Validation of the SOFTSYS Methodology: Both GPR and FWD data combined was used to validate the developed SOFTSYS approach. Any pavement core information also obtained during field testing was also very useful. Monitoring and improving the quality of field data was sought out by integrating advances in sensor installation and sensing technologies as well as utilizing wireless data transfer.

1.4 Report Organization

Chapter 2 of this report introduces FWD testing as the most popular pavement nondestructive testing and evaluation approach and gives a complete literature review of the backcalculation methods including the background information provided on the advanced methods used in this study, i.e., ANNs and GAs. The development of ANN based structural models are described in Chapter 3 for full-depth asphalt pavements found/constructed in Illinois on both natural and lime stabilized subgrade soils. The developed ANN models are also validated with synthetic FWD data in Chapter 3. Chapter 3 also introduces the SOFTSYS approach based on the combined use of ANNs and GAs for pavement layer modulus and thickness determinations applied mainly to full-depth asphalt pavements built on natural and lime stabilized subgrade soils. Chapter 4 includes field validation of the SOFTSYS methodology. Finally, a summary and the major findings of the research study are given in Chapter 5.

CHAPTER 2. LITERATURE SURVEY

2.1 Backcalculation Problem

In the area of transportation geotechnics, the practice of determining the pavement layer properties using surface deflections is commonly referred to as backcalculation. The backcalculation of layer properties including pavement layer moduli and even layer thicknesses from surface deflection measurements plays a major role in the structural evaluation of pavements, design of overlays and management of in-service pavements. There are mainly two approaches to determine the existing condition of a pavement; either by destructive or non-destructive means. In the last three decades, the improvements in technology have caused the non-destructive testing (NDT) methods to become more popular since there is neither disturbance to the integrity of the material nor the sampling of it. Moreover, they are quite easy to use, repeatable, and they can be performed much more rapidly than destructive tests. These advantages result in much less overall cost in the long run when compared to those of the destructive testing methods. Against all the advantages, the reliability of NDT methods certainly depends on the accurate interpretations of the test results and the precise determination of the pavement layer material properties, such as pavement layer stiffness or modulus and layer thickness. Falling Weight Deflectometer (FWD) testing is the most popular NDT method for evaluating pavements. It provides pavement surface deflections recorded by several offset sensors in response to a constant load dropped from a specific distance at a certain frequency. These deflections are essentially used for structural evaluation of pavements.

2.2 *Falling Weight Deflectometer Testing*

Falling Weight Deflectometers (FWDs) have been known as NDT devices which can exert an impulsive load on the pavement and record the resulting deflections on the pavement surfaces at several distances from the load. As the name implies, an FWD imparts its test load by means of a specified weight (usually between 110 and 660 lbs.) falling a given distance (up to 16 in.) and striking a buffered plate resting on the pavement surface (see Figure 2.1). It can produce a peak dynamic force typically between 1,500 and 24,000 lbs in 25-30 milliseconds (see Figure 2.2). The load is transmitted from the rubber buffers to pavement through a 5.91-in. radius steel plate underlain by a rubber pad, which helps applying the load uniformly on the pavement surface. The FWD impulse load duration of 25 to 30 milliseconds approximates the same load duration of a vehicle traveling at 40 to 50 mph (Ulliditz and Stubstad 1985).

Deflections with FWD equipment are typically measured at the center of the load and up to six other locations. A typical test configuration is shown in Figure 2-3. One major advantage of FWD is that it is better than any other testing equipment in replicating the load histories and deflections produced by moving vehicles. This deflection profile or basin is primarily affected by the properties of individual pavement layers as well as the magnitude and frequency of the loading (Shahin 2005). In comparing elastic properties calculated from an earlier Dynaflect test with results from the FWD, it was found that dynamic inertia effects were less important in the FWD results due to the higher frequencies(Roesset and Shao 1985). Hoffman and Thompson (1981) compared the FWD with the Road Rater Model 400B and the Benkelman Beam NDT equipment. They concluded that the FWD produced a deflection which best represented conditions under a moving wheel load. Since FWD is the closest device for replicating the deflections of a moving truck (Ulliditz and Stubstad 1985), it has been widely accepted worldwide. Among many FWD's described in the literature, the three most commonly used and commercially available ones are the following:

1) Dynatest Model 8000 (Dynatest Consulting, Inc.);
2) KUAB FWD Models 50 and 150 (KUAB America);

3) JILS FWD (Foundation Mechanics, Inc.).

Figure 2.1. Dynatest Falling Weight Deflectometer device.

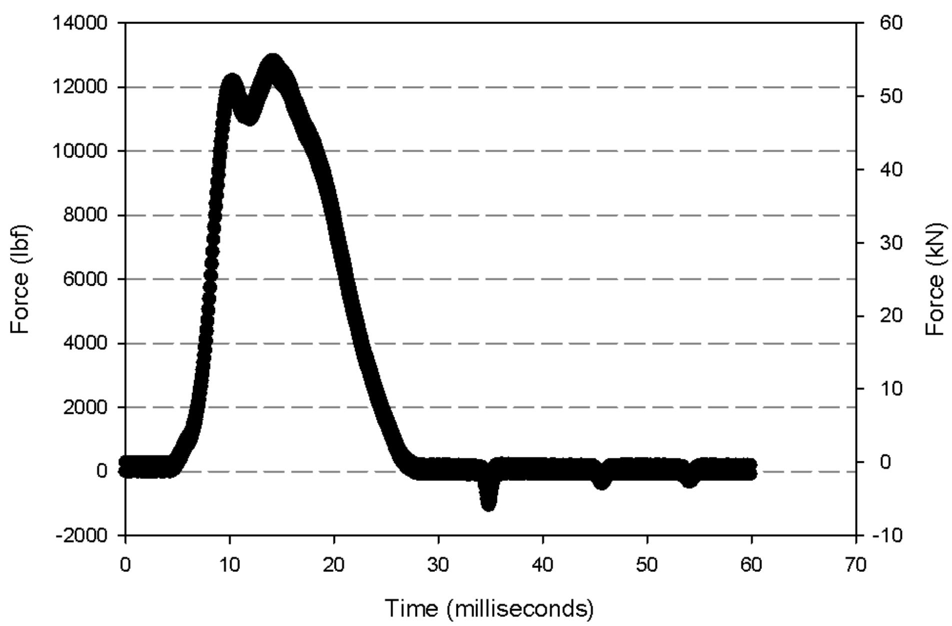

Figure 2.2. Haversine loading applied by FWD.

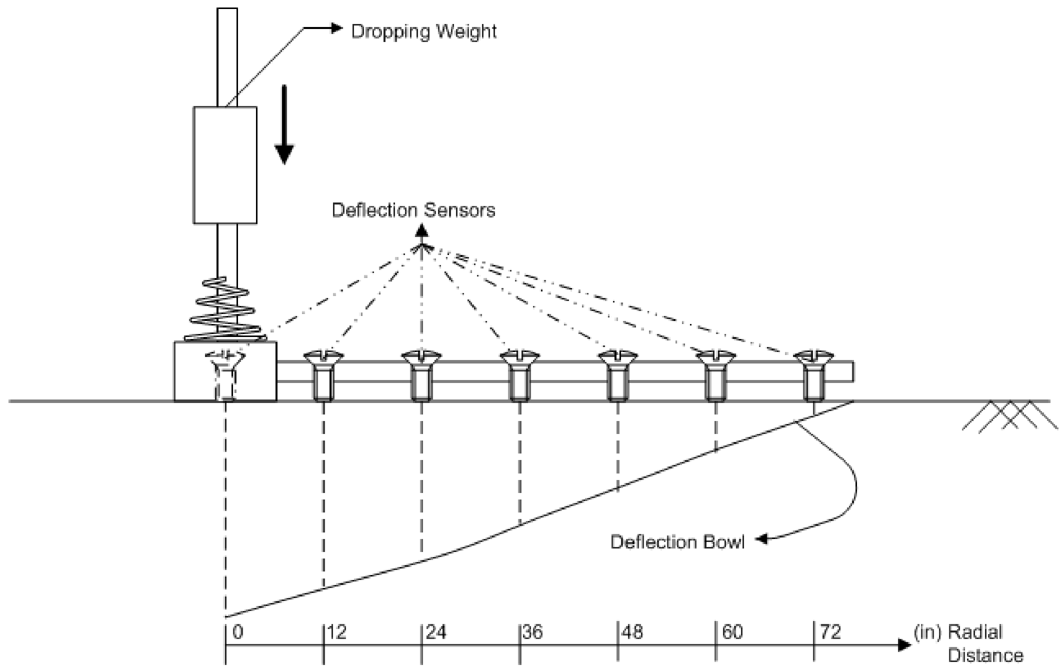

Figure 2.3. Locations of FWD sensors and schematic drawing.

FWD test deflection basins can be successfully interpreted to identify the existing condition of a pavement under traffic loading. For example, at a specified temperature, small deflections may indicate the response of a strong pavement structure, while larger ones might dictate the existence of weaker sections. Diagnosing the current conditions of pavements, however, requires inversion of mechanical properties through evaluation of FWD data.

2.3 Backcalculation Methods

Backcalculation is an inverse type of engineering problem, which is generally hard to solve analytically due to its ill-posed nature. The sensitivity of solutions, i.e., backcalculated layer properties, to the deflections as the variables of the inverse problem is generally quite high. In addition, the solutions typically require searching of a multidimensional nonlinear space formed by the variables, where traditional numerical approaches do not operate well (Liu and Han 2003). The computational procedure to effectively solve this problem usually includes both a pavement response model and an optimization algorithm. Indeed, the key steps for an effective solution are to understand the nature of the problem and select the appropriate methodology that relaxes the complexity of the inversion process.

The concept of backcalculation for pavements became popular in the last three decades along with wide use of mechanistic-empirical methods in the design of pavements and developments in pavement management systems. Backcalculation approaches for obtaining pavement moduli using NDT data can be grouped into three methods (Anderson 1988):

- Simplified methods;
- Gradient relaxation methods; and
- Direct interpolation methods.

Among the different types of methods listed, the most popular ones are gradient relaxation methods. In this type, generally a mathematical model of the pavement is constructed and subjected to the appropriate NDT load to obtain surface deflections as a function of pavement layer properties. This model can then be run with various layer properties until a satisfactory solution set is found for which the measured deflection basin is produced (see Figure 2.4).

Alkasawneh (2007) summarized the main steps of the backcalculation as follows:

1. Define the input parameters of the pavement system including thickness of each layer, Poisson's ratio, etc.

2. Assume moduli seed values for the pavement system. Seed moduli values can be assumed based on experience or based on typical moduli values. Moduli values can be different based on the forward method implemented in the backcalculation program.

3. Calculate the pavement deflections, using the forward program, at the FWD geophone locations (along the surface).

4. Compare the calculated deflections with the measured deflections. If the difference between the calculated and measured deflections is acceptable, then the assumed layer moduli are the actual moduli. Otherwise, the assumed layer moduli are not the actual moduli and the assumed moduli should be refined.

5. Repeat steps if necessary.

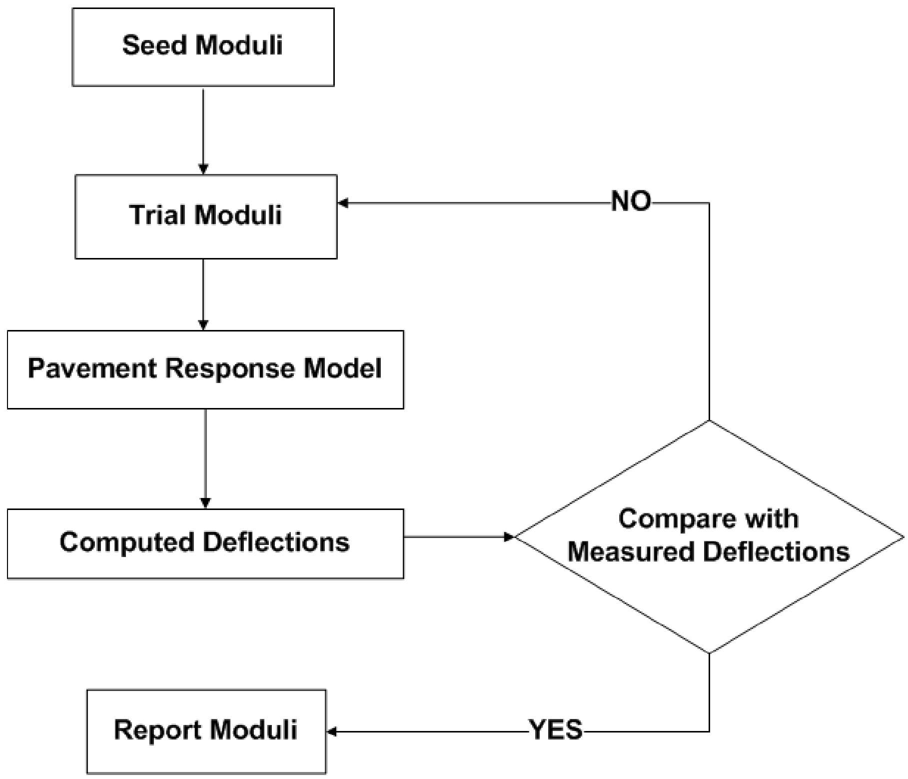

Figure 2.4. Traditional iterative backcalculation procedure (Meier 1995).

In addition to these, many computational methods were proposed. Linear regression methods, artificial neural networks (ANNs), genetic algorithms (GAs), and fuzzy systems were mainly utilized as backcalculation techniques. A recent study by Goktepe et al. (2006) provides an extensive summary of these methods. Particularly, many researchers found soft computing methods to be useful due to their advantages such as non-universality and noise tolerance (Ghaboussi 2001; Ghaboussi and Wu 1998), which can properly deal with the difficulties naturally existing in the backcalculation problem.

2.4 *Soft Computing Methods*

There has been a tremendous research effort to solve the complex problems by applying techniques which produce rather not perfect, but sufficiently precise results given the scope of the problem. These techniques are generally known as Soft Computing methods, which mainly include ANN's, GA's and fuzzy logic based computing methods, etc. All of these methods have wide range of applications in engineering problems. In this section, as a sub-class of soft computing methods, the development of GA's and ANNs for pavement backcalculation studies will be reviewed.

2.4.1 **Genetic Algorithms**

Genetic Algorithms (GAs) are class of computational models working based on the evolutionary process in nature. GAs use the adaptation based random directed search techniques inspired by natural selection to obtain robust and computationally efficient solutions for engineering problems. They have been very popular in the last three decades due to their attractive features such as they do not require a previous knowledge of the problem domain, their robustness has been well established. There are numerous successful implementations in the literature for search and optimization problems as well as machine learning (Goldberg 1989).

Many researchers have investigated the application of GAs in optimization and design (Michalewicz 1996). The benefits of GAs over other methods used in search, including mathematical programming and heuristic search methods are (Rasheed and Hirsh 1997):

- The provision of a global search method, which is more effective for searching multi-modal and deceptive problem domains than the local search methods provided by traditional and heuristic search methods.

- The ability to easily incorporate discrete, continuous, and mixed variables into the constraint formulation.

- The ability to handle arbitrary objective functions that are nonlinear, discontinuous, ill-defined, and deceptive without requiring gradient information.

- The ability to perform fitness evaluations and genetic manipulations independently for each individual, which makes GAs suitable for parallel computation.

In addition to this, Cox (2005) summarized the advantages and disadvantages of the GAs as follows:

- The ability to solve highly nonlinear, noisy and discontinuous problems
- The ability to solve complex optimization problems
- A complete dependence on the fitness function
- A sensitivity to genetic algorithm parameters
- A sensitivity to genome coding

Variations in each of the above items have been examined by researchers, and several generations of improvements within each area have been realized. The theory describing the behavior of GAs, however, remains grounded in the schema theorem and the principle of minimal building blocks as defined by Holland (1975) and Goldberg (1989). Both principles recommend the selection of a representation of fixed length that encodes the parameters of the problem in binary form. This is readily confirmed by the vast number of applications that use this standard GA representation.

Operation of GAs is conceptually different than other methodologies in four different ways (Goldberg 1989)

1. GAs work with coding of the parameters, not the parameters themselves.
2. GAs use population of solutions, not a single solution.
3. GAs use the payoff (objective) information, not additional information or derivatives, etc.
4. GAs use probabilistic transition rules, not the deterministic ones.

GAs encode the variables of the problem into a finite set of strings of alphabets of certain cardinality (number of possible elements in the set). These strings are the potential solutions to the problem and referred to as chromosomes, the alphabets are referred to as genes and the values of the genes are called alleles (Burke and Kendall 2005). The total encoded parameter information in the GA string is called genotype and the decoded form is named as phenotype. Table 2-1 summarizes the genetic terms GAs borrow to explain the form and processing of the GA representation and operators.

Table 2-1 The definitions of terms used in Genetic Algorithms

Parameter	*Explanation*
Gene	encoded parameter value
Allele	all possible values that can be encoded for a specific parameter
Genotype	the total encoded parameter information in the GA string
Phenotype	the decoded solution from the GA string
Crossover	exchanging string segments between two selected GA strings
Mutation	changing a single bit or value randomly on a single GA string
Selection	performing a "survival of the fittest" reproduction of GA strings

GAs also work using a fitness measure to evaluate the effectiveness of the obtained solutions and to produce better solutions to effectively build up natural selection. This measure can either be an objective function that is a mathematical model or a computer simulation or an subjective function where humans can choose better solutions compared to other ones.

The concept of population is an important aspect in GAs. As the name implies, GAs rely on the population of candidate solutions. The size of the population can be specified by the user and it is one of the important factors affecting the performance and scalability of GAs. For example, small population sizes may lead to premature solutions while the large populations may result in extensive computation times (Burke and Kendall 2005).

The major steps of GAs are as follows:

1. Initialization: The initial population of candidate solutions is generated (usually randomly) across the search space. Here, the domain specific knowledge or other information can be incorporated.

2. Evaluation: Once the measure for fitness and the termination criteria are determined, the candidates of initial population are evaluated based on this criterion. If the criteria for termination are not satisfied, the evolution is carried through the first generation, with the strings in the initial population being the parent strings of the next generation.

3. Selection: Selection allows more copies of the solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions. There are many selection mechanisms to provide better members to the population with evolving generations such as roulette wheel selection, stochastic universal selection, ranking selection and tournament selection, some of which are going to be described in the next section.

4. Recombination: In this step, two or more parental solutions are combined to create new candidates (i.e., offsprings) of the next generation, which are possibly better solutions. While there are many ways of doing this, the main idea is to provide efficiency for the algorithm to produce offsprings which will inherit parental traits in a novel manner (Goldberg 2002) .

5. Mutation: While recombination operates on two or more candidates, mutation works on single solution to modify it randomly to create diversity in the population. It is applied to each gene with a small probability. Similar to other operators of GAs, there are also many mutation techniques, such as bitwise mutation or problem specific mutation operators.

6. Replacement: The offsprings created by the above genetic operators replace the original parental population by replacement techniques such as elitist replacement, generation-wise replacement and steady state replacement, etc.

2.4.1.1 Simple Genetic Algorithms (SGA's)

SGAs are identified by the use of three standard genetic operators: selection scheme (generally roulette wheel selection), simple crossover, and simple mutation as defined by Goldberg (1989). These three genetic operators are applied to a population of fixed length strings consisting solely of binary bits (0 or 1) that represent a fixed set of parameter values. Real or integer parameter values are encoded in the string in a predetermined order using "n" bit binary representation for each parameter. The resulting string of binary bits is called the genotype. Simple crossover and mutation are performed on the genotype. The binary bit strings are decoded into the real or integer parameter values to obtain the solution, which is called the phenotype. The expressed phenotype provides the solution evaluated by the fitness function.

The steps required to apply the SGA are shown in Figure 2.5. The designer selects the size of the population and randomly initializes all of the individuals in the population. The solution represented by each individual is decoded from the genotype and evaluated using the defined fitness function. The genetic operations of selection, crossover, and mutation are then performed to determine the new population. The iterative process of evaluation and genetic manipulation is continued until convergence is reached. The SGA evolutionary search process is summarized in six steps:

1. Generate random initial population of n individuals;
2. Determine the fitness of each individual;
3. Select n individuals based on fitness using fitness proportional selection;
4. Perform crossover and mutation on selected individuals;
5. Form new population of n individuals; and
6. Repeat steps 2 through 5 until the stopping criterion is satisfied.

