BACKCALCULATION OF PAVEMENT LAYER PROPERTIES USING ARTIFICIAL NEURAL NETWORK BASED GRAVITATIONAL SEARCH ALGORITHM

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ABSTRACT

BACKCALCULATION OF PAVEMENT LAYER PROPERTIES USING ARTIFICIAL NEURAL NETWORK BASED GRAVITATIONAL SEARCH ALGORITHM

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Transportation agencies need to make accurate decisions about maintenance strategies to provide sustainability of pavements. Non-destructive pavement evaluation means play a crucial role when making such assessments. A commonly used method is to use Falling Weight Deflectometer (FWD) device which measures the surface deflections under imposed loadings. Determination of layer properties through the use of FWD deflections is known as pavement layer backcalculation. This process requires the use of mathematical pavement model to simulate the deflections, which is called forward response model. Calculated deflections from this model are then compared with the field deflections measured through FWD in an iterative manner, which requires intelligent schemes as this process is time-consuming and sometimes produces erroneous results. In this study, an artificial intelligence based inversion algorithm is presented to backcalculate the flexible pavement layer properties. A hybrid approach is proposed using the combination of Artificial Neural Networks (ANN) and a recently developed metaheuristic optimization technique Gravitational Search Algorithm (GSA). The forward calculation engine is based on the finite element analysis of flexible pavements and its surrogate ANN model, which is used to eliminate the time-consuming stages for computing the deflections. GSA is utilized as an efficient search algorithm to seed the ANN model to obtain the deflections in a quick way. The performance of the proposed algorithm is then validated using both synthetically created FWD data and the ones obtained from actual field FWD data. The proposed method is also validated by comparing two well-accepted backcalculation software, EVERCALC and MODULUS. To present the effectiveness of the GSA method, Simple Genetic Algorithm (SGA) is also utilized for comparison purposes. The findings show that the proposed algorithm can predict layer moduli with high accuracy for various types of flexible pavements.

Keywords: Flexible Pavement, Backcalculation, Artificial Neural Networks, Gravitational Search Algorithm, Falling Weight Deflectometer

ÖZ

YAPAY SİNİR AĞLARI TABANLI YERÇEKİMSEL ARAMA ALGORİTMASI KULLANILARAK ESNEK ÜSTYAPI KATMAN ÖZELLİKLERİNİN GERİ-HESAPLANMASI

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Ulaştırma konusunda ilgili kuruluşların, yol üstyapılarının sürdürülebilirliğini sağlamak amacıyla uygun bakım stratejileri belirlemeleri gerekmektedir. Bu bağlamda üstyapıların değerlendirilmesinde hasarsız test yöntemleri önemli rol oynamaktadır. Bu yöntemlerden en çok tercih edilenlerden bir tanesi, kaplama yüzeyine uyguladığı yüke karşı oluşan düşey yer değiştirme miktarlarını ölçen, Düşen Ağırlık Deflektometresi (FWD) kullanmaktır. Ölçülen bu yer değiştirmeleri kullanarak yapının mekanik özelliklerinin belirlenmesine geri-hesaplama adı verilir. Bu işlemde yer değiştirmeleri simüle etmek amacıyla ileri hesaplama modeli olarak bilinen matematiksel modeller kullanılmaktadır. İleri hesaplama modeli ile hesaplanan yer değiştirmeler FWD ile elde edilenlerle tekrarlı olarak karşılaştırılır. Geri-hesaplama işlemleri uzun zaman aldığından ve bazı durumlarda hatalı sonuçlar verebildiğinden, problemlerin çözümleri için akıllı yaklaşımlara ihtiyaç duyulmaktadır. Bu çalışmada esnek üstyapıların mekanik özelliklerinin geri-hesaplanmasında kullanılacak Yapay Sinir Ağları (YSA) ve Yerçekimsel Arama Algoritması (GSA) tabanlı, GSA-ANN olarak adlandırlan, hibrit bir model sunulmuştur. Önerilen bu algoritmada, yer değiştirmelerin hesaplanmasına ayrılan zamanı azaltmak amacıyla, ileri hesaplama modeli olarak sonlu elemanlar analizlerine dayanan YSA modelleri kullanılmıştır. YSA'ya en uygun girdi değerleri ise etkili bir arama algoritması olan GSA tarafından seçilmiştir. Önerilen algoritmanın etkinliği, sentetik olarak oluşturulan ve araziden elde edilen veriler kullanılarak tahkik edilmiştir. GSA-ANN üstyapı geri-hesaplamasında kabul görmüş EVERCALC ve MODULUS programlarıyla karşılaştırılmıştır. Ayrıca, GSA'nın etkinliğini farklı bir algoritma ile karşılaştırarak değerlendirmek amacıyla Basit Genetik Algoritma (SGA) kullanılmıştır. Elde edilen sonuçlar göstermiştir ki, geliştirilen algoritma değisik özelliklerdeki esnek üstyapıların mekanik özelliklerini yüksek doğrulukta tahmin edebilmektedir.

Anahtar Kelimeler: Esnek Kaplama, Geri-hesaplama, Yapay Sinir Ağları, Yerçekimsel Arama Algoritması, Düşen Ağırlık Deflektometresi

To my family…

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LIST OF ABBREVIATIONS

AASHTO	:	American Association of State Highway and Transportation Officials
AC	:	Asphalt Concrete
AI	:	Artificial Intelligence
ANFIS	:	Adaptive Neuro-Fuzzy Inference System
ANN	:	Artificial Neural Networks
AVCF	:	Area Value with Correction Factor
BGSA	:	Binary Gravitational Search Algorithm
CBR	:	California Bearing Ratio
CFP	:	Conventional Flexible Pavement
DE	:	Differential Evolution
FDP	:	Full-depth Flexible Pavement
FDP-LSS	:	Full-depth Flexible Pavement on Lime Stabilized Soil
FE	:	Finite Element
FEM	:	Finite Element Method
FHWA	:	Federal Highway Administration
FWD	:	Falling Weight Deflectometer
GA	:	Genetic Algorithm
GPR	:	Ground Penetrating Radar
GPS	:	General Pavement Studies
GSA	:	Gravitational Search Algorithm
HMA	:	Hot Mixed Asphalt
HWD	:	Heavy Weight Deflectometer
KGM	:	General Directorate of Highways
LTPP	:	Long-Term Pavement Performance
LWD	:	Light Weight Deflectometer

MAPE	:	Mean Absolute Percentage Error
MEPDG	:	Mechanistic-Empirical Pavement Design Guide
MET	:	Method of Equivalent Thickness
MGSA	:	Modified Gravitational Search Algorithm
MRL	:	Material Reference Library
NCHRP	:	National Highway Research Program
NDT	:	Non-Destructive Testing
PCC	:	Portland Cement Concrete
PSO	:	Particle Swarm Optimization
RDD	:	Rolling Dynamic Deflectometer
RMS	:	Root Mean Square
RMSE	:	Root Mean Square Error
RWD	:	Rolling Weight Deflectometer
SASW	:	Spectral Analysis of Surface Waves
SCE	:	Shuffled Complex Evolution
SHRP	:	Strategic Highway Research Program
SMP	:	Seasonal Monitoring Program
SPA	:	Seismic Pavement Analyzer
SPS	:	Specific Pavement Studies
SVM	:	Support Vector Machines
TTI	:	Texas Transportation Institute
TxDOT	:	Texas Department of Transportation
WSDOT	:	Washington Department of Transportation

CHAPTER 1

INTRODUCTION

1.1 Background

Highways have similar functions with the blood vessels of human body considering their transportation duty. To maintain one's life, blood circulation is enabled by the arteries and required blood is supplied to the organs. In the same manner, goods and people are moved from a point to another through the highways which help to sustain a country. Nowadays, development level of a country is thought to be directly related with comprehensiveness and functionality of its transportation systems.

Highways are the integral part of the transportation systems and funds supplied by governments indicate their importance for the countries. For the year 2014, USA which has the largest highway network in the world allocated approximately 68 billion dollar for Federal Highway Administration (FHWA) from the budget of the government (U.S. Department of Transportation 2014**).** The amount of the fund was increased 60% according to year 2012. In Turkey, the budget for General Directorate of Highways (KGM) was determined as 7.1 billion Turkish Liras which shows 3% increment in comparing to the previous year (TBMM Plan ve Bütçe Komisyonu 2014).

Serviceability and safety are the significant issues for the roads that should be considered by the transportation agencies of countries. Regardless of the material used within pavement layers and construction methods, every highway is exposed to traffic loading and environmental effects which deteriorate the pavement structure over time (see Figure 1). In order to maintain the serviceability and safety level high and to slow down the deterioration, maintenance and rehabilitation processes are required. Considering the sizable investments, right decisions should be taken for in service pavements about which of them requires maintenance or rehabilitation. For these actions, accurate determination of geometrical and mechanical properties of pavements are essential issues that are needed to be regarded. With the objective of structural evaluation of existing pavements, non-destructive testing (NDT) methods are frequently preferred as compared to destructive ones because they keep the integrity of structures by fast and easy implementations. One of the commonly employed NDT devices is Falling Weight Deflectometer (FWD) which measures the surface deflections under imposed loading. Through the use of FWD deflections in several analyses, structural capacity of pavement can be evaluated and therefore rehabilitation and maintenance needs can be properly determined.

Figure 1 Deterioration of Flexible Pavements

Pavement layer backcalculation is the process of estimating mechanical properties of pavement layers which uses the measured deflections by FWD. Backcalculation is an inverse type problem whose solutions may sometimes be problematic. In a typical solution method of this problem, a pavement section of whose layer properties are backcalculated is modelled numerically and FWD test is simulated on this section. Using the numerical model, surface deflections are computed and the results are compared with the measured deflections from the field. In backcalculation, it is aimed to numerically simulate the pavement section whose deflection responses are reasonably closer to the ones measured with FWD. Finding the optimum solution of a pavement layer backcalculation problem requires iterative processes so that layer properties of numerical model are changed iteratively. In each step, layer moduli values are updated for the next iteration so as to minimize the deflection differences. A search method is employed in order to minimize the deflection differences and to determine the new layer properties for the following iteration. At the end, layer properties which produce most approximate surface deflections to the field measurements are reported as the solution of the problem.

Pavement layer backcalculation problem is composed of two main parts; forward response modelling and search method. Both components are the significant in the sense of obtaining accurate layer properties. Numerical modelling of pavement and FWD simulation are named as forward response modelling. Layered elastic theory is the most commonly employed forward response analysis approach due to provided calculation simplicity. This theory makes some assumptions for material behaviors and geometrical properties which simplify the problem. Among these assumptions, most significant one is the linear elastic material behavior for all the pavement layers that may influence the accuracy of the backcalculated layer properties. Unbound granular base/subbase layers and subgrade soils have stress sensitive nature that their stiffness properties are changed according to the stress states. Therefore, these pavement geomaterials cannot be adequately characterized by linear elasticity. The limitations of layered elastic theory can be handled by another approach: finite element method (FEM). In contrast to elastic layered theory, FEM based analyses use more complex mathematical models to solve the pavement sections and they produce more realistic solutions than elastic layered theory. This superiority originates from the ability of FEM based analyses dealing with the nonlinearity of materials and making fewer assumptions. Nowadays, several general purpose finite element softwares are available and also, there are programs which are specifically focusing on the pavement analysis. Beside the advantages provided by FEM based solutions, time-consuming analysis and complex computational stages are the drawbacks of this approach. Since the backcalculation is an iterative process and it requires great number of analyses, FEM based forward response engines may not be practical. Thereby, a proper way of relaxing computational difficulties is required to eliminate the complexity of computation and to decrease the runtime of the analyses.

In order to overcome the limitations of traditional forward response models, soft computing techniques can be implemented. The term soft computing refers to combination of several artificial intelligence (AI) methods which are performed for handling computationally intense, complex and hard to solve problems by using conventional (hard) computing techniques. While soft computing methods are tolerating impression, uncertainty and approximation, they give robust and low cost solutions. Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), fuzzy mathematical programming and evolutionary computation methods are the main components of soft computing (Kecman 2001). Generally, these methods are inspired by human mind, evolutionary theory and the behavior of the living creatures and objects encountered in the nature. Among all these methods, ANNs are the one of most applied AI methods in pavement layer backcalculation studies as surrogate engine for forward response analysis. Owing to the capability of ANN of establishing nonlinear relationship between input and output values of a system, accurate analyses can be conducted by neural networks. Besides, runtime of backcalculation analyses can be reduced dramatically by comparing to the FEM based solutions. Initial applications of ANN in pavement layer backcalculation show that ANN based forward response engines produce fast and accurate solutions just as the ones obtained with conventional methods (Meier and Rix 1994, 1995; Meier 1995). By these studies, effectiveness of ANNs were proven and their usage in pavement layer backcalculation have been increased through the time (Bosurgi and Trifirò 2005; Ceylan and Gopalakrishnan 2006; Ceylan et al. 2005; Gopalakrishnan 2009a; Nazzal and Tatari 2013; Pekcan 2010; Pekcan et al. 2008; Saltan and Terzi 2009; Saltan et al. 2012; Tutumluer et al. 2009).

Accuracy of the deflections calculated by the forward response analysis is directly related with the provided input values to the system regardless of the employed forward model either FEM or ANN based engines. Selection of appropriate input values to the models are conducted by a search method which is the second significant part of pavement layer backcalculation problems. Since the function of search method is to minimize the difference between calculated and measured deflections and to determine the new layer moduli for the following iteration, the process can be considered as an optimization routine. Several soft computing techniques can be employed in pavement layer backcalculation as a search method. Through the use of an objective function, search algorithm can calculate the deflection differences and by using the values of the function, it estimates the new layer properties. After completing the iterations, most representative layer moduli found by search algorithm are reported as the solution of the problem. Choosing the proper optimization algorithm is crucial issue for backcalculation procedures. In recent years, use of metaheuristic optimization algorithms as search algorithm has been increased owing to several advantages that they provide. In this context, some evolutionary and swarm intelligence algorithms such as genetic algorithm (GA) and particle swarm optimization (PSO) method, have been implemented to seek the search space for finding the most appropriate input values of the forward response model (Bosurgi and Trifirò 2005; Gopalakrishnan 2009a; Rakesh et al. 2006; Tutumluer et al. 2009). Performance of these search algorithms may show variations according to complexity of problem to be solved. Moreover, there is no specific algorithm which works perfectly for all types problems. Therefore, further studies on this topic could be improved the quality of backcalculated pavement layer properties.

1.2 Objectives and Scope of the Thesis

Overall aim of this thesis is to develop an inversion algorithm to backcalculate flexible pavement layer properties. By this algorithm, it is intended to solve pavement backcalculation problems in a fast and robust manner. Primary objectives of the proposed algorithm are presented below.

First objective of this study is to predict realistic deflections occurred on pavement surface. For this purpose, previously developed ANN forward response models for full-depth asphalt pavement (FDP), conventional flexible pavement (CFP) and full-depth asphalt pavement on lime stabilized soils (FDP-LSS) are used in this study

(Pekcan 2010). While developing the ANN models, researcher used FEM based pavement analysis and design software; ILLI-PAVE which takes into account the nonlinear elasticity of pavement geomaterials. Another objective is to combine ANN forward response models with a search method in order develop a complete backcalculation algorithm. A newly developed metaheuristic search technique; Gravitational Search Algorithm (GSA) is performed as a search routine to provide input values to the ANN forward models. As a consequence of this, it is aimed to propose a backcalculation algorithm named as GSA-ANN. The third objective is to evaluate performance of the proposed backcalculation algorithm. For this purpose, used ANN models and developed GSA-ANN algorithm are performed for the data obtained from different sources. The pavement sections which are simulated synthetically by ILLI-PAVE computer program are utilized to assess the ANN and GSA-ANN. However, it is not sufficient to validate the backcalculation model using only synthetically derived data. In order to gather more reliable solutions, field data extracted from the United States FHWA's Long-Term Pavement Performance (LTPP) Program which is most comprehensive research program performed ever are used for further verification (Quintus and Simpson 2002). Another goal of this study is to prove the validity of proposed algorithm by using two well-known conventional backcalculation software: EVERCALC and MODULUS for comparison purposes. Moreover, in order to assess the performance of GSA search method, another optimization technique which is Simple Genetic Algorithm (SGA) is combined with the same ANN models and obtained algorithm is performed to solve the same test data sets with GSA-ANN algorithm. By this way, solutions of GSA and SGA based algorithms are compared to prove the effectiveness of the GSA approach.

At the end of this study, fast, reliable and validated backcalculation algorithm namely GSA-ANN is intended to be developed which provide decision makers opportunity to make real time assessment of stiffness properties for in-service pavements which can be utilized for rehabilitation and maintenance operations.

1.3 Thesis Organization

This thesis is composed of five chapters that provide information about the topics covered in the study. In Chapter 2, an extensive literature review is presented to introduce the issues about pavement backcalculation. For this purpose, flexible type pavement structures and characterization of geomaterials are described prior to backcalculation problem. The main components of pavement backcalculation namely FWD measurements, forward modelling aspects of pavement sections and utilized traditional and nontraditional backcalculation methods are expressed respectively to provide a comprehensive background and better understanding to the current study. Chapter 3 introduces the development of proposed GSA-ANN algorithm to evaluate stiffness related layer properties of different types of pavements. Development stages of employed ANN models are provided by starting in all aspects of ILLI-PAVE analysis steps of which includes FWD simulation, meshing of analyses domain, and material characterizations. After that, combining GSA method and ANN models to form the entire algorithm is presented. In Chapter 4, validation and performance evaluation of the proposed algorithm for using both synthetically generated and field deflection data are presented. Also, comparison of backcalculation results with conventional backcalculation softwares: EVERCAL and MODULUS are made using field measurements. Apart from these, another search algorithm namely SGA, is also performed for synthetic and field data and then results are presented in Chapter 4. Finally, a summary of the study and conclusions together with recommendations for future work are included in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Every pavement structure is subjected to traffic loading and environmental effects during its lifetime and as a normal consequence of these conditions, deterioration of structural layers occurs with different forms having different characteristics such as cracking, rutting and swelling etc. Considering the great deal of money funded to construction of highways, transportation agencies need to determine proper strategies to make provisions against the deterioration processes with maintenance and rehabilitation operations like sealing and overlay constructions. It is an essential issue to derive information from in-service pavements without causing any permanent damage to the structural layers. For this reason, non-destructive testing methods become more preferable than destructive ones. Using the non-destructive test results, especially deflection measurements, stiffness related pavement properties can be determined and this process is called as backcalculation which enables significant information about structural capacity of pavement sections. Methodologies utilized for backcalculation influence the accuracy of calculated stiffness properties, and therefore several studies have been conducted on this topic to develop better approaches. This literature review focuses on previously accomplished practices and current studies on pavement layer backcalculation subject. First of all, backcalculation problem is summarized, and then flexible pavement types and non-destructive testing of pavements are reviewed. After that, a pavement information database of LTPP

Program which includes the most comprehensive information about pavements of USA and Canada are explained. At the end, forward modelling of pavements and techniques employed for backcalculation are described, respectively.

2.2 Backcalculation Problem

Problems can be classified into two categories as forward and inverse types. In forward problems, outputs of a system can be calculated through the known input properties. Unlike the forward problems, input properties and system parameters can be estimated through the measured data in inverse type problems (See Figure 2). Backcalculation of pavement layer properties is a type of inverse problem of which estimates the stiffness related layer properties by using deflection measurements of FWD tests. Determined moduli for layers comprising of different materials and subgrade soils can give valuable information about the structural capacity of the entire pavement structure. Using these data, decision makers on pavement engineering have opportunity to evaluate structures if they need any rehabilitation or maintenance operation in an effort to sustain required performance of the pavement for future traffic and environmental conditions. A typical pavement layer backcalculation operation is composed of two different parts. First one is the forward response modelling of the pavements which calculates surface deflections utilizing either simple or complex equations. In forward response modelling, pavement section whose layer properties to be backcalculated is simulated and deflections under FWD loading are calculated through the use of assumed layer properties. After that, computed deflections and measured deflections are compared and according to difference between them, new layer moduli are estimated by a search method which is another essential part of backcalculation operations. Updated layer moduli values by the search method are given as new inputs of the forward response engine to calculate new deflections and this process continues until reaching the termination criteria which may be a tolerable error rate between deflections or maximum number of iterations. At the end, the layer properties of pavement section which produce most approximate deflection values to the field ones are reported as the solution of the backcalculation of the problem. A flowchart summarizing the backcalculation processes is presented in Figure 3**.** As it is an iterative process, all the steps are handled through the instrument of computer programs. Accuracy of the interpreted layer moduli depends on the methods utilized in backcalculation processes. Choosing the method for both forward calculation of surface deflections and searching new layer moduli play crucial roles in obtaining realistic and accurate results. Layered elastic theory and FEM based pavement response analysis are the most popular forward calculation approaches. First method is the simplest one for modelling the pavement due to several assumptions considered for material and layer conditions. FEM is the second approach employed as forward response engine which is more capable than layered elastic theory in terms of modelling pavement layers realistically. In this approach, deflections are calculated with less assumptions but more computational effort because of complex equations that FEM makes use of. Researchers employ several optimization methods for searching and updating the input stiffness properties of forward engine for successive iterations. Each search method has advantages and disadvantages according to applied problem and there is no algorithm which perfectly works for all types of problems. This makes backcalculation problems open to be improved in term of the accuracy of interpreted layers moduli by changing the search method for forward analysis.

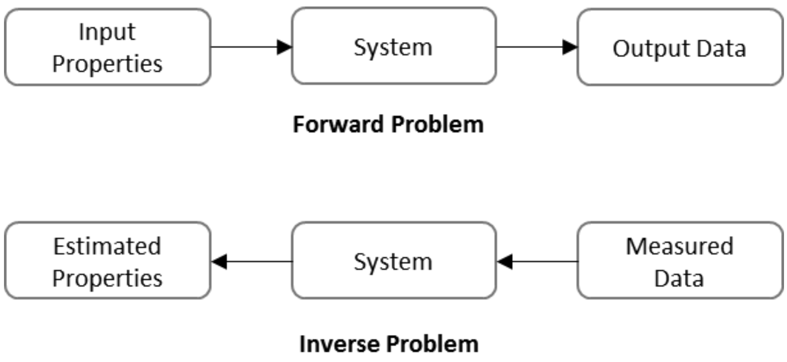


Figure 2 Forward and Inverse Problems

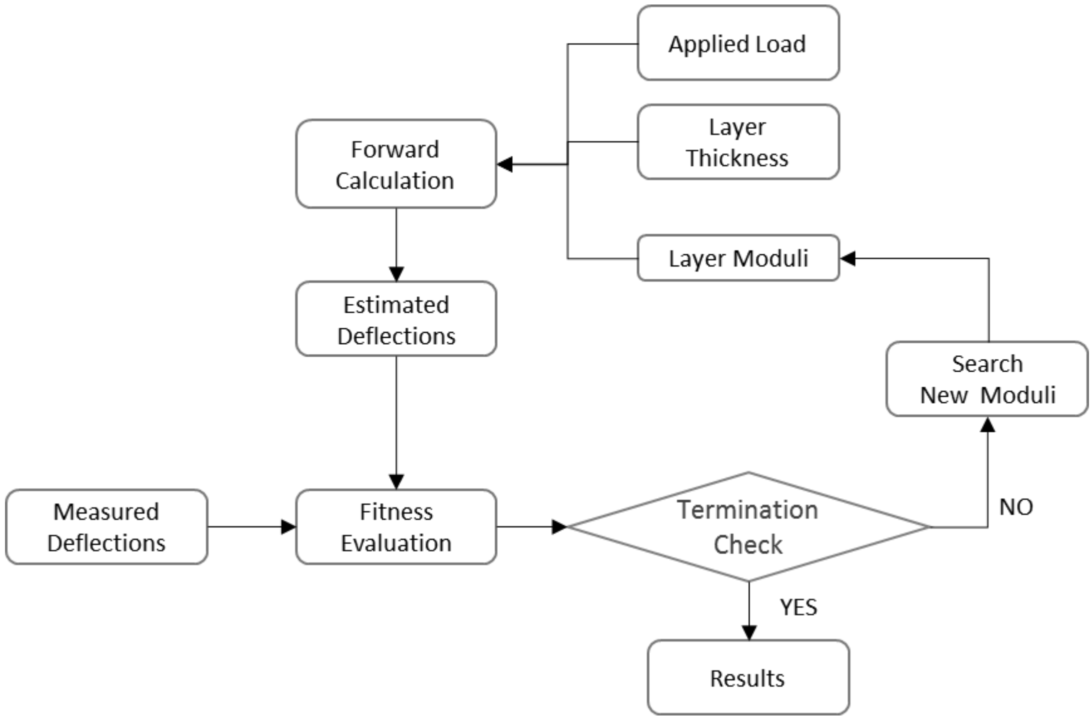


Figure 3 A Typical Backcalculation Scheme

2.3 Flexible Pavements

Regarding the construction materials used for covering the surface, pavements can be classified into three groups as flexible, rigid and composite. Flexible pavement term tends to be used to refer the usage of bituminous or asphalt materials in structural layers of pavements. The word "flexible" comes from the flexing behavior of asphalt layers under traffic loading. In contrast to this, rigid pavements composed of Portland Cement Concrete (PCC) are stiffer than flexible ones due to the higher modulus of elasticity of concrete. Stress distributions for both flexible and rigid pavement are presented in Figure 4. Composite pavements are the structures that are constructed by making using of Hot Mixed Asphalt (HMA) and PCC together. Among the pavement types, flexible pavements have the widest applications through the highways in all over the world. Regardless of materials constituted within the layer, function of a pavement is to transmit the traffic loading to the natural soil substantially. For this purpose, pavements are created with several number of layers of those takes the load and then spread out to the following layer below. Therefore, the pressure induced by the applied load is lessened while moving from the top layer which exposed to much pressure, to the subgrade. A typical flexible pavement section is composed of superimposed courses of surface, base and subbase laying over the natural subgrade. In surface layer asphalt materials are employed while base and subgrade layers are granular and fine grained geomaterials. Constructed pavement layers should have enough thicknesses for load transferring while enabling safe and comfortable driving with adequate smoothness and friction of its surface. At the same time, surface and base layers must be impervious to protect beneath layers against water movement throughout the layers (Karagöz 2004).