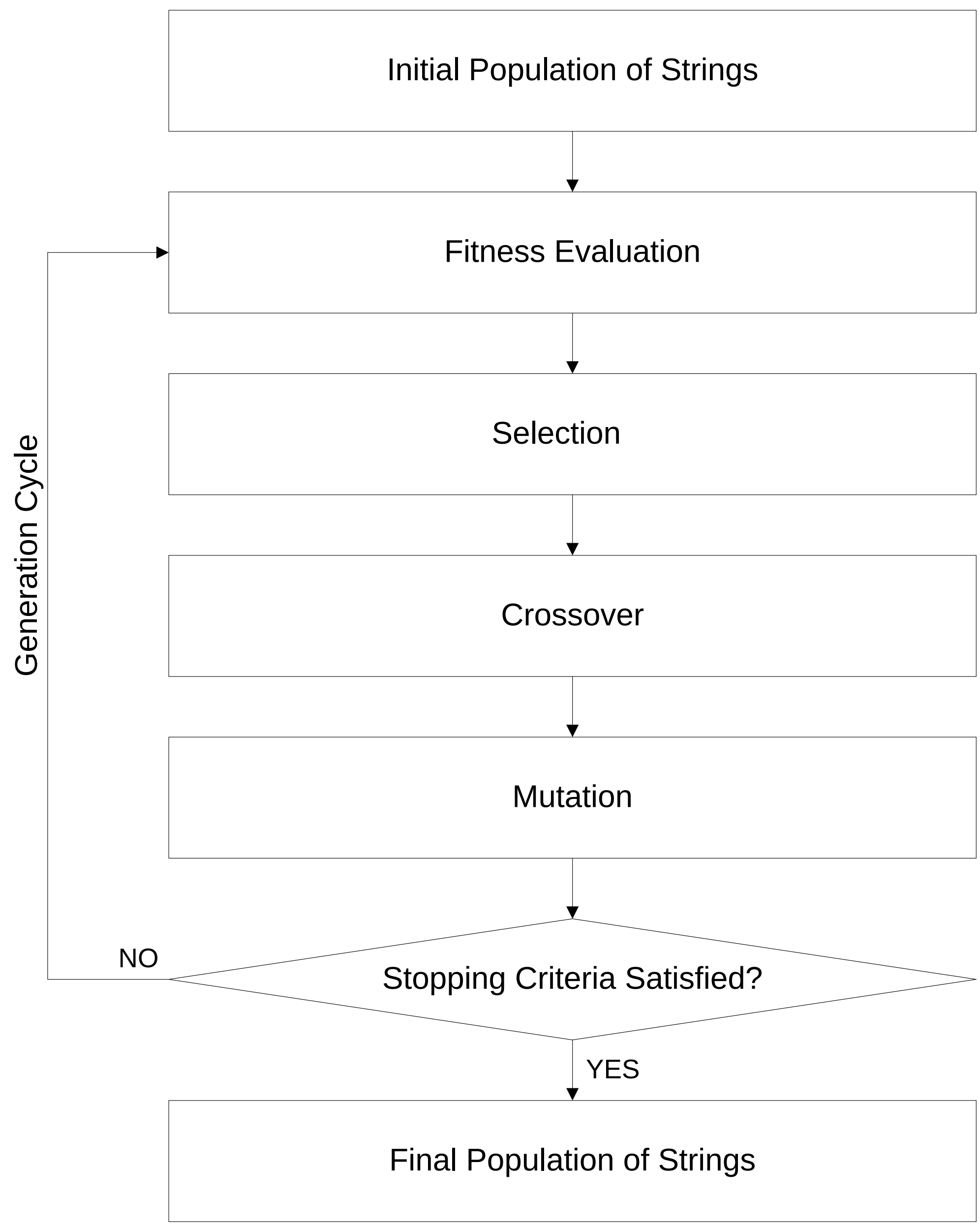

Figure 2.5. Simple genetic algorithm (SGA) (Raich 1999).

2.4.1.1.1 Simple Genetic Algorithm Genotype/Phenotype Representation

In SGAs, each parameter value is represented as “n” bit binary number. The encoded binary values are concatenated together to form a binary string. The order of the encoding is predetermined by n one to one mapping of the parameter values to the encoded binary values. The string length is fixed in SGA and is determined by adding the lengths of the individual n bit binary numbers. The number of bits, n, used to encode each parameter sets explicitly the range of the parameter values, such as a 2-bit binary number that is used to represent the integer numbers (0,1,2,3). If other ranges of integer or decimal precision numbers are required, a mapping is used to adjust the ranges for continuous parameters or to assign values for discrete parameters. An example for multivariable phenotype representation is provided in Table 2-2 and Table 2-3.

Table 2-2 Real Value Representation of Phenotypes

<table>
<tr><th>Population</th><th>Variable 1</th><th>Variable 2</th><th>Variable 3</th></tr>
<tr><td>1</td><td>17</td><td>89</td><td>21</td></tr>
<tr><td>2</td><td>25</td><td>54</td><td>10</td></tr>
<tr><td>3</td><td></td><td></td><td></td></tr>
<tr><td>4</td><td></td><td></td><td></td></tr>
<tr><td>5</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
<tr><td>…</td><td rowspan="3">…
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<tr><td>maxPop</td><td></td><td></td><td></td></tr>
</table>

Table 2-3 Bit String Representation of Phenotypes for Use in Genetic Algorithms

Population	Variable 1					Variable 2							Variable 3				
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1	0	0	0	1	1	0	1	1	0	0	1	1	0	1	0	1
2	1	1	0	0	1	0	1	1	0	1	1	0	0	1	0	1	0
3																	
4																	
5																	
…	…					…							…				
…	…					…							…				
…	…					…							…				
max Pop																	

2.4.1.1.2 Roulette Wheel Selection in Simple Genetic Algorithm

Roulette wheel selection, which is also called fitness proportional selection, was one of the first selection methods investigated and is still popular in GAs. A fitness value is assigned to each individual based on the evaluation of the defined fitness function, and individuals of the population are selected in proportion to their fitness. Each individual j in the population will have a probability of selection $\rho(x_j)$ based on its fitness value $f(x_j)$ divided by the sum of the fitness values of the population (Equation (2.1)):

$$\rho(x_j) = \frac{f(x_j)}{\sum_{i=1}^{m} f(x_i)} \tag{2.1}$$

where m is the number of individuals in the population. An individual with a high fitness will have an increased chance of being selected for recombination; those individuals with low fitness may not be selected at all.

Example Problem: Suppose it is desired to maximize the function given in Equation (2.2).

$$z = (x-7)^2 + (y-3)^2 \tag{2.2}$$

with both x and y given on an integer interval [0,7]. For this function, the roulette wheel algorithm is explained in Table 2-4:

Table 2-4 Randomly Created Initial Population for the Example Problem (Population Size = 4)

(a) Initial Population (j)	(b) Phenotype (x,y)	(c) Fitness (f_i)	(d) Genotype (x,y)	(e) Normalized Fitness (%) (f_i /SUM)	(f) $S_i = \sum_{i=1}^{j} f_i$	(g) Random Number Generator b/w 0-100	(h) New Parent ID
1	(4,1)	13	100001	12.7	12.7	67	4
2	(1,4)	37	001100	36.3	49.0	1	1
3	(6,2)	2	110010	2.0	51.0	69	4
4	(0,4)	50	000100	49.0	100.0	8	1
SUM		102			100		

1. The members of the population are numbered.
2. Let's assume that the initial population is created randomly for (x,y) in [0,7] interval.
3. The fitness values (in this case, it is the function we want to maximize) are calculated.

4. Phenotypes are encoded into Genotypes using 3 bits to represent x and y separately. The bit values for “x” and “y” are then combined together to form a bit string.
5. The fitness values are normalized with respect to SUM of all fitness.
6. Cumulative sum is used to rank the fitness along a straight line between 1 and 100. It gives the sum of all fitness values from individual one to individual i.
7. Random Number Generator is used to create random numbers between 0 and 100.
8. The first individual whose cumulative sum S_i is equal or greater than this integer will be chosen as a parent.

2.4.1.1.3 Genetic Manipulation in Simple Genetic Algorithm

In SGAs, two individuals are randomly paired from the set of selected individuals to undergo single point crossover. For each pair of strings, a bit location is selected randomly, the string is cut virtually at this location (called locus), and the portions of the strings beyond the cut are exchanged as shown in Figure 2.6. Crossover supports the recombination of good building blocks by placing the building blocks in new contexts on different individuals (Holland 1975).

Bit mutations are used by SGAs to prevent the loss of diversity in the population by introducing new genetic information or reintroducing previously lost information (Goldberg 1989). For the SGA binary representation, a mutation is applied probabilistically to each bit in an individual by flipping the bit value from zero to one, or vice versa (see Figure 2.7). The mutation rate typically is set at a low level of about 1 mutation per 1000 bits. After mutation has been performed, the new population consists of the children created by the process of crossover and mutation from the parents selected from the population.

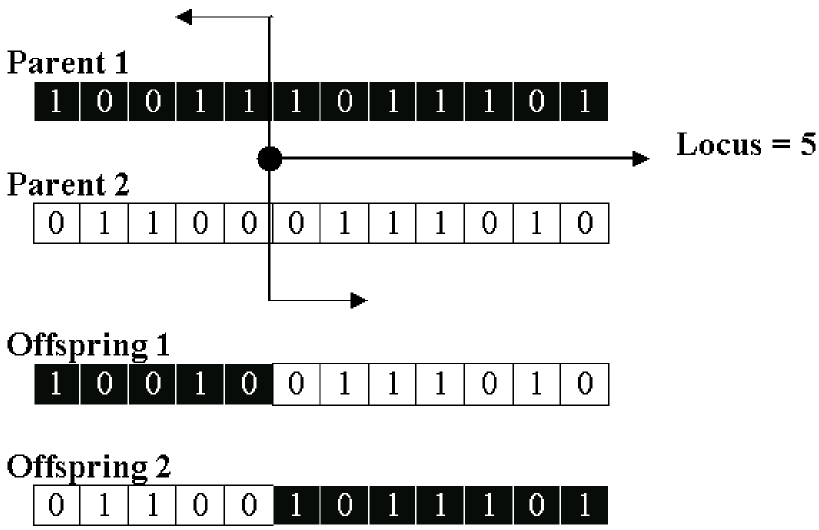


Figure 2.6. Crossover operation.

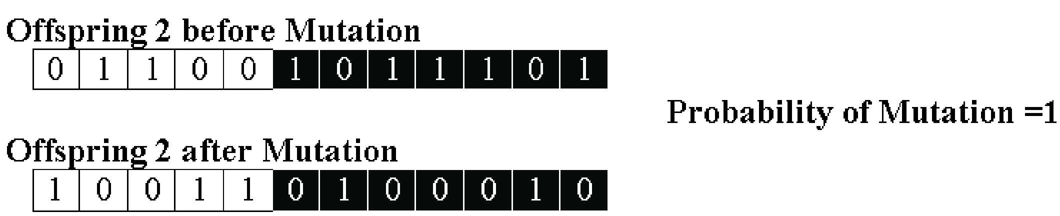


Figure 2.7. Mutation operation with probability of mutation = 1.

The SGA continues the evolution process until a maximum number of generations is reached or a stated convergence criteria has been satisfied for the fitness or population convergence.

2.4.1.2 Genetic Algorithms in Backcalculation

GAs were effectively utilized for the solution of pavement layer backcalculation problem in the past. A binary coded simple genetic algorithm with single point crossover, mutation and ranking selection mechanism was first introduced as a novel method for backcalculation of pavement layer moduli (Fwa et al. 1997). In this study, a deflection based objective function was utilized, which seeks for matching deflections calculated from one of the two different deflection computation approaches (BISAR or Odemark equivalent layer method) with that from FWD testing. It was also proven that the SGA algorithm approach performed better when compared to conventional backcalculation software that implements different search routines. A similar approach was later developed for backcalculation of pavement layers with the deflection values obtained from elastic layer system analyses (Kameyama et al. 1998). The method of heuristic crossover for floating point implementation was used along with dynamic mutation operator. Moreover, the implemented ranking selection was modified through exterminating the resembling chromosomes to prevent the danger of premature convergence. Reddy et al. (2002) developed a GA based backcalculation program that implements the same philosophy using an elastic layered pavement software to compute surface deflections. Reddy et al. (2004) also later determined a set of optimum parameters for backcalculating pavement layer properties using elastic programs. The optimal set of GA parameters (population size, crossover and mutation probabilities) was determined using a heuristic approach implemented through running a GA based backcalculation program called BACKGA.

The research studies referenced above and others (Al-Khoury et al. 2001; Ceylan et al. 2005; Loizos and Plati 2007; Meier et al. 1997; Pichler et al. 2003; Rakesh et al. 2006; Saltan and Terzi 2004; Willett et al. 2006) describe the computational approaches to determine the pavement layer properties. Most of the methodologies presented can only estimate pavement layer properties with the already known design thicknesses. The ones that can determine the thickness, however, require large computational time. Moreover, they all require advanced material properties to be known in advance, which is very expensive and difficult. As a result, they are not practical to implement in the field or even as a theory based solution to the problem.

The previous studies proved that GAs were successful in finding the solution for the backcalculation problem. However, all the proposed methodologies use the solutions of elastic layered programs or the programs mainly employed at the design stage of pavements for matching deflections obtained from FWD tests. On the other hand, loading conditions for pavements induce high nonlinearity in material behavior. Therefore, proper pavement modeling requires consideration of nonlinear pavement layer properties, which makes the solution of the backcalculation problem even more difficult.

In this project, the applicability and performance of a new SGA approach adopted is investigated to backcalculate the layer moduli and thicknesses of full-depth asphalt pavements built on natural subgrade and / or lime stabilized soil layer in the field using the pavement responses obtained from the nonlinear finite element program ILLI-PAVE solutions.

2.4.2 **Artificial Neural Networks**

ANNs are computational models for information processing. ANNs are mainly classified as a subclass of soft computing tools that duplicate some of their fundamental properties from biological systems (Haykin 1999; Hertz et al. 1991; Reed and Marks 1999). They can be trained to perform certain tasks. They are mainly used as one of the most powerful data-mining methods. They can tolerate the error in the dataset to a certain extent (called imprecision tolerance) and they are mostly valid within the ranges of the training datasets (called non-universality). They are quite robust and practical techniques for computationally complex problems (Ghaboussi 2001). In many civil engineering applications, they are used as nontraditional computing tools that can capture nonlinear relationships between inputs and outputs of natural phenomena or any numerical methods such that well established non-linear regression tools fail due to the complex nature of the problem (Ghaboussi and Wu 1998).

The main type of ANNs is referred to as a multilayer, feed-forward neural network composed of single processing elements called perceptrons (Rosenblatt 1958). The following are essential to feed-forward neural networks:

1. A feed-forward propagation rule,
2. A network topology (i.e., the number of nodes, layers, and their connectivity),

3. A learning rule.

The error back-propagation algorithm (also known as the generalized delta rule) is the most commonly used learning rule. The feed-forward neural networks which use the error back-propagation learning rule are generally referred to as back-propagation neural networks. A typical back-propagation neural network used in this study is sketched in Figure 2.8. The multilayered back-propagation ANN has usually one input layer, one output layer, and the constructed processing elements (artificial neurons) named as hidden layers. The hidden layers are sandwiched between the input and output layers. The network operation consists of a highly nonlinear functional mapping of the neurons in hidden layers between the input and output variables.

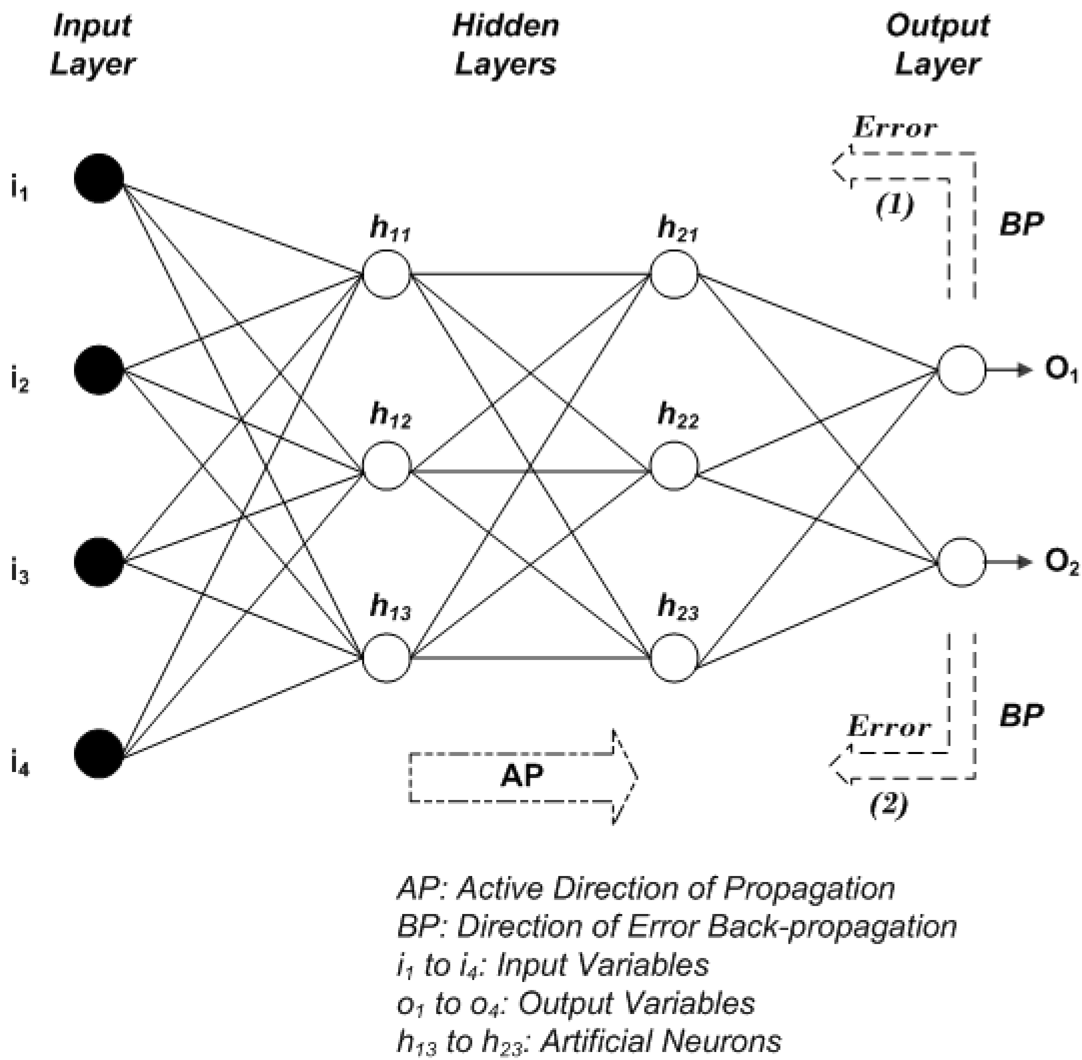


Figure 2.8. A typical backpropagation neural network (Tutumluer 1995).

2.4.2.1 Backpropagation Learning Algorithm

In perceptrons, each artificial neuron or processing element receives several input signals X_j originating from previous nodes and then processes each signal considering its connection weight W_{ij} (see Figure 2.9). The relationship between the input signals and the level of internal activity of the processing element is given by:

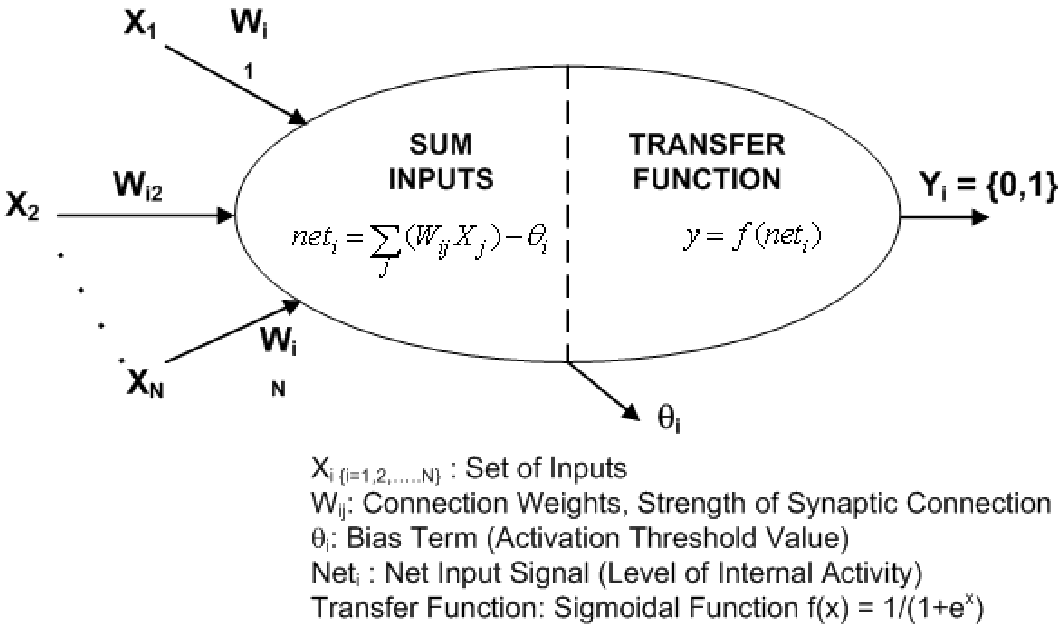


Figure 2.9. Summation and transfer functions of a typical artificial neuron. (Tutumluer 1995)

$$net_i = \sum_{j=1}^{N} (W_{ij}\ X_j) - \theta_i \tag{2.3}$$

where,

net_i = Net input signal (level of internal activity);
W_{ij} = Connection weight between artificial neurons i and j;
X_j = Value of signal coming from previous node j;
θ_i = Bias term of node i (corresponds to an activation threshold);
N = Number of input signals from previous nodes.

When the weighted sum of the input signals exceeds the activation threshold θ_i, the artificial neuron outputs a signal y_i dictated by a transfer function f(x). The output signal is then expressed as a function of the net input signal by:

$$y_i = f(net_i) \tag{2.4}$$

where,

$$f(x) = \frac{1}{(1+e^{-x})} \qquad (2.5)$$

is a sigmoidal function which gives a value between 0 and 1 for the output y_i.

The neural network modifies the connection weights between the layers and the node biases in ensuing iterations to allow a type of learning for the network. The weights and node biases are shifted until the error between the desired output and the actual output is minimized. The learning process is described as follows: "Learning (or training) is the process whose objective is to adjust the link weights and node biases so that when presented with a set of inputs, ANN produces the desired outputs."

After each feed-forward sweep of the ANN is completed in the direction of activation, the squared error terms E^k between the outputs y_i and the target values t_i (actual values in the output layer) are computed from the following:

$$E^k = \frac{1}{2}\sum_i [t_i^k - y_i^k]^2 \qquad (2.6)$$

where i denotes the individual neurons, and superscript k represents the individual data values from the training data set. Note that the output y_i in the above equation is actually a function of the sigmoidal function given in Equation 2-3.

The change in the connection weights (ΔW_{ij}) between the nodes to be adjusted during the learning process is related to the minimization of the average squared error E. To minimize the squared error E^k, the derivative of the error with respect to the connection weight W_{ij} between nodes i and j is required as follows:

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} = -\eta \sum_k \left(\frac{\partial E^k}{\partial W_{ij}} \right) \qquad (2.7)$$

where η is a learning coefficient > 0. Using the chain rule of differentiation, the derivative term $\partial E^k / \partial W_{ij}$ can now be written as:

$$-\frac{\partial E^k}{\partial W_{ij}} = -\frac{\partial E^k}{\partial y_i}\frac{\partial y_i}{\partial net_i}\frac{\partial net_i}{\partial W_{ij}} = -\delta_i^k \frac{\partial net_i}{\partial W_{ij}} = -\delta_i^k X_j \tag{2.8}$$

in which $\delta_i^k = (\partial E^k / \partial y_i) * (\partial y_i / \partial net_i)$ is defined as "delta" term of the generalized delta rule and is given by:

$$\delta_i^k = \begin{Bmatrix} f'(net_i^k)\ (t_i^k - y_i^k) & \textit{for output layers} \\ f'(net_i^k) \sum_m \delta_m^k W_{im} & \textit{for hidden layers} \end{Bmatrix} \tag{2.9}$$

where the letter "m" represents the nodes in the network below the current i'th layer towards the output layer (see Figure 2.8). Since the back-propagation algorithm starts from the output layer, the calculations progress implicitly in the direction towards the input layer. The derivative of the sigmoidal function f'(x) to be used in the above equation can be given in terms of the function:

$$f'(x) = f(x)\ \{1 - f(x)\} \tag{2.10}$$

now substitute Equation (2.10) in Equation (2.9) for easy computation of deltas.

During each iteration (it), the connection weights from node j to i are updated as follows:

$$W_{ij}(it+1) = W_{ij}(it) + \eta \sum_k \delta_i^k\ X_j^k + \alpha\ [W_{ij}(it) - W_{ij}(it-1)] \tag{2.11}$$

where α is called the momentum (or acceleration) term added to stabilize the training process. The summation is done over all individual data in the training set. The inputs to the nodes in the back-propagation direction are taken from the outputs of the nodes in the preceding layer, i.e., $X_j^k = y_j^k = o_j^k$ (for the first hidden layer). Similarly, the bias term θ_i is also updated at each iteration by an equation of the form:

$$\theta_i(it+1) = \theta_i(it) + \eta \sum_k \delta_i^k + \alpha\,[\theta_i(it) - \theta_i(it-1)] \tag{2.12}$$

As the iterations progress, the network repeatedly cycles through the training set. The parameters α and η in Equations (2.11) and (2.12) help provide an accurate approximation of the unknown mean squared error (MSE) minimum. Iterations must be continued until an apparent decrease in the maximum MSE to an acceptable level is observed. By using the momentum term α in the search, settling into a local minimum or oscillating endlessly about the global minimum can be prevented.

2.4.2.2 FWD Backcalculation using ANNs

When FWD backcalculation is considered, an ANN model can be trained to map deflection basins back onto their corresponding pavement layer moduli. One way to train such a network would be to use experimentally determined deflection basins along with independently measured pavement layer thicknesses and moduli. However, it is often difficult to obtain representative, undisturbed samples with which to make a laboratory determination of the pavement layer moduli. Furthermore, because laboratory testing is expensive, there is an insufficient quantity of experimental data covering a broad-enough range of pavement layer moduli and pavement layer thicknesses to successfully train a neural network (Meier 1995).

Instead, synthetic deflection basins calculated using pavement analysis programs such as ILLI-PAVE can be used to create synthetic deflection basins. This allows precise control of the pavement layer properties used to train the network. The basic neural network training procedure developed for this study can be viewed as a closed loop (see Figure 2.10). A mathematical model is used to calculate a synthetic deflection basin for a presumed set of pavement layer properties. The artificial neural network is then taught to perform the inverse operation of mapping the synthetic deflection basin back onto the presumed set of properties. At first, the neural network produces a random mapping;

however, by repeating the training process many times for many different pavement profiles, the neural network will eventually learn the appropriate inversion function (Meier 1995).

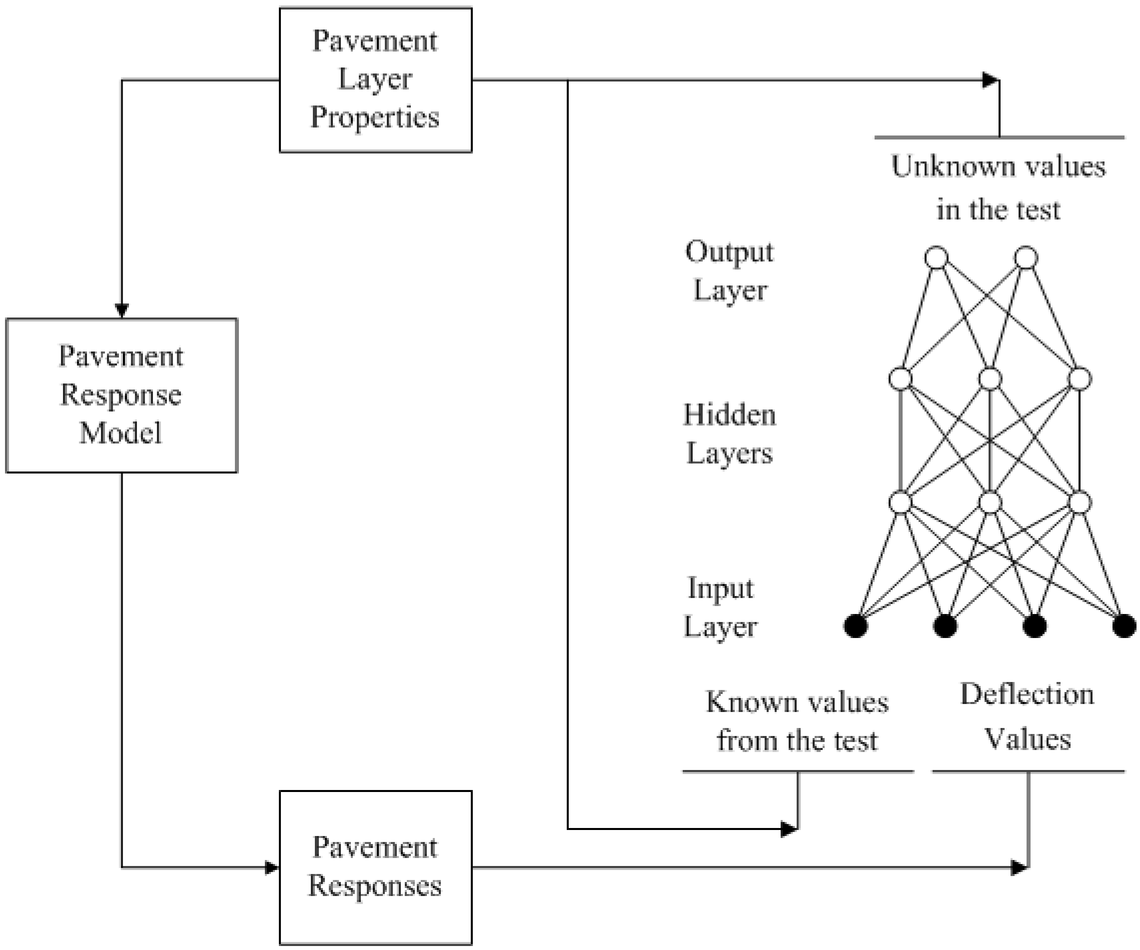
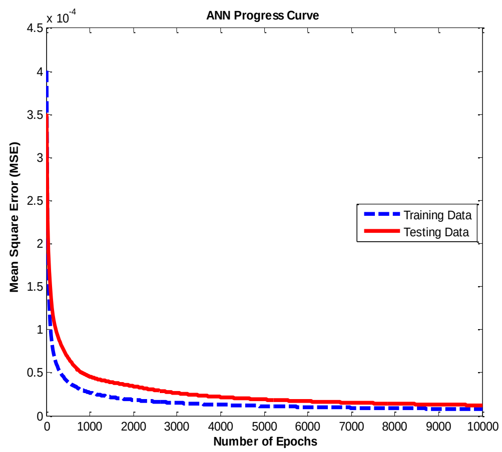


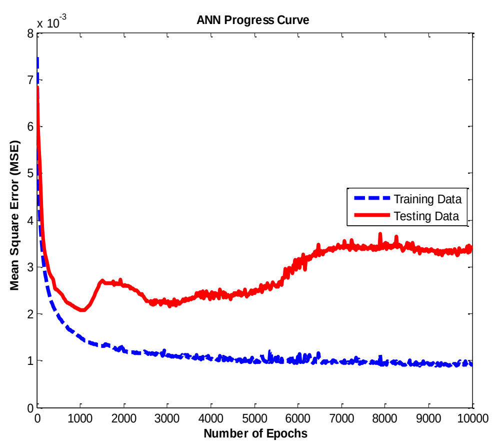
Figure 2.10. Direct Pavement Backcalculation Procedure Using Neural Network

Trained ANN models need to be tested based on an independent dataset within the ranges that they were trained. A sufficiently wide dataset obtained from the pavement analysis can be chosen independently considering the given ranges of material and geometry properties and used as the testing dataset for the verification of proper ANN learning. The remaining data are then used for the training and learning procedure. Whether the trained ANN models are capable of producing the same database (with the given inputs to obtain outputs or vice versa) can be checked quickly in this manner.

Figure 2.11 (a) and (b) show proper and improper learning curves for training and testing datasets. Improper learning causes ANNs to memorize the given training dataset and to lose the capability of generalization (Reed and Marks 1999). Although training takes a long computation time, testing is often much faster (on the order of micro seconds) with the already set weighted connections. This advantage also facilitates the use of trained ANNs as quick pavement analysis tools for a field engineer to use them without the need for any complex inputs.



a. Proper learning.



b. Improper Learning.

Figure 2.11. Typical ANN learning curves.

CHAPTER 3. SOFTSYS

3.1 Introduction

A typical pavement structure, as shown in Figure 3.1, can be identified using four different properties listed below (Selezneva et al. 2002). These properties need to be determined to best define a pavement rehabilitation strategy:

- Layer descriptions (e.g., surface, overlay, base, and subgrade);
- Material type descriptions of pavement layers;
- Layer thicknesses;
- Layer thickness variability.

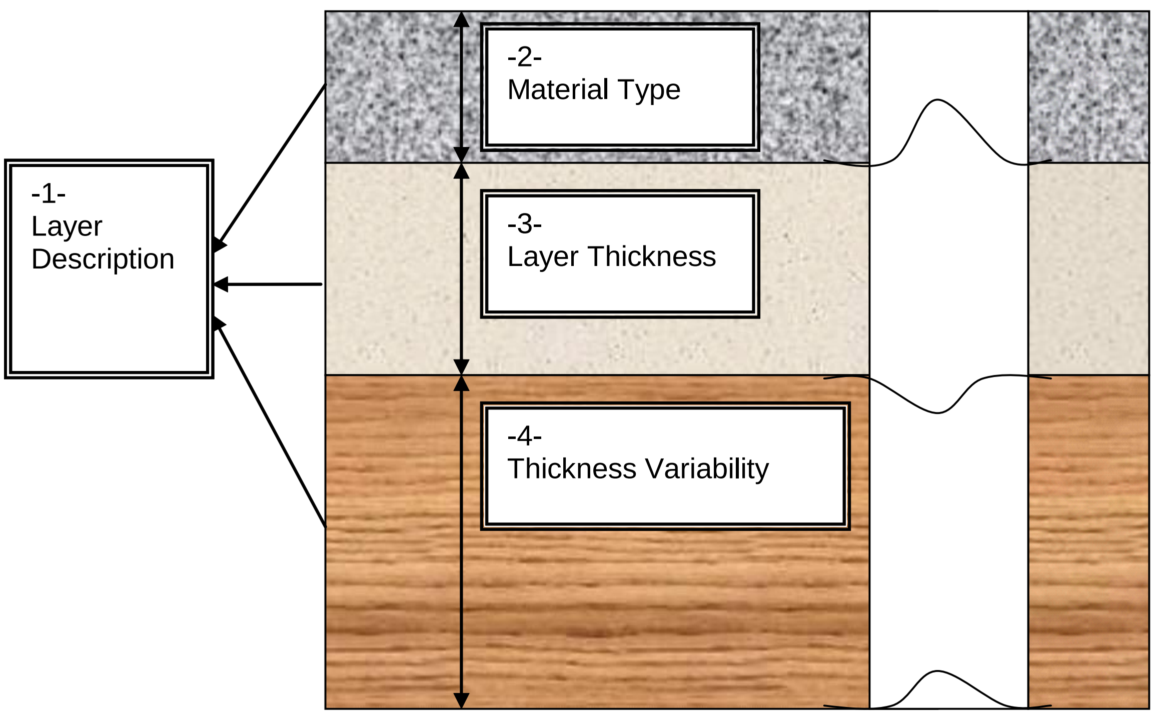


Figure 3.1. Typical pavement system parameters to be determined.

Knowing pavement layer thicknesses is critical to predicting pavement performance, establishing pavement load carrying capacity and developing pavement maintenance and rehabilitation strategies. Accurate determination of pavement layer thicknesses usually requires proper sampling from the pavement section (through the use of destructive testing). This is usually not preferred since it prevents functionality of a pavement and disrupts traffic. Moreover, thickness measurements obtained from only a few extracted cores may not always represent adequately the thickness profile. It is important to ensure that the thickness of materials being placed by the contractor is acceptably close to specifications (Sener et al. 1998).

The layer thickness information, a key structural design input, is mainly required for many types of analyses including backcalculation of pavement moduli, mechanistic analysis of pavement structures, and performance modeling. Due to poor workmanship and/or limitations of construction equipment used to build roads, construction quality of pavements may not be at a desired level. This might cause the thickness constructed on site to be considerably different than the designed thickness. Furthermore, in many cases, the lack of proper design documentation for existing roads makes it extremely difficult to rehabilitate certain pavements without the knowledge of pavement layer thicknesses. Insufficient knowledge of layer thicknesses during pavement response testing is often a major limitation in pavement condition assessment.

The current methods to determine the thickness usually require coring of pavement or using some advanced nondestructive testing equipment such as Ground Penetrating Radar (GPR). These techniques are rather expensive or may result in destruction of pavement layer profile. On the other hand, if FWD tests are conducted, for example, in 5 ft intervals of the road section, in which the abrupt change in the thickness is not expected, the thickness profile along the pavement section can be determined with reasonably good accuracy and in real time.

To address the current challenges, an innovative methodology, called SOFTSYS, was developed to perform the following tasks in real time as part of conducting FWD tests:

- Determination of pavement thickness;
- Estimation of pavement moduli;
- Identifying pavement parameters such as Poison's ratio.

SOFTSYS is introduced for interpreting the results of a FWD test. It is a computational method to describe the properties of pavement layers. Among those, the layer thickness plays the crucial role in determining the remaining life since it is a major factor contributing to structural adequacy of the pavement. The outstanding contribution of SOFTSYS is that it is able to estimate the pavement layer thicknesses reliably in addition to their stiffness properties. Using only FWD test results (i.e. deflections) as inputs, SOFTSYS calculates all the necessary properties for pavement evaluation. To do this, SOFTSYS uses a combination of nontraditional computing tools, such as Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs). Using quick and robust algorithms in SOFTSYS, real time evaluation of the pavements becomes feasible to also verify as-constructed pavement design parameters in the field.

3.2 Basics of SOFTSYS

SOFTSYS interprets FWD test results and performs pavement structural analysis based on the Finite Element Method (FEM). FEM provides modeling of pavement structure due to applied wheel loading to compute pavement deflections. Unlike the linear elastic theory commonly used in pavement analysis, nonlinear unbound aggregate base and subgrade soil characterization models are used in the FEM. This accounts for the typical hardening behavior of unbound aggregate bases and softening nature of fine-grained subgrade soils under increasing stress states. The results of the nonlinear finite element approach have been proven to be consistent with the deflections obtained from NDT of pavements. Since FEM internally captures the nonlinear material properties to simulate the real pavement behavior, SOFTSYS, therefore, has an inherent capability of incorporating the nonlinear properties of aggregate and soil layers underneath pavements.

3.2.1 **ILLI-PAVE Finite Element Modeling**

An integral part of SOFTSYS is the implementation of finite element method. For this purpose, ILLI-PAVE 2005 finite element (FE) program, the most recent version of this extensively tested and validated ILLI-PAVE pavement analysis program for over three decades, was used as an advanced structural model for solving deflection profiles and responses of the typical full-depth pavements (FDP) and full-depth pavements on lime stabilized soils (FDP-LSS). ILLI-PAVE uses an axisymmetric revolution of the cross-section to model the layered flexible pavement structure. Unlike the linear elastic theory commonly used in pavement analysis, nonlinear unbound aggregate base and subgrade soil characterization models are used in the ILLI-PAVE program to account for typical hardening behavior of base course granular materials and softening nature of fine-grained subgrade soils under increasing stress states. Among the several modifications implemented in the new ILLI-PAVE 2005 finite element code are:

- increased number of elements (degrees of freedom);
- new/updated material models for the granular materials and subgrade soils;
- enhanced iterative solution methods;
- Fortran 90 coding and compilation, and
- a new user-friendly Borland Delphi pre-/post-processing interface to assist in the analysis (Gomez-Ramirez et al. 2002)(see Figure 3.2).

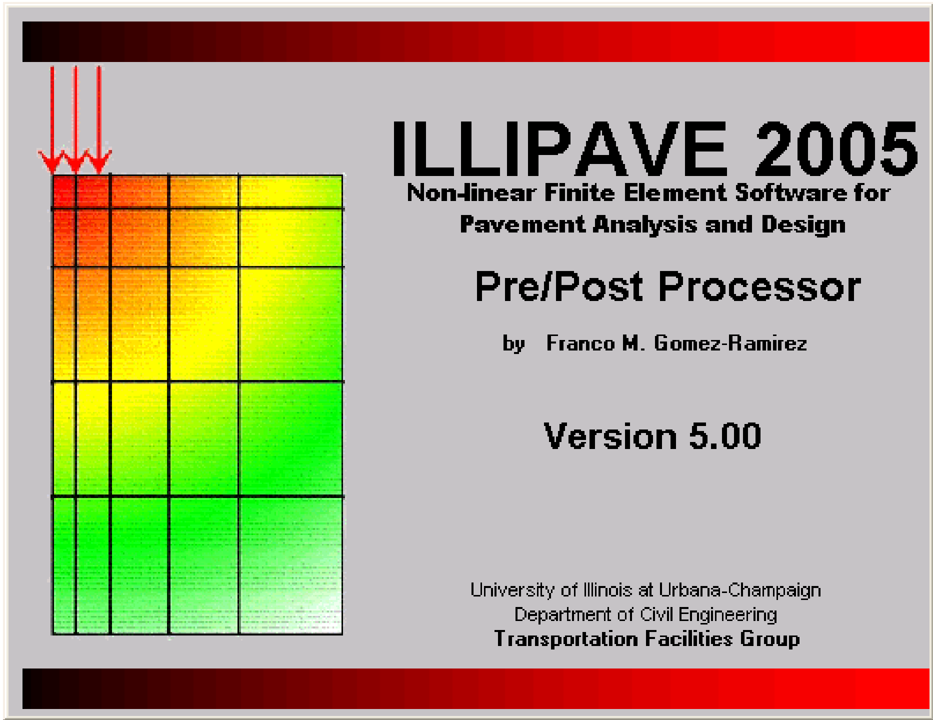


Figure 3.2. ILLIPAVE 2005 finite element software for pavement analysis.