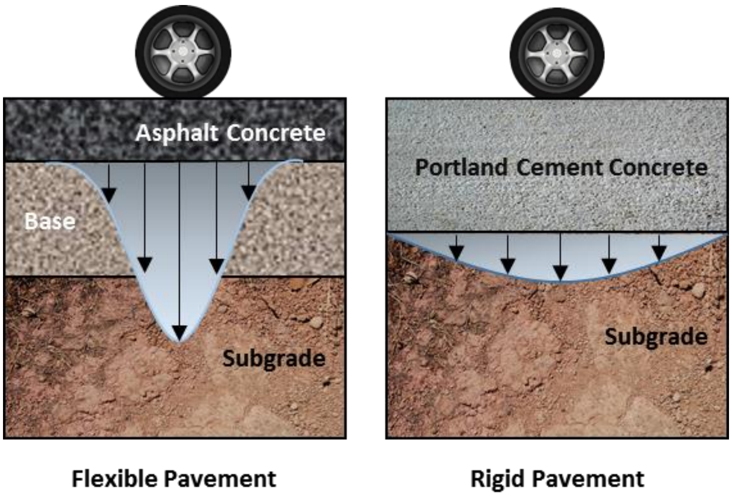


Figure 4 Stress Distributions for Rigid and Flexible Pavements

The underlying philosophy of the placement order of pavement layers is to construct sustainable and solid section to make sure that entire structure can resist to applied loads. For this reason, HMA materials which have greatest bearing capacity are placed on the top of the structural layers to withstand the highest pressure values occurred on the pavement surface. Materials having less load bearing capacity are located beneath the asphalt layers where the impacts are relatively small.

There are some situations faced in design and construction stage of highways. These are lack of local materials, low strength of natural soils, excessive traffic loadings or economical issues that are needed to be taken into account for proper design operations. Pavements have to accomplish their expected functions and performance in all these cases. In order to do this, full-depth asphalt pavement (FDP) and conventional flexible pavement (CFP) concepts are emerged as two different flexible pavement types. FDP is generally chosen to build while excessive vehicle traffic is expected during the service time of the road or in the case of lack of enough base materials. In this approach, one or more asphalt layers are directly constructed over subgrade that may be improved with stabilization using lime or cement whether the subgrade is weak. This type of full-depth asphalt pavement constructed over lime stabilized soil is also within the scope of this study and abbreviated as FDP-LSS. Since HMA materials are petroleum products, construction of FDPs is quite expensive. Therefore, amount of asphalt may be limited in some cases to lower the overall project costs. For instance, a relatively tiny asphalt layer is constructed as top layer where the stress intensity is high and below this course, base/subbase layers constituted with granular materials which are cheap compared to bituminous materials are built. This type of structure is called as CFP which can be preferred to construct as a consequence of availability of local materials, considered project costs and lack of heavy traffic loading (Huang 2003). Typical cross sections for FDP and CFP are shown in Figure 5.

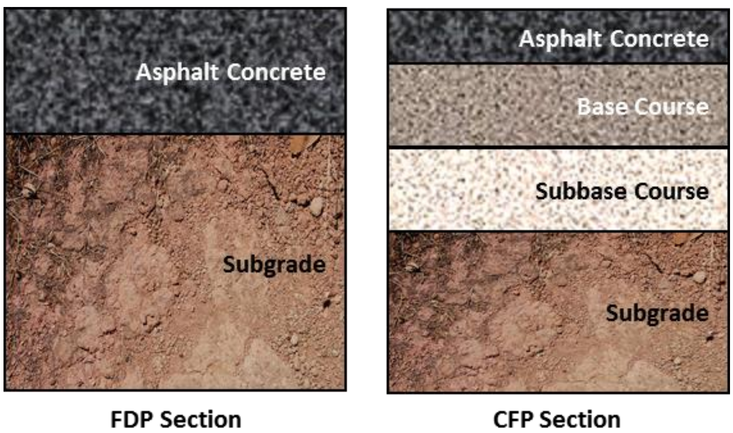


Figure 5 Typical Cross Section for FDP and CFP

Pavement responses associated with loading states play a major role in mechanistic-empirical methods to estimate the distress of structural layers of in-service pavement with the help of field data. Tensile strain occurred at the bottom of asphalt layer is first time recommended to use as a failure criteria in order to prevent against to fatigue cracking by Saal and Pell (1960). Other critical response; vertical compressive strain on the subgrade is related with the rutting failure mechanisms (Kerkhoven and Dormen 1953; Huang 2003). In Figure 6, critical responses for a layered structure is presented. Where $\mathcal{E}_{AC}$ refers to the critical tensile strain occurred beneath the asphalt layer, $\mathcal{E}_{SG}$ is the critical compressive strain occurred above the subgrade and σ_{dev} is the deviator stress on the subgrade.

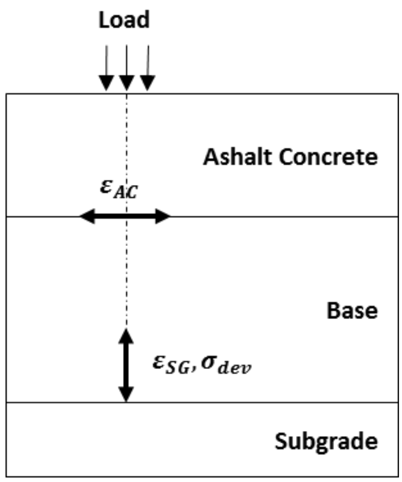


Figure 6 Critical Pavement Responses Occurred in a Layered Structure

2.4 Non-destructive Testing of Pavements

Assessment of pavement structures is conducted to check whether the highway can carry the future traffic loading while being subjected to environmental conditions over the time. As a result of successful evaluation of pavements, effective rehabilitation and maintenance strategies can be developed. By this way, reasons of failure in structural components and deteriorations can be addressed and necessary operations are employed to prevent the overall structure from distress. For that purpose, it is essential to perform in-situ tests which examine the layer properties. Coring is an approach of testing which makes holes on the pavement sections that need to be filled with material. Even if it is repaired, considering number of coring along the roads and time required for taking samples, implementation of such destructive techniques may not be feasible. Thus, NDTs become more popular among the highway community in the way of providing structural integrity and their fast and easy applications. Non-destructive tests examine the pavement structures in two different manners, deflection basin and wave propagation which are occurred in response to imposed loading states on pavement surface.

Spectral analysis of surface waves (SASW) is a geophysical NDT method of which evaluates stiffness related layer properties and thicknesses of pavements (Nazarian and Stokoe 1984). In this method, a dynamic source which is able to generate surface waves in different wavelengths applies load on the pavement. Occurred stress waves are recorded by means of the successively located at least two geophones. Using the calculated travel time between geophones and phase differences, effective-velocity dispersion curve is developed which can be used for determining layer moduli and layer thicknesses (Li 2008; Nazarian and Stokoe 1989).

Ground penetrating radar (GPR) is another geophysical method which utilizes the radio waves to evaluate pavement structures especially to find layer thicknesses. It can also detect the discontinuities within the layers such as voids and cracks. In this approach, high-frequency radio waves are transmitted into the pavement layers and then they are reflected back to the receiver of GPR. Due to the material characteristics of each individual subsurface layers, signals are reflected in different energy levels. By combining these signals, section profile can be visualized and then, thickness of layers can be determined (Loizos and Plati 2007; Paker et al. 1999). Another popular technique based on seismic wave propagation is seismic pavement analyzer (SPA). Just as SASW and GPR devices, SPA is also used for determining stiffness and thickness of layers in addition to detecting cracks. The device has pneumatic hammers having different size that creates different wavelengths when they imposed vibration on the pavement. Sensors located at certain distances away from the hammers measure these vibrations and mechanical properties in addition to thickness of layers can be determined by manipulating received vibrations in each wavelength (Nazarian et al. 1993).

Use of deflection measurement for the purpose evaluating structural capacity of pavement is another non-destructive data gathering approach. Just as involved in this study, deflection basins are used for backcalculating stiffness related pavement layer properties. Considering loading type, deflection basin measurements can be classified into three main groups: static, steady-state vibration, and impulsive loads.

As a simple and easy approach, static load or in other word slowly moving load cannot model actual loadings applied on pavements. Another limitation of static type of applications is to find fixed reference location during deflections measurements. For these reasons, using such deflections in mechanistic design methods may not be possible without empirical correlations. In this topic, the Benkelman beam is the most known deflection measuring device. Basically, the beam is composed of measurement probe connected to a supporting beam and deflections are read from a dial gauge located on the supporting beam as shown in Figure 7. For this test, a vehicle which can apply 80 kN single axle load is employed as a loading source and operators place the end of the measurement probe between the rear dual tires. While the vehicle moving away slowly from the Benkelman beam, rebound deflection is measured with dial gauge. After the test is applied for several preselected locations deflection basin can be generated. There are also measurement devices working with the same principles which are California travelling deflectometer and LaCroix Deflectometer developed in USA and France, respectively (Huang 2003).

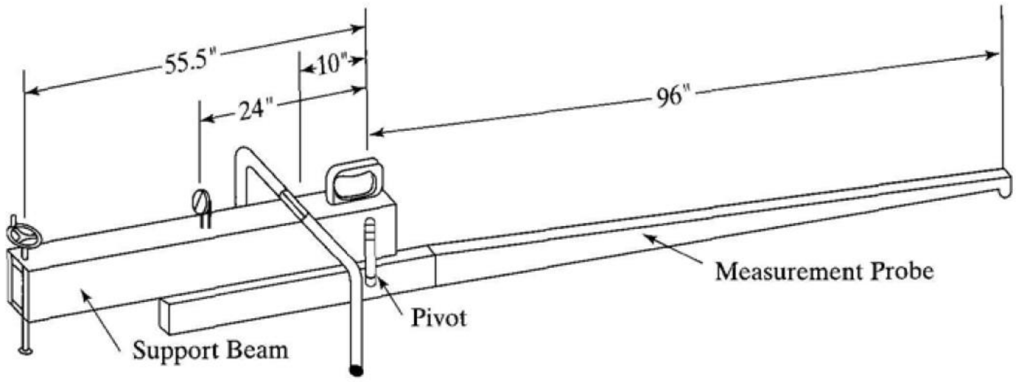


Figure 7 Benkelman Beam (Huang 2003)

Steady-state vibrational loading is the second type of deflection measurement approach. Deflections are produced as a result of superposition of static load and sinusoidal dynamic force. In order to measure the deflections, velocity sensors are used by locating the first one under the load application point and the others are placed with designated intervals such as 0.3 m. Basic advantages of steady-state loading over static loading are the ability of detecting inconsistent deflection measurement and no need a reference point for the measurement. However, there are also drawbacks of such devices that steady-state vibration does not simulate the real-like traffic loadings and in case of using large static loads, behavior of stress sensitive materials can be affected (Huang 2003). Dynaflect is a popular device applying steady-state vibrational loading which can exert static load within a narrow range while applying a constant dynamics force. Road rater is another testing device in this dynamic loading category. In contrast to Dynaflect, it can apply both static and dynamic loads within a wide range of loads and frequencies. The rolling dynamic deflectometer (RDD) is the newest one among the other vibrational devices. Instead of obtaining deflection measurements station by station, RDD determines them continuously (Sveinsdóttir 2011).

Impulsive load based deflection measuring technique is the last but not the least one. By dropping a weight over a loading plate on pavement surface, deflection are generated and sensed by geophones arranged in designated intervals. The impulse force emerged in response to applied load can be varied by changing the drop height and amount of weight. The major advantage of impulsive load based method is to simulate actual moving load in terms of loading duration and its magnitude (Huang 2003). For this reason, impulse loading devices have been performed extensively by pavement agencies for more than three decades (Alavi et al. 2008). Falling weight deflectometer falls into this category that has several types which are elaborated in the following subsection.

2.4.1. Falling Weight Deflectometer

In transportation community, falling weight deflectometers have been used for the evaluation of structural capacity of highways and airport runways. Flexible and rigid pavement can be assessed with these devices in design, maintenance and rehabilitation operations. Owing to the capability of FWDs to simulate actual traffic conditions, they have been performed for more than three decades (Alavi et al. 2008). For this reason, FWDs are widely accepted and used in all around world and there are several manufacturers producing them such as KUAB, Dynatest, Carl Bro and JILS. The device is mounted on trailer or a test vehicle as shown in Figure 8.

Figure 8 Trailer Mounted FWD Device (“Cornell Local Roads Program” 2005)

A typical FWD device is comprised of two essential components that are loading and measurement mechanisms. Loading system includes the falling weight, loading plate and corresponding controlling apparatus and the measurement system includes geophones and associated data acquisition systems (Doré and Zubeck 2009). An FWD works by dropping a falling weight and measuring the corresponding deflections at designated radial distances. Using a spring mass system, falling weight is released from a certain height which can be adjusted according to desired impulse level to a circular loading plate which has diameters of 305 or 457 mm (12 or 18 in.). The resulting applied force can be changed in the rage of 7 to 240 kN with respect to producer and model of the device (Alavi et al. 2008). The duration of the applied load is approximately 30 ms which is about the same load application duration of a travelling vehicle at 64 to 80 kmh (40 to 50 mph) (Ullidtz and Stubstad 1985). As a result of FWD loading, haversine shaped pulse is emerged as illustrated in Figure 9.

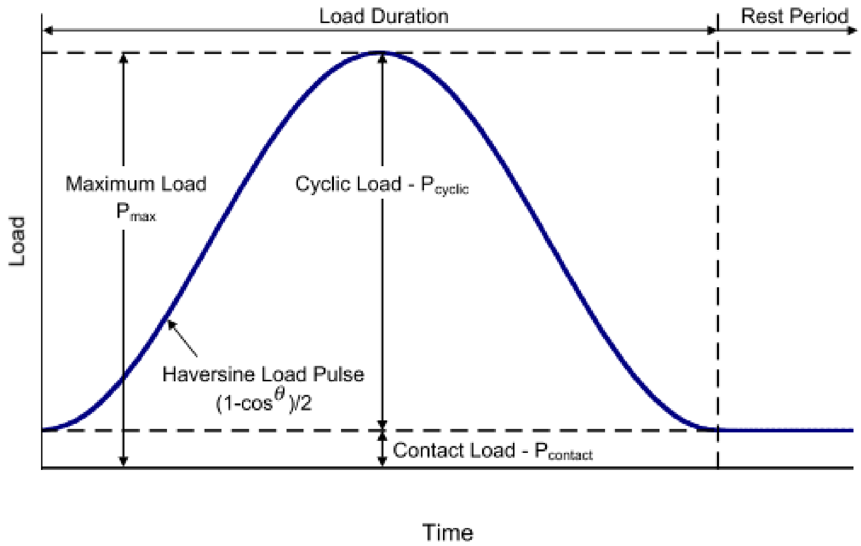


Figure 9 Haversine Shaped Loading (NCHRP 2004)

In order to ensure the uniformity of transmitted load and shape of the occurred pulse, cylindrical rubber buffer is mounted under the falling weight system (Schmalzer 2006). As a consequence of the applied load, occurred surface deflections are measured by means of a set of sensors or geophones located at designated radial distances. Deflection basin is generated by using the peak deflections measured in each sensor. The number of sensors differs according to configuration of the device that may change 7 to 15 sensors. In each different array of sensors, the first one is located at the center of loading plate and other ones are placed with increasing radial distances by considering first sensor as reference point. Precise sensor distances for seven-sensored FWDs are 0, 203, 305, 457, 610, 914 and 1,524 mm (0, 8, 12, 18, 24, 36 and 60 in.). A typical test configuration formed with seven geophones with corresponding deflection basin is illustrated in Figure 10.

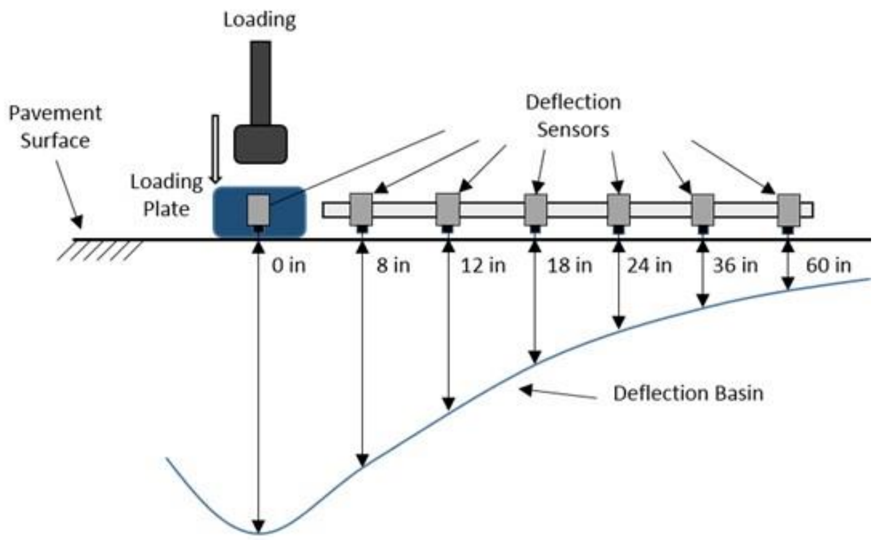


Figure 10 FWD Setup and Deflection Basin

Obtained deflection basins can be used for different purposes. First one is to calculate deflection basin indices and normalized basin area by the way of simple mathematical operations. These calculated values are the basic indicators of mechanical properties of overall pavement section and individual structural layers (Doré and Zubeck 2009). In another use of deflection basin, existence of a stiff pavement can be identified by utilizing regression equations for where the zero deflection occurs (Rohde and Scullion 1990).

There are three different types of deflectometers: light weight deflectometer (LWD), heavy weight deflectometer (HWD) and rolling weight deflectometer (RWD). LWD is the portable version of FWD which can be used by one operator and the device is generally implemented to determine the base and subgrade stiffness properties during construction stages. Other deflectometer type is HWD which is employed when greater loads are needed to be replicated. It is primarily utilized for evaluation of airport runways. Unlike LWD and HWD devices, RWD can collect continuous deflection data instead of gathering from separate road portions. So that it provides faster applications than FWD (Huang 2003).

Loading, climate and pavement conditions can lead to variations in deflection measurements. While conducting non-destructive testing, they should be taken into account. The duration and magnitude of applied loads have major effects on deflection basins. In NDT applications, it is desired to simulate real-like vertical traffic loadings so that the amount of load and its application duration should be well selected. Because of the stress sensitive nature of some pavement geomaterials, applied loads may cause abnormal deflections so that nonlinear material behavior should be considered in analyses stages. Temperature and moisture also affect the stiffness properties of layers. In high temperatures, stiffness properties of hot mixed asphalt layers decrease and in connection with this deflections increase. For this reason, pavement deflection profile may change regarding the seasons. For example, in winter seasons, pavements are the strongest so that deflections are smaller than the other seasons. When the season of spring starts, melting frost water leave the structure that may cause deflections to decrease immediately. Cracks and rutting distresses are another factors influence the deflection measurements that need to be taken into account as well (Huang 2003; Papagiannakis and Masad 2008).

Deflection measurements play a key role in mechanistic-empirical pavement design and rehabilitation strategies. FWD is considered as an effective and robust assessment tool by pavement agencies and researchers for more than three decades. It has been widely applied in pavement backcalculation studies in order to acquire deflection data which are used for estimating stiffness related properties especially pavement layer moduli (Abdallah and Nazarian 2009; Asli et al. 2012; Ceylan and Gopalakrishnan 2006; Ceylan et al. 2005; Goktepe et al. 2006; Gopalakrishnan et al. 2009, 2013; Hu et al. 2007; Khaitan and Gopalakrishnan 2010; Kim and Im 2005; Lav et al. 2009).

2.5 Long-Term Pavement Performance Program

Considering the great deal of money funded in constructing and repairing of highways, transportation agencies need to determine proper strategies to use the investments effectively. As it is stated in Chapter 1, USA has the largest highway network in the world and the country makes great amount of investments for building, maintaining and rehabilitation operations. The Long-Term Pavement Performance (LTPP) Program was developed in mid-eighties within the scope of Strategic Highway Research Program (SHRP) in order to collect pavement performance data in all around the USA and Canada. The overall objective of LTPP program is to identify how and why pavements performs as they do which may lead to improve new pavement design, maintenance and rehabilitation strategies that can extend pavement life. (Transportation Research Board 2001). The core functions of LTPP program can be divided into four main categories: data collection and management, data analysis, product development and communications, respectively. The performance data are gathered from more than 2,400 different pavement test sections for HMA, PCC and composite pavements through the use of different test methods. The LTPP database is composed of several modules including data a broad array of topics such as inventory, traffic, climate, monitoring and material testing, maintenance and rehabilitation etc. For every test section, FWD tests are conducted to measure the deflections periodically in addition to distress observations and pavement surface profiles investigated with profilometers. Observed test sections are divided into two main categories; General Pavement Studies (GPS) and Specific Pavement Studies (SPS). Common types of in-use pavements are included in GPS category and SPS test sections contains the pavements constructed specifically to examine sections against different factors. There are also a number of sites in both GPS and SPS sections which are examined in terms of climatic conditions and the studies are conducted as a part of Seasonal Monitoring Program (SMP). FWD tests are applied periodically that GPS section are monitored in five-year periods while SPS are in two-year periods. On the other hand, SMP test sites are investigated every month in one or two year periods (Quintus and Simpson 2002). To achieve the LTPP’s objectives on understanding the pavement’s behavior, materials are explored in detail and a facility named as material reference library (MRL) is established to store the asphalt, Portland cement and aggregate samples used in general and specific pavement studies. In material testing processes, flexible pavement samples are evaluated for several aspects of engineering properties such as asphalt content, specific gravity of the surface layer and resilient modulus, moisture/density relations and classification of granular materials in base layers. Another core function of LTPP program is to convert performance data to useful information through several analyses. The overall aims of these analyses are to understand how they perform as they do, to control the quality of data measured from the field and to verify, improve or develop design and rehabilitation approaches, respectively. Characterization of traffic and materials in addition to evaluation of environmental effects and pavement response data give valuable insight on existing pavement and lead to proper strategy selection for design and repairing operations. As the results of LTPP analyses, significant products including methods, guidelines and procedures are emerged together with the softwares such as LTPPBind and rigid pavement design software. As a communication function of LTPP, the data are provided to accessible through the databases. InfoPave is a web interface of where the whole collected LTPP data are readily available on internet that enables the easy access for the people who deals with pavements in all around the world. (Quintus and Simpson 2002; Transportation Research Board 2001, 2009).