3.2.1.1 Falling Weight Deflectometer Simulation

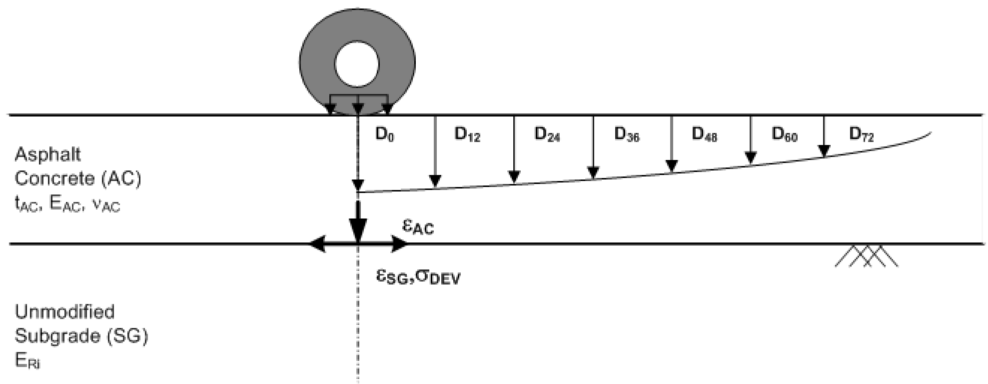
Pavement FE modeling was performed in this study using an axisymmetric (FE) mesh for all pavement sections considered. Using ILLI-PAVE FE program, FWD tests on flexible pavements were modeled with the standard 9-kip equivalent single axle loading applied as uniform tire pressure of 80 psi over a circular area of 6 in. radius. The FE mesh was selected according to the uniform spacing option of the FWD sensors as follows: 0 in., 8 in., 12 in., 18 in., 24 in., 36 in., 48 in., 60 in. and 72 in. away from the center of the FWD plate. The surface deflections corresponding to the locations of these FWD sensors were abbreviated as D_0, D_8, D_{12}, D_{18}, D_{24}, D_{36}, D_{48}, D_{60} and D_{72}, respectively.

These deflections are in conformity with the uniform spacing commonly used in FWD testing by many state highway agencies (Table 3-1). Typically, finer mesh spacing was used in the loaded area with the horizontal spacing adjusted according to the locations of the geophones used in FWD tests. In addition to the deflections, the critical pavement responses, i.e., horizontal strain at the bottom of AC layer (ε_{AC}), vertical strain at the top of the subgrade (ε_{SG}), and the vertical deviator stress on top of the subgrade (σ_{DEV}) directly at the centerline of the FWD loading, were also extracted from ILLI-PAVE results. Figure 3.3 (a) and (b) show the locations of these responses obtained from different types of flexible pavements. These critical pavement responses play a crucial role in the context of mechanistic-empirical asphalt pavement design procedures as they directly relate to major failure mechanisms due to excessive fatigue cracking and rutting in the wheel paths.

Table 3-1 Falling Weight Deflectometer Sensor Spacing

Sensor Spacing (in.)	0	8	12	18	24	36	48	60	72
Uniform (used in this study)	+		+		+	+	+	+	+
State Highway Research Program (SHRP)	+	+	+	+	+	+		+	

A total analysis depth of 300 in. was selected for all pavements analyzed. Depending on the thicknesses of the layers, an aspect ratio of 1 was mainly used in the finite elements with a limiting value of 4 to get consistent pavement response predictions from ILLI-PAVE FE analyses (Pekcan et al. 2006). The vertical and horizontal spacings in the FE mesh were chosen appropriately so that there was neither numerical instability nor inconsistency in the results due to meshing. Figure 3.4 shows a sample ILLI-PAVE FE mesh that was used in the analyses of FDP-LSS. The thicknesses of all layers were selected to have appropriate ranges encountered for most flexible pavements in Illinois, Ohio and Indiana.



(a) full-depth asphalt pavements

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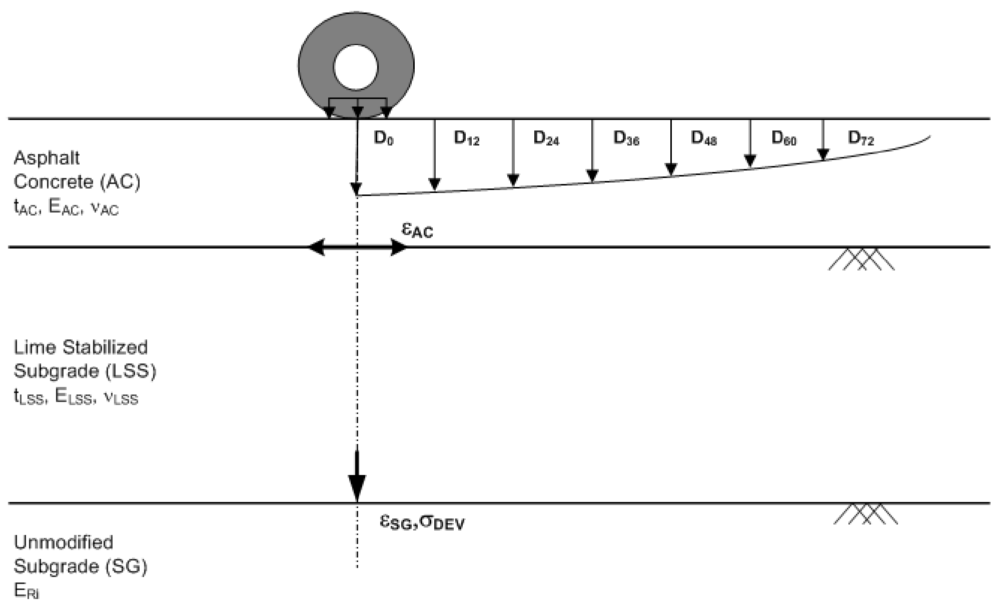


(b) full-depth asphalt pavements built on lime stabilized soils

Figure 3.3. Locations of critical pavement responses and deflections.

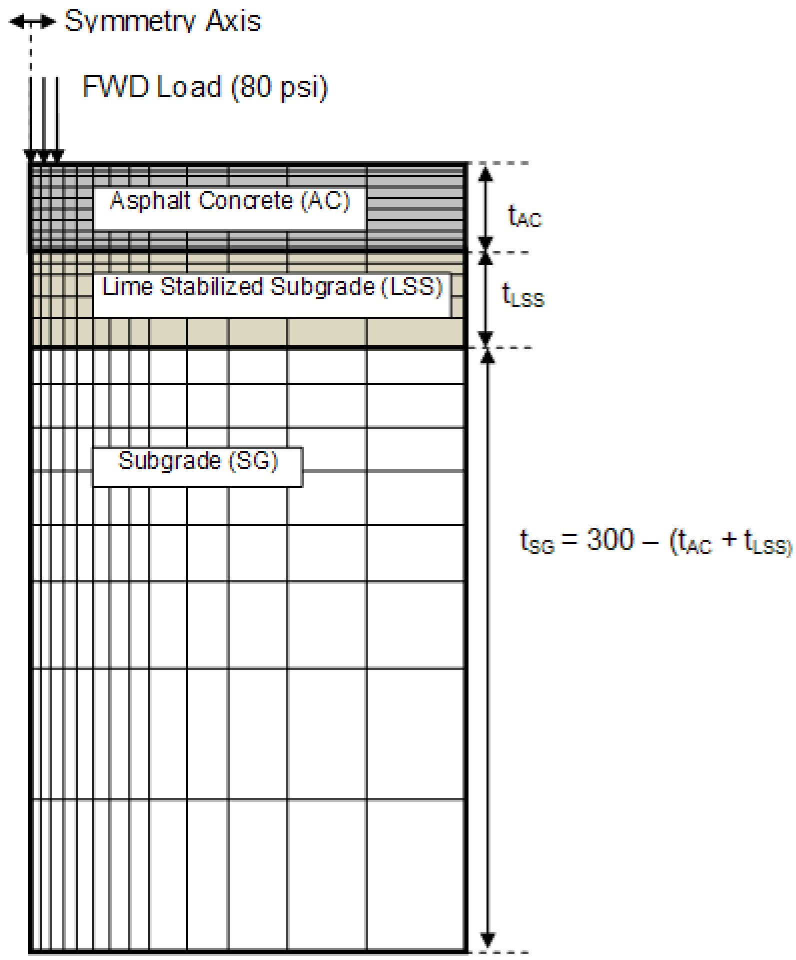


Figure 3.4. Finite element mesh for full-depth pavements on lime stabilized subgrade.

3.2.1.2 Pavement Layer Characterization

Adequately characterizing pavement layer behavior plays a crucial role for an accurate backcalculation of the layer moduli. Accordingly, modeling of FDP and CFP requires accurate material characterizations for the asphalt concrete, granular base and fine-grained subgrade soil layers. After material shakedown has taken place due to construction loading and early trafficking of the pavements, most of the deformations under a passing truck wheel are recoverable and hence considered resilient or elastic. The resilient modulus (M_R), defined by repeated wheel load stress divided by recoverable strain, is therefore the elastic modulus (E) often used to describe flexible pavement layer behavior under traffic loading.

In ILLI-PAVE FE models of the different flexible pavements analyzed, the asphalt concrete (AC) surface course was always represented with elastic properties, layer modulus E_{AC} and Poisson's ratio ν_{AC}, for the instant loading during FWD testing. The value of ν_{AC} was taken constant as 0.35.

The modeling of fine-grained subgrade soils, mainly encountered in Illinois, has received more attention in the last three decades since it has a major impact on all the responses predicted under traffic loading within the context of M-E design. Fine-grained subgrade soils exhibit nonlinear behavior when subjected to traffic loading (Ceylan et al. 2005; Thompson and Robnett 1979). The subgrade stiffness characterized by the resilient modulus (M_R) is usually expressed as a function of the applied the deviator stress through nonlinear modulus response models. These models were developed based on the results of repeated load triaxial tests, which forms the basis of evaluating resilient properties of fine-grained soils (AASHTO-T307-99. 2000).

Illinois subgrade soils are mostly fine-grained, exhibit stress softening behavior, and can be characterized using the bilinear arithmetic model (Thompson and Elliott 1985; Thompson and Robnett 1979) with the modulus-deviator stress relationship shown in Figure 3.5. The upper limit deviator stress in the bilinear model, σ_{dul}, is dependent on the breakpoint modulus, E_{Ri}, which is also a function of the unconfined compressive strength, Qu, expressed by Equation 3.1 (Thompson and Robnett 1979). E_{Ri} is a characteristic property of the fine-grained soil often computed for Illinois soils at a breakpoint deviator stress σ_{di} of 6 psi. The corresponding values and parameters of the bilinear model used in the analyses are also given in Figure 3.5.

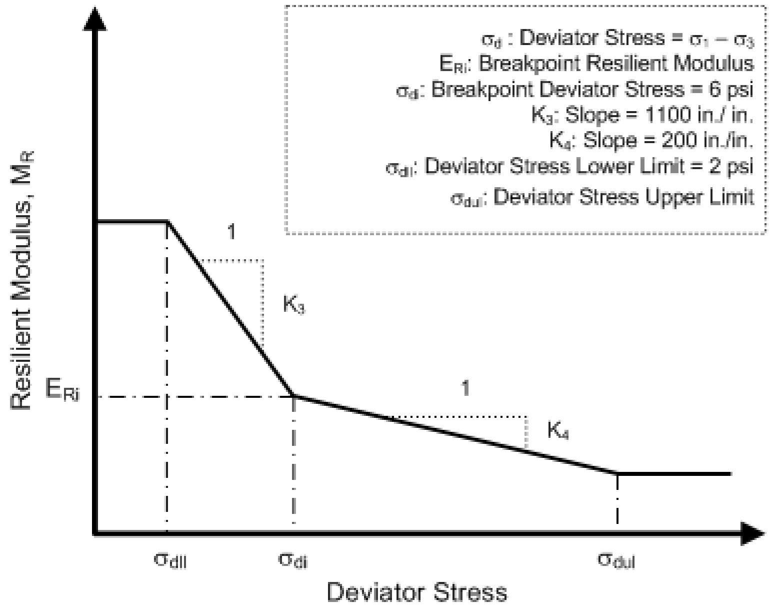


Figure 3.5. Bilinear model to characterize stress dependency of fine-grained soils (Thompson and Robnett 1979).

$$\sigma_{dul}(psi) = Q_u(psi) = \frac{E_{RI} \cdot (ksi) - 0.86}{0.307} \tag{3.1}$$

3.2.1.3 ILLI-PAVE Database for Flexible Pavements

Randomly selected combinations of material and thickness inputs were provided to ILLI-PAVE to generate batch analyses. A total of 24,000 ILLI-PAVE runs were made for FDP and 26,000 for FDP-LSS in order to fully cover the material property ranges given in Table 3-2 and Table 3-2Table 3-3. To make sure that ANN models had the ability to perform correctly for representative field conditions, the ranges of layer thickness values and material property inputs were extended up to ±20% beyond the actual field values. The surface deflections corresponding to the locations of the FWD sensors and the critical pavement responses, i.e., horizontal strain at the bottom of AC layer (ε_{AC}), vertical strain at the top of the subgrade (ε_{SG}), and the deviator stress on top of the subgrade (σ_{DEV}), directly at the centerline of the FWD loading were then extracted from the ILLI-PAVE output files.

Table 3-2 Geometries and Material Properties of Full-Depth Flexible Pavements Analyzed

Material Type	Thickness (in.)	Material Model	Elasticity Modulus (ksi)	Poisson's Ratio
Asphalt Concrete (AC)	5-24	Linear Elastic	100 – 2 000	0.35
Fine Grained Subgrade (SG)	(300- t_{AC})	Nonlinear Bilinear Model	1-14	0.45

Table 3-3 Geometries and Material Properties of Full-Depth Flexible Pavements on Lime Stabilized Soils Analyzed

Material Type	Thickness (in.)	Material Model	Elasticity Modulus (ksi)	Poisson's Ratio
Asphalt Concrete (AC)	4-24	Linear Elastic	100 – 2 500	0.35
Lime Stabilized Subgrade (LSS)	4-20	Linear Elastic	16-150	0.31
Fine-grained Subgrade (SG)	(300- t_{AC} - t_{LSS})	Nonlinear Bilinear Model	1-15	0.45

This database, which inherently captured the nonlinear FE approximations, was then used to train and develop an ANN-based structural analysis toolbox containing several ANN models for forward analyses of flexible pavements.

3.2.2 **ANN Structural Models**

The implementation of soft computing methods is the next stage in the algorithm. The convergence of SOFTSYS when used with FEM only is quite slow. Therefore, FEM is replaced by ANNs since they work much faster and can still perform similar higher order function approximations as FEM. In addition, when ANNs are properly trained, they can tolerate errors that FWD tests might involve. This has been a major limitation with the classical approaches developed for interpretation of the test results.

The multi-layered, feed-forward backpropagation type neural networks are mainly implemented for complex valued network level problems. In this project, backpropagation type ANNs were trained for the backcalculation of pavement layer moduli using the previously developed database with the input and output variables. Trained ANN models were tested based on an independent dataset within the ranges that they were trained. Approximately 1000 runs of all the datasets were independently and randomly chosen considering the given ranges of material and geometry properties and used as the testing datasets for the verification of proper ANN learning. The remaining ILLI-PAVE runs in the datasets were used for the training and/or learning task. The trained ANN models were checked quickly in this manner to determine whether or not they were capable of producing the same database results (with the given inputs to obtain outputs or vice versa). Although training of each ANN model required a long computation time, with the already set weighted connections, testing was much faster (on the order of micro seconds). This advantage allows a field engineer to use trained ANN models as quick pavement analysis tools without the need for any complex inputs

3.2.2.1 Forward Analysis Models

There are mainly two ANN models designed to compute the responses of flexible pavements under a typical FWD loading. They were developed for FDP and FDP-LSS pavements using the different geometries and layer properties. Although the input variables of these models are different by the nature, the outputs are the same for FDP-FW1 and FDP-LSS-FW1 and they are given in Table 3-4. Both models were developed to predict the surface deflection values D_0, D_{12}, D_{24}, and D_{36}. In addition, for both models, the ANN architectures were chosen to have two hidden layers with 60 neurons in each layer. This was according to the findings from previous ANN trainings performed by Ceylan et al. (2005). Finally, the ANN models were trained for 10,000 epochs.

Table 3-4 Forward Artificial Neural Network Models for Flexible Pavements

Type	Inputs	Outputs
FDP-FW1	t_{AC},E_{AC}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}
FDP-LSS-FW1	t_{AC}, t_{LSS}, E_{AC}, E_{LSS}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}

One of the basic advantages of the developed ANN models is that they do not require complicated FE inputs that are either difficult or costly to obtain through laboratory and field characterizations for the analyses of flexible pavements. Yet, the solutions are still considering the needed sophistication in analysis, such as, the stress dependent subgrade behavior and the lime-stabilized subgrade layer as an additional layer on top of the natural unmodified grade, and the realistic layered pavement structure of flexible pavements.

3.2.2.2 Performances of the Developed ANN Models

ANN forward calculation models developed for the analyses of flexible pavements were verified for satisfactory performances using the independent testing data extracted from the database of the ILLI-PAVE FE solutions. The performances of ANN models were indicated by comparing predictions with the ILLI-PAVE FE results using average absolute error (AAE) values. AAE is defined in Equation 3.2 where the measured value is the result of ILLI-PAVE while the calculated one is obtained through ANN models.

$$Average\ Absolute\ Error\ (AAE) = \frac{\sum_{i=1}^{n} \left| (Measured_i - Calculated_i) / Measured_i \right|}{n} \times 100 \tag{3.2}$$

The results of ANN training analyses are presented for both FDP pavements and pavements built on LSS using the AAEs of deflection values in Figure 3.6 and Figure 3.7, respectively. Figure 3.6 shows the deflections of FDPs predicted by ANN models at the FWD geophone locations D_0, D_{12}, D_{24}, and D_{36} to match accurately with the ILLI-PAVE results for AAE values obtained between 0.2 to 0.5%. Similarly, comparisons of ANNs with ILLI-PAVE results produced AAE values between 0.2 to 0.4% for FDP-LSS.

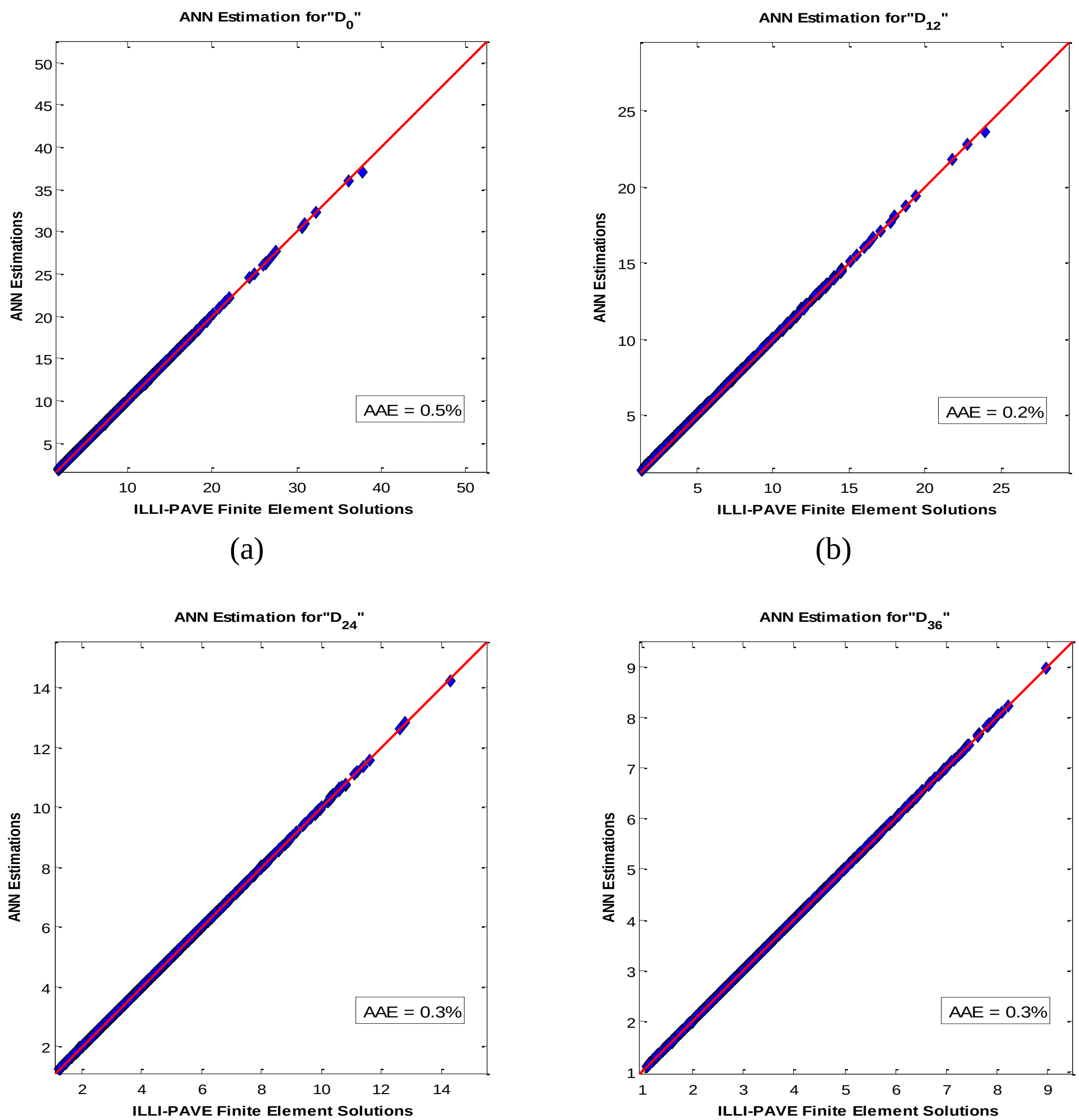


Figure 3.6. Comparisons of ANN structural model predictions with ILLI-PAVE results for full-depth asphalt pavement surface deflections (in mils).

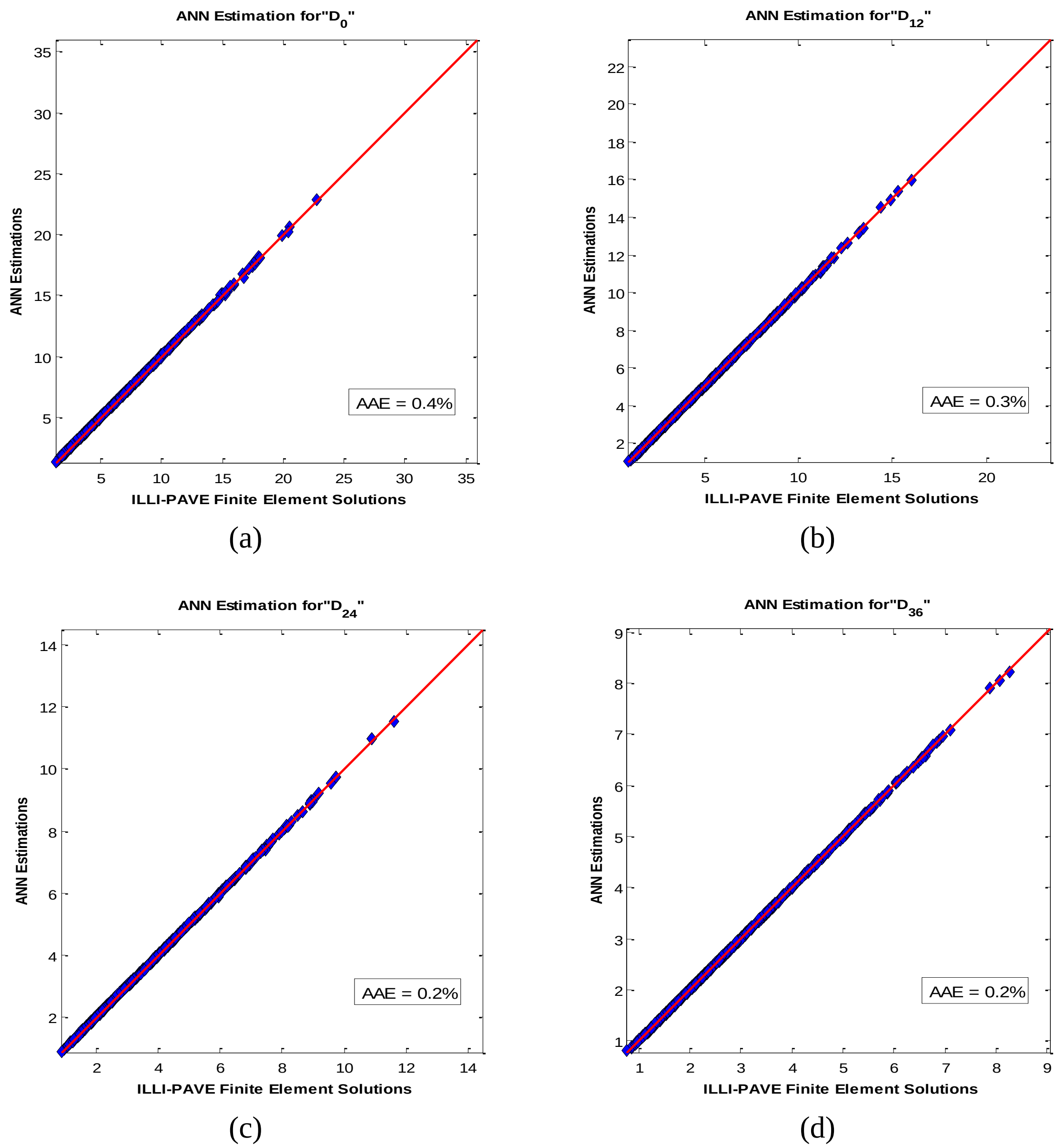


Figure 3.7. Comparisons of ANN structural model predictions with ILLI-PAVE results for surface deflections (in mils) of full-depth asphalt pavements built on lime stabilized soils.

3.2.3 Genetic Algorithms as Search Tools

As discussed in Chapter 2, GAs are computational models based on natural evolution (Holland 1975). They are powerful optimization and search methods. GA methodology is highly robust and imprecision tolerant. The results are not necessarily exact instead are accurate to a certain degree of approximation (Ghaboussi 2001).

In the previous section, it was proven that properly trained artificial neural network (ANN) models as computational intelligence or soft computing tools are capable of predicting displacements with average errors much smaller than those obtained with the statistically formulated algorithms currently in use by Illinois DOT. These models then trained with the results of the ILLI-PAVE solutions have been found to be viable alternatives to predict the deflections based on the FWD data. These ANN models can be reliably used together with GA's in a hybrid way.

In SOFTSYS, GAs work for random search with the operators inspired by the natural evolution. The major components of GAs are; the genotype / phenotype presentation of parameters of the problem domain (i.e., pavement layer moduli and thicknesses), fitness evaluation (mathematical expression as a measure of the difference between the surface deflections obtained by the FWD test and the ones calculated from ANN model), selection scheme, crossover method, and mutation. A collection of input parameters within a reasonable range are created randomly to have the database of all possible combinations of pavement layer material properties including material moduli and thickness encountered in the pavement. These are then fed into the ANN model as testing data set to compute the corresponding deflection profiles. The testing of all data sets created by GAs is done within a second, which is quite insensitive to number of testing data. GAs, then, sort input data set based on the imposed fitness function calculated using the outputs of ANN results and the deflection profile obtained by FWD testing. Natural evolution operators; selection, crossover, and mutation are then applied to the so-called parents and to their offspring to establish the most satisfactory data set for the surface profile obtained from FWD. Finally, an iterative algorithm called "fine tuner" implemented into SOFTSYS has been intended to improve the precision of the obtained results. The fitness evaluation is given in Equation 3.3. The flowchart of SOFTSYS is also provided in Figure 3.8.

$$Fitness = \frac{1}{1 + \sum_{i=1}^{4} (\beta * (\frac{FWD_i - ANN_i}{FWD_i}))^{\alpha}} \quad (3.3)$$

In conclusion, SOFTSYS features high reliability and advanced technology for predicting repeatable results in a quick and robust fashion to enable practical engineering interpretations of FWD test data essentially needed for nondestructive evaluation of pavements.

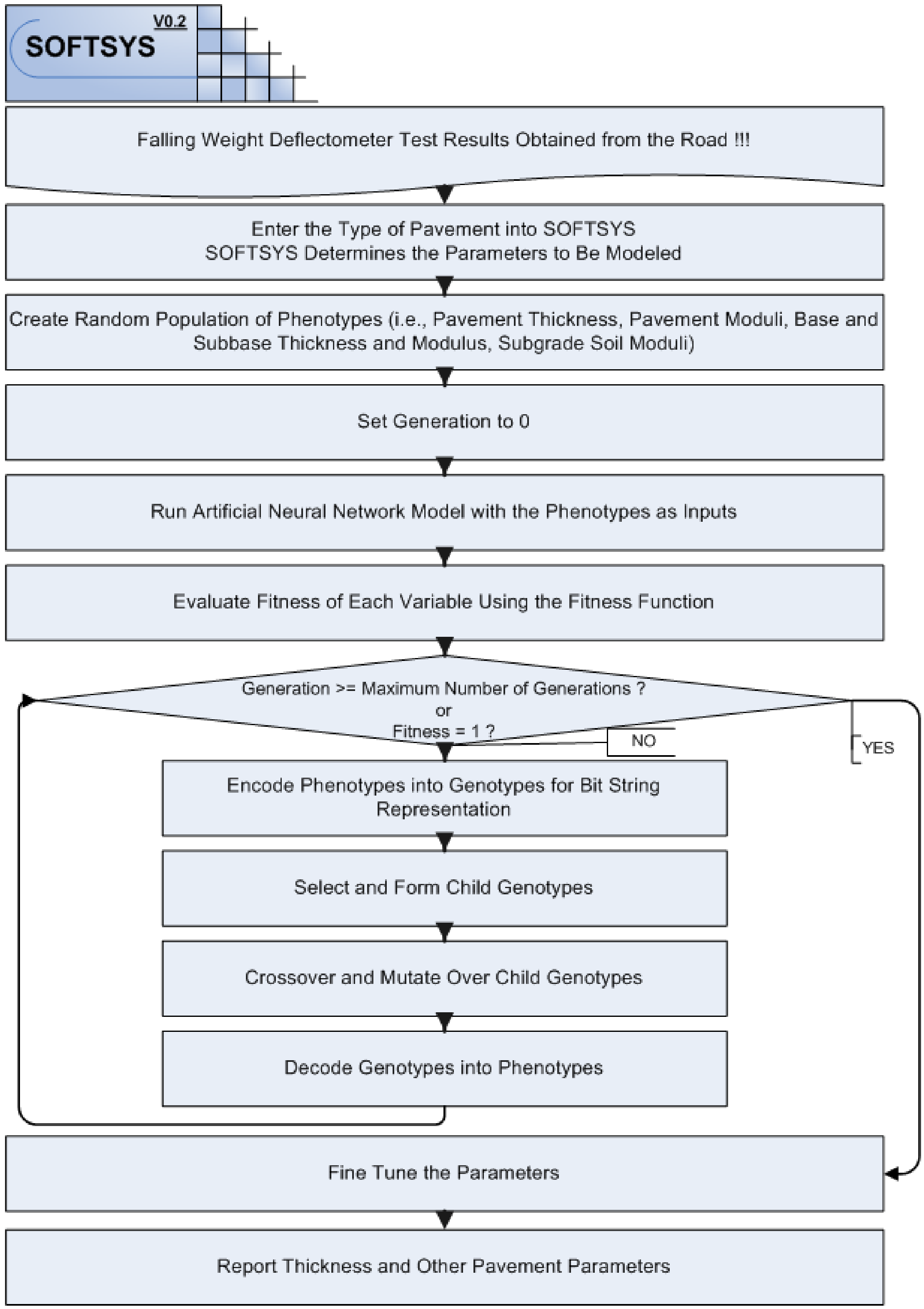


Figure 3.8. SOFTSYS algorithm.

CHAPTER 4. SOFTSYS MODELS AND VALIDATION

4.1 Backcalculation Models

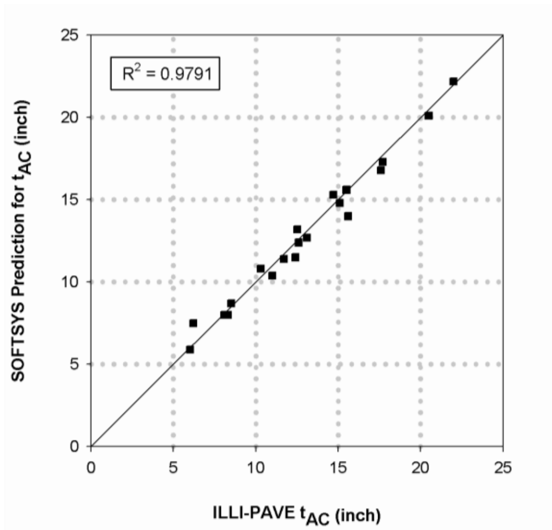
There are two main backcalculation models developed for SOFTSYS in the scope of this project. These are provided in Table 4-1. The first one, FDP-M1, predicts t_{AC}, E_{AC} and E_{RI} with the use of information obtained from FWD test data (D_0, D_{12}, D_{24}, D_{36}) in addition to the design thickness of FDP. The second model, FDP-LSS-M1, uses deflection information without the need of thickness entry for asphalt layer for FDP-LSS. This model predicts the asphalt thickness using FWD deflections together with the lime stabilized layer thickness. Both models use the same forward ANN structural model, which replaces ILLI-PAVE FE program successfully (the performance of the corresponding ANN model was provided in the previous chapter).

Table 4-1 Falling Weight Deflectometer Sensor Spacing

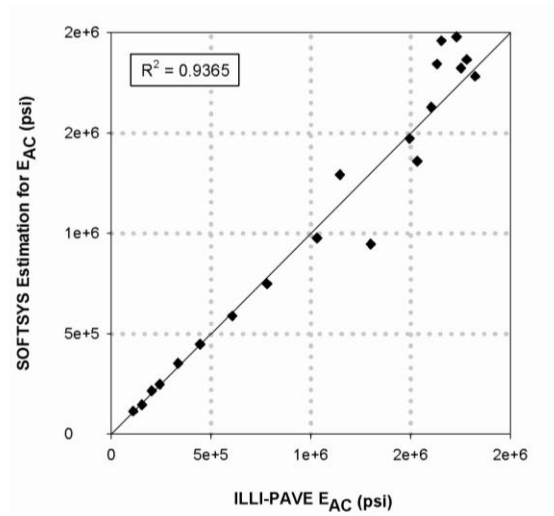
Model Name	Inputs	Outputs
FDP-M1	D_0, D_{12}, D_{24}, D_{36}	t_{AC} , E_{AC}, E_{RI}
FDP-LSS-M1	D_0, D_{12}, D_{24}, D_{36}, t_{LSS}	t_{AC}, E_{AC}, E_{LSS}, E_{RI}

4.2 Performances of Developed SOFTSYS Models

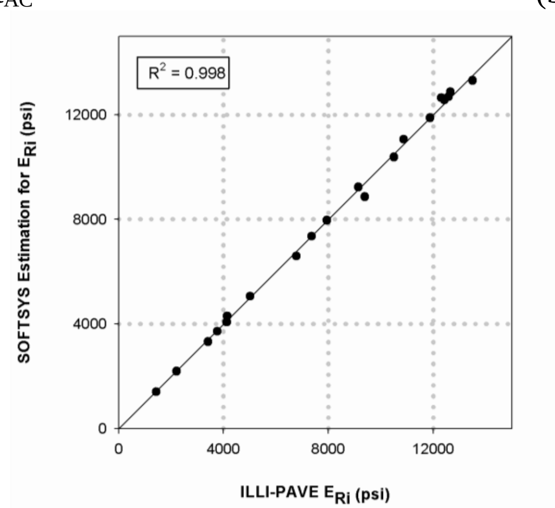
The performances of SOFTSYS models were measured using the synthetic FWD data. For this purpose, 20 stations were selected randomly from the ILLI-PAVE database previously obtained for training ANNs to analyze FDPs. This database was named as IP-SYNTH (stands for synthetic ILLI-PAVE) FWD database. IP-SYNTH was then analyzed using SOFTSYS models. Figure 4.1 provides the predictions of SOFTSYS and compares them with those of ILLI-PAVE.



(a) t_{AC}



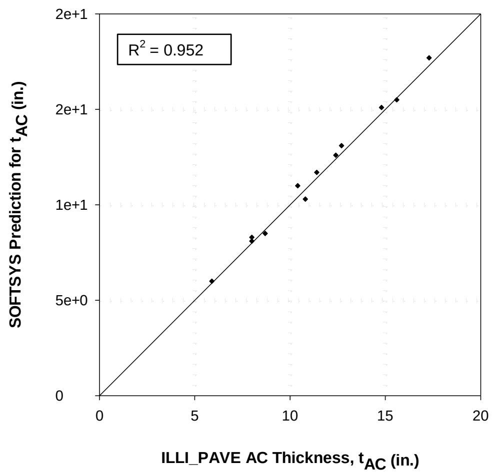
(b) E_{AC}



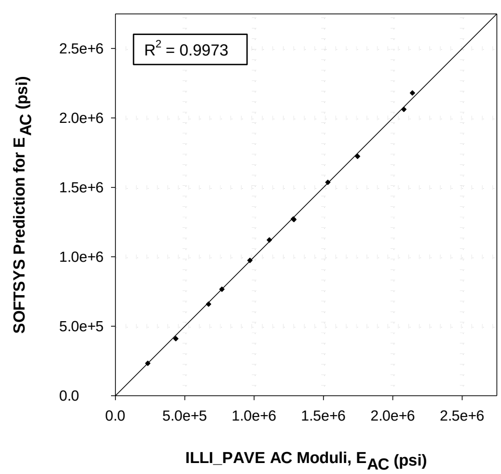
(c) E_{RI}

Figure 4.1. SOFTSYS FDP-M1 predictions.

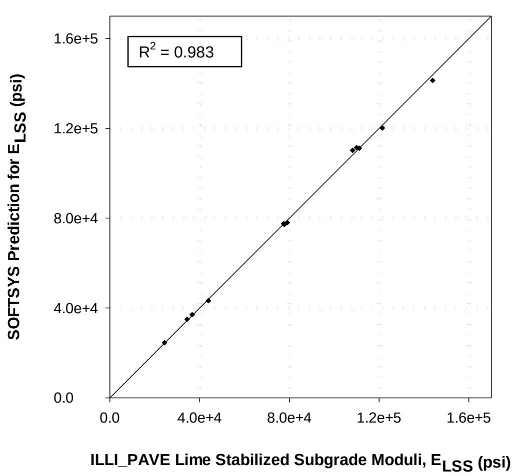
A similar study was performed to verify the performance of FDP-LSS-M1 model. This time 12 stations were randomly chosen from ILLI-PAVE training database. The performances are plotted in Figure 4.2.



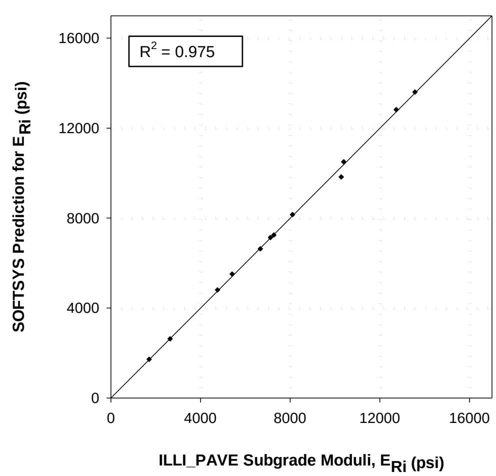
(a) t_{AC}



(b) E_{AC}



(c) E_{LSS}



(d) E_{RI}

Figure 4.2. SOFTSYS FDP-LSS-M1 predictions.

4.3 Field Validation

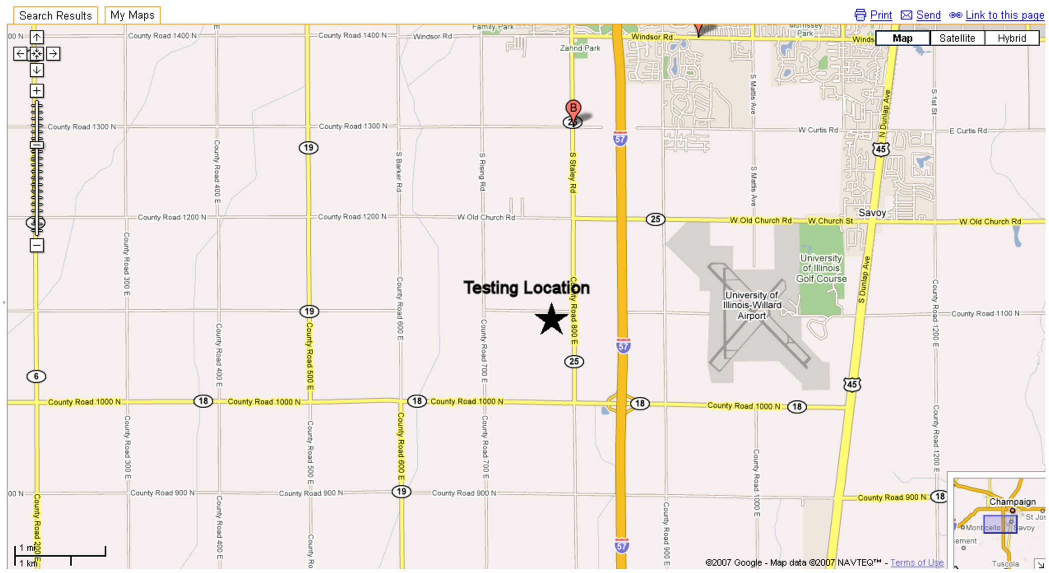
4.3.1 **Staley Road Test Sections**

The promising preliminary results obtained with the SOFTSYS approach gave high R^2 values of about 0.97 for FDP and 0.95 for FDP-LSS (equivalent to average absolute error, AAE, values on the order of 6% and 9%, respectively) for predicting asphalt concrete layer thickness. These results, however, had to be validated with actual field data because the FWD database used in testing the SOFTSYS performance was obtained synthetically. For this purpose, field FWD data were first collected from Staley Road, in Champaign, Illinois and used for the performance validations of the developed SOFTSYS models. The Staley Road data included only FWD results along with the temperature information collected in August, i.e. in warm weather conditions. There were, however, no cores taken from the pavement sections at the FWD locations.