2.6 Forward Calculation of Deflection Basin

Forward calculation of deflection basin is the most critical step of pavement layer backcalculation operations. Using geometrical and mechanical properties of layers as input properties of forward calculation software, pavement responses such as stress, strain and deflections can be computed. In backcalculation, it is essential to simulate test section in the way of presenting real-like surface deflections under actual traffic and environmental conditions. There are three different commonly employed methods as forward response modelling of pavements which are method of equivalent thickness (MET), multi-layered elastic theory and finite element method (FEM) explained in detail through the following sections, respectively.

2.6.1 Method of Equivalent Thickness

Method of equivalent thickness bases on the theory proposed by Boussinesq (1885). Through the use of his theory, stresses, strains and deflections occurred in a layer under subjected point load can easily be determined. While calculating the responses, the theory assumes that pavement consists of homogenous and isotropic layers which is on semi-infinite elastic space. Considered point load in the theory does not reflect the actual loading condition of a wheel so that this concentrated point load are integrated to a circular loaded area. Axisymmetric stress state due to this circular loading is depicted in Figure 11

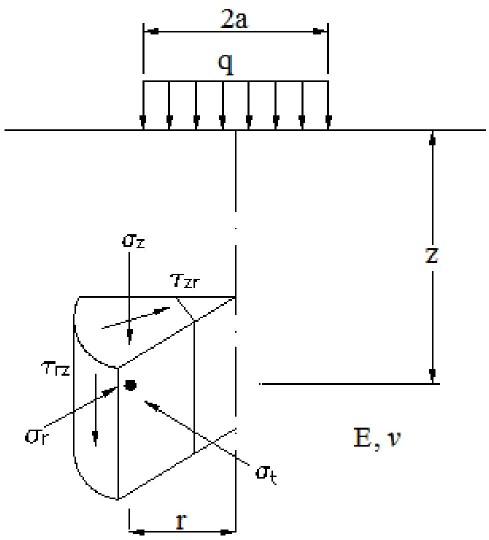


Figure 11 Axisymmetric Stress Sate Due to Circular Loading (Huang 2003)

Uniformly distributed load applied to the pavement surface and occurred stress, strain and deflections are defined with the following equations:

$$\sigma_z = q\left[1 - \frac{z^3}{(a^2+z^2)^{1.5}}\right] \tag{1}$$

$$\sigma_r = \frac{q}{2}\left[1 + 2\upsilon - \frac{2(1+\upsilon)z}{(a^2+z^2)^{0.5}} + \frac{z^3}{(a^2+z^2)^{1.5}}\right] \tag{2}$$

$$\epsilon_z = \frac{(1+\upsilon)q}{E}\left[1 - 2\upsilon + \frac{2\upsilon z}{(a^2+z^2)^{0.5}} - \frac{z^3}{(a^2+z^2)^{1.5}}\right] \tag{3}$$

$$\epsilon_r = \frac{(1+\upsilon)q}{2E}\left[1 - 2\upsilon - \frac{2(1-\upsilon)z}{(a^2+z^2)^{0.5}} + \frac{z^3}{(a^2+z^2)^{1.5}}\right] \tag{4}$$

$$\omega = \frac{(1+\upsilon)qa}{2E}\left\{\frac{a}{(a^2+z^2)^{0.5}} + \frac{1-2\upsilon}{a}\left[(a^2+z^2)^{0.5} - z\right]\right\} \tag{5}$$

Where, $\sigma_z, \sigma_r, \varepsilon_z\ and\ \varepsilon_r$ refer that vertical stress, radial stress, vertical strain and radial strain, respectively. On the other hand, q is the uniform pressure, a is radius of the circular area, z is depth from the surface, v is Poisson's ratio, E is modulus of elasticity and w is vertical deflection.

Since the Boussinesq's equations are only applicable for single isotropic and homogenous layer, the theory itself is insufficient to simulate in practice layered structures. Hence, there was a need of a method which is valid for multi-layered pavement structures composing of different materials. Odemark (1943) developed method of equivalent thickness which transforms multi-layered structures including layers with different thicknesses and elastic moduli into an equivalent structure of those all the layers have the same moduli but different thicknesses. Equivalent thickness of each layer is defines with the following equation:

$$h_e = fh_1\left[\frac{E_1}{E_2}\left(\frac{1-\upsilon_2^2}{1-\upsilon_1^2}\right)\right]^{1/3} \tag{6}$$

Where, h_e refers to the equivalent thickness, h_1 is the thickness of first layer and $E_1, E_2, \upsilon_1\ and\ \upsilon_2$ refer to elastic modulus and Poisson's ratio for first and second layers, respectively. f is the correction factor enables better approximation to the layered elastic theory and it is related with number of layers and corresponding thicknesses, modular ratios and Poisson's ratios. By applying Odemark's method, all the layers are transformed successively into an equivalent system regarding the same modulus. By this way, the system becomes suitable for application of Boussinesq's equations to calculate deflection basins under imposed loading on multi-layered pavement structures.

2.6.2 Multi-layered Elastic Theory

A typical flexible pavement has multi-layered structure that the layers composed of strong materials are located on top and the layers which are composed of relatively weaker materials are placed beneath them. Analytical solutions for two-layer structures are proposed first time by Burmister (1943). After a few years, he advanced the theory to be applicable on three-layer structures. Today, n-layer (multi-layered) structures can be analyzed with this approach as an extended version of Burmister's theory presented by Schiffman (1962). A schematic of a multi-layered system is illustrated in Figure 12.

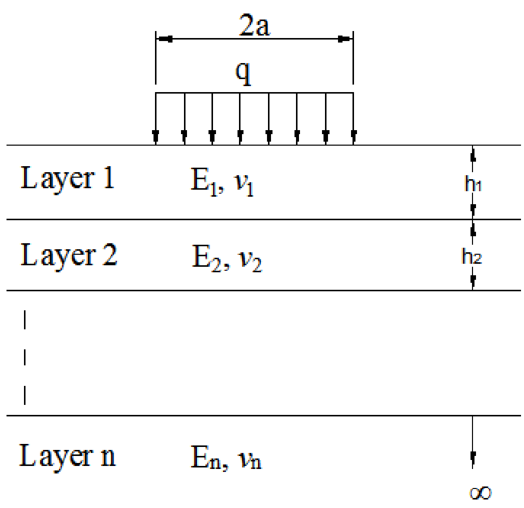


Figure 12 Multi-layered Pavement Structure Subjected to a Circular Loading (Huang 2003)

Stress, strain and displacement responses in a multi-layered system can be calculated through the multi-layered elastic theory by making basic assumptions which are listed below: (Huang 2003; Yoder and Witczak 1975).

- Each pavement structure is composed of several layers of materials which are homogenous, isotropic and linearly elastic.
- Layers are defined with two mechanical properties, elastic modulus, E and Poisson's ratio, v.
- Each layer is infinite in lateral directions and all the layers except the undermost have a finite thickness, h.
- Full friction exists between the layers throughout each interface.
- Circular load with uniform pressure is imposed to the pavement surface.
- There is no shearing force on the surface.

Responses of a multi-layered system are obtained by solving a boundary value problem. For this purpose fourth order differential equation is solved for the boundary conditions of pavement in question. The stress function of each layer is defined with φ and the following equation need to be satisfied.

$$\nabla^4\varphi = 0 \tag{7}$$

In an axisymmetric problem, the equation will be presented as follows:

$$\nabla^4 = \left(\frac{\partial^2}{\partial r^2} + \frac{1}{r}\,\frac{\partial}{\partial r} + \frac{\partial^2}{\partial z^2}\right)\left(\frac{\partial^2}{\partial r^2} + \frac{1}{r}\,\frac{\partial}{\partial r} + \frac{\partial^2}{\partial_z^2}\right) \tag{8}$$

The stress function φ is solved by satisfying the boundary conditions and the corresponding stress and displacement responses can be calculated by the following equations:

$$u = \frac{1+\upsilon}{E} \frac{\partial^2 \phi}{\partial z \partial r} \tag{9}$$

$$w = \frac{1+\upsilon}{E} \left[2(1-\upsilon)\nabla^2 \phi - \frac{\partial^2 \phi}{\partial z^2} \right] \tag{10}$$

$$\sigma_z = \frac{\partial}{\partial z} \left[(2-\upsilon)\nabla^2 \phi - \frac{\partial^2 \phi}{\partial z^2} \right] \tag{11}$$

$$\sigma_t = \frac{\partial}{\partial z} \left(\upsilon \nabla^2 \phi - \frac{1}{r} \frac{\partial \phi}{\partial z} \right) \tag{12}$$

$$\tau_{rz} = \frac{\partial}{\partial r} \left[(1-\upsilon)\nabla^2 \phi - \frac{\partial^2 \phi}{\partial z^2} \right] \tag{13}$$

$$\sigma_r = \frac{\partial}{\partial z} \left(\upsilon \nabla^2 \phi - \frac{\partial^2 \phi}{\partial r^2} \right) \tag{14}$$

Where *w* is the vertical deflection that can be used in backcalculation.

In structural analysis of pavements, several computer programs utilize the multi-layered elastic theory. CHEVRON is the first pavement analysis software developed by Warren and Dieckmann (1963). Hwang and Witczak (1979) improved the CHEVRON and named the new software DAMA. This program takes into account the stress dependent nature of unbound granular materials and also it is capable of calculating pavement responses up to five-layer structures. Another multi-layered elastic theory based program is BISAR developed by De Jong, et al. (1973) in Shell Company and the software can handle multiple loading conditions. In 1986, ELSYM5 program which can analyze five-layer pavements under multiple loads was developed at the University of California by Kopperman et al. Later on, Van Cauwelaert, et al. (1989) developed the program WESLEA in order to calculate stress, strain and displacements of maximum five-layer structures in varying interface frictions under up to twenty wheel loads. The last example of softwares that uses the multi-layered elastic theory is KENLAYER (Huang 1993). Among these computer programs, KENLAYER is the most capable one in modelling pavement responses realistically that is because of incorporating nonlinear elastic and viscoelastic behavior of materials in the analyses. These analysis softwares have been used as a forward response engine in backcalculation softwares for decades.

Although extensive usage of multi-layered elastic theory in calculating pavement responses, the theory has several drawbacks which affect the accuracy of results. These limitations arise from the considered assumptions in the theory. As mentioned above, all the layers are regarded as linearly elastic, in fact they are not. Asphalt concrete is a mixture that presents viscoelastic behavior, so that its stiffness properties is associated with time and temperature. And also base/subbase and subgrade geomaterials show nonlinear behavior that stiffness related properties changes according to stress states. On the other hand, the theory assumes that all the materials within the layers are isotropic and homogenous which are not the real cases for the materials (Tutumluer and Thompson 1997). The loading pattern taken into account in the theory is not perfectly circular and uniformly distributed which is another limitation of the method for reaching the actual pavement responses. Most of these difficulties can be handled by the use of another approach which finite element method.

2.6.3 Finite Element Method

Many engineering problems having complex geometries can be expressed with partial differential equations of which are not easy to be solved using analytical methods. Numerical methods such as FEM enable approximate solutions to these equations for the problems including complex geometrical and material properties. Due to these abilities, finite element (FE) analysis approach have been commonly used in structural analysis of pavements. Through the advancing computer technology, FEM has been adapted for solving the problems of different engineering areas. For example, the method can be employed for conducting stress and thermal analyses of mechanical products such as valves, pressure vessels, automotive engines and aircrafts under the umbrella of mechanical engineering. Almost every civil engineering structures like dams, buildings and tunnels can be analyzed using FEM based softwares (Fish and Belytschko 2007). Due to the versatility of FEM, it can be applied in other areas including complex problems over the years.

The main idea behind the FEM is to solve governing equation of a complex structure in a continuous domain by dividing into smaller units called finite elements. So that interconnection of each finite element presents entire structure as shown in Figure 13. The method develops the formulation for the approximate solution of each element and then they are assembled to obtain the general solution of the whole structure. FEM provides approximate and simplified solutions to the structural problems however, when the number of finite elements increase, problems become computationally intensive to be solved manually. So that it is essential to employ computers in finite element analysis. At present, there are many general and specific purpose FEM based structural analysis softwares which are well-accepted in most of the engineering branches.

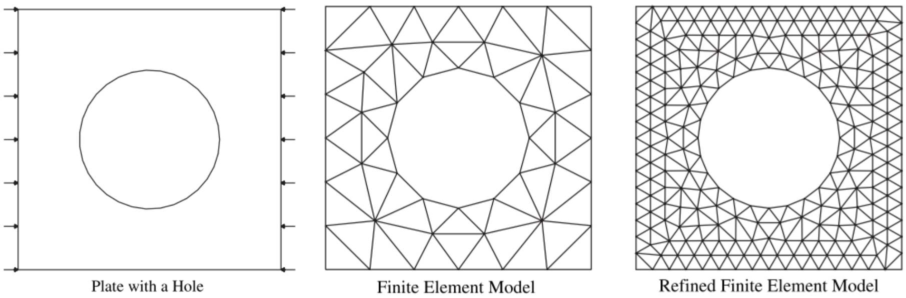


Figure 13 Finite Element Representation of a Body (Fish and Belytschko 2007)

FEM can be also utilized for structural analysis of pavements. In contrast to the multi-layered elastic theory, it can handle complicated geometry of pavement structures, non-uniform loadings and complex material properties. So that FEM is capable of modelling pavement responses more accurate than elastic theory that may directly affect the backcalculated pavement layer properties.

Application of the method in specific purpose pavement analysis softwares includes five major steps. First one is the preprocessing that required geometrical and material properties of structure are described to the software. Layer thicknesses, boundary conditions, and stiffness related material properties such elastic modulus, Poisson’s ratio need to be given as inputs and also constitutive material models are selected. Considering the geometrical properties and loading conditions, the structure in question is discretized into finite elements called as meshing and by this way, nodal coordinates and element connectivity are determined by the software. Second step is the element formulation; partial differential equations such as potential energy function is defined for each element in order to obtain stiffness matrices. Combining the equation of individual elements to form the global stiffness matrix of the entire structure is the third step of the analysis. Fourth step is the solution of the final equation by applying the boundary conditions of the problem domain. Post-processing is the final step of which consists of determining the responses of interest. In other words, stress and strain values of elements, nodal displacements and reactions can be calculated and these responses can also be visualized (Ahmed 2010; Fish and Belytschko 2007; Karagöz 2004).

General purpose finite element based softwares such as ABAQUS, ADINA and ANSYS can be used for pavement response analysis. Although their capability of solving complex various engineering problems, it may not be practical to perform them as forward response engine in pavement layer backcalculation problems. Beside these softwares, there are also FEM based computer programs specifically developed for pavement analysis and design purposes. The prime objective of these softwares is to simulate approximate pavement behavior to the real conditions under traffic loading so that associated pavement responses are computed using various constitutive relations for nonlinear base/subbase and subgrade materials. These pavement analysis and design computer programs base on two different modeling approach as three-dimensional and two-dimensional (axisymmetric). Revolution of the cross-sectional area of pavement structure employed in the axisymmetric modelling. ILLI-PAVE, MICH-PAVE, GAPPS7, SENOL and DIANA are the softwares which use two-dimensional axisymmetric modelling approach.

2.6.4 Material Characterization

HMA layers located on top of the other layers are composed of bituminous material which exhibits viscoelastic behavior means that the material has both elastic behavior of solid and viscous behavior of liquid. Thus, their stiffness properties is directly related with time and temperature. Taken into account the viscoelastic behavior of asphalt layers increases the number of variables to be handled that makes the analysis more complex. For the sake of computation simplicity, HMA layers were considered as linearly elastic in several studies for backcalculation purposes (Ceylan and Gopalakrishnan 2006; Gopalakrishnan 2009a; Khaitan and Gopalakrishnan 2010; Meier 1995; Nazzal and Tatari 2013; Rakesh et al. 2006).

As mentioned earlier, base/subbase and subgrade materials exhibit stress dependent behavior. By increasing stress state, granular and fine grained materials shows stress hardening and softening nature, respectively. Here, a concept emerges related with stiffness properties of such layers named resilient modulus need to be well characterized for both types of granular and fine grained materials.

2.6.4.1 Resilient Modulus Concept

Resilient modulus is an elastic modulus defined for stress dependent granular and fine grained subgrade soils. Figure 14 presents the resilient modulus laboratory test results under repeated loading conditions. As can be seen from the initial stage of load applications, significant plastic deformations occur besides the elastic deformations. With the increasing number of load applications, amount of permanent deformation starts to decrease and after 100 to 200 load applications it is regarded as there is no considerable plastic deformation. In the final stage, strain is defined with ε_r. Using these data, resilient modulus M_R is expressed as follows (Huang 2003):

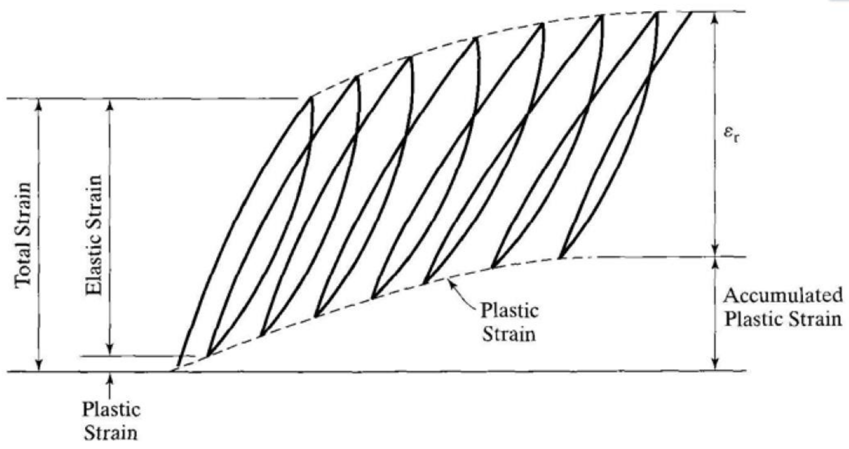


Figure 14 Deformation Under Repeated Loading (Huang 2003)

$$M_R = \frac{\sigma_d}{\epsilon_r} \tag{15}$$

Where σ_d is deviator stress which is equal to axial stress in unconfined compression laboratory test. Since the negligible effect of confining pressure in low stress states and temperatures, unconfined compression test can also be implemented. However, in other cases, triaxial test is usually performed to examine the resilient behavior of materials. A typical triaxial test setup is illustrated in Figure 15.

AASHTO, European, ICAR and Harmonized protocols have been established different test procedures for investigating resilient modulus of materials under repeated loadings. AASHTO protocols such as T 274: "*Resilient Modulus of Subgrade Soils"* and T 294: "*Resilient Modulus of Unbound Granular Base/Subbase Materials and Subgrade Soils"* are the standard test procedures established in the past of which had been widely used. In order to eliminate the encountered problems and deficiencies in these protocols, AASHTO provided a new protocol called 307: "*Determining the Resilient Modulus of Soils and Aggregate Materials*". According to this protocol, granular and fine grained cylindrical specimens are subjected to repeated axial loadings under confining pressure to measure the recoverable strains trough the deformations. Using the deviator stress and recoverable strain, resilient modulus of the tested material can be calculated.

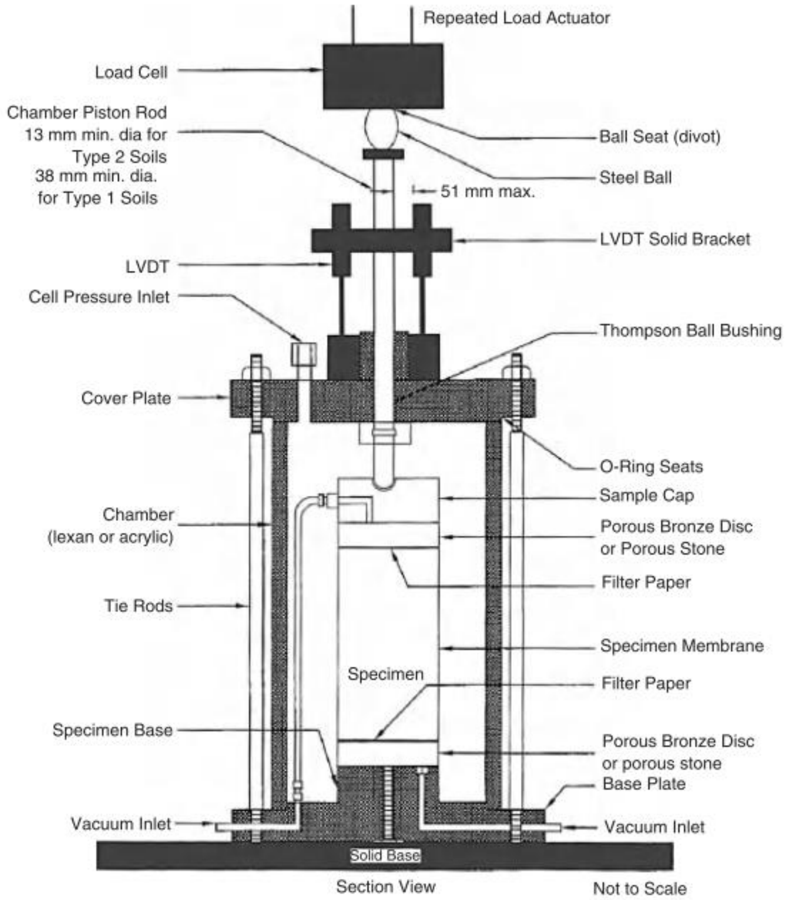


Figure 15 Triaxial Compression Test Cell Setup (Papagiannakis and Masad 2008)

In repeated load test, it is essential to model a moving wheel loading as close as possible to actual field conditions. So that load duration and shape of stress pulse should be well selected. For this purpose, haversine shaped loading is chosen to be exposed to the sample in AASHTO T 307 standard test protocol. The duration of a load cycle is considered as 1 second formed with 0.1 second for load duration and 0.9 second for the resting period till the following loading. The test is performed using triaxial test apparatus proposed by AASHTO shown in Figure 15. The minimum sample size should satisfy the 1:2 diameter to length ratio. According to the current protocol, the test can be divided into two main stages. First one is conditioning stage that different combinations of confining and deviator stress are imposed to the sample for 500 to 1000 load repetitions. After completing the conditioning, second stage is started that successive loadings with varying dynamic cyclic stress and confining pressure. This stage includes several steps to measure the recoverable deformation. Each step is accomplished in constant confining pressure under increasing deviator stress and then confining pressure is changed for the next step to be exposed the same deviator stress with the previous step. The number of steps, load application sequences and corresponding load amounts are presented AASHTO T 307 protocol in detail. At the end of the test, recoverable or resilient strain is calculated from the deformation data and together with the deviator stress resilient modulus can be calculated for each loading conditions.

2.6.4.2 Empirical Correlations with CBR and R Value

Strength of pavement materials can be examined through several field and laboratory tests. Usually, they are not performed to determine resilient modulus directly, however empirical correlations can be established between test results and resilient modulus M_R.

The California Bearing Ratio (CBR) test is employed for evaluating load-bearing capacity of pavement subgrade and base layers. In this test, a standard piston penetrates the soil and required pressures at certain amount of displacements are recorded. Then this pressure values are divided to equivalent pressures to obtain the same displacements on standard crashed rocks that the ratio gives the *CBR* value of the soil (Yoder and Witczak 1975). To define the correlation between M_R and *CBR* values following equation is proposed:

$$M_R = K_1(CBR)^{K_2} \tag{16}$$

For K_1 and K_2 constants, researchers proposed different values. For instance, Heukelom and Foster (1960) suggested to use K_1 = 1,500 and K_2 = 1.0, Lister and Powell (1987) established the values as K_1 = 2,555 and K_2 = 0.64 and the Council of

Scientific and Industrial Research proposed the constants as K_1 = 3,000 and K_2 = 0.65. It is reported according to available laboratory results, M_R - *CBR* correlation of fine grained soils is more reasonable than granular materials (Huang 2003).