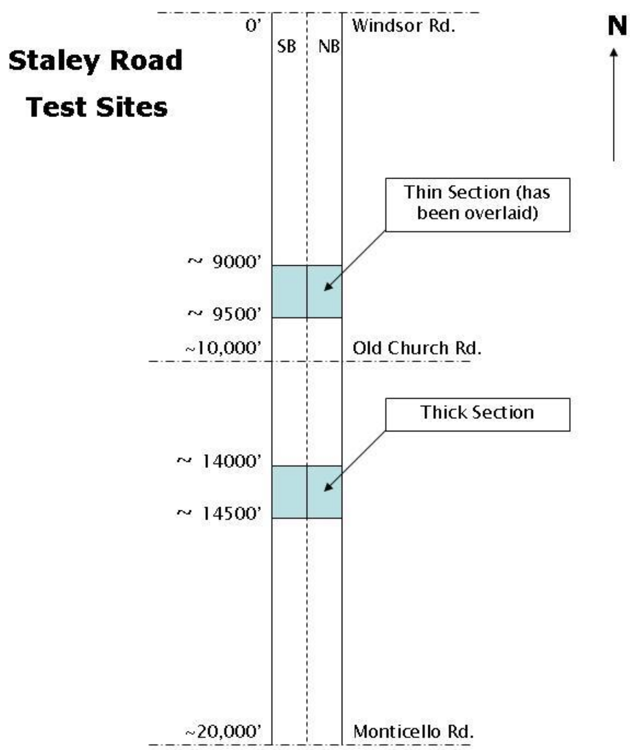
Staley Road runs in a north-south direction and is located on the west end of the City of Champaign in Champaign County, Illinois [see Figure 3.2 (a) and (b)]. The design pavement cross section consists of 12 in. of HMA constructed on LSS with a thickness of 12 in. The FWD tests were performed on about 1,000 ft. of the highway stretch. The pavement temperature was approximately 100^{o}F when the FWD tests were performed. Figure 4.4 shows the locations of FWD testing points along the pavement section. In this figure, the locations of metal plates on the road and reference points are also shown for the sake of completeness.

4.3.1.1 GPR testing

GPR technique has been identified as a reliable means to determine thicknesses of pavement sections in the field. In addition to use of GPR, construction thickness data have been obtained to determine pavement thicknesses in the field and establish a database to use in the validation of SOFTSYS pavement thickness predictions. The variability in the field determined or as-constructed thicknesses as well as other pavement layer properties are the critical factors in these validation efforts. Therefore, along with performing FWD tests, GPR testing and field thickness data collection need to be performed on the test sections so that the thickness variations or changes in the construction quality may be effectively assessed from the field data.



(a) Map of Staley Road test location



(b) Layout of Staley Road test sections

Figure 4.3. Location of Staley Road and test sections.

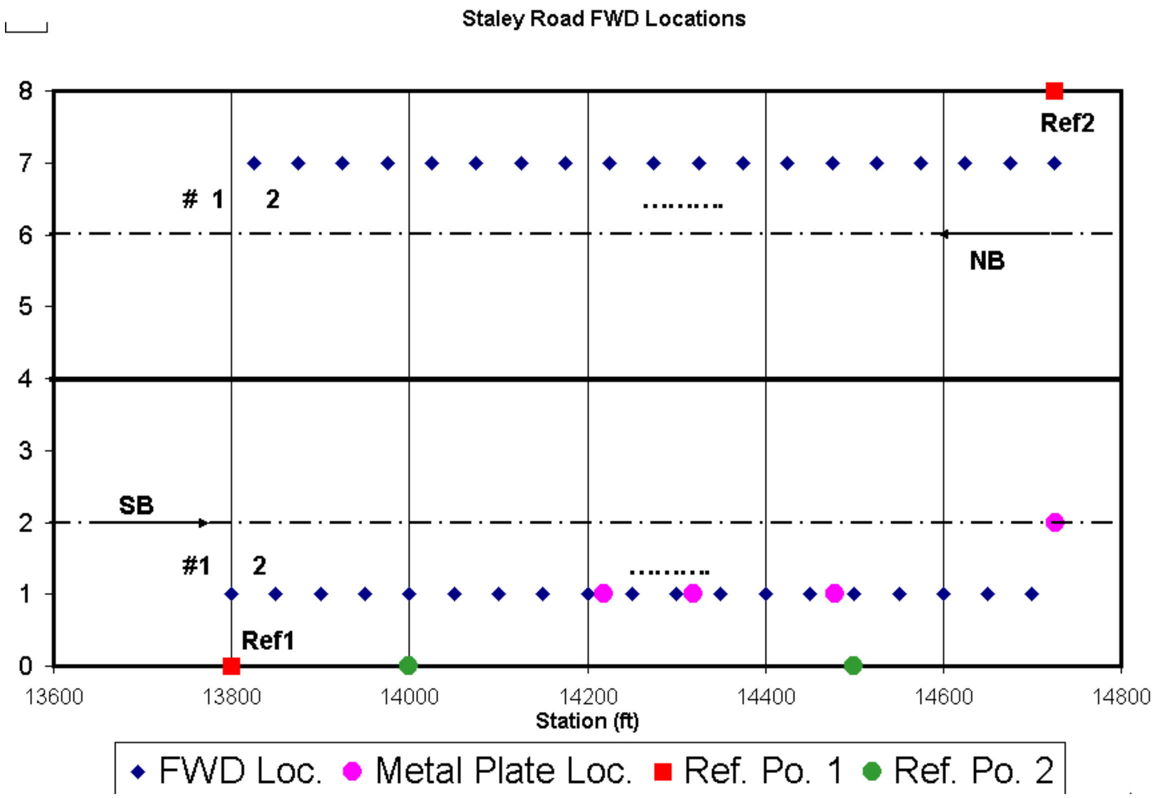
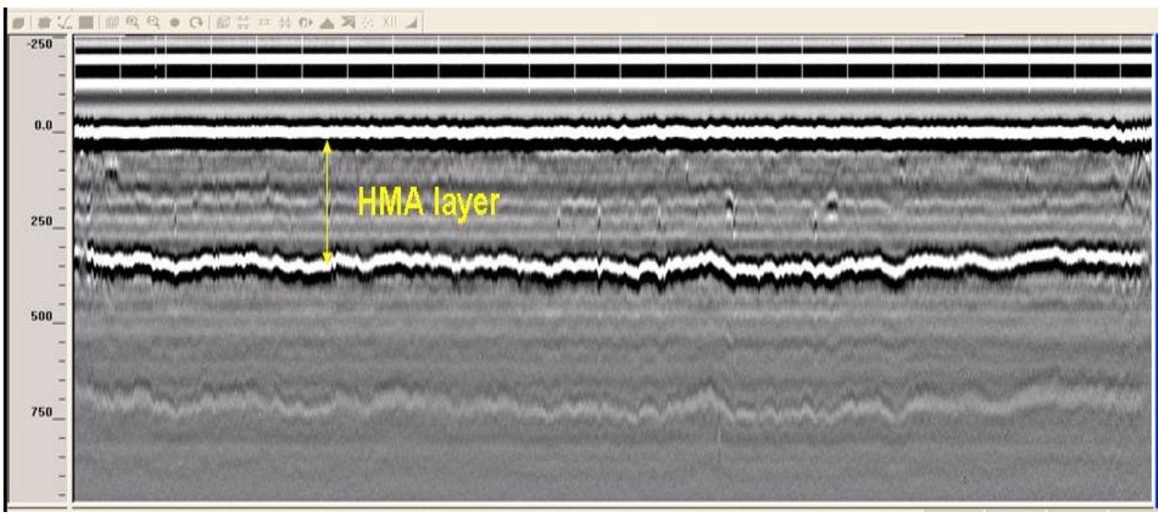


Figure 4.4. Locations of FWD tests along the Staley Road sections.

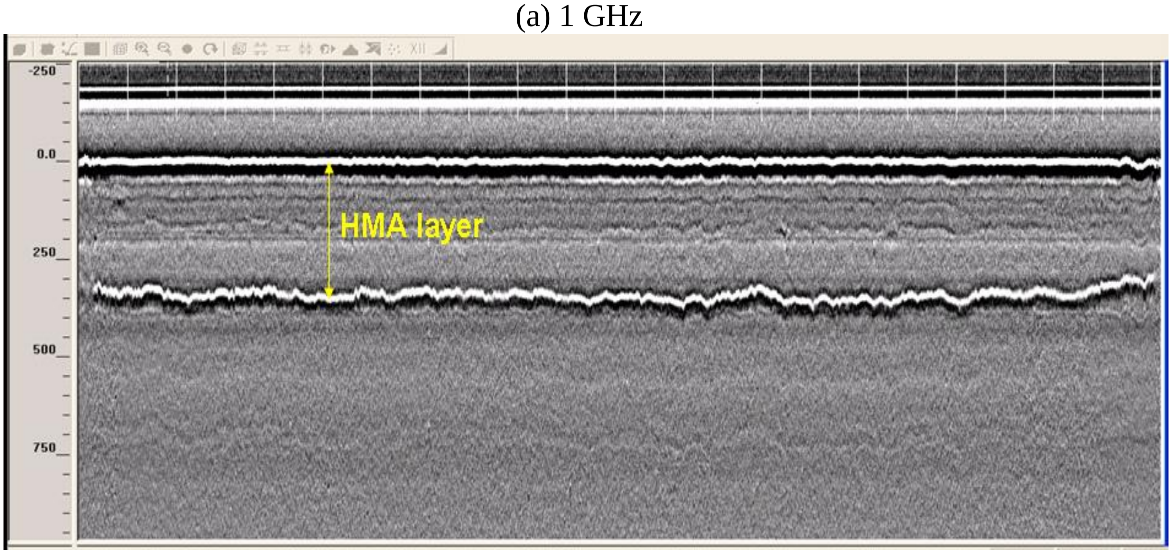
Two sets of GPR tests were performed along the Staley road in the same locations where FWD test data were obtained. The details of the GPR tests are provided in Table 4-2. The first set of GPR tests was performed to obtain the asphalt thickness data from the road, and the second one was aimed at verifying the first results and increasing reliability. In the first set of tests, North and South bound lanes of the test section were tested using both ground and air coupled antennae. In the second set of tests, only air coupled antenna was used to verify the previously determined asphalt thickness data. The GPR interpretations for both lanes (right wheel paths) are provided in Figure 4.5 and Figure 4.6. The 1 GHz air antenna was able to capture the HMA and lime stabilized interfaces. However, the 2 GHz air antenna was able to verify the HMA thickness, but not the lime stabilized interface. The interpretation of data collected with the ground coupled antenna did not produce meaningful results, which may be due to several reasons such as noise, or moisture on the surface of the pavement.

Table 4-2 GPR Test Conditions Along Staley Road Pavement Sections

	Test 1	Test 2
Section	13+800 => 14+750	13+800 => 14+750
Antenna Used	Ground + Air	Air
Air Condition	Clear (No rain 3 days before testing)	Clear (No rain 3 days before testing)

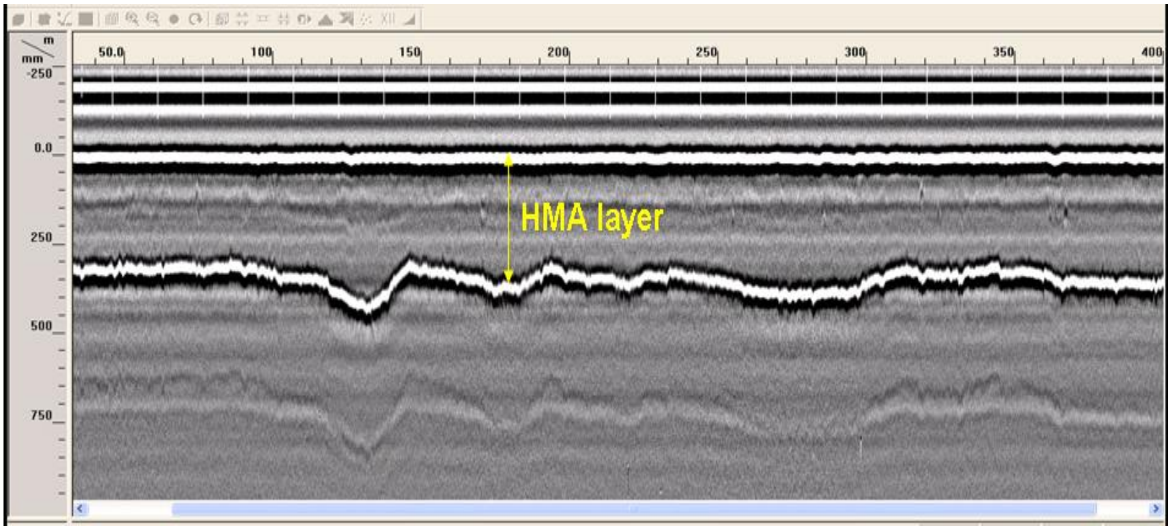


(a) 1 GHz

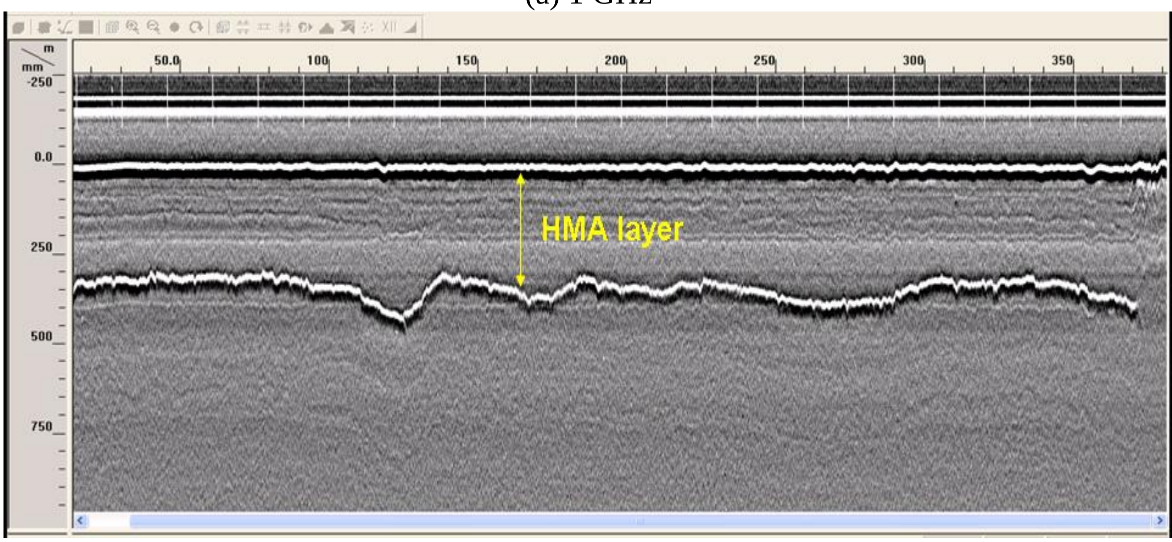


(b) 2 GHz

Figure 4.5. GPR test results: north bound right wheel path.



(a) 1 GHz



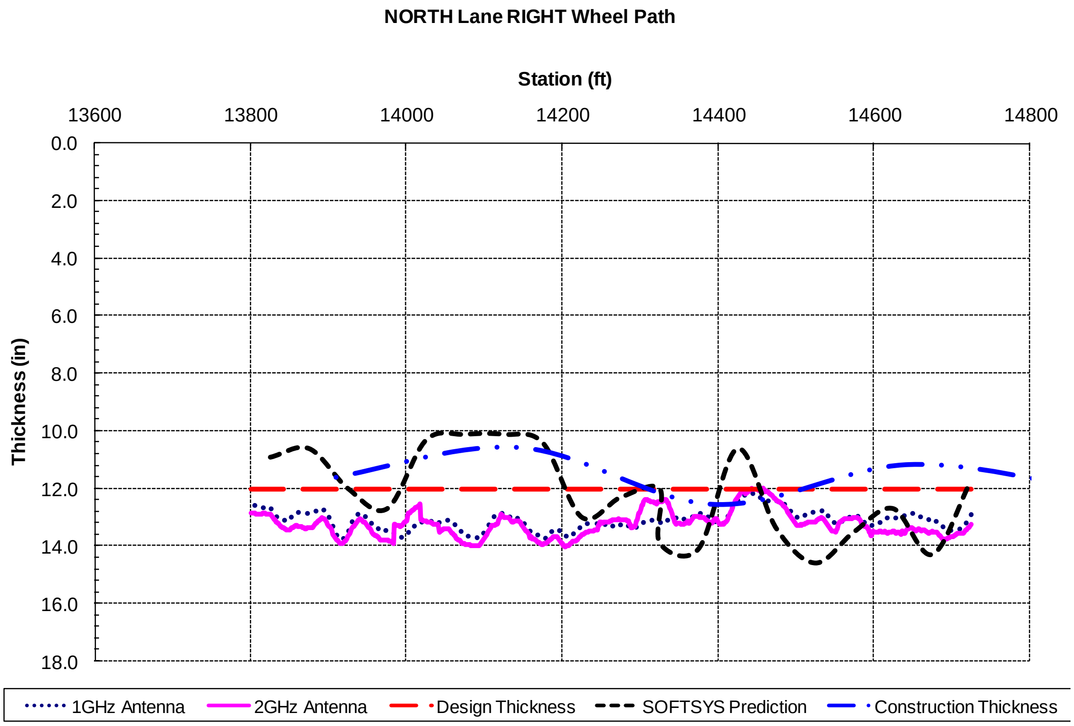
(b) 2 GHz

Figure 4.6. GPR test results: north bound right wheel path.

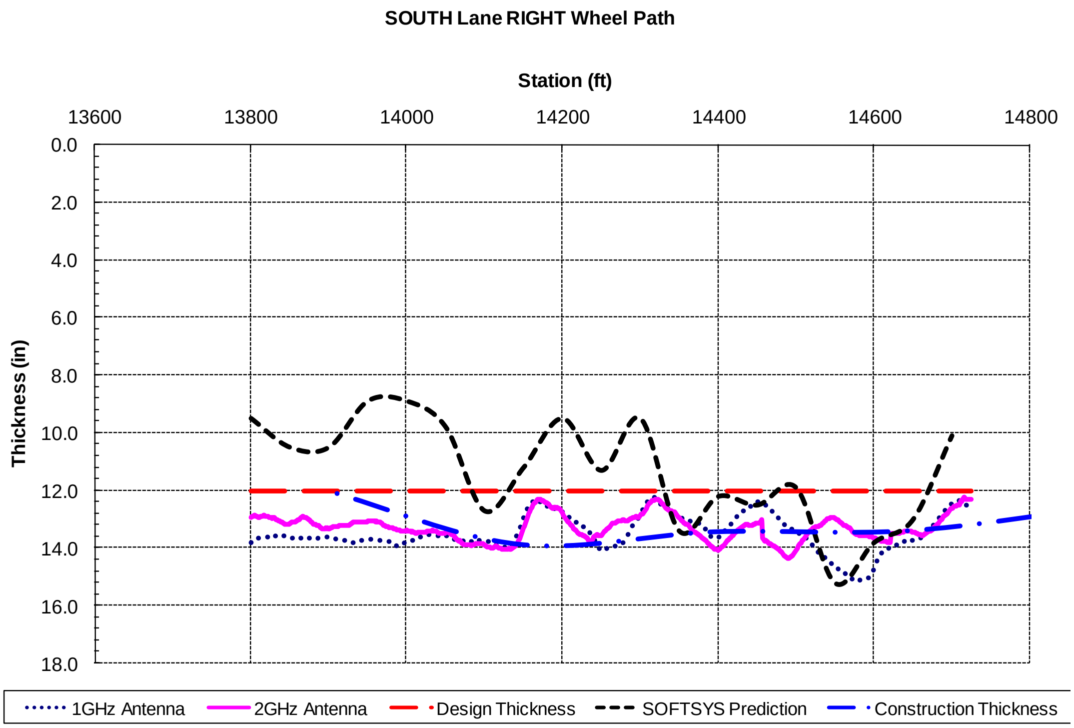
The data obtained from GPR indicated that the constructed pavement thickness was generally thicker than the design thickness (by approximately 1 in.) although there were sections that were even thinner than the design thickness. The thickness data from the field were deemed to be essential to calibrate the GPR test results. For this purpose, the elevation data were obtained from the time when the road was constructed. There were three observation points identified within the pavement section where FWD tests were performed. These elevation points were then used to sufficiently compare GPR test results. Finally, the SOFTSYS predictions were also compared with the thickness data both from GPR testing and the construction thicknesses to validate the thickness finder portion of the SOFTSYS program. No temperature correction was included in backcalculation of pavement layer properties.

Figure 4.7 (a) to (d) provide the thickness estimations of SOFTSYS from the FWD data together with the thicknesses obtained from both GPR and construction survey data. The thicknesses obtained using SOFTSYS captured the construction data well on the North lane [see Figure 4.7 (a)]. However, SOFTSYS generally predicted lower thicknesses on the South lane [see Figure 4.7 (b)]. The SOFTSYS predictions for both E_{AC} and E_{Ri} are also given in Figure 4.7 (c) and (d), respectively.