Another test method being used for strength evaluation purpose of pavement materials is to use of stabilometer. This device measures the internal friction of materials called resistance value, *R*. In Figure 16, typical section of a stabilometer is illustrated.

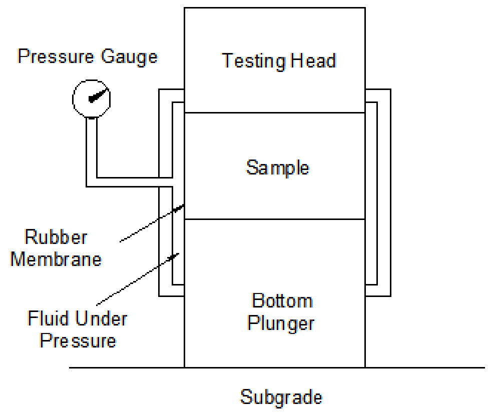


Figure 16 Typical Section of Stabilometer (Huang 2003)

A stabilometer is a type of triaxial compression test that applies a standard vertical load which is 1.1 MPa (160 psi) over the specimen and measures occurred lateral pressure in the fluid which is transmitted through the sample. The resistance value, *R* can be calculated with the following equation:

$$R = 100 - \frac{100}{(2.5/D_2)\ (p_v/p_h - 1) + 1} \tag{17}$$

where p_v is the standard vertical pressure, p_h is the resulting lateral pressure due to p_v. D_2 is the amount of displacement of fluid under pressure which is necessary to increase lateral pressure from 35 to 690 kPa (5 to 100 psi). In 1982, Asphalt Institute established a correlation between M_R and *R* as presented below:

$$M_R = 1155 + 555R \tag{18}$$

Apart from *CBR* and *R* correlations, Van Til et al. (1972) conducted a study to propose the relations between resilient modulus and other test methods as shown in Figure 17. It should be noted that these correlations rely on the local conditions where they are developed and they can be used just as a guide unless more reliable resilient modulus information is available. These correlations does not take into account the stress sensitive behavior of granular and fine grained materials which is another drawback of this chart. Therefore, use of empirical correlations may not be efficient all the time (Huang 2003; Yoder and Witczak 1975).

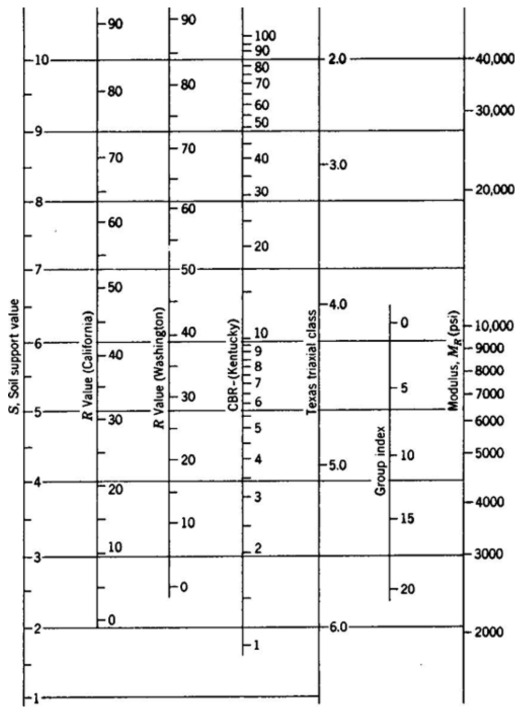


Figure 17 Resilient Modulus Correlation Chart with Several Test Parameters (Huang 2003)

2.6.4.3 Material Models for Unbound Granular Materials

In pavement design, unbound granular materials play an essential role in the performance of the structure. These materials are used to form base and subbase layers that have functions of transmitting the imposed traffic loading to the natural soil and preventing the subgrade against environmental effects. Aggregates with varying sizes, water and air voids between the particles constitute the unbound granular materials and the mechanical behavior of such materials is related with interaction between the aggregates and the behavior of each aggregate particle itself. It is known that, there are several conditions affecting this internal structure of granular materials. Subjected load levels, density, moisture content and gradation of aggregates are the conditions that can influence the mechanical responses of pavement structures and they are needed to be considered in modeling stages. However, it could be quite problematic to regard all of the influencing factors in characterization of such materials. With increasing stress levels, granular materials exhibit stress hardening behavior means that increase in stiffness properties according to imposed loading. For this reason, as expressed in the previous section, resilient modulus is used to define mechanical properties of unbound granular materials in addition to Poisson's ratio. For over the years, researchers have been conducted several studies in order to model nonlinear granular material properties with constitutive laws using laboratory and field tests (Kim 2007). These models are summarized in this section respectively.

Seed et al. (1967) proposed the confining pressure model to express the resilient modulus in terms of confining pressure.

$$M_R = K_1(\sigma_3)^{K_2} \tag{19}$$

where σ_3 is confining pressure, K_1 and K_2 are the model constants obtained from triaxial tests.

Another model based on stress state is K–θ model which is developed by Hicks and Monismith (1971).

$$M_R = K(\theta)^n \tag{20}$$

where θ is bulk stress or in order words sum of principal stress = $\sigma_1 + \sigma_2 + \sigma_3$, K and n are the constant obtained from triaxial tests. The model neglects the shear stresses which directly affects the resilient modulus value. However, due to its simplicity K-θ model is still used despite this deficiency (Kim 2007). In Figure 18, determination of resilient modulus using triaxial test data is presented. Here, resilient modulus is plotted against the bulk stress on logarithmic scale that resilient modulus corresponding to 1 psi bulk stress refers to *K* constant and the slope of the line gives the *n* value (Huang 2003). In Table 1 typical *K* and *n* values for different type of granular materials are presented.

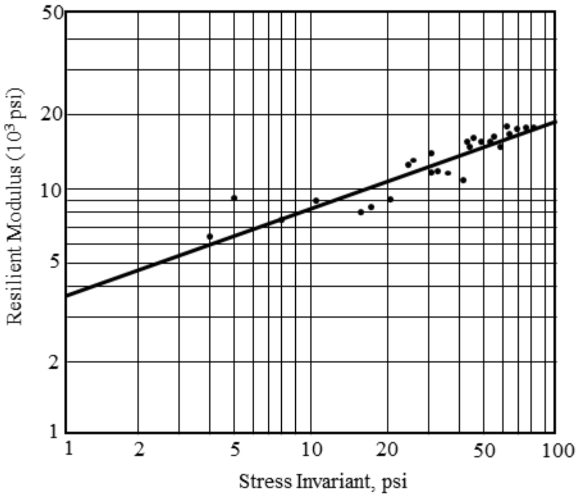


Figure 18 Determination of *K* and *n* Constants from Triaxial Test Results (Huang 2003)

Table 1 Typical K-θ model parameters for different type of granular materials (Rada and Witczak 1981)

Granular Material Type	Number of Data Points	K (psi)		n	
		Mean	Standard Deviation	Mean	Standard Deviation
Silty Sands	8	1620	780	0.62	0.13
Sand-Gravel	37	4480	4300	0.53	0.17
Sand-Aggregate Blends	78	4350	2630	0.59	0.13
Crushed Stone	115	7210	7490	0.45	0.23

Shackel (1973) proposed a model using octahedral shear stress and octahedral normal stress for both granular and cohesive soils.

$$M_r = K_1 \left[\frac{(\tau_{oct})^{K_2}}{(\sigma_{oct})^{K_3}} \right] \tag{21}$$

where σ_{oct} is octahedral normal stress and τ_{oct} is octahedral shear stress which are defined in terms of the first and the second stress invariants, I_1 and I_2 as shown below:

$$\sigma_{oct} = \frac{1}{3}(\sigma_1 + \sigma_2 + \sigma_3) = \frac{1}{3}\mathrm{I}_1 \tag{22}$$

$$\tau_{oct} = \frac{1}{3}[(\sigma_1 - \sigma_2)^2 + (\sigma_2 - \sigma_3)^2 + (\sigma_1 - \sigma_3)^2]^{\frac{1}{2}} = \frac{\sqrt{2}}{3}(\mathrm{I}_1^2 - 3\mathrm{I}_2)^{\frac{1}{2}} \tag{23}$$

As mentioned above K-θ model has a weakness since it does not consider the shear behavior. So that Uzan (1985) improved the model by adding the deviator stress component to incorporate the effect of shear behavior. The resulting Uzan model is presented in the following form:

$$M_R = K_1(\Theta)^{K_2}(\sigma_d)^{K_3} \tag{24}$$

where σ_3 is confining pressure, θ is bulk stress = $\sigma_1 + \sigma_2 + \sigma_3$ K_1, K_2 and K_3 are regression constants determined by test results. In this study, Uzan (1985) illustrated the effect of neglecting and taking into account shear stress in K-θ model and Uzan model, respectively as shown in Figure 19. As it can be clearly seen from the figures Uzan model shows good agreement with the test data better than K-θ model.

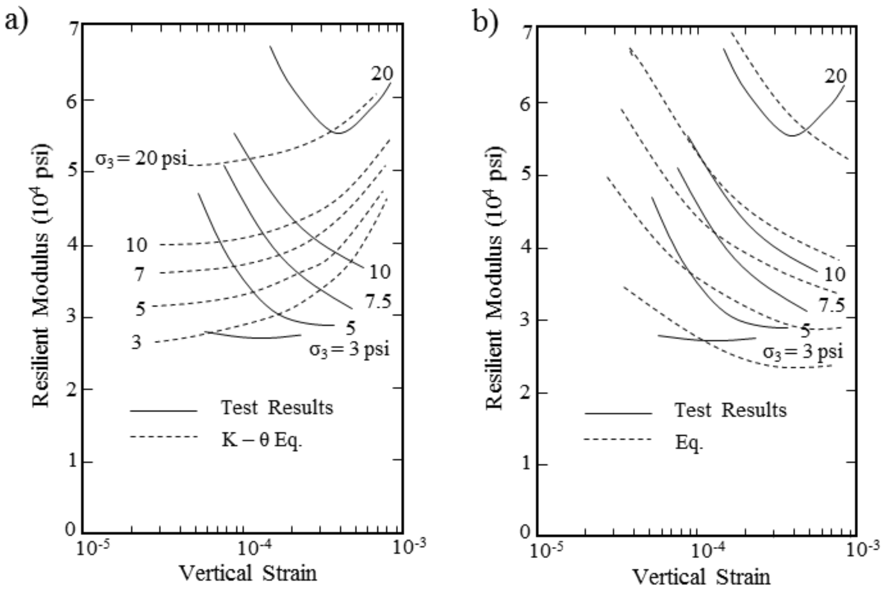


Figure 19 Comparison of test results and a) K-θ Model b) Uzan Model (Uzan 1985)

Uzan model is modified by replacing the deviator stress component with the octahedral shear stress and in order to make the model parameters dimensionless, stress components are divided to atmospheric pressure (pa) for normalization purpose (Witczak and Uzan 1988). The proposed correlation is named as Universal Octahedral Shear Stress Model as presented below:

$$M_R = K_1 p_a (\frac{I_1}{p_a})^{K_2} (\frac{\tau_{oct}}{p_a})^{K_3} \tag{25}$$

Where I_1 is the first stress invariant = $\sigma_1 + \sigma_2 + \sigma_3$, τ_{oct} is octahedral shear stress and p_a is the atmospheric pressure and K_1, K_2 and K_3 are the constants obtained from test results.

$$\tau_{oct} = \frac{1}{3}[(\sigma_1 - \sigma_2)^2 + (\sigma_2 - \sigma_3)^2 + (\sigma_1 - \sigma_3)^2]^{\frac{1}{2}} = \frac{\sqrt{2}}{3}(I_1^2 - 3I_2)^{\frac{1}{2}} \tag{26}$$

Itani (1990) proposed a model which incorporates the several stress sates as variables in the model. The model is presented in the following form:

$$M_R = K_1 p_a (\frac{\sigma_\Theta}{p_a})^{K_2} (\sigma_d)^{K_3} (\sigma_3)^{K_4} \tag{27}$$

where σ_θ is bulk stress = $\sigma_1 + \sigma_2 + \sigma_3$, σ_3 is confining pressure, p_a is the atmospheric pressure and K_1, K_2, K_3 and K_4 are the model constants obtained from test results.

In NCHRP 1-37A, MEPDG, a correlation is developed for both unbound granular and fine-grained subgrade materials. This model characterizes the stiffening and softening effect of bulk and shear stress, respectively using *K* regression constants (Kim 2007).

$$M_R = K_1 p_a \left(\frac{\Theta}{p_a}\right)^{K_2} (\frac{\tau_{oct}}{p_a} + 1)^{K_3} \tag{28}$$

where θ is sum of the principal stresses = $\sigma_1 + \sigma_2 + \sigma_3$, τ_{oct} is octahedral shear stress, p_a is the atmospheric pressure and K_1, K_2 and K_3 are the regression constants obtained from test results.

2.6.4.4 Material Models for Fine Grained Subgrade Soils

Subgrade is the one of the most significant component of a pavement structure located underneath the base and surface layers. Its behavior under imposed traffic loading and environmental effects overrides among the other conditions influencing the pavement design parameters and performance. Thus, characterization of subgrade materials should be well performed to obtain reliable pavement design. There are several factors which affect the characterization of subgrade materials include loading states and physical conditions such as compaction, Atterberg limits, moisture and dry density of soils. Mechanical behavior of fine-grained subgrade soils can be represented with resilient properties because of the stress sensitive behavior of the soils just as the unbound granular materials. Fine grained soils exhibit stress softening behavior that resilient modulus decrease with the increasing deviator stress. According the study conducted by Thompson and Robnett (1979) it is reported that resilient modulus of fine-grained subgrade soils is a function of deviator stress and confining pressure is less significant by comparing to deviator stress. So that it is essential to develop mathematical models of fine-grained soils showing nonlinear behavior regarding the relation between deviator stress effecting and resilient modulus.

Over the years, various constitutive equations were established by different researchers to better characterize the fine-grained soils incorporating effecting factors. Brown (1979) established a mathematical model that considers mean normal stress which is caused by overburden pressure and occurred deviator stress due to wheel loading. The model is presented as follows:

$$M_R = A\left(\frac{p_0}{q_R}\right)^B \tag{29}$$

where p_0 is effective mean normal stress and q_R is the deviatoric stress. A and B are the subgrade soil constants having rages 2.9 to 29.0 and 0 to 0.5, respectively. In later studies, Loach (1987) improved the Brown's model by combining another deviator stress term to the model as shown in the following equation:

$$M_R = Cq_R\left(\frac{p_0}{q_R}\right)^D \tag{30}$$

here, C and D are the fine-grained material constants varying between 10 to 100 and 1 to 2, respectively (Kim 2007).

Semilog model is another constitutive equation developed by Fredlund et al. (1977) to characterize resilient modulus in terms of deviator stress.

$$log(M_R) = k - n\sigma_d \tag{31}$$

Where k and n are the model constants having ranges 3.6 to 4.3 and 0.005 to 0.09, respectively.

Thompson and Robnett (1979) proposed the bilinear or arithmetic model which is one of the most popular constitutive models employed in stress dependent modulus characterization. As illustrated in Figure 20, the bilinear curve is plotted in order to show the relationship between deviator stress and resilient modulus based on the cyclic triaxial test results. Corresponding resilient modulus at the intersection point of the curves refers to breakpoint resilient modulus, E_{Ri} which can be utilized to classify fine-grained subgrade soils as being soft, medium or stiff. Also it is a good indicator of resilient behavior of materials than other material constants. σ_{di} is the deviator stress associated with breakpoint resilient modulus, K_3 and K_4 are the material constants calculated from the slopes of the lines (Thompson and Robnett 1979). In this model, resilient of fine-grained materials under deviator stress can be calculated using the following equations:

$$M_R = E_{Ri} + K_3(\sigma_{di} - \sigma_d) \text{ when } \sigma_d \leq \sigma_{di} \quad (32a)$$

$$M_R = E_{Ri} + K_4(\sigma_d - \sigma_{di}) \text{ when } \sigma_d \geq \sigma_{di} \quad (32b)$$

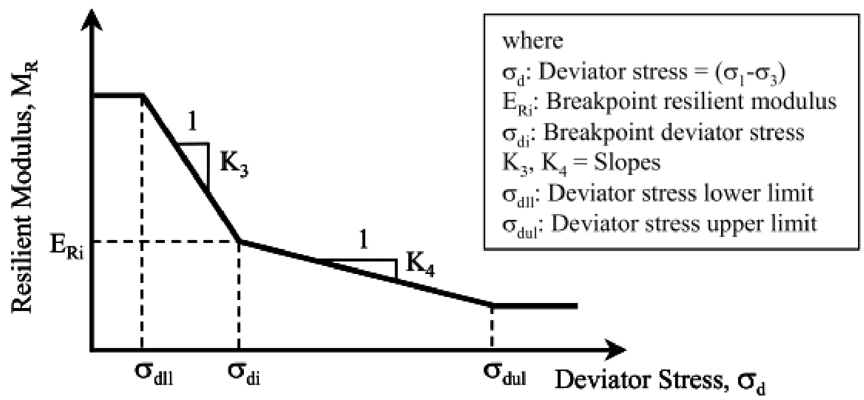


Figure 20 Bilinear or Arithmetic Model for Stress Dependent Modulus Characterization of Fine-Grained Soils (Thompson and Robnett 1979)

2.6.5 A Pavement Analysis and Design Software: ILLI-PAVE

ILLI-PAVE is the one of the FEM based pavement analysis design softwares developed at University of Illinois at Urbana-Champaign (Raad and Figueroa 1980). This computer program considers the pavement in two-dimensional or axisymmetric domain that the entire structure is formed by the revolution of cross-sectional area. Nonlinear elastic material behaviors are incorporated into analyses with this software. In this respect, unbound granular materials presenting stress hardening under increasing loading conditions can be modelled with three different models: confining pressure model (Equation (19)), K-θ model (Equation (20)) and Uzan model (Equation (24)). Nonlinear nature of fine-grained subgrade soils are also incorporated into the ILLI-PAVE as three different constitutive equations: Semilog model (Equation (31)), Log-log model and Arithmetic model (Equation (32)) that each of them relates the resilient behavior with deviatoric stress. In the analyses of pavement, since the principal stress components of layers are updated iteratively, to ensure the stresses not to exceed the strength of the materials, the software utilizes Mohr-Coulomb failure criteria in each iteration.

For moreover than three decades, ILLI-PAVE has been used extensively for the purpose of nonlinear structural analysis of flexible pavements. Since the software takes into account the nonlinearity of materials and handles complex geometries, it can adequately characterize the pavement responses. There have been several studies which use ILLI-PAVE software in the current literature. Terrell et al. (2003) investigated stiffness properties of granular layers in inverted type flexible pavements using field tests and researchers used ILLI-PAVE software in calculating the stress components. In another study, Kuo and Huang (2006) compared pavement responses obtained by 3D analysis of ABAQUS software with the solutions obtained from ILLI-PAVE. The software is widely used in pavement layer backcalculation to estimate pavement deflections basins by simulating FWD test and calculating the associated deflections at designated sensor locations. Tutumluer et al. (2009) employed the ILLI-PAVE in order to generate a database including deflection basins and corresponding pavement structures which are utilized to train ANN forward response models. Using these neural network models, an innovative methodology named as SOFTSYS is developed to backcalculate flexible pavements' layer thickness and stiffness properties. There are similar studies that ILLI-PAVE is successfully implemented to generate ANN models. Using the input-output pairs of ILLI-PAVE, reliable and robust neural network models can be developed (Khaitan and Gopalakrishnan 2010; Pekcan et al. 2009; Ceylan and Gopalakrishnan 2006; Pekcan et al. 2008; Gopalakrishnan 2009). Beside the analysis of highway pavements, airport runways can also be investigated. In the study conducted by Gopalakrishnan and Thompson (2006), stiffness related layer properties of runways were backcalculated. Researchers preferred to utilize ILLI-PAVE software in forward calculation engine to replicate the HWD loading on highway pavement.

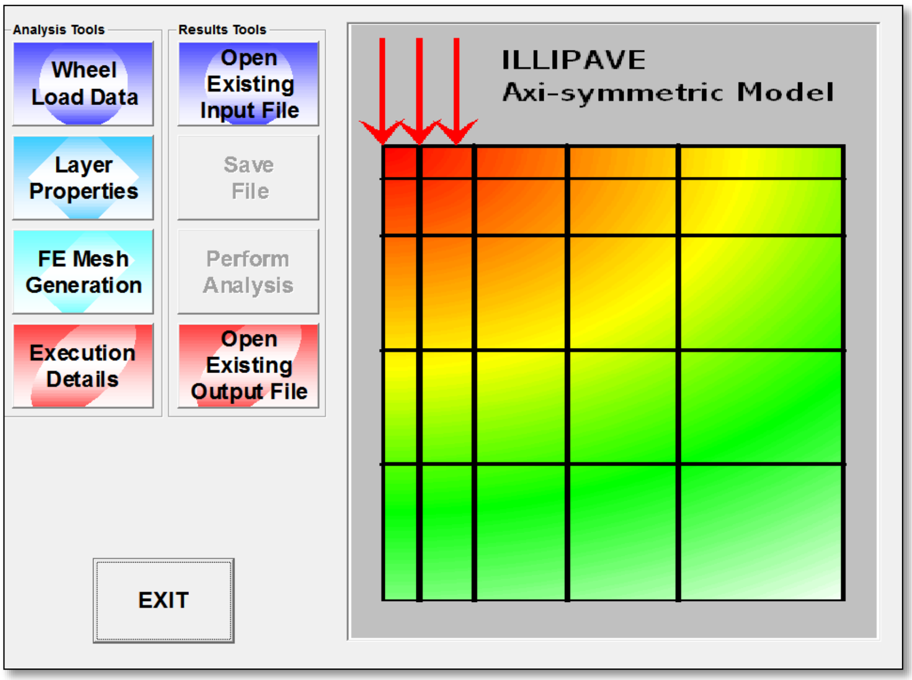


Figure 21 ILLI-PAVE 2005 User Interface

2.7 Backcalculation of Layer Moduli

Backcalculation is a process of evaluating structural capacity of in service pavements by using non-destructive test results. Researchers have been implemented several methods in pavement backcalculation issues. Difference of each backcalculation technique comes from the utilized forward response engine and search approach. Due to the inherent nature of pavement structures and environmental conditions, sensitivity of stiffness properties and pavement responses is rather high therefore, it is essential to find out the nature of the problem and to choose the most suitable approaches for backcalculation (Onur Pekcan et al. 2008). Depending on the forward response modeling in terms of loading, material characterization and employed optimization algorithms, backcalculation methods could be classified into different categories (Goktepe et al. 2006).

2.7.1 Backcalculation Methods

Goktepe et al. (2006) conducted a study which reviews the advances in pavement layer backcalculation. According to this study, backcalculation methods can be divided into three main categories by considering the type of forward calculation and analysis approaches as static, dynamic and adaptive as shown in Figure 22.

In static backcalculation approach, pavement responses can be modelled using either multi-layered elastic theory or FEM based softwares. Taking into account the nonlinearity of base/subbase and subgrade materials in response analysis, increase the accuracy of the backcalculated layer properties. Optimization methods used in conjunction with the forward model also influences the accuracy of outputs of the backcalculation analysis. One of the static approaches is the closed form backcalculation algorithm which calculates layer moduli directly using layer thicknesses and deflections at some specific points (Fwa et al. 2000). 2L-BACK backcalculation software based on Burmister's theory for two-layer flexible pavements uses closed form algorithms (Fwa and Rani 2005). There are also computer programs rely on the closed form solutions for rigid pavements such as ILLI-BACK and NUS-BACK. In order to estimate deflections at specific locations, every backcalculation program carries out several numerical processes. For this purpose iterative methods, regression equations and optimization algorithms are employed in these computer programs (Swett 2007). Parameter identification algorithms like least squares, gradient descent and Gauss-Newton methods could be used for minimizing the error between calculated and measured deflection basins. Here, defined objective function is tried to be minimized without trapping local minima and to provide best match between theoretical and measured deflection basins. Researchers have been described several objective functions to be used so as to provide deflection convergence (Harichandran and Mahmood 1993; Sivaneswaran et al. 1991). The iterative approach can be illustrated using multivariate equivalent of linear interpolation as depicted in Figure 23 that process starts with deflection calculations corresponding to the supplied minimum and maximum layer moduli. Iterations continue until reaching the different between deflections less than 10% which is thought that convergence is obtained (Bush and Alexander 1985). Another static backcalculation approach is the database method. This approach employs previously created database of deflection basins associated with the various layer thicknesses and moduli values varying within particular ranges instead of computing the deflection basins iteratively. MODULUS backcalculation software is one of the popular software that works with the database method (Uzan et al. 1988).

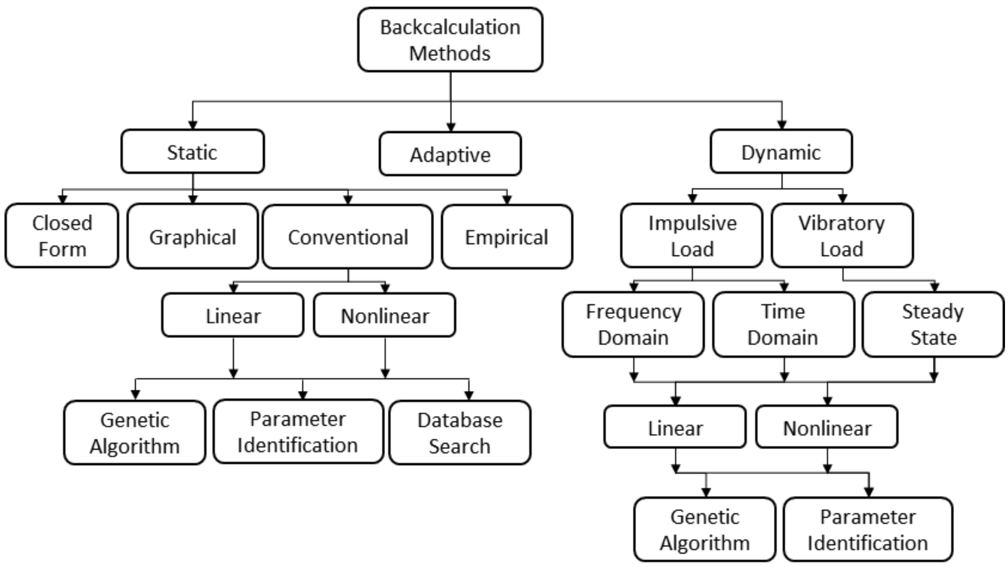


Figure 22 Classification of Backcalculation Methods (Goktepe et al. 2006)

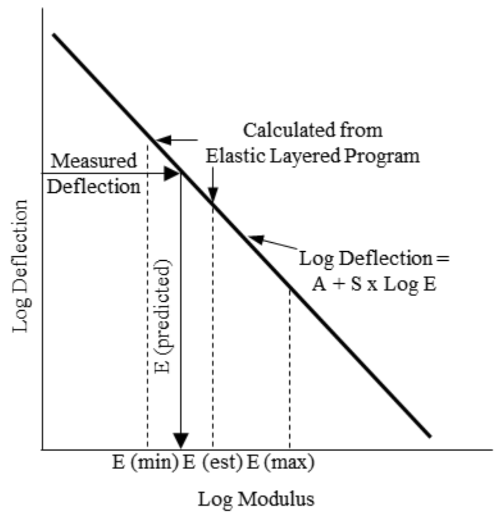


Figure 23 Iterative Process for Pavement Layer Backcalculation (Huang 2003)

As expressed in the study of Goktepe et al. (2006), dynamic backcalculation methods are another conventional approach used in investigation of flexible pavement properties. The distinctive features of dynamic backcalculation methods against the static ones are loading conditions applied over pavement surface and forward analysis routines. In contrast to using peak applied loads which is regarded in static backcalculation methods, dynamic manner uses impulsive and vibratory loads in time and frequency domains, respectively. Generally fast fourier transformations are implemented in the way of calculating deflection basins. Dynamic response analysis enables more realistic pavement structure characterization under traffic loadings since it incorporates into the viscoelastic material behavior of asphalt layers. Therefore, the complex moduli characterizes the AC layer when analysis is conducted in frequency domain and creep compliance is used to define the material properties in time domain. Despite the sensitive modelling capability of dynamic analysis, when the nonlinearity of materials are considered it becomes more complex. Therefore, in most of the dynamic analysis materials are assumed as exhibiting linearly (Goktepe et al. 2006). In deflection matching steps, the same optimization approaches with static ones can be performed to evaluate the stiffness properties. For instance, Asli et al. (2012) assessed the flexible pavement stiffness related properties dynamically using least square based method.

In addition to expressed optimization approaches above, artificial intelligence methods as nontraditional manner are performed in both static and dynamic backcalculation methods. Most commonly used one among these type of algorithms is genetic algorithm (GA) which is developed by inspiring the evolutionary theory (Goldberg 1989). Several researcher have been used GA extensively for years in pavement layer backcalculation as a search method (Bosurgi and Trifirò 2005; Hu et al. 2007; Nazzal and Tatari 2013; Pan et al. 2012; Pekcan 2010; Rakesh et al. 2006; Tsai et al. 2009). Not also evolutionary algorithms employed in backcalculation but also another metaheuristic optimization algorithms like particle swarm optimization (PSO), differential evolution (DE) algorithm and Shuffled Complex Evolution (SCE) are implemented to estimate stiffness properties of flexible pavement layers (Gopalakrishnan et al. 2009; Khaitan and Gopalakrishnan 2010). In this study, a newly developed metaheuristic search method: Gravitational Search Algorithm (GSA) is utilized in optimization processes (Rashedi et al. 2009a). All the employed methods in this study will be expressed in detail within the following section.

The last but not the least methods for flexible pavement layer backcalculation are adaptive ones. Artificial neural networks and adaptive neuro-fuzzy inference system (ANFIS) are the integral parts of this nontraditional backcalculation approach. An adaptive system is generated using input-output pairs of response analyses so that it can establish the nonlinear relationship between moduli and deflection values (Ceylan and Gopalakrishnan 2006; Meier and Rix 1994; O Pekcan et al. 2008; Rakesh et al. 2006; Saltan and Terzi˙ 2008). A typical scheme for adaptive backcalculation procedures is presented in Figure 24. Since this study mainly focuses on nontraditional backcalculation methods, ANN and other optimization methods will be expressed comprehensively in the following sections.

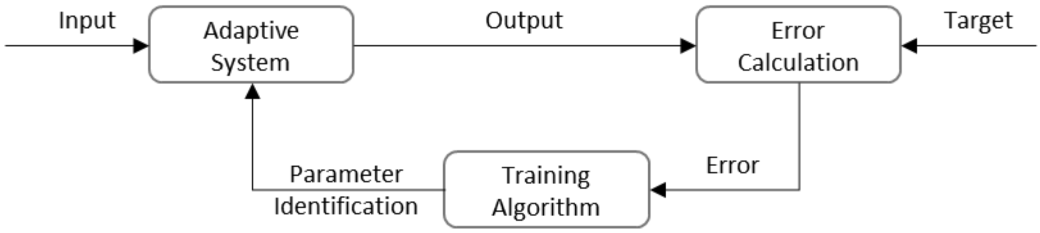


Figure 24 A Typical scheme for Adaptive Backcalculation Procedures (Goktepe et al. 2006)

2.7.2 Soft Computing Methods Used in Pavement Backcalculation

It is usually quite hard to solve some problems consisting of several variables which make the problems resource-intensive and complicated. Sometimes conventional optimization methods may not be sufficient to manage such complex tasks. Soft computing concept as nontraditional approach emerges in respect of overcoming the deficiency of hard (conventional) computing methods that it can present approximate solutions by managing the impression and uncertainty (Magdalena 2010). By this way, limitations in complicated problems may be handled using soft computing techniques in almost every engineering branch. These nontraditional methods are generally inspired by the nature. They can mimic the behavior of living creature, objects and human mind to replicate the learning processes etc. In this context, various algorithms developed including ANN, support vector machines, fuzzy logic, evolutionary and metaheuristic algorithms (Kecman 2001; Waszczyszyn and Slonski 2010). Just as the other engineering branch, soft computing methods are accepted and validated through numerous studies in pavement engineering that are successfully implemented in flexible pavement backcalculation (Goktepe et al. 2006).

Among the nontraditional computing methods GAs are the most popular one which has been applied in several pavement backcalculation studies. GA was first time proposed in John Holland's "*Adaptation in Natural and Artificial Systems*" book in 1975. The algorithm bases on the evolutionary theory of Darwin which can be phrased as "*survival of the fittest*" in the natural selection. The theory was converted to a mathematical model using computer applications and GA is implemented as a search algorithm in optimization problems. Since GA relies on the evolutionary theory, it replicates the sequence of actions of the theory. The process starts with a randomly generated population including certain number individuals or namely phenotypes and each one is defined in binary form (0s and 1s). Fitness of the each individual is evaluated solving the objective function of the problem in the way that GA seeks the entire search space defined to the algorithm prior to analysis. According the fitness calculations, best individuals are selected and exposed to evolutionary operations like crossover and mutation to generate a new population for the next iteration (Pan et al. 2012; Mitchell 1995; Goldberg 1989).

Each technique in soft computing has different advantages depending on the inherent nature of the method. In fact, combination of the superiorities of methods may result more powerful tools than the usage of single technique in problem solving. Adherence to this complementary manner, soft computing methods can be applied together called as hybridization. As robust and versatile search algorithm GA has been increasingly applied either individually or in hybrid manner by the researchers of pavement community in recent years. Tsai et al. (2009) established a paper to present the versatility of GA in pavement analysis and design operations. In this study researchers conducted 4 cases which are related with asphalt material properties. GA consists of several parameters and there is no available guideline of choosing these parameters in pavement backcalculation. Reddy et al. (2004) conducted a study on determining the optimum parameters for backcalculation. As mentioned above, GA could be employed with other artificial intelligence methods that one important example of such hybrid use is performed with ANN. Neural network models which are the integral part of backcalculation methods namely adaptive ones are the most common nontraditional approaches. Details of ANN will be expressed separately in the following section because it is one of major topics focused in this study. In GA and ANN hybrid manner, Rakesh et al. (2006) conducted a study. Previously developed GA based backcalculation model called as BACKGA was improved by combining the model with ANN forward calculation subroutine. So that resulting algorithm could have reliability and robustness of each method. Similar to this, Nazzal and Tatari (2013) utilized GA and ANN together to evaluate the subgrade resilient modulus by making use of the soil index properties. In another study, Gopalakrishnan (2009), proposed a toolbox (namely NGOT) which uses the GA and ANN together to backcalculate layer moduli by simulating nonlinear material behaviors within FEM based pavement models. Analogous to this, Pekcan et al. (2009) developed a computer program called SOFTSYS. Regarding the nonlinearity of materials in ILLI-PAVE software databases were developed to train the corresponding ANN models. Instead of using ILLI-PAVE program as forward subroutine in each iteration, ANN was employed because of the provided computational effectiveness of neural networks. GA was adopted the ANN to be used in searching the possible solution space. In conclusion, achieved software can estimate the layer thickness and Poisson’s ratio in addition to layer moduli.

Reviewed studies so far are based on the static backcalculation approaches, unlike these Hu et al. (2007) developed a backcalculation program called DBFWD-GA which is based on dynamic forward response modelling. As its name implies, GA based analysis backcalculates the layer moduli for three or four-layer structures. Another software developed by researchers utilizing GA is BackGenetic3D developed by Pan et al. (2012) which is capable of predicting layer moduli and thickness. Not only backcalculation operations are conducted in pavement managements but also other conditions can be investigated which may affect the maintenance and rehabilitation procedures. In this manner an hybrid implementation of GA and ANN was used create sideway force coefficient and accident prediction models by Bosurgi and Trifirò (2005).

Another hybrid application of ANN is proposed by Khaitan and Gopalakrishnan (2010) that differential evolution (DE) metaheuristic algorithm incorporated to neural network model. DE algorithm is employed for the purpose of exploring search space and finding the most suitable solutions. As a result, a toolbox named as I-PAT was developed for evaluation of stiffness properties of flexible pavements. Swarm based metaheuristic optimization algorithms have been used in pavement backcalculation as well. The major idea behind these techniques is to investigate the search space efficiently to achieve the optimal input values for forward response model. Particle swarm optimization (PSO) is an iterative algorithm for solving problem using a population in the same manner with GAs. Individuals in the population are defined with position and velocity. Fitness of each individual is assessed according to its position and movement of the particles are determined by the locations. Through the iterations individuals tend to move toward the individual which has the best position is the solution of the problem (Kennedy 1995). Gopalakrishnan (2009b) proposed in his another study to use two different metaheuristic search algorithms incorporated with ANN which are PSO and shuffled complex evolution (SCE) algorithms.

In this study a hybrid use of two nontraditional optimization method is proposed. Previously developed ANN models are employed as a surrogate model for ILLI-PAVE FEM based solutions. Besides, a newly developed metaheuristic algorithm: GSA as a search method which explores the search space to find the most appropriate input properties of ANN is also utilized. Proposed hybrid use is first time implemented in the way of evaluating pavement layer properties in the current literature.

2.7.2.1 Artificial Neural Networks

ANN is one of the most popular soft computing techniques inspired by the behavior of neurons in the nervous system of a live being. A number of interconnected artificial neurons forms a neural network which refers to computational model of a certain problem (Gurney 2005). Each connection between the neurons has different weights that inputs are multiplied by these weights and signals to be transmitted are determined through mathematical functions. Since the capability of handling resource-intensive problems which are hard to solve by traditional methods, ANN have been widely implemented in different areas of engineering. It can establish the nonlinear relation between the input and output variables while eliminating complex computation and it can also tolerate error in the utilized data (Onur Pekcan et al. 2008).

Among the numerous ANN types, feed-forward neural network is the first and simple one. The network is consisted of a number of processing units namely perceptron in a layered architecture. As the name implies for feed-forward networks information transmitting via neurons is in only forward direction. A typical multilayered feed-forward network includes input, hidden and output layers of each one has different number of interconnected neurons with reference to regarded problem. In order to develop a multilayer feed-forward neural network, it is necessary to use a learning rule that error back-propagation is the best known one used for training (learning) purpose. The feed-forward neural networks using back-propagation algorithm as a learning rule can be named as back-propagation neural networks that a scheme presents the general structure of such networks is illustrated in Figure 25 (Onur Pekcan et al. 2008)**.**

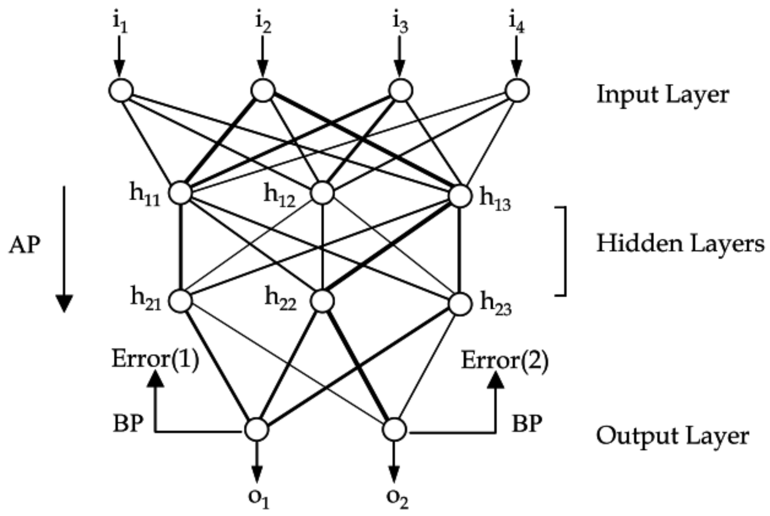


Figure 25 Structure of a Typical Back-propagation Neural Network (Onur Pekcan et al. 2008)

Where *AP* and *BP* refer to directions of activation and error back-propagation while i_1 to i_4 and o_1 to o_2 are the input and output variables of the problem. h_{11} to h_{23} are neurons in hidden layers. Figure 26 shows the components of a perceptron and performed processes in a typical neuron.

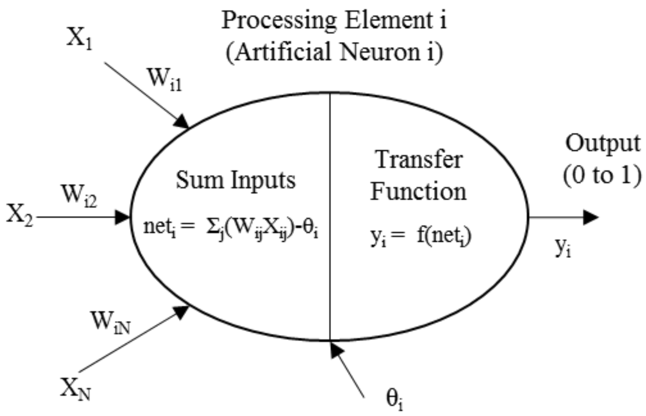


Figure 26 Structure of a Typical Processing Unit (Onur Pekcan et al. 2008)

where W_{ij} is connection weights and X_i is input signal for N number of prior neurons. θ_i refers to activation threshold, net_i is the net input signal while y_i is the output signal.

In the activation propagation direction, input signals which are transmitted from the prior processing units reach to the new neuron. Then, they are evaluated according to their connection weights. Each input signal is multiplied by its corresponding connection weight to calculate the internal activity of the neuron in terms of weighted summation of input signals. Giving response of the neuron is assessed in such a way of exceeding activation threshold or bias that net input signal is calculated using the given equation:

$$net_i = \sum_{j=1}^{N} (W_{ij}X_j) - \theta_i \tag{33}$$

If the calculated net input signal exceeds the threshold limit value, the neuron responses as y_i in accordance with the selected transfer function *f(x).* The output signal can be expressed with regard to net internal activity in the following form:

$$y_i = f(net_i) \tag{34}$$

Transfer functions can be classified as linear, threshold and sigmoidal. Among those, sigmoidal transfer function can present better similarity with real neurons over the other two. The output signal value y_i can change between 0 and 1 as the results of given sigmoidal function:

$$f(x) = \frac{1}{(1+e^{-x})} \tag{35}$$

Through the provided input and output data sets back-propagation algorithm seeks the relation between each neuron by adjusting their connection weights in successive iterations. The main idea behind the back-propagation learning rule is to minimize the difference (error) between desired and calculated output values which can be named as supervised learning. The training or learning process begins with randomly initialized connection weights and then they are updated according to the degree of error along with the iterations. At the end of each individual step of forward propagation the error E^k is calculated using an objective function:

$$E^k = \frac{1}{2}\sum_i [t_i^k - y_i^k]^2 \tag{36}$$

where t_i^k is the actual output for neuron i and k data in the training data set. As mentioned above, connection weights are adjusted according to calculated error. The amount of change between i and j neurons ΔW_{ij} can be expressed by calculating the derivative of the error term according to connection weight

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} = -\eta \sum_k \left(\frac{\partial E^k}{\partial W_{ij}}\right) \tag{37}$$

where η is the learning coefficient which is greater than zero. By applying chain rule the term $\frac{\partial E^k}{\partial W_{ij}}$ can be rewritten in the way of delta term δ_i^k in the generalized delta rule.

$$-\frac{\partial E^k}{\partial W_{ij}} = -\frac{\partial E^k}{\partial y_i}\frac{\partial y_i}{\partial net_i}\frac{\partial net_i}{\partial W_{ij}} = -\delta_i^k \frac{\partial net_i}{\partial W_{ij}} = -\delta_i^k X_j \tag{38}$$

Since actual and estimated output signals are already available the delta term can be computed in output layer. In hidden layers, due to unknown output signals to be sent the delta term $\delta_m{}^k$ is employed to calculate the current delta value which uses the neurons *m* located in the previous layer of *i*-th layer. The generalized delta rule can be expressed in the following form:

$$\delta_i^k = \begin{Bmatrix} \left(t_i^k - y_i^k\right) f'\left(net_i^k\right) & \quad for\ output\ layers \\ \sum_m \delta_m^k W_{im} f'\left(net_i^k\right) & \quad for\ hidden\ layers \end{Bmatrix} \tag{39}$$

Derivative of the sigmoidal function is given as:

$$f'(x) = f(x)\{1 - f(x)\} \tag{40}$$

After activation propagation stages are completed, back-propagation begins from the output layer toward the input layer by adjusting the link weights in successive iterations. In this case, outputs of the activation direction become the inputs of the backpropagation direction. The new connection weight of *i* and *j* neurons can be updated for the following iterations utilizing the given equation:

$$W_{ij}(it+1) = W_{ij}(it) + \eta \sum_k \delta_i^K X_j^K + \alpha[W_{ij}(it) - W_{ij}(it-1)] \tag{41}$$

α is the momentum term which takes into account the weight changes in previous iterations used to prevent the algorithm to trap in local minimum and to cause oscillation (Onur Pekcan et al. 2008). Analogous with the link weights, bias values are also modified in the same manner:

$$\theta_i(it+1) = \theta_i(it) + \eta\sum_k \delta_i^k + \alpha[\theta_i(it) - \theta_i(it-1)] \tag{42}$$

These steps are repeated for each data in the training set iteratively to reach the minimum error between desired and calculated outputs.

Owing to the the ability of ANN in solving resource-intensive complex problems fast and accurately, it has been extensively applied in pavement problems. As an adaptive backcalculation method, initial applications of ANN in pavement evaluation were conducted by Meier and Rix (1993) for surface wave inversions. They also employed neural network to backcalculate the layer properties as a surrogate model of elastic forward analysis using FWD measurements and dynamic deflection basins modelling studies as well (Meier and Rix 1994, 1995). Obtained successful outputs from these studies increase the use of ANN in pavement layer backcalculation studies. FEM based analysis softwares as forward response engine have been become popular to solve the pavement structures but runtime of the computer programs is quite high due to the inherent nature of FE analysis. To overcome such limitations ANN models were replaced with forward FE analysis stages in numerous studies which estimates layers' thickness, stiffness properties and emerged responses in specific locations of structural layers (Ceylan and Gopalakrishnan 2006; Ceylan et al. 2005; Hassani 2008; Pekcan 2010; Saltan et al. 2012; Sharma and Das 2008).

2.7.2.2 Gravitational Search Algorithm

GSA is a metaheuristic optimization algorithm developed by Rashedi et al. (2009). The algorithm is inspired by the Newton's law of universal gravitation of which refers that each object in the universe moves to each other due the gravitational force emerging between the objects. This gravitational force, F can be defined as a function of gravitational constant, distance between the objects and their masses as shown below:

$$F = G\frac{M_1 M_2}{R^2} \tag{43}$$

where G is the gravitational constant which is the function of age of the universe, M_1 and M_2 are the mass of the first and the second object, R is the corresponding distance between them. Movement of the objects in the universe could be expressed with Newton's second law of motion which refers that when a force is exposed to a body, it gains acceleration depending on its mass. Behavior of objects in the universe can be depicted as in Figure 27. Newton's second law of motion is defined as follows:

$$a = \frac{F}{M} \tag{44}$$

Where a is the acceleration of the object.

In accordance with Equations (32) and (33) Rashedi et al. (2009) proposed GSA algorithm. Researchers adopted the major ideas behind these theories to be applicable in solving high dimensional nonlinear optimization problems. In this novel algorithm, population is composed of a certain number of agents (objects) which can change their locations due to the interaction between agents caused by the gravitational forces. In law of gravity, there is a tendency of an object to move toward the object which is heavier, and thus objects are assessed according to their masses in GSA. Through the iterations masses are updated using the objective function value which evaluates the objects. At the end of the iterations or when it is reached to termination criteria, the position of the heaviest mass is considered as the solution of the problem (Rashedi et al. 2009a).