In an attempt to further verify the SOFTSYS results, another model was developed to take into account the LSS layer (named FDP-LSS M2) since Staley Road was built on lime modified soil. The predictions are given in Figure 4.8 (a) to (g). Similar to the ones obtained from FDP-M2 model, the thicknesses obtained using FDP-LSS M2 were in good agreement with the construction data on the North lane [see Figure 4-13 (a)]. On the other hand, SOFTSYS generally predicted lower thicknesses on the South lane [see Figure 4.8 (b)]. Finally, the SOFTSYS estimations for E_{AC}, E_{LSS}, and E_{Ri} are also given in Figure 4.8 (c) to (e), respectively. In general, the variations of AC layer thicknesses observed were attributed to the variations of the FWD test data.

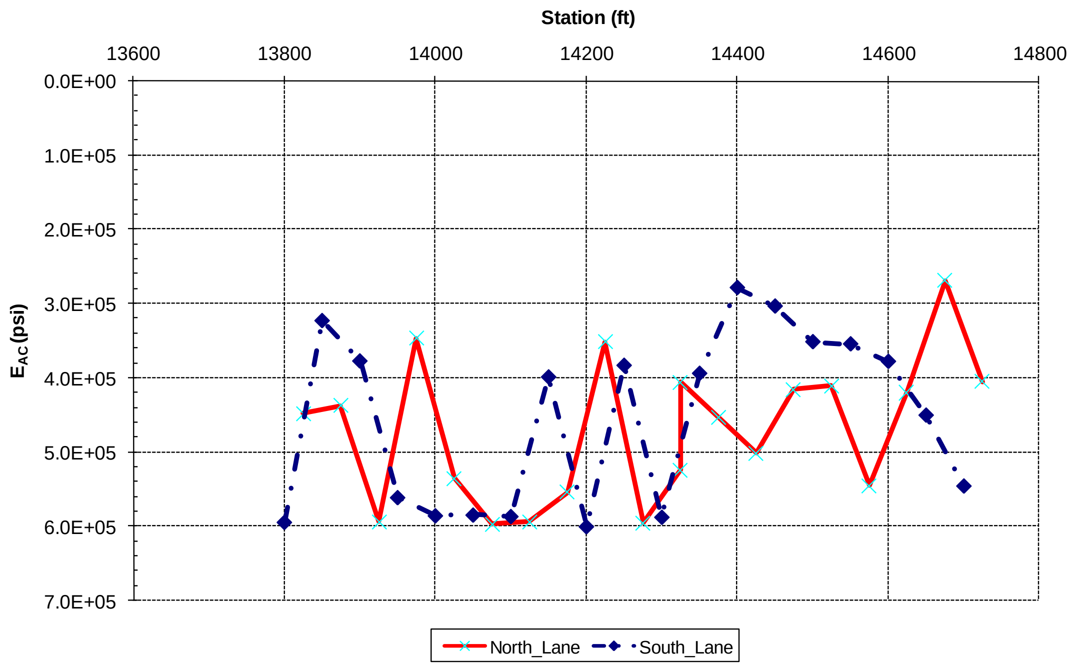


(a) t_{AC} northbound

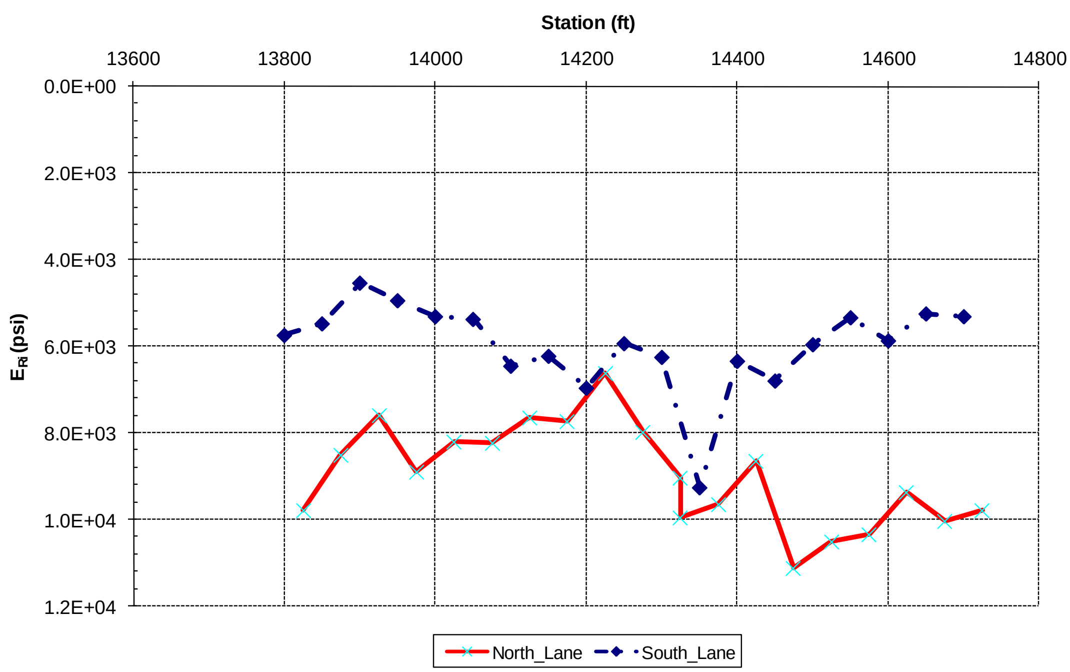


(b) t_{AC} southbound

Figure 4.7. Estimation of pavement layer properties using SOFTSYS FDP-M1 of Staley Road in Illinois.

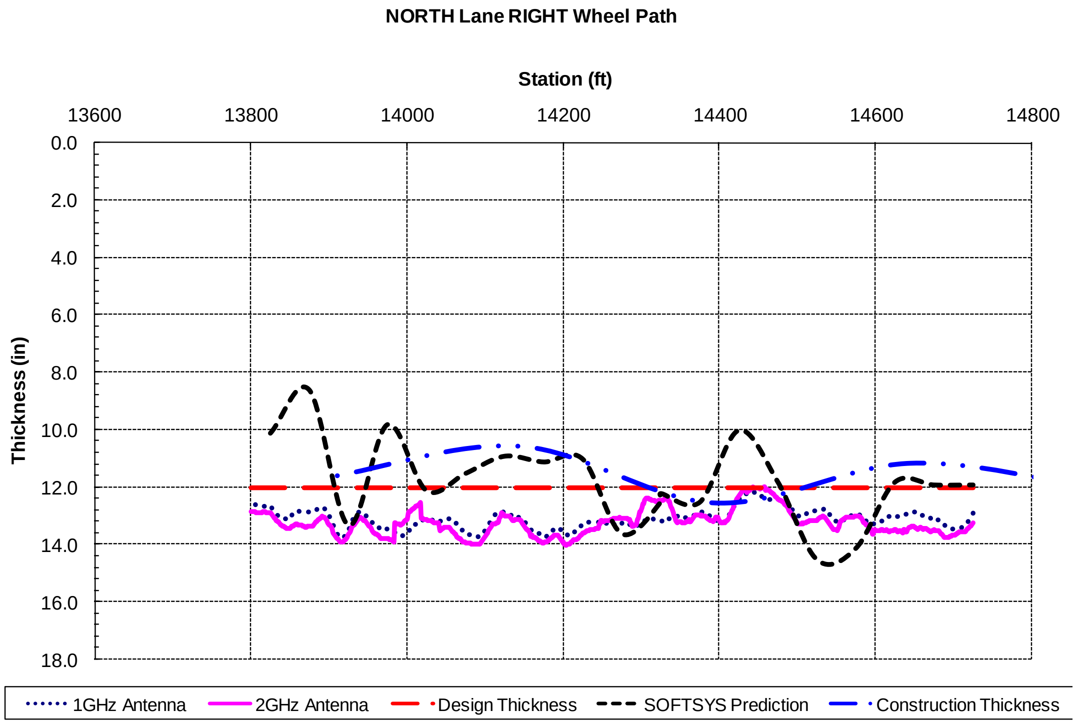


(c) E_{AC}

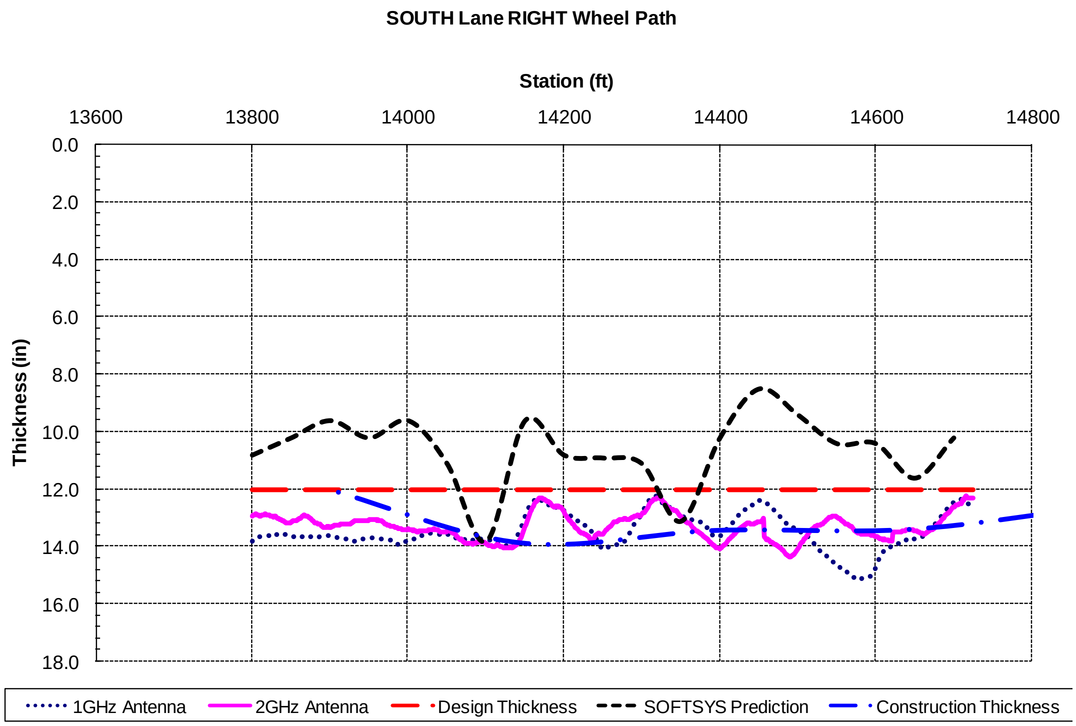


(d) E_{Ri}

Figure 4.7. Estimation of pavement layer properties using SOFTSYS FDP-M1 of Staley Road in Illinois (cont'd).

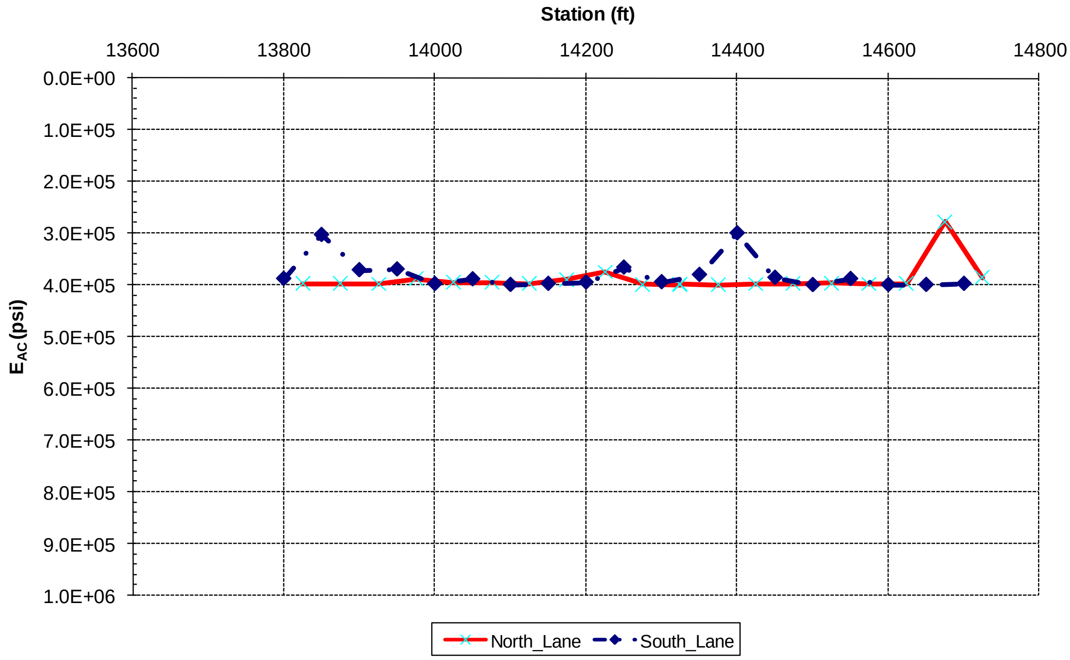


(a) t_{AC} northbound

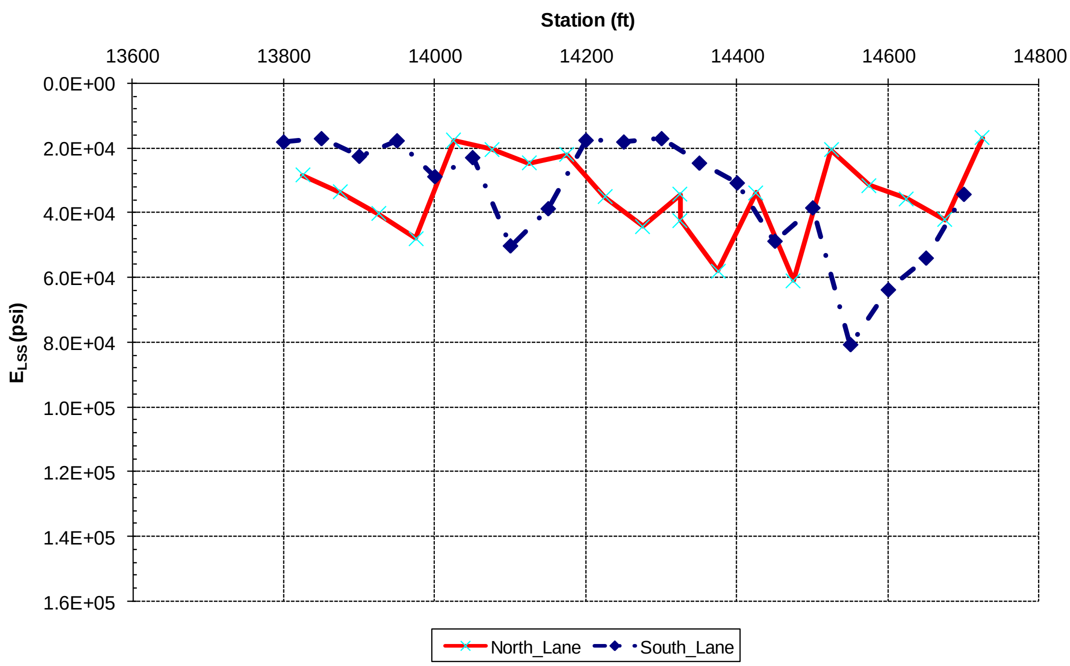


(b) t_{AC} southbound

Figure 4.8. Estimation of pavement layer properties using SOFTSYS FDP-LSS M1 of Staley Road in Illinois.

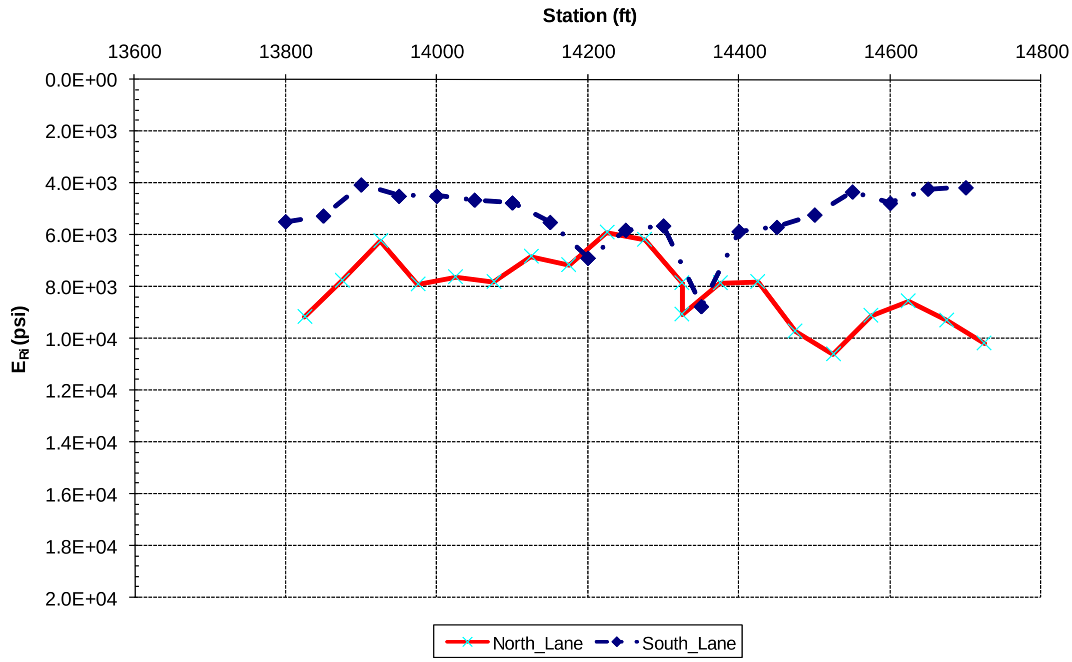


(c) E_{AC}



(d) E_{LSS}

Figure 4.8. Estimation of pavement layer properties using SOFTSYS FDP-LSS M1 of Staley Road in Illinois (cont'd).



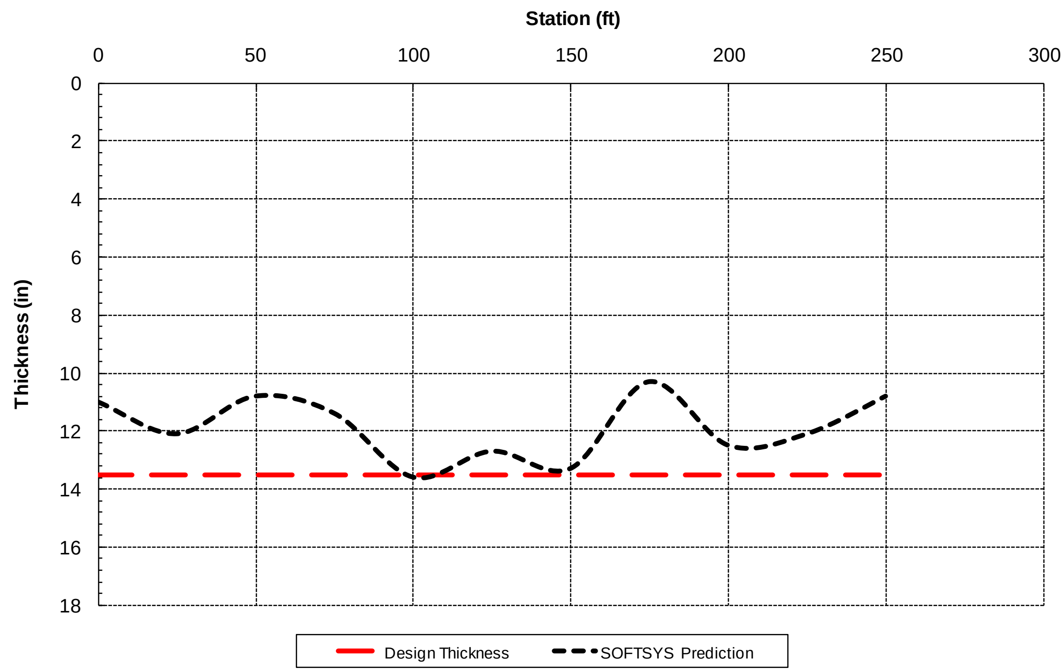
(e) E_{Ri}

Figure 4.8. Estimation of pavement layer properties using SOFTSYS FDP-LSS M1 of Staley Road in Illinois (cont'd).