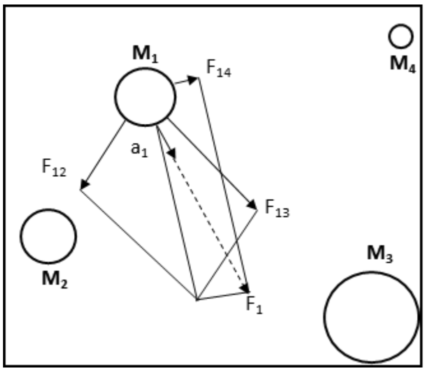


Figure 27 Resultant Force Acting on an Agent and Corresponding Acceleration (Rashedi et al. 2009a)

GSA includes different successive steps and details of each one is expressed below. Prior to the initialization step, search space is defined for each dimension. Following to this, a population composed of N number of agents is created:

$$X_i = \left(x_i^1, \dots, x_i^d, \dots, x_i^n\right), \quad \text{for } i = 1,2,\dots,N \tag{45}$$

where, x_i^d refers to the positions of the i-th agent in d-th dimension and n is the dimension of search space.

Fitness of each agent is evaluated through the objective function defined specifically for the problem in question. Best and worst fitness parameters are determined for the problems as being maximization or minimization. Best and worst agents according to their fitness of a minimization problem are presented below:

$$best(t) = \min_{j\in\{1,\dots,N\}} fit_j(t) \tag{46a}$$

$$worst(t) = \max_{j\in\{1,\dots,N\}} fit_j(t) \tag{36b}$$

where, $fit_j(t)$ refers to the fitness of the j-th agent at t-th iteration , *best*(t) and *worst*(t) are the best and worst fitness at t-th iteration, respectively. Best and worst values should be considered reversely for maximization problems.

After fitness evaluation, gravitational and inertial masses of agents are calculated by the following equations:

$$M_{ai} = M_{pi} = M_{ii} = M_i, \qquad i = 1, 2, \dots, N \tag{47}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{48}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{49}$$

where, M_{ai}, M_{pi} *and* M_{ii} are the active gravitational mass, passive gravitational mass, and inertial mass of the *i*-th agent, respectively. According to weak and strong equivalent principle; inertial, active and passive gravitational masses are assumed to be the same (Kenyon 1990; Schutz 2009).

As mentioned above, gravitational constant G is a function of age of the universe. In GSA it is initialized with a certain value and by successive iterations it is reduced (Mansouri et al. 1999; Rashedi et al. 2009a). The constant is expressed as shown below:

$$G(t) = G_0 e^{(-\alpha t/t_{max})} \tag{50}$$

G_0 and α are the constants where t is the current iteration and t_{max} is the maximum number of iteration.

To compute the acceleration of each object in the population, total force imposed to one agent is calculation as follow:

$$F_i^d(t) = \sum_{j \in \mathrm{K_{best}}, j \neq i} rand_j \, F_{ij}^d(t) \tag{51}$$

where, $rand_j$ is a randomly selected number in the inverval [0,1] and K_{best} is the certain number of agents which have best fitness values. In order to avoid the algorithm to trap in local optimum locations, only a group of agents having best fitnesses are considered to attract the other agents. In the first iteration, K_{best} is adjusted to number of agent in the population means that all the agents apply force to the others. After iterations proceeded, K_{best} is arranged to be decreased linearly and set to 2% of population number at the final iteration. This refers that at the end of the iterations only 2% of agents apply gravitational force to others for the purpose of enhancing the performance of the algorithm (Rashedi et al. 2009a).

Gravitational force applied to *i*-th agent by the *j*-th agent can be defined with $F_{ij}^{d}(t)$ for dimension *n* and iteration *t*. It is specified by the following equation:

$$F_{ij}^{d}(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \tag{52}$$

where, M_{pi} is the passive gravitational mass of agent *i* and M_{ai} is the active gravitational mass of agent *j*. $R_{ij}(t)$ refers the Euclidian distance between the agents these agents at the iteration *t*. Lastly, $G(t)$ is the calculated gravitational force and ε stands for a small constant.

$$R_{ij}(t) = \| X_i(t), X_j(t) \|_2 \tag{53}$$

From the Newton's second law of motion, acceleration of an agent *i* in the *d*-th dimension is computed as following:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{54}$$

Finally, after discovering all the necessary parameters, velocity, *v* and position, *x* to be employed in the next iteration are calculated. Corresponding relations are given as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{55}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (56)$$

After completing the first iteration, best agent in the population presents the global best agent namely solution of the problem. Throughout the iterations GSA records the information of best agents. In each iteration, the algorithm compares the associated fitness of best agent with previous iteration and if the last best agent has better fitness than previous global best agent, it is updated as new global solution of the problem. These processes are continued until reaching the termination criteria of which can be maximum number of iteration or obtaining certain threshold value. A flowchart of GSA is given in Figure 28.

Although GSA is a relatively new search algorithm, it has been applied in several studies in different scientific branches. For example, Behrang et al. (2011) used the GSA algorithm to estimate the oil consumptions of Iran by solving linear and nonlinear relations. In another studies, researchers implemented GSA in electrical engineering topics which are composed of nonlinear constrained problems (Duman et al. 2011, 2012, Chatterjee et al. 2010). There are also modified version of GSA proposed by the researchers. Rashedi et al. (2009b) established the binary gravitational search algorithm (BGSA) as the name implies this algorithm is the binary version of the typical GSA. A hybrid application of GSA and PSO was developed by Tsai et al. (2013) called as gravitational particle swarm (GPS) and it was reported that the hybrid algorithm provides some improvements to the current GSA and PSO.

Just as the other engineering branches, GSA has been applied in civil engineering problems (especially geotechnical issues) as well. Khajehzadeh and Taha (2012) utilized the GSA in optimization of shallow foundations that the algorithm minimizes the cost of structure while considering the constraints which are based on the failure conditions or minimum requirements of structural and geotechnical parameters. In another geotechnical engineering problem: optimization of retaining structures, GSA was successfully applied. Similar to shallow foundation problem proposed algorithm tries to minimize overall cost of the retaining structures by taking into account the structural and geotechnical constraints (Khajehzadeh and Eslami 2012). The same researchers improved the GSA algorithm by employing adaptive velocity parameter which adjust the velocity of agents with regard to the state of convergence. Modified version of GSA named as MGSA is evaluated on several benckmark problems and in solving slope stability problem. The aim in such problems is to obtain minimum factor of safety and reliability index (Khajehzadeh et al. 2012).

Although extensive research has been carried out using GSA, no single study exists in pavement engineering. In this study, GSA is selected to use a search algorithm on the basis of presented reliability and robustness in the way of searching solution space in previous studies.

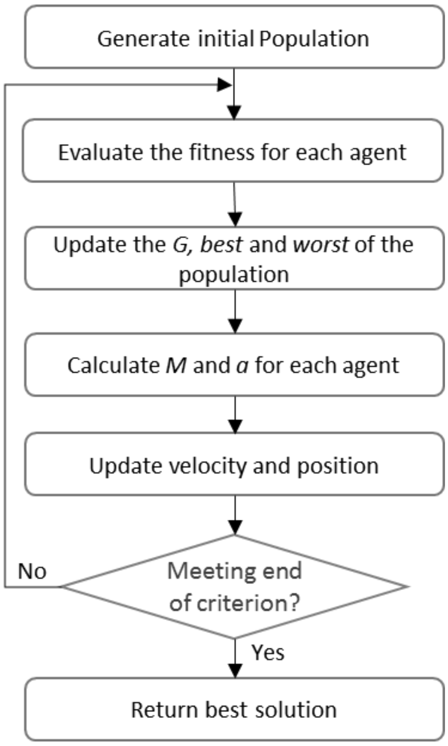


Figure 28 Flowchart of GSA (Rashedi et al. 2009a)

2.7.2.3 Genetic Algorithms

Genetic algorithms are metaheuristic search methods classified in the evolutionary algorithms which are based on the natural selection process. By simulating the evolutionary theory, GAs seek the search space to find the optimum solutions of the problems. Just as being in the nature, GAs use the approach behind the natural selection which is “*survival of the fittest*” (Goldberg 1989). A typical GA operation starts with the random generation of a population. The size of the population and the search space are determined according to the problem to be solved. Each individual in the population is regarded as the possible solution of the problem that they are also named as phenotypes in natural selection. GA uses the binary strings that the properties of individuals (namely chromosomes in evolutionary theory) are stored within these strings. Since this operation is an iterative process, each iteration refers to a generation where the population is evaluated. Each individual is assessed by means of an objective function specifically assigned to the problem to be solved. Through the use of the fitness of each agent regarding the values of the objective function, a selection step is implemented to the individuals to prepare a new population for the next generation. In this step, individuals which have the higher fitness values are selected and their properties are stored during the generations in order to enable “*survival of the fittest*” approach. Following step is to develop the new population for the next generation. For this purpose, genetic operators in the natural selections are replicated such as crossover and mutation. By the use of crossover, a pair of parent individuals are selected to generate a new individual namely child and it is aimed to transfer the properties of better individuals to their children. Mutation is another genetic operator used to provide population diversity by changing a single individual (Goldberg 1989; Mitchell 1995). Then the new population is formed and maintained to begin the new generation. These operations continue until reaching the termination criteria.

GA is the one of the most adapted metaheuristic search algorithms to the pavement layer backcalculation studies that is why it is selected in this study to compare with GSA. In recent studies, GA has been applied as search method for ANN forward response models and the hybrid use is employed for backcalculating stiffness related pavement layer properties (Bosurgi and Trifirò 2005; Gopalakrishnan 2009a; Nazzal and Tatari 2013; Pekcan 2010; Rakesh et al. 2006).

2.7.3 Backcalculation Softwares Used in the Study

Pavement backcalculation is an important component in pavement management systems. Estimating the stiffness related layer properties plays a key role in evaluating the structural capability of pavements in overlay design and remaining life analysis. Pavement agencies and researchers in pavement community use various software for the purpose backcalculating layer moduli. Each software has distinctive characteristics of those forward response analysis approach, material characterization and utilized search method which may lead a backcalculation software being different from the others. In order to validate the proposed algorithm in this thesis, it is essential to compare the results of the algorithm with the other softwares. In this respect, two conventional backcalculation softwares; EVERCAL 5.0 and MODULUS 6.0 are utilized for the comparison.

2.7.3.1 EVERCALC

EVERCALC 5.0 backcalculation software was developed by Washington Department of Transportation (WSDOT). The program makes use of WESLEA layered elastic analysis program for the forward calculation of deflection basins. As a search method, EVERCALC uses modified Augmented Gauss-Newton algorithm. Maximum five-layered pavement structures can be analyzed by this program. An FWD test can be simulated for maximum ten geophones and twelve drops per one station. Root mean square (RMS) error objective function is used while comparing the calculated and measured deflection basins.

$$RMS = \sqrt{\frac{1}{n_d}\sum_{i=1}^{n}\left(\frac{d_{ci} - d_{mi}}{d_{mi}}\right)^2 (100)} \tag{57}$$

Where n_d is the number of deflection sensors and d_{ci} and d_{mi} are the calculated and measured deflections, respectively.

Although employed multi-layered elastic theory by the software, it is able to determine stress sensitivity coefficients of geomaterials in the case of providing deflection data for more than one load level. By this way, nonlinearity of materials might be taken into account while backcalculating the stiffness properties. For unbound granular base materials, the software can predict K and n coefficients in K-θ model presented in Equation (20) and for fine-grained subgrade soils K_1 and K_2 coefficient in confining pressure model as presented in Equation (19).

EVERCALC offers two alternatives for defining initial layer moduli which will be used in the first iteration. Either program can compute the moduli values by means of internal regression equations or user can define a set of moduli himself to the software. The software decides to terminate the processes when at least one of the criterions is satisfied that of reaching predefined deflection tolerance, moduli tolerance or maximum number of iterations. It is reported that 1% tolerance is enough to terminate the program (Washington Department of Transportation 2005).

Since the stiffness properties of asphalt layers are directly affected through the change in temperature, sometimes it might be necessary to convert backcalculation results into laboratory conditions. EVERCALC is capable of normalizing modulus of elasticity to the 25°C through regression equations. The software can also investigate the existence of a rigid layer beneath the subgrade and associated depth can be calculated (Washington Department of Transportation 2005). A general data entry screen and deflection entry interface are shown in Figure 30 and 31, respectively. A flowchart of EVERCALC is presented in Figure 29.

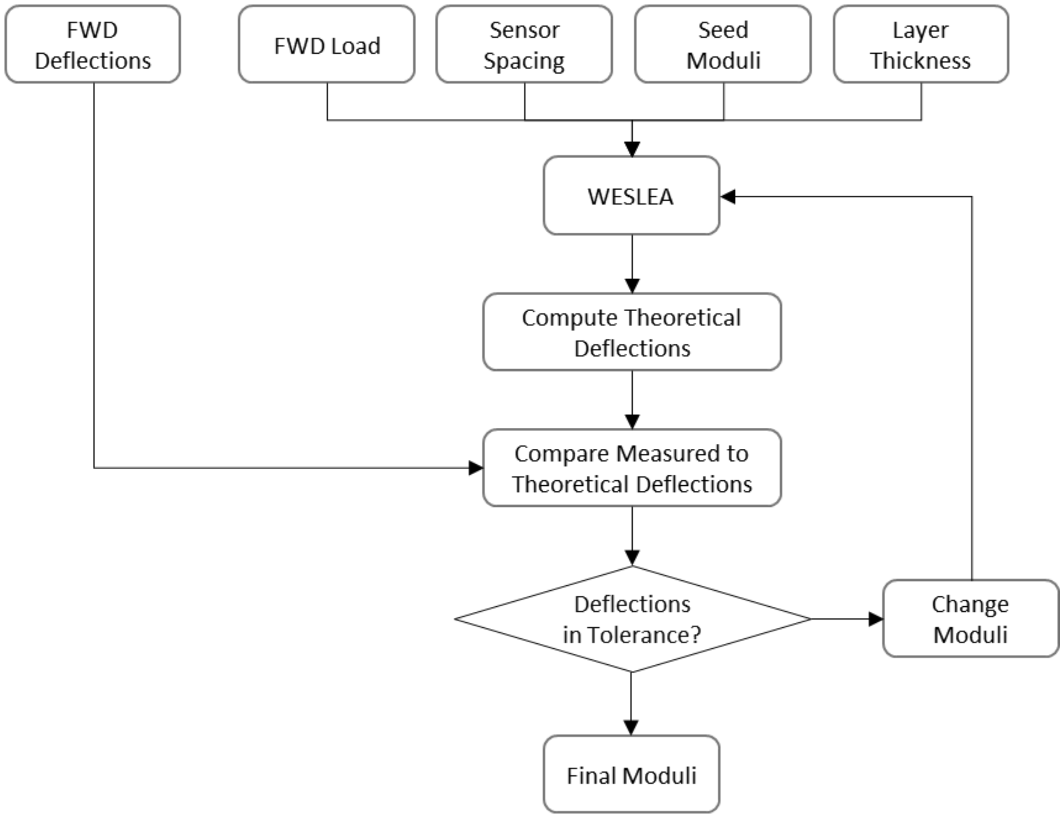


Figure 29 A typical flowchart of EVERCALC software (Washington Department of Transportation 2005)

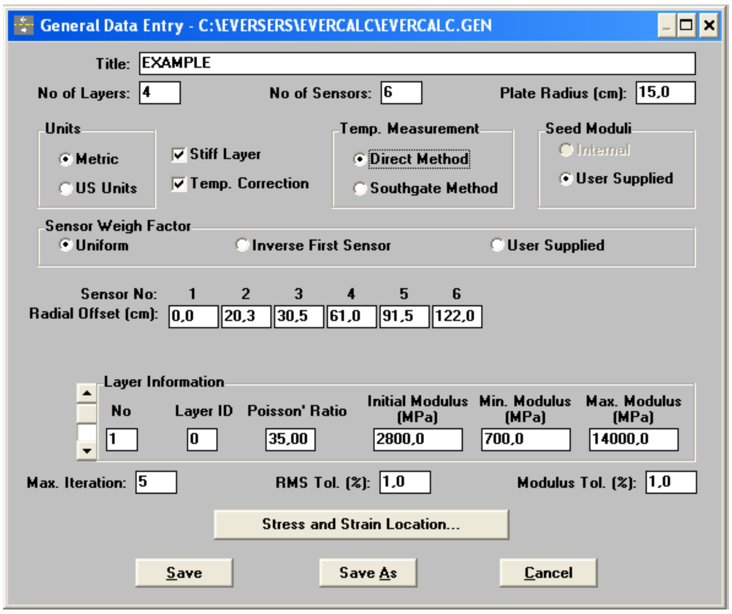


Figure 30 EVERCALC General Data Entry Screen

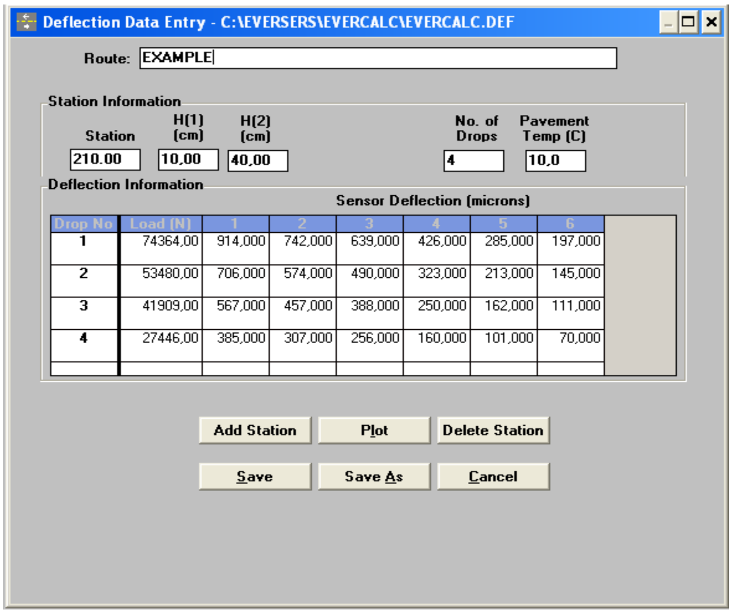


Figure 31 EVERCALC Deflection Basin Entry Interface

2.7.3.2 MODULUS

MODULUS 5.1 is another pavement backcalculation software works in MS-DOS environment employed in this study. The software was developed by Texas Transportation Institute (TTI) for the use of Texas Department of Transportation (TxDOT) in the studies of performing pavement backcalculation operations and remaining life analyses. Forward response analysis of the software bases on the solutions of WESLEA layered elastic analysis program. Unlike the EVERCALC software, MODULUS does not run forward response engine in each iteration. Instead, it uses a database which includes input properties and corresponding deflections of WESLEA analyses that previously generated and stored embedded into the MODULUS. As a search method, MODULUS uses pattern search technique to extract the set of moduli which presents the best fitted deflection basin to the field deflection basin. The software is able to analyze maximum four layered structures and it also determines the depth of rigid layer beneath thee subgrade (Liu and Scullion 2001; Ahmed 2010). The main interface of MODULUS 5.1 is shown in Figure 32.

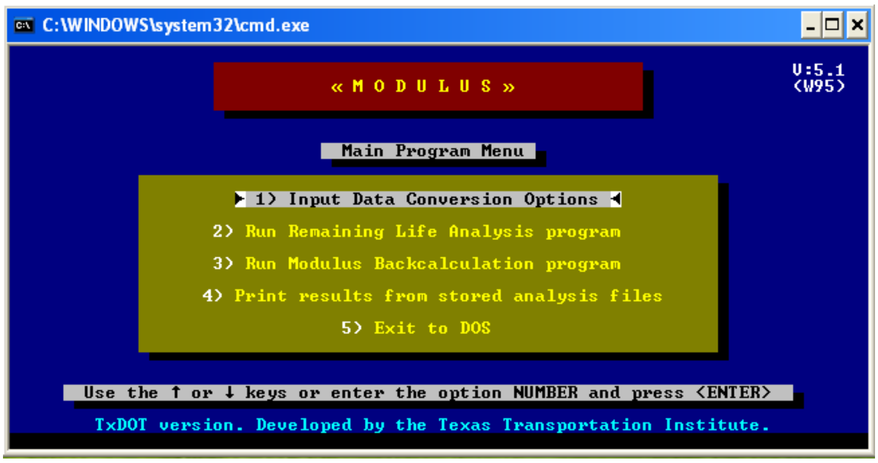


Figure 32 Main Screen of MODULUS 5.1

CHAPTER 3

BACKCALCULATION METHODOLOGY

3.1 Introduction

This chapter focuses on the description of development stages of proposed backcalculation algorithm namely GSA-ANN. In this study, previously developed ANN models by Pekcan (2010) are employed as forward response modelling of pavements. Researcher produced these models using the solutions of ILLI-PAVE FEM based software. Proposed algorithm is also performed with the data generated by this software to evaluate its performance. Therefore, details of the finite element modelling of pavement by ILLI-PAVE is expressed in detail to provide insight about the analyses. Then, both linear and nonlinear material characterization taken into account in the analyses are explained, respectively. Apart from these, additional computer programs which the researcher employed while generating the ANN models are also presented in this chapter. Also, combination of ANN models with the GSA search method are provided to show how GSA-ANN backcalculation algorithm is formed. Finally, to provide better understanding about the proposed algorithm, a sample full-depth asphalt pavement section's layer properties are backcalculated by introducing all the steps individually.

3.2 Finite Element Modeling of Pavements Using ILLI-PAVE Software

In pavement layer backcalculation problems, structural analysis of pavements is the overriding factor in terms of obtaining real-like deflections. In a typical ILLI-PAVE analysis, first step is to define loading conditions to the software. After that layer properties are introduced which are number of layers and corresponding thicknesses, material related features like constitutive material model and general properties of used geomaterials. In this step, nonlinear material behaviors which are the most representative nature of base and subgrade materials are taken into account. The software can analyze up to ten-layered pavement structures. Prior to analyzing the pavements, proper evaluation domain is determined in terms of mesh dimensions and spacing. At the end, analysis is completed and deflections are extracted together with the pavement responses, like stress and strain at any point examined in the axisymmetric domain. These expressed steps are general overview of a typical ILLI-PAVE run and they were conducted for developing ANN models of FDP, CFP and FDP-LSS type test sections and also for the performance evaluation of GSA-ANN algorithm. In subsections, detailed information about these steps are given respectively.

3.2.1 Simulation of Falling Weight Deflectometer Test

FWD device generates various level of transient impulsive forces by dropping a weight from different heights to the loading plate. Associated with the loading states, transient displacements occur on the pavement surface where the maximum value is in the load application point and less deflections are emerged radially more distant locations. Usually, the force is subjected over a circular plate of 152 mm (6 in.) radius in FWD tests and occurred impulse is propagated through the plate. In this study, a 40 kN (9 kip) equivalent single axle load (ESAL) applied over the loading plate corresponds to 552 kPa (80 psi) uniform pressure is defined to the software. Occurred deflections at the radially located sensors can be calculated using proper mesh spacing. The most commonly used sensor locations away from the load application point in FWD tests are listed in Table 2. Deflections at these specific locations can be abbreviated as D_0, D_8, D_{12}, D_{18}, D_{24}, D_{36}, D_{48}, D_{60}, D_{72} and D_{-12}, respectively.

Table 2 Sensor Spacing Types of Falling Weight Deflectometer

Sensor Locations	**in**	0	8	12	18	24	36	48	60	72	-12
	mm	0	203	305	457	610	914	1219	1524	1829	-305
Uniform		✓		✓		✓	✓	✓	✓	✓	
7-sensored		✓	✓	✓	✓	✓	✓		✓		
9-sensored		✓	✓	✓	✓	✓	✓	✓	✓		✓

In this study, uniform sensor spacing is selected to calculate and extract deflection data which are D_0, D_{12}, D_{24} and D_{36}. Therefore, proper element dimensions are adjusted in meshing stage in order to extract deflection data from the exact sensor locations consistent with the selected uniform sensor spacing.

3.2.2 Meshing of the Axisymmetric Models

Meshing is one of the major factors which directly affect the accuracy of calculated responses and entire performance of the FE software. In this respect, in the case of utilizing finer meshes in the analysis domain, precision of stress, strain and displacement responses increase but the runtime of the FE analyses increases proportional to desired accuracy. Thus, exercising finer meshes may sometimes be problematic in figuring out the problems having complex geometries. It is essential to balance mesh intervals and element dimensions regarding the process speed and desired level of accuracy.

The analyzed pavement is introduced to the ILLI-PAVE as a cross-sectional area which has symmetry about a vertical axis which is named as 2D axisymmetric model (see Figure 33). The entire model can be formed by the rotation of ZR cross-sectional region about the Z axis where R refers to the radial direction. By this way, a 3D pavement model can be converted into 2D or axisymmetric model which is easier and faster to handle. The dimensions of the 2D domain in radial and vertical directions are the important properties for the meshing stage which may affect the accuracy of analysis results. Boundary conditions should not influence the propagation of stresses throughout the domain. Therefore, proper depth and radial distance from the load application point till the boundaries should be selected. In the present study, total analysis depth is treated as 7620 mm (300 in.) and the radial distance is considered as 14572 mm (80 in.) away from load application location for all the three type of pavements in question so that the effects of boundary can be neglected. Thickness of the surface and base courses (if exist) are subtracted from the total analysis depth to define the subgrade depth to the below boundary. The bottom boundary is simulated using fixed support conditions while roller supports employed in vertical boundaries which allows to move through the associated direction.

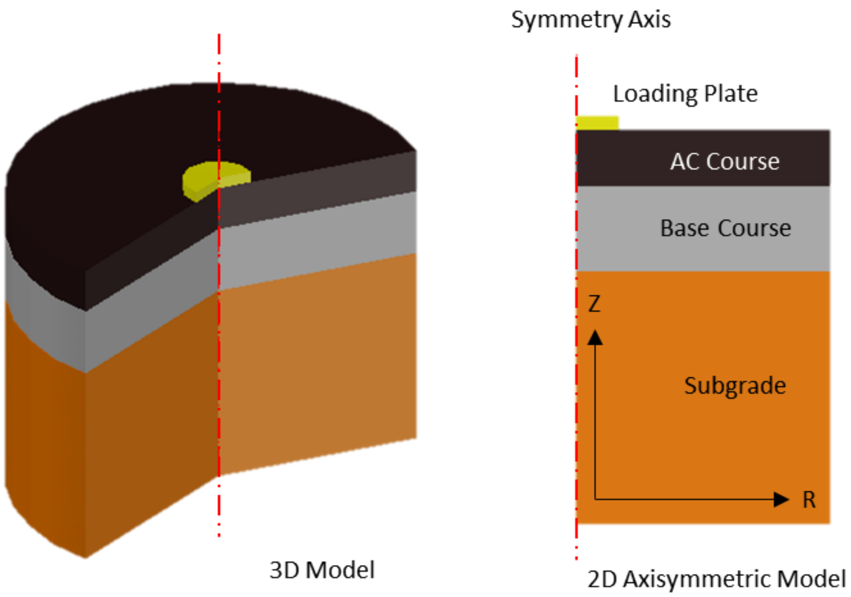


Figure 33 2D Axisymmetric Model and 3D Model

Since FWD sensors are placed to certain locations, appropriate mesh adjustment is needed to calculate the deflections exactly at the same coordinates with these sensors. ILLI-PAVE uses 4-noded quadrilateral mesh units to form the whole domain as a grid. The size of each element at its corresponding coordinates are adjusted in such a way that each sensor location fits to that of associated node coordinates. To better observe the pavement responses and displacements, and also to provide stress waves to propagate throughout the domain regularly, finer meshes are used around loaded and sensor placed areas. Moreover, relatively thinner surface and base layers to the subgrade are also modelled with smaller mesh elements around the loading area. The ratio of the longest edge over to the shortest one of a mesh element namely aspect ratio is generally adjusted to 1 with an upper value of 4. The influence of FWD load decreases while moving toward the domain boundaries, and therefore coarser meshes or in other words bigger mesh units are used at more distant regions from the loading location. In Figure 34, generated meshes for each of FDP, CFP and FDP-LSS sections are illustrated. Columns of the meshes are placed the radial distances of 1, 2, 3, 4, 5, 6, 8, 12, 18, 24, 36, 48, 60, 72, 90, 108, 126, 144 and 180 in. from the initial vertical line while rows are adjusted distances of 2, 3, 5, 7, 9, 11, 13, 14, 17, 20, 25, 35, 55, 100, 150, 200, 250 and 300 in. from the initial lateral line.

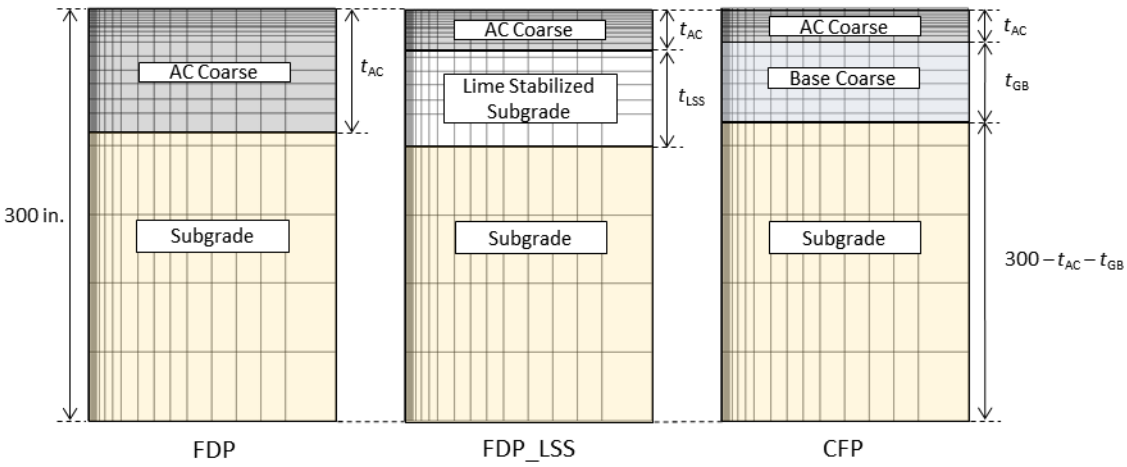


Figure 34 Meshing of FDP, FDP-LSS and CFP Sections

3.2.3 Material Characterization

Flexible pavements are composed of several layers of different materials located over the natural subgrade. The nature of each material should be well comprehended under imposed traffic loading in the manner of design and analysis. It is obvious that appropriate modelling of these materials is one of the overriding factors in backcalculation of layer properties. The upper most layer of flexible pavements is produced from bituminous material called as asphalt concrete (AC) which actually exhibits viscoelastic behavior associated with temperature and time. For the sake of computational simplicity, asphalt layers were considered as linear elastic so that mechanical properties of surface layers were presented with elastic modulus E_{AC} and Poisson's ratio v_{AC} along with the analyses.

Conventional flexible pavement is other flexible pavement type constructed with base/subbase layer beneath the surface course. The function of such layers is to transmit the occurred impact of traffic loading to the natural subgrade by protecting it against the environmental influences. They are constructed with unbound granular materials whose behavior depends on imposed stress level. Unbound granular materials harden under increasing load levels and this can be modelled in ILLI-PAVE software through the use of material models established by several researchers. As reviewed in section 2.6.4.3, there are various resilient modulus models for unbound granular materials. Among these ones, ILLI-PAVE utilizes just three of them; confining pressure model (Equation (19)), K-θ model (Equation (20)) and Uzan model (Equation (24)). In this study, K-θ equation is employed to calculate resilient modulus such that the model is the function of bulk stress, θ beside the K and n model parameters (Hicks and Monismith 1971). These model parameters are correlated to each other through the Equation (58) which is established by using the test results presented in Figure 35. Typical K and n parameters acquired for different type of granular materials are also presented in Table 1.

$$\log_{10}(K) = 4.657 - 1.807n \tag{58}$$

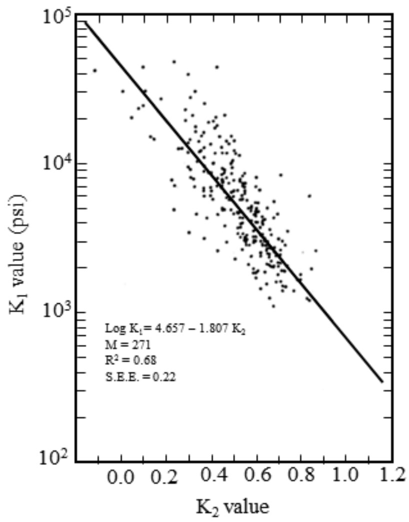


Figure 35 Relation Between Parameters of K-θ Model (Rada and Witczak 1981)

Consequently, ILLI-PAVE computes the modulus of granular materials iteratively by adjusting bulk stress in each iteration for defined K parameter. From now on, the parameter K will be states as K_{GB} to refer the granular base layer in CFP sections. Therefore, unbound granular layers are characterized with its stiffness constant, K_{GB} and Poisson's ratio, v_{GB}

Subgrade is the natural soil located beneath the structural layers of all type pavements. Similar to unbound granular layers, subgrade exhibits nonlinearly under imposed traffic loading so that resilient properties of such soils can be used to present the material behaviors. Although subgrade could be composed of granular or fine-grained materials, this study focuses on only fine-grained subgrade soil patterns. In contrast to granular materials, fine-grained soils soften under increasing load states which reduces the strength of the materials. According to the study conducted by Thompson and Robnett (1979), it is reported that resilient modulus of fine-grained subgrade soils is a function of deviator stress and confining pressure is less significant by comparing to deviator stress. For this reason, developed constitutive equations generally establish the relation between resilient modulus and deviatoric stress. Among the utilized subgrade material models in ILLI-PAVE, bilinear or arithmetic constitutive equations (Equation (32)) are utilized to characterize the fine-grained natural soils. In this model, relationship between deviator stress and resilient modulus are illustrated in Figure 20 with parameters of E_{Ri}, σ_{di}, K_3 and K_4. Resilient modulus at the breakpoint of linear curves is named as breakpoint resilient modulus E_{Ri} which is the corresponding moduli at the breakpoint deviator stress, σ_{di}. E_{Ri} is the main stiffness property presenting resilient behavior rather than other material parameters of those K_3 and K_4 are considered as constants originating from the study conducted by Thompson and Elliott (1985). Based on this study, the maximum resilient modulus could be acquired under 13.8 kPa (2 psi) deviatoric stress which is the lower limit of deviatoric stress, σ_{dll} . Minimum resilient modulus associated with maximum deviatoric stress, σ_{dul} could be limited to the unconfined compressive strength of the soil, Q_{u} which can expressed as a function of E_{Ri}: (Thompson and Robnett 1979)

$$\sigma_{dul}(psi) = Q_u(psi) = \frac{E_{Ri}(ksi) - 0.86}{0.307} \tag{59}$$

In this study, breakpoint deviator stress of 41.3 kPa (6 psi) is treated for local fine-grained materials. K_3 and K_4 slopes are taken constant as 1100 and 200, respectively that the values are proposed as a consequence of laboratory studies conducted by Thompson and Robnett (1979) and Thompson and Elliott (1985).

Sometimes it is essential to improve strength of soil which is not strong enough to construct pavements above. In these cases, as an easy and effective approach lime stabilization can be applied so that mechanical properties of natural soils significantly advanced. Pekcan et al. (2009) investigated the deflection behaviors of stabilized pavements in their studies and it was obviously observed that great differences between the deflections basins of non-treated and treated soils. Therefore, this study addresses to take into account the lime stabilized soils as a separate layer in backcalculation of pavements of which is constructed over stabilized soils. In this study, lime stabilized sections of full-depth asphalt pavements are also analyzed. Stabilized layers are treated as linearly elastic for computation simplicity and they are characterized with the properties of elastic modulus E_{LSS} and Poisson's ratio v_{LSS}.

3.2.4 Defining Layer Properties

Prior to analyze pavement sections for calculating deflection values at FWD sensor locations, geometrical and mechanical layer properties should be defined to the software. In order to create ANN forward calculation engine, it is required to generate a great number of deflection bowls associated with various combination of input properties in previously defined ranges. Range of thicknesses of layers and corresponding stiffness properties of different paving materials vary according the type of flexible pavement. Utilized ANN model for FDPs and testing data sets of GSA-ANN algorithm were created with the following ranges for thickness of asphalt course, t_{AC}, elastic modulus, E_{AC} and breakpoint deviator stress for fine-grained subgrade soil, E_{Ri}:

Table 3 Ranges of Layer Properties for Full-Depth Asphalt Pavements

Material Type	**Layer Thickness Range**	**Material Model**	**Layer Modulus Range**	**Poisson's Ratio**
Asphalt Concrete	t_{AC} = 127 - 635 mm (5 - 24 in.)	Linear Elastic	E_{AC} = 689 - 13,780 MPa (100 - 2,000 ksi)	0.35
Fine-Grained Subgrade	7620 - t_{AC} mm (300 - t_{AC} in.)	Nonlinear Bilinear Model	E_{Ri} = 6.9 – 96.5 MPa (1 – 14 ksi)	0.45

24,000 different combinations of thickness and moduli of layers for FDPs fully covering the entire ranges defined in Table 3 were analyzed and together with their results in terms of deflections, Pekcan (2010) generated the FDP ANN model.

In the analyses of conventional flexible pavements, considered thickness of AC and unbound granular layer and moduli ranges of each layer are presented in Table 4. Asphalt layer properties are considered as the same as the FDP sections. As for the granular base layer, K_{GB} parameter in the K-θ material model is defined to characterize resilient modulus property of unbound layer along with the thickness of granular base, $t_{GB.}$ Fine-grained subgrade is presented with breakpoint deviator stress, E_{Ri} as well. The range of K_{GB} parameter is selected on the basis of the data set obtained from their studies of Rada and Witczak (1981) which are also presented in Table 4. CFP ANN model was also developed by the 24,000 ILLI-PAVE runs executed by covering the predefined ranges (Pekcan 2010).

Table 4 Ranges of Layer Properties for Conventional Flexible Pavements

Material Type	**Layer Thickness Range**	**Material Model**	**Layer Modulus Range**	**Poisson's Ratio**
Asphalt Concrete	t_{AC} = 76 - 381 mm (3 - 15 in.)	Linear Elastic	E_{AC} = 689 - 13,780 MPa (100 - 2,000 ksi)	0.35
Granular Base	t_{GB} =102 – 559 mm (4– 22 in.)	Nonlinear K-θ Model	K_{GB} = 20.7 – 82.7 MPa (3 – 12 ksi)	0.35 for $K_{GB} \geq 5$ ksi
				0.40 for $K_{GB} < 5$ ksi
Fine-Grained Subgrade	7620 - t_{AC}- t_{GB} mm (300 - t_{AC} - t_{GB} in.)	Nonlinear Bilinear Model	E_{Ri} = 6.9 – 96.5 MPa (1 – 14 ksi)	0.45

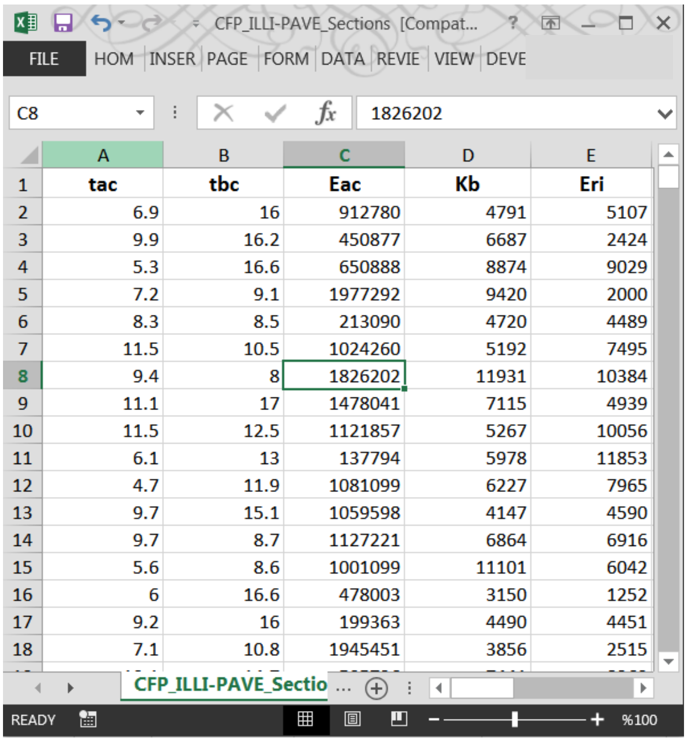
In the analyses of full-depth asphalt pavements on lime stabilized soils, AC course and subgrade thickness and stiffness properties are evaluated in the same manner with FDP and CFP sections. Lime stabilized subgrade layers are treated as linearly elastic with the parameters of elastic modulus, E_{LSS}, thickness, $t_{LSS,}$ and also breakpoint deviator stress for fine-grained subgrade soil, E_{Ri} is used. Corresponding layer properties of FDP-LSS are presented in Table 5. 26,000 different combinations of input parameters were executed with ILLI-PAVE to form FDP-LSS ANN model (Pekcan 2010).

Table 5 Ranges of Layer Properties for Full-Depth Asphalt Pavements on Lime Stabilized Subgrades

Material Type	**Layer Thickness Range**	**Material Model**	**Layer Modulus Range**	**Poisson's Ratio**
Asphalt Concrete	t_{AC} = 102 - 635 mm (4 - 24 in.)	Linear Elastic	E_{AC} = 689 - 13,780 MPa (100 - 2,000 ksi)	0.35
Lime Stabilized Subgrade	t_{LSS} =102 – 508 mm (4 – 20 in.)	Linear Elastic	E_{LSS} = 110 – 1,034 MPa (16 – 150 ksi)	0.31
Fine-Grained Subgrade	7620 - t_{AC}- t_{LSS} mm (300 - t_{AC} - t_{LSS} in.)	Nonlinear Bilinear Model	E_{Ri} = 6.9 – 96.5 MPa (1 – 14 ksi)	0.45

3.2.5 Analyzing Pavement Sections and Creating Data Sets

By considering the great number of FE analysis to be performed with ILLI-PAVE, providing input parameters of each run separately is an extremely challenging and time-consuming task. In this respect, it is required to use additional computer programs which enable researchers fast and practical input data generation and analysis opportunity. In this context, input parameters of each flexible pavement which are randomly selected within the specified ranges are stored in MS Excel file as given in Figure 36. The parameters included in databases for FDP sections: t_{AC}, E_{AC} and E_{Ri} for CFP sections: t_{AC}, $t_{GB,}$ E_{AC}, K_{GB} and E_{Ri} and for FDP-LSS sections: t_{AC}, $t_{LSS,}$ E_{AC}, E_{LSS} and E_{Ri}.



	A	B	C	D	E
1	tac	tbc	Eac	Kb	Eri
2	6.9	16	912780	4791	5107
3	9.9	16.2	450877	6687	2424
4	5.3	16.6	650888	8874	9029
5	7.2	9.1	1977292	9420	2000
6	8.3	8.5	213090	4720	4489
7	11.5	10.5	1024260	5192	7495
8	9.4	8	1826202	11931	10384
9	11.1	17	1478041	7115	4939
10	11.5	12.5	1121857	5267	10056
11	6.1	13	137794	5978	11853
12	4.7	11.9	1081099	6227	7965
13	9.7	15.1	1059598	4147	4590
14	9.7	8.7	1127221	6864	6916
15	5.6	8.6	1001099	11101	6042
16	6	16.6	478003	3150	1252
17	9.2	16	199363	4490	4451
18	7.1	10.8	1945451	3856	2515

Figure 36 Example of Input Data Stored to be Analyzed with ILLI-PAVE

It is necessary to convert these input values of ILLI-PAVE into its input file format of "*.ili*". In order to generate input files from Excel data sheets an auxiliary computer program written with Borland Delphi programming language developed by Pekcan (2006) is employed. By means of this input file generator, desired number of input files can be generated using the thickness and stiffness properties in the data sets through only one run and could be saved to the same directory (Pekcan 2010). The interface of this software is shown in Figure 37.

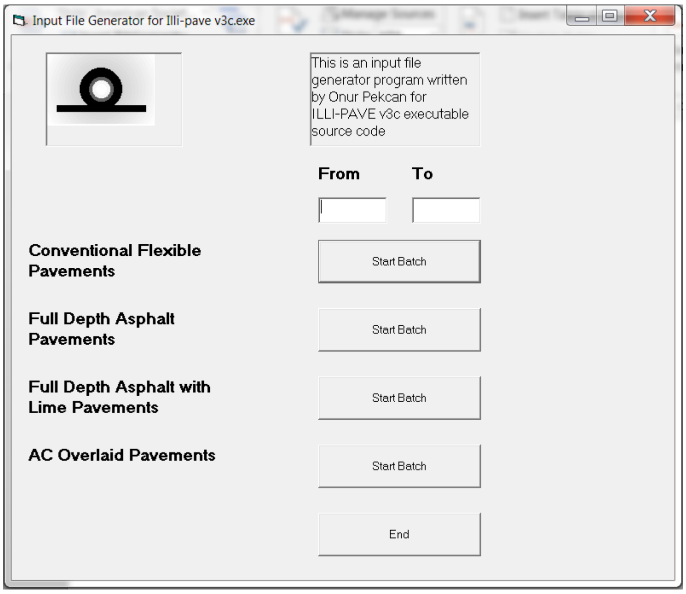


Figure 37 Input File Generator for ILLI-PAVE

Analyzing pavement sections with ILLI-PAVE is a tedious task in itself and therefore another additional computer program is employed namely ILLI-PAVE Auto Analysis to analyze the pavements and extract the deflection data. Analogous to input file generator, this software is also written in Borland Delphi programming language. It uses the analysis engine of ILLI-PAVE 2005 and is able to analyze input files collectively. Previously developed input data sets of ILLI-PAVE are handled by using auto analysis software. Moreover, it can extract the deflections at FWD sensor locations and critical responses at designated points. Obtained analyses results are then recorded to an MS Excel database beside their corresponding input properties. These database could be used to develop ANN models and also to evaluate the performance of proposed GSA-ANN algorithm. An example data set for CFP sections is illustrated in Figure 38.

tac	tbc	Eac	Kb	Eri	do	d8	d12	d18	d24	d36	d48	d60	d72	eAC	eSG	SIGDEV
6.9	16	912780	4791	5107	13.32	11.8	10.74	9.2	7.81	5.52	3.77	2.51	1.64	105.22	191.05	2.38
9.9	16.2	450877	6687	2424	14.2	12.42	11.44	10.05	8.76	6.52	4.72	3.32	2.29	116.22	202.54	1.85
5.3	16.6	650888	8874	9029	14.76	12.14	10.39	8.16	6.43	4.04	2.48	1.51	0.94	149.98	241.06	3.64
7.2	9.1	1977292	9420	2000	10.84	10.07	9.47	8.55	7.63	5.95	4.5	3.32	2.4	57.24	178.69	1.43
8.3	8.5	213090	4720	4489	20.17	16.28	14.17	11.46	9.22	5.93	3.72	2.31	1.45	232.01	468.9	3.87
11.5	10.5	1024260	5192	7495	6.85	6.12	5.73	5.17	4.62	3.6	2.72	1.99	1.42	48.53	84.94	1.56
9.4	8	1826202	11931	10384	5.59	5.08	4.75	4.26	3.77	2.9	2.15	1.55	1.09	38.21	85.94	1.72
11.1	17	1478041	7115	4939	6.44	5.9	5.59	5.12	4.65	3.75	2.94	2.24	1.67	38.38	72.36	1.13
11.5	12.5	1121857	5267	10056	6.07	5.41	5.06	4.55	4.06	3.14	2.35	1.71	1.21	44.12	67.3	1.56
6.1	13	137794	5978	11853	20.91	14.7	11.53	8.04	5.72	3.08	1.73	1.05	0.67	313.75	421.74	6.09
4.7	11.9	1081099	6227	7965	15	12.67	11	8.79	7.04	4.53	2.82	1.71	1.05	126.1	296.47	3.78
9.7	15.1	1059598	4147	4590	9.26	8.41	7.88	7.08	6.3	4.86	3.64	2.64	1.87	62.67	112.31	1.4
9.7	8.7	1127221	6864	6916	7.88	7.09	6.6	5.89	5.2	3.95	2.91	2.08	1.45	57.05	118.01	1.81
5.6	8.6	1001099	11101	6042	13.91	12.06	10.74	8.9	7.34	4.96	3.25	2.08	1.33	112.56	315.11	3.44
6	16.6	478003	3150	1252	24.8	21.59	19.34	16.2	13.49	9.25	6.14	3.98	2.56	200.62	413.41	1.28
9.2	16	199363	4490	4451	18.91	15.19	13.33	10.96	8.98	5.95	3.85	2.45	1.55	212.62	286.48	2.88
7.1	10.8	1945451	3856	2515	11.11	10.3	9.67	8.7	7.74	5.98	4.48	3.27	2.34	60.22	159.37	1.38
10.1	14.7	505736	7441	8369	10.09	8.57	7.77	6.67	5.68	4.03	2.77	1.85	1.22	96.63	134.91	2.39
4.4	6.3	565688	5379	4886	23.38	18.99	15.98	12.19	9.39	5.71	3.41	2.04	1.26	217.46	757.85	5.1
7.9	6.4	1661798	10987	11725	6.69	5.99	5.51	4.81	4.15	3.02	2.12	1.45	0.97	50.94	119.07	2.32
6.1	7.5	881576	3220	11559	11.78	10.01	8.78	7.11	5.73	3.68	2.27	1.37	0.83	114.82	241.21	3.86
11.9	7	379741	11840	8235	9.67	7.95	7.18	6.18	5.3	3.8	2.65	1.8	1.2	92.43	178.19	2.81

Figure 38 An Example Data Set for CFP Analyses of ILLI-PAVE

3.3 ANN Based Forward Analysis Models

In order to properly train an ANN model, a great number of analyses is required so that it is expected from the analyses to fully cover the ranges of input properties. Because of the required excessive runtime for the thousands of FE analyses, operations for generating ANN model are time-consuming tasks. For this reason, ANN models for FDP, CFP and FDP-LSS type flexible pavements developed by Pekcan (2010) are employed in this study. Through the use of ANNs as forward response models, runtime of backcalculation operations is dramatically reduced. FWD tests are applied to a road portion for certain times along with the stations. Sometimes, the distance between each station may be less than 10 m. By considering the length of highways, it is obviously seen that many FWD tests are needed to be conducted. In the case of implementing backcalculation operations at each station and also regarding the iterative manner, computational intensive problems are emerged that is why ANN models are selected to analyze the pavement sections. By using ANN models, deflections are estimated for the given thickness and modulus values with high accuracy and faster than a typical FE analysis.