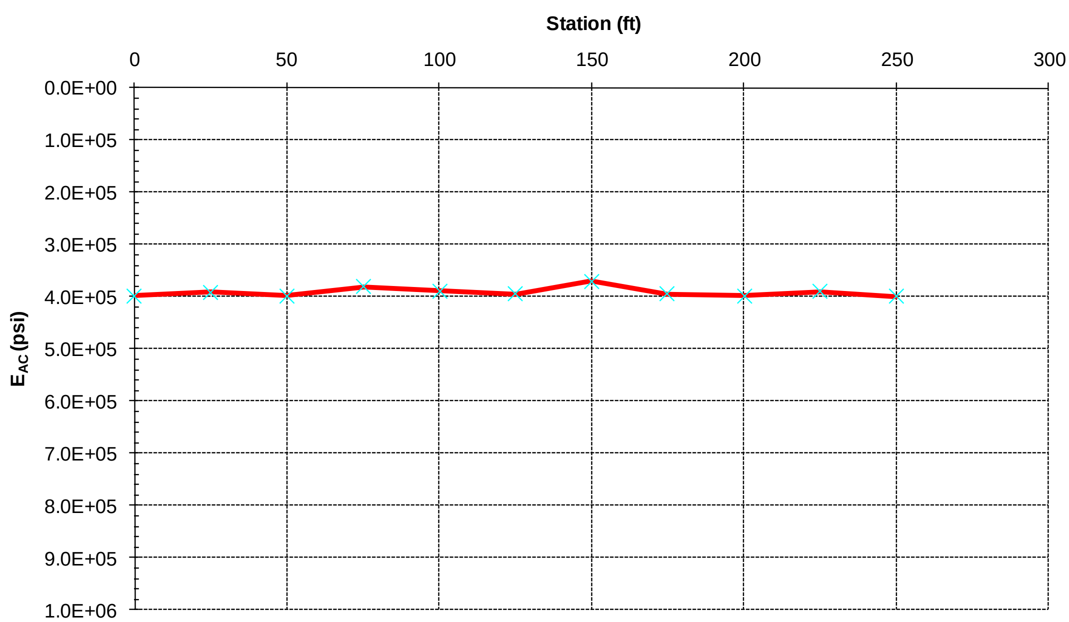
4.3.2 LTPP Database Verification

The Federal Highway Administration's Long Term Pavement Performance (LTPP) database was searched for validation of SOFTSYS models. The states of Illinois, Indiana and Ohio were mainly considered in this search utilizing the latest version of LTPP database (v2009.01). The "General Pavement Studies" section of the LTPP database was mainly investigated. It was found out that only few number of flexible pavement sections were reported in these states and they were mostly built on treated base layers.

The SOFTSYS analysis results are presented here for a full-depth flexible pavement built on lime stabilized soil layer in Allen County, Indiana. The design pavement section consists of the following: a seal coat (0.5 in. of AC), an original surface layer (0.5 in. of AC), an AC layer below surface (2.1 in.), another AC layer (10.3 in.), a treated base layer (5.3 in.) and finally, fine-grained subgrade soil. The FWD data were collected on April 14, 1994. The pavement properties predicted using SOFTSYS are given below in Figure 4.9 (a) to (d).

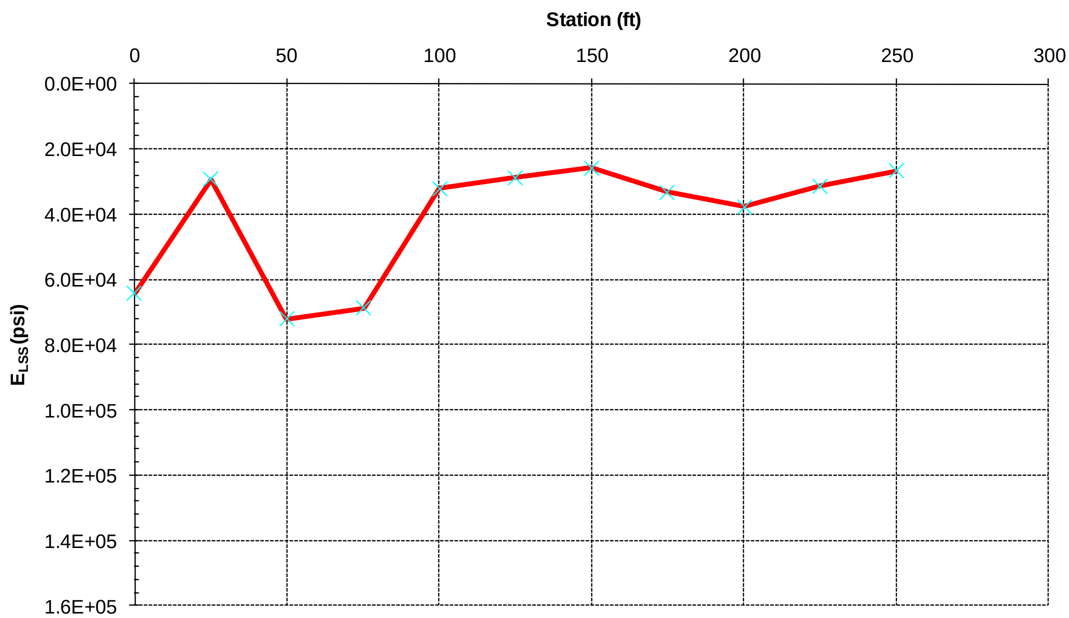


(a) t_{AC}

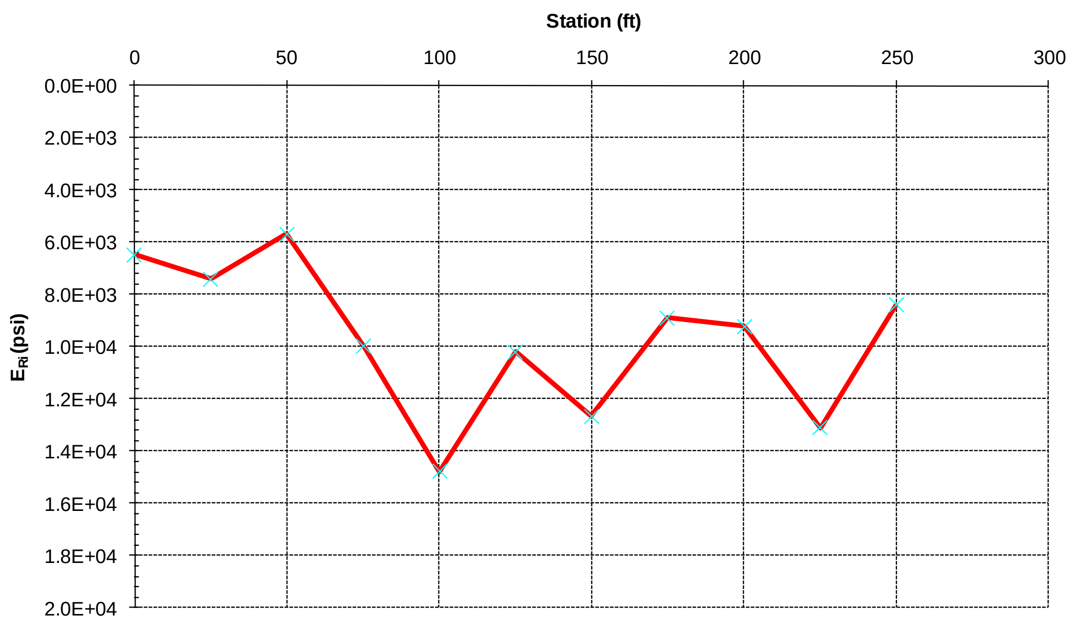


(b) E_{AC}

Figure 4.9. Estimation of pavement layer properties using SOFTSYS FDP-LSS-M1 of Allen County road in Indiana.



(c) E_{LSS}

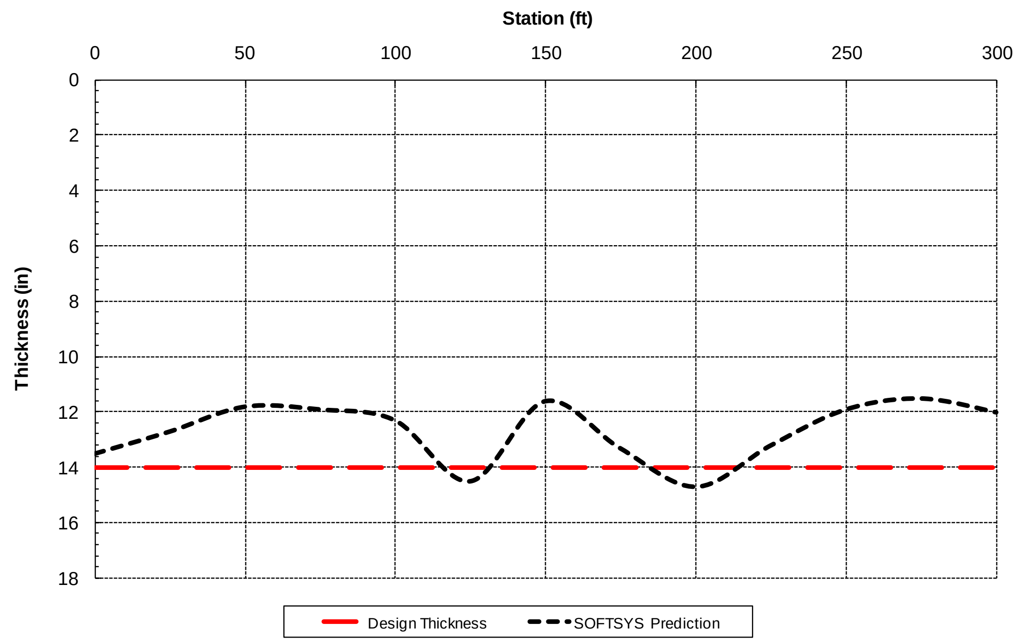


(d) E_{Ri}

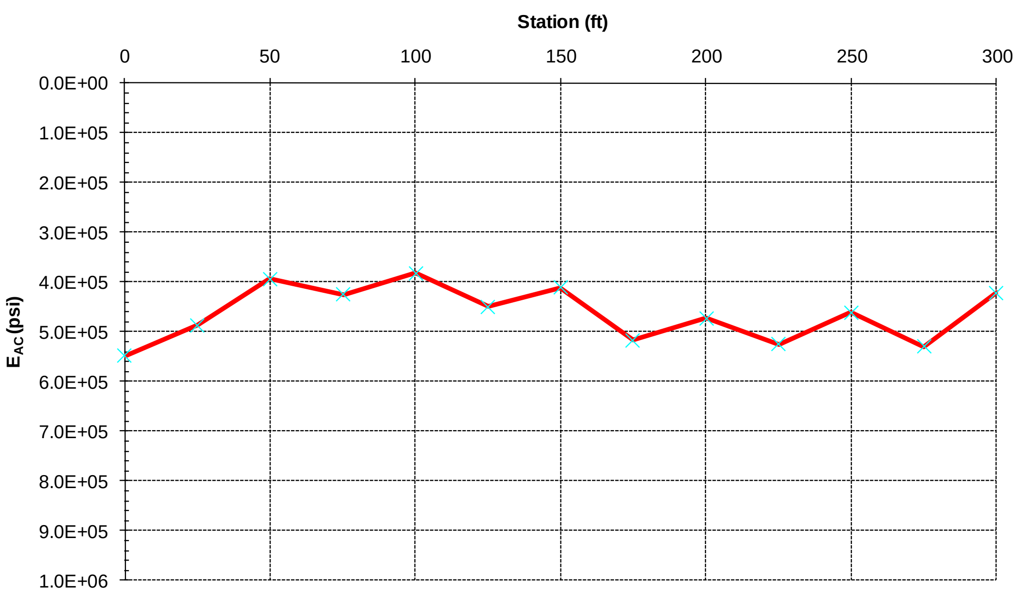
Figure 4.9. Estimation of pavement layer properties using SOFTSYS FDP-LSS-M1 of Allen County road in Indiana (cont'd).

4.3.3 **Roseville Bypass**

Roseville Bypass is a connector road to accommodate US-67 traffic in Illinois. The design pavement cross section consists of 14 in. of HMA and a 12-in. thick LSS layer. The FWD tests were performed on part C of the Roseville Bypass, which is a connector road approximately 300 ft. in length. The pavement temperature was reported as 97^{o}F along the road during the FWD tests. The estimations of SOFTSYS analyses are given in Figure 4.9 (a) to (d).

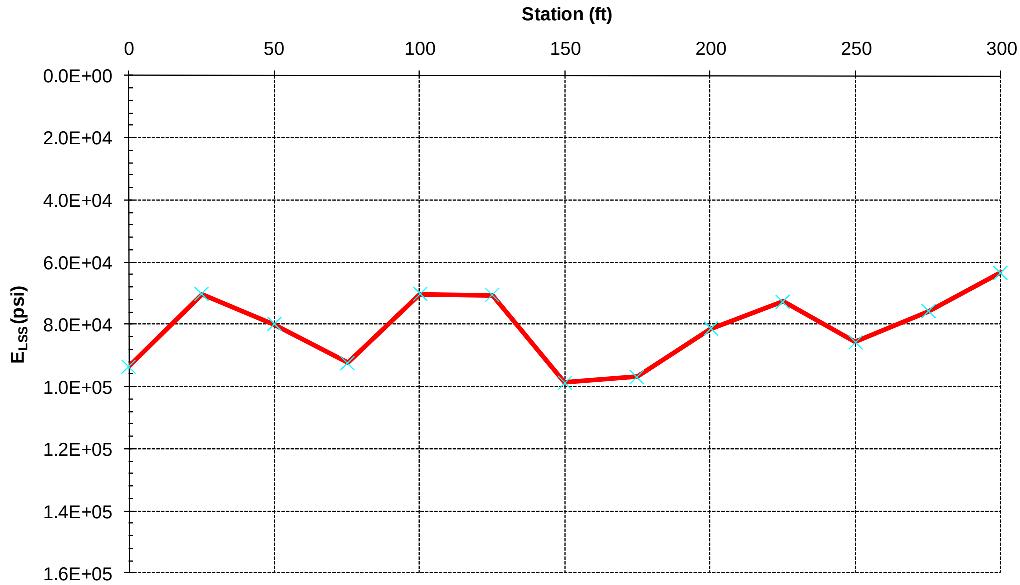


(a) t_{AC}

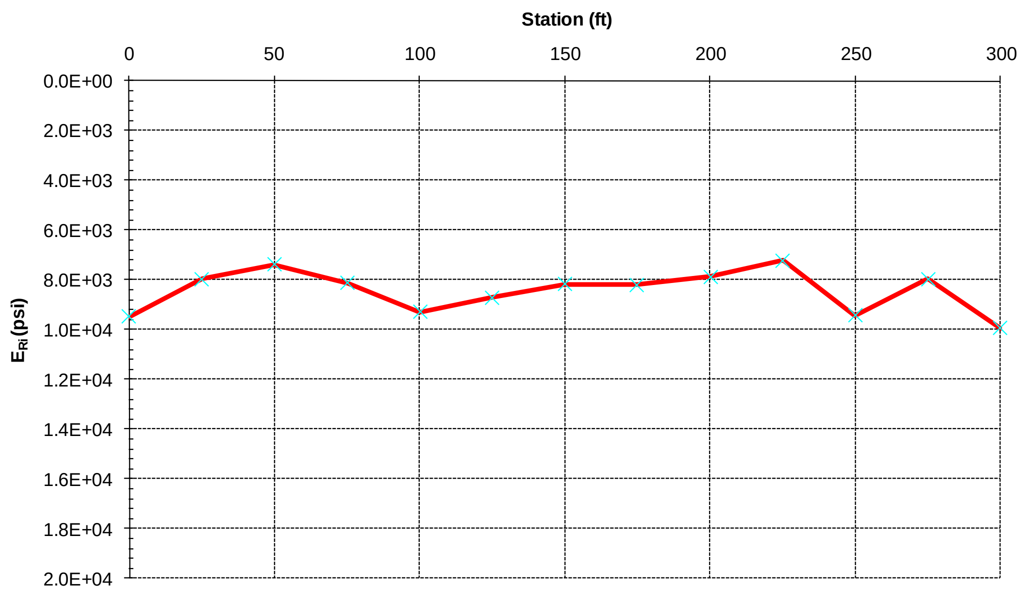


(b) E_{AC}

Figure 4.10. Estimation of pavement layer properties using SOFTSYS FDP-LSS-M1 of Roseville Bypass in Illinois.



(c) E_{LSS}



(d) E_{Ri}

Figure 4.10. Estimation of pavement layer properties using SOFTSYS FDP-LSS-M1 of Roseville Bypass in Illinois (cont'd).

CHAPTER 5. SUMMARY AND CONCLUSIONS

5.1 Summary

Pavement condition assessment in the field conducted by the use of Falling Weight Deflectometer (FWD) often requires the use of linear elastic pavement layered analysis tools to backcalculate layer moduli. However, both the subgrade soils and unbound aggregate base/subbase layers exhibit nonlinear, stress dependent geomaterial behavior. Sophisticated pavement structural models are needed to perform nonlinear analyses for more accurate solutions with fast computation schemes. This study has focused first on the use of ANN pavement structural models developed with the results of the ILLI-PAVE finite element (FE) program to predict pavement deflections under FWD loading. Then an innovative soft computing application, referred to herein as SOFTSYS, has been introduced for the hybrid use of Genetic Algorithms (GAs) and artificial neural networks (ANNs) to estimate pavement layer properties including the hot mix asphalt concrete (HMA) thickness from only the FWD test data collected on full-depth asphalt pavements built on both natural and lime modified subgrades.

First, information was collected on the types, typical geometries, and layer properties of different flexible pavements existing in the States of Illinois, Indiana and Ohio. This information was crucial for conducting many ILLI-PAVE FE analyses of typical pavement geometries and layer material properties and creating the synthetic pavement deflection basin data which represented the response behavior of flexible pavements in these states.

Then, the ILLI-PAVE finite element program, extensively tested and validated for over three decades, was used as an advanced structural model for solving deflection profiles and responses of the mainly identified typical Full-Depth Asphalt Pavements and Full-Depth Asphalt Pavements on Lime Stabilized Soils. Pavement deflection basins were created by the ILLI-PAVE FE runs under the standard 9,000-lb FWD loading. Pavement deflection and response databases established from the ILLI-PAVE FE solutions in this manner covered all combinations of the different pavement geometries, layer thicknesses, and layer moduli.

Using these databases, forward calculation ANN models were developed. Different ANN model network architectures were searched and trained to determine the optimum architectures that best captured the behavior of the these flexible pavement sections. In each case, a portion of the ANN model training data was separated as an independent testing set to check the performance of the trained ANN architecture. Several different network architectures were also trained using different number of input parameters. These network architectures were designed for directly predicting the deflections on top of asphalt layer under FWD loading.

The framework SOFTSYS, which stands for Soft Computing Based Pavement and Geomaterial System Analyzer, was developed as a new pavement analyzer to perform both forward and backcalculation analyses by the hybrid use of GA and ANN models thus enabling full-depth asphalt pavement analyses without knowing the HMA layer thickness. SOFTSYS performances were needed to be validated with actual field data. For this purpose, Ground Penetrating Radar (GPR) was selected as the most reliable way of determining layer thicknesses of medium to long stretches of field pavement sections. In addition, construction thickness data were also required to determine the thicknesses of in-service pavements. The variability in the thickness as well as other pavement properties was a critical issue. Therefore, along with the FWD testing, GPR testing was also conducted to obtain pavement thickness data. The SOFTSYS thickness predictions were then successfully validated through comparisons with the GPR test results and the thickness data from pavement section construction.

Only limited full-depth asphalt pavement sections were available in the Federal Highway Administration’s Long Term Pavement Performance (LTPP) database. Two such pavement sections from states of Indiana and Illinois were used to further verify applicability of SOFTSYS approach. The SOFTSYS estimations proved to be successful in estimating design thicknesses for both of these sections.

5.2 Conclusions

The performances of the developed surrogate ANN structural models (forward models) were well above satisfactory; i.e., these ANN models could be used in lieu of finite element analyses for the quick and accurate predictions of the surface deflections and the critical responses of all types of full-depth flexible pavements found/constructed in Illinois, Indiana and Ohio. The results of pavement structural modeling with the ILLI-PAVE FE program proved that improvements due to the constructed lime stabilized subgrade soil layer had to be captured separately in the analyses since significant differences were found between the critical pavement responses of full-depth pavements on unmodified subgrade and lime stabilized subgrade. Therefore, for correctly modeling the pavement response and behavior with the lime stabilized subgrade soil layer, separate forward analysis approaches were developed to accurately predict pavement deflection profiles and pavement critical responses under FWD loading.

Thickness variability was a real issue in the field, and destructive pavement coring was not always a viable option to determine layer thickness. The SOFTSYS, Soft Computing Based Pavement and Geomaterial System Analyzer, framework developed as a software tool was used successfully to backcalculate the layer moduli and the HMA thicknesses of the full-depth asphalt pavements analyzed. SOFTSYS was shown to work effectively with the synthetic data obtained from ILLI-PAVE FE solutions. The very promising SOFTSYS results obtained indicated average absolute errors (AAEs) on the order of 6% and 9% for the HMA thickness estimation for full depth pavements and full depth pavements built on lime stabilized soil layers.

The field validations of SOFTSYS with Staley Road FWD data in Illinois also produced meaningful results. Higher deflection values correlated well with the thinner backcalculated HMA thicknesses. In addition, the thickness data obtained from GPR testing matched reasonably well with the SOFTSYS results although in some locations the maximum difference between the two results was up to 3 in. The variations of HMA thickness observed were attributed to variations in the FWD data. The data obtained from GPR also indicated that the constructed HMA thicknesses were generally greater than the design thickness (by approximately 1 in.) although there were sections that were even thinner than the design thickness. The thickness data from the field were deemed to be essential to calibrate the GPR test results. In addition, the validations of SOFTSYS with LTPP design data proved that proper calibration of parameters is a must to obtain reliable results from the SOFTSYS methodology.

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