All of the employed ANN models cover the predefined geometrical and mechanical layer properties in section 3.2. FDP and CFP neural network models were created by using 2 hidden layers of each one includes 60 neuros. FDP-LSS forward model was also developed with 2 hidden layers but it employs 20 neurons in each hidden layer in contrast to other two models. There are 3 neurons in input layer and 4 neurons in output layer of FDF forward model while CFP and FDP-LSS include 5 neurons in input layer, 4 neurons in output layer. Regarded parameters of input and output neurons are given in Table 6. The number of hidden layers and neurons are originating from a similar training application conducted by Ceylan et al. (2005). All the models were trained for 10,000 epochs (Pekcan 2010).

Table 6 Input and Output Variables of Forward ANN Models

Pavement Type	**Inputs**	**Outputs**
FDP	t_{AC}, E_{AC}, E_{Ri}	D_0, D_{12}, D_{24}, D_{36}
CFP	t_{AC}, $t_{GB,}$ E_{AC}, K_{GB}, E_{Ri}	D_0, D_{12}, D_{24}, D_{36}
FDP_LSS	t_{AC}, $t_{LSS,}$ E_{AC}, E_{LSS}, E_{Ri}	D_0, D_{12}, D_{24}, D_{36}

3.4 Development of GSA-ANN Backcalculation Algorithm

This section introduces how the proposed backcalculation algorithm namely GSA-ANN is developed. As the name of algorithm implies that the combination of gravitational search method and neural network models are utilized to perform pavement layer backcalculation. For this purpose, MATLAB R2012 software is used to code the entire algorithm. First of all, GSA optimization technique is written by following the steps explained in Section 2.7.2.2. After that each neural network model is embedded to GSA code as a function which makes forward response calculation for given input properties to predict deflections. By making use of the GSA-ANN algorithm, it is possible to backcalculate layer properties of FDP, CFP and FDP-LSS type flexible pavements. GSA-ANN backcalculation approach can be summarized in 9 steps:

Algorithm: GSA-ANN Backcalculation Algorithm

1 Define necessary parameters of the pavement to be analyzed;

2 Generate a random initial population for *N* number of agents which consists of stiffness properties of pavement layers to be backcalculated;

3 Provide the population to ANN model and calculate deflections;

4 Evaluate fitness of each agent in the population by comparing calculated and measured deflections. Then select the worst and best fitted agents according to Equation (36);

5 Calculate mass of each agent using Equation (38) and (39);

6 Compute the total force imposed to each agent with Equation (42);

7 Calculate acceleration of each agent by utilizing Equation (44);

8 Update the velocity and position to generate a new population by employing Equation (45) and (46);

9 Repeat steps 3 to 8 until reaching maximum number of iterations.

MATLAB is a computing environment which works with m-files consisting of commands or functions in it. As the name implies that the extension of these files is "*.m*". It is essential to write each command sequentially that MATLAB can properly execute the program. GSA-ANN code is divided into several m-files of each one performs different task. To create an integrated code, each individual m-file is gathered under the umbrella of a main script that calls the commands in a sequence. The process of the GSA-ANN code is summarized below respectively.

In MATLAB, functions are declared in the following form that for the given inputs, $x_1, \ldots, x_N$, the *functionName* returns the output values, $y_1, \ldots, y_M$.

$$\text{function} \quad [y_1, \ldots, y_M] = functionName(x_1, \ldots, x_N) \tag{60}$$

The data analyzed in MATLAB are stored either in arrays or matrices by considering the dimensions of variables to be analyzed. *main.m* is the major file where the variables are declared as globally and also it requests from the user to provide values of necessary input parameters which are listed below together with their definitions:

main.m: definition of input variables

N: number of agents in the population

maxTestNumber: number of test sections/stations to be analyzed.

maxIterationNumber: number of iterations

Rpower: power of Euclidean distance in Equation (42). In fact this value is 2 of which bases on Newton's law of universal gravitation but it gives better results when *Rpower* is considered as 1 according to Rashedi et al. (2009a).

pavementType: type of flexible pavement (FDP, CFP or FDP-LSS)

deflectionFileName: directory of MS Excel file which stores FWD deflection data to be evaluated.

main.m reads the field deflections from directory specified with *deflectionFileName* variable and records them to the array of *deflection_measured* for the current section/station in order to use it later to evaluate fitness of agents. The only function that *main.m* includes is *GSA.m* which is called after all the essential variables are introduced. It consists of other integral functions of GSA to be executed in turn. *GSA.m* is declared in the same form with Equation (60) and input and output are presented in Table 7:

Table 7 Input and Output Variables of *GSA.m*

Function	Input Variables	Output Variables
GSA	*N* *maxIterationNumber* *Rpower* *pavementType* *deflection_measured* *i*	*fitness_best* *solution_best* *deflection_calculated* *cost*

Where *i* refers to the number of test section/station currently dealing with. Actually, the outputs of the GSA function correspond to solution of the backcalculation problem. After performing all the functions of GSA, four outputs are returned of which are expressed as below.

GSA.m: definitions of output variables

solution_best: backcalculated stiffness properties which are the most representative ones with the field conditions.

deflection_calculated: calculated deflections of *solution_best* using ANN.

fitness_best: corresponding fitness value of *solution_best* which corresponds how well *deflection_calculated* was agreed with *deflection_measured.*

cost: array of calculated *fitness_best* values for each iteration. By using this performance of GSA-ANN code on reaching the solution could be plotted.

Both measured and calculated deflection data are stored in the array form as given below:

$$(deflection\_measured)_i = (deflection\_calculated)_i = [D_0, D_{12}, D_{24}, D_{36}] \quad (61)$$

Backcalculated stiffness properties of each type of pavement are also expressed in the following form:

For FDP; $$(solution\_best)_i = [E_{AC}, E_{Ri}] \quad (62a)$$

For CFP; $$(solution\_best)_i = [E_{AC}, K_{GB}, E_{Ri}] \quad (62b)$$

For FDP-LSS; $$(solution\_best)_i = [E_{AC}, E_{LSS}, E_{Ri}] \quad (62c)$$

The outputs which are listed above are provided by *GSA.m* executions. These results are products of a series of function evaluations of GSA optimization method adapted for backcalculation. These functions are introduced according to sequence of actions.

At the initial stage of a GSA run, ranges of parameters to be backcalculated are assigned according to predefined *pavementType* value. *objflimits* is the function which stores the ranges of input parameters and it is also the first called function when *GSA* is executed. *pavementType* takes only strings of 'FDP', 'CFP' and 'FDP-LSS' and number of layers with the corresponding moduli ranges for each pavement type are called from *objflimits.m* file. For the given pavement type, number of layers and corresponding moduli ranges are assigned to the variables by *objflimits* function. In order to obtain properly backcalculated data, ranges of material properties should be consistent with limits to that of defined ones used for creating ANN forward models (see Table 3 to 5). The form of *objflimits* function is denoted as follows:

$$[up, down, dim] = objflimits(pavementType) \tag{63}$$

where *dim* refers to the dimension of population to be analyzed. For pavement layer backcalculation, each stiffness property to be predicted corresponds to one dimension so that FDP sections have 2 dimensional search domain while CFP and FDP-LSS have 3 dimensional. *up* and *down* that are the extends for each dimension in other words lower and higher layer moduli. Following to this, initialization stage is performed to create a random population of stiffness properties. *initialization.m* is performed with the form given below:

$$[X_{kj}] = initialization(dim, N, up, down) \tag{64}$$

Referring to Equation (35), population, X_{kj} is composed of *N* number of agents (*k = 1 to N)* in *n (j = 1 to dim)* dimensional search space. This means that population has a matrix form of *dim* number of columns by *N* number of rows and each one stores the stiffness data.

Since backcalculation is an iterative process, parameters are estimated successively to improve the quality of input data in terms of how our calculated deflections fit with the measured ones from the field. For this reason, *GSA* function starts with the initialized population, *Xij*, repeat its all functions for predefined *maxIterationNumber* times by adjusting the population in every iteration. Prior to begining the first iteration, essential arrays and matrices are created which are listed below:

Velocity; $$V_{kj} = zeros(N, \mathrm{dim}) \quad (65a)$$

Best Stiffness; $$(solution\_best)_i = zeros(1, \mathrm{dim}) \quad (65b)$$

ANN Deflections; $$(deflection\_calculated)_i = zeros(1,4) \quad (65c)$$

zeros(a,b) denotes an a by b matrix whose all units are zero. Due to being in first iteration, all the agents in the population are motionless, and therefore all the velocities are set to zero. Other two arrays presented above are generated to record the results of the problem in these arrays.

After forming the necessary parameters listed above, *iteration* is set to 1. Since the population generated randomly, there may be some agents that violate the limits of *up* and *down.* To prevent agents of exceeding the boundaries, all agents are checked and if any of them exists which violates the limitations of those are initialized again. Next step is the assessment of population. In order to evaluate the agents in the way of forward response calculations, ANN is needed to be performed which is embedded to the objective function of GSA. Through the provided data with *main.m* and *GSA.m,* objective function, *objf.m* could be executed. In this study, mean absolute percentage error (MAPE) (see Equation (68)) is selected as the objective function to calculate the difference between deflection basins. Input and output variables of this function are listed in Table 8.

Table 8 Input and Output Variables of *objf.m*

Function	**Input Variables**	**Output Variables**
objf	*X* *pavementType* *deflection_measured* *iteration* *fitness_best* *solution_best* *deflection_calculated*	*MAPE* *deflection_calculated* *fitness_best* *solution_best* *cost*

ANN models for each type of pavement are put together to a MATLAB function namely *runANN.m* which is also embedded into the *objf.m* file. According to predefined *pavementType,* the code decides which model to use. For the purpose of calculating deflections at D_0, D_{12}, D_{24} and D_{36} sensor locations, ANN requests thickness and modulus properties of the layers of the associated *pavementType.* At previous stages, N set of agents in *dim* dimension are initialized as positions which correspond to stiffness properties of the test section. Accordingly, thickness of each layer (extracted from the input directory of MS Excel file) in the same test section/station are assigned to the each agent. The input matrix of ANN for test section i can be expressed as follows:

$$(inputANN)_i = [thickness, X_{kj}] \tag{66}$$

The dimension of *inputANN* matrix differs according to *pavementType*. For example, 'FDP' *inputANN* consists of N by 3 elements that one column refers to the thickness while the other two denote to the stiffness properties. 'CFP' and 'FDP-LSS' *inputANNs* include N by 5 elements of which are 2 thicknesses and 3 stiffness properties. By running the *runANN.m,* ANN forward response engine estimates the deflections for the current section/station i which are presented in the following form:

$$[(deflection\_calculated)_i] = runANN((inputANN)_i) \tag{67}$$

The next step is to determine how *deflection_calculated* fits the *deflection_measured* values. This is the fitness evaluation part of the algorithm which assesses the test section in question. By this way, how close deflections obtained from our simulated pavement sections (presented with population) with an in-situ pavement section can be assessed. The approximation between two deflection sets denotes to our success of modelling field sections mathematically so that assumed stiffness properties are considered as the representative features of the field conditions. In this respect, employed objective function, MAPE is presented below:

$$MAPE_k = 100 \times \frac{1}{n}\sum_{t=1}^{n}\left|\frac{deflection\_measured_t - deflection\_calculated_t}{deflection\_measured_t}\right| \quad (68)$$

Where n is the number of sensors which is 4 in this study. $MAPE_k$ is an array of N by 1 dimension that stores the fitness values of each agent. Using these data, best fitted agent is determined which is specified with *solution_best* and its corresponding fitness value *fitness_best.* For the current *iteration,* these values are recorded to their specific arrays in an attempt to be compared for the future iterations. Also *fitness_best* value of *iteration* is recorded to the *cost* array.

As explained in Section 2.7.2.2 mass of each agent in the population is calculated through the fitness values. By using Equation (38) and (39), *massCalculation.m* computes the masses a using the fitness values stored in $MAPE_k$ array.. The form of the function are expressed as given below:

$$[M_k] = massCalculation(MAPE_k) \quad (69)$$

Following stage is to determine gravitational constant, $G_{iteration}$ which is a function of age of the universe (Mansouri et al. 1999) (see Equation (40)). In GSA code, this age is imitated with the current *iteration*, *maxIterationNumber* and two constants of G_0 and α. Originating from our experimental studies G_0 is taken as 10^8 and α is taken into account as 0.5. $G_{iteration}$ is adjusted for each iteration using following function:

$$[G_{iteration}] = GconsCalculation(iteration, maxIterationNumber) \quad (70)$$

The next stage is to calculate the applied force by the agents to each other. This force is the function of agent's mass, M_k, Euclidian distance between other agents, R_{kj} (see Equation (43)), difference between objects positions, X_{kj} and gravitational constant $G_{iteration}$. In order to calculate the total force which acts on the agent k Equation (41) and (42) are utilized. K_{best} is set to 2% which refers to, at the last iteration, only 2% percent number of agents having best fitness value in the population will apply gravitational force to prevent the algorithm trapping in local minimum solutions. In the first iteration, all the agents apply force to each other and throughout the iterations, regarded force applied by agents are linearly decreased to 2% of the population. *accCalculation* function determines the accelerations of agents (see Equation (44)) and its input-output variables are presented in Table 9.

Table 9 Input and Output Variables of *accCalculation.m* file

Function	Input Variables	Output Variables
accCalculation	*M* *X* $G_{iteration}$ *Rnorm and Rpower* *iteration* *maxIterationNumber*	*a*

After calculating accelerations of agents in corresponding dimensions, it is required to update velocity them. Motionless agents whose velocities were assigned as zero, (see Equation (65a) for agent *k*, in dimension *j*) before the algorithm executed. In ensuing iterations, they gain acceleration due to exposed overall gravitational force, F_{kj}, so that they awake to move toward the best agent in the population. Through the influence of updated velocities, agents change their positions, X_{kj}. These velocity and position adjustments are executed in the function of *agentMovement* which employs the Equation (45) and (46), respectively and it can be expressed in the following form:

$$[X_{kj}, V_{kj}] = agentMovement(X_{kj}, a_{kj}V_{kj}) \tag{71}$$

The new X_{kj} and V_{kj} matrices are saved in an effort to be used in next iteration. The same stages are repeated from checking against possible boundary violations of positions to the updating the new positions until the *maxIterationNumber.* At the end, dependent output variables of *GSA* which are *fitness_best*, *solution_best, deflection_calculated* and *cost* are printed out. The data stored in *solution_best* refers to the calculated layer moduli of analyzed pavement section that are specified in Equation (62). A general flowchart of GSA-ANN algorithm is illustrated in Figure 39.

3.5 Solving a Sample Backcalculation Problem Using GSA-ANN

In this section, a sample backcalculation problem are solved using developed GSA-ANN approach to provide better understanding about the working schemes of the proposed approach. A sample FDP section is created by using ILLI-PAVE software and elastic moduli of AC layer and breakpoint resilient modulus of fine-grained subgrade soil are backcalculated through the use of proposed algorithm. The aim of this analysis is to find closest moduli values to the sample moduli values calculated with GSA-ANN. The input and output values of sample section which are stored in MS Excel file is presented in Table 10. Stages of the code is provided respectively.

Table 10 Sample FDP Section's Input and Output Data

Input Variables			**Output Variables (mils)**								
Thickness (inch)	E_{AC} (psi)	E_{Ri} (psi)	D_0	D_8	D_{12}	D_{18}	D_{24}	D_{36}	D_{48}	D_{60}	D_{72}
13.2	889,744	5,393	6.71	5.96	5.60	5.11	4.62	3.69	2.86	2.15	1.58

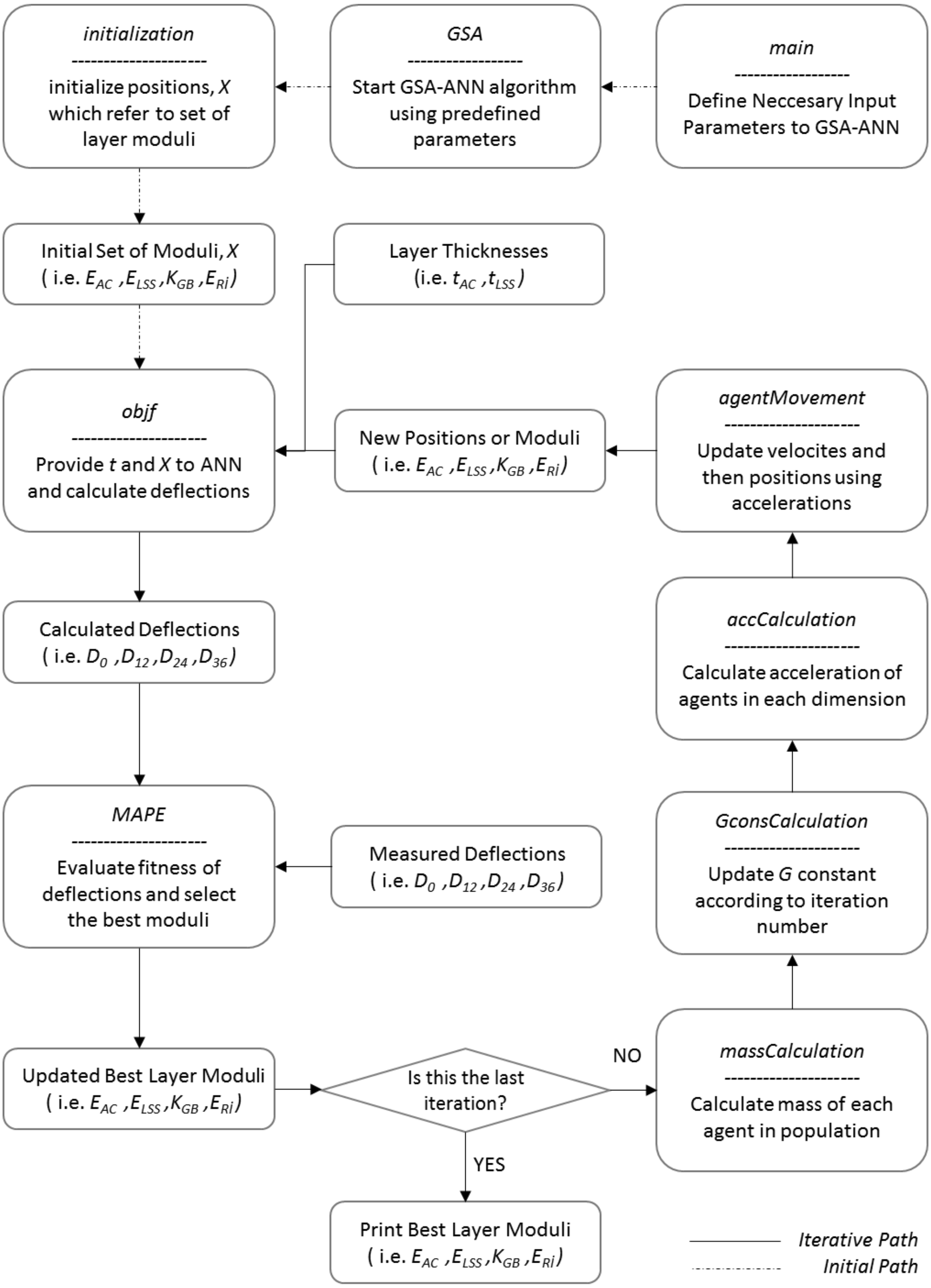


Figure 39 General Flowchart of GSA-ANN Backcalculation Code

Required values of the variables are defined to the *main.m* which are listed below:

Table 11 Input Parameters and Corresponding Values of GSA-ANN for Sample Pavement Section

Variable	Value
N	15
maxIterationNumber	50
maxTestNumber	1
pavementType	‘FDP’
α	0.5
G_0	10^8

Using the values above, algorithm determines the properties of search space in terms of dimension, *dim*, lower and upper limits of the moduli, *low* and *up* which are extracted by *objflimits* function. Corresponding values for these parameters are specified in the table below:

Table 12 Dimension and Ranges of Search Space

Variable	Assigned Array
dim	[2]
up	[2,000,000 14,000]
low	[10,000 1,000]

A population is created for the given *N* number of agents and their positions (layer moduli) are initialized through the *initialization.m* file by considering the values in Table 12. Then, velocities of all agents are assigned as zero since they are motionless in the first iteration. Initial values of positions and velocities are presented in the Table 13. In order to store the obtained best results for each iteration, *fitness_best* and *solution_best* arrays are also created and zero value assigned to each one as shown in Table 14.

Table 13 Initial Positions and Velocities for the Sample Problem

Agent	X_{kj}		V_{kj}	
	E_{AC}	E_{Ri}		
1	1631300	2845	0	0
2	1812526	6483	0	0
3	262704	12905	0	0
4	1827618	11299	0	0
5	1268395	13473	0	0
6	204105	9525	0	0
7	564211	1464	0	0
8	1098294	12039	0	0
9	1915439	13142	0	0
10	1930128	9824	0	0
11	323650	10851	0	0
12	1941480	10661	0	0
13	1914762	6099	0	0
14	975898	9521	0	0
15	1602558	3225	0	0

Table 14 Initial *fitness_best* and *solution_best* arrays

Variable	**Assigned Array**
fitness_best	[0]
solution_best	[0 0]

Next, iterative process begins by setting the *iteration* as 1 and thickness of AC layer of sample section is extracted from the corresponding MS Excel file shown in Table 10. The thickness value of 13.2 in. (335 mm) is incorporated into the position matrix to provide the data into ANN model. By executing forward response model in *objf.m* file corresponding deflections are calculated using FDP ANN model. Then, calculated deflections are compared with the actual deflections in Table 10 through *MAPE* objective function (see Equation (68)). Obtained results are shown in the table below:

Table 15 Calculated Deflections and Obtained Errors for Iteration-1

Iteration-1								
Agent	**t_{AC} (in.)**	**X_{kj}**		**Calculated Deflections by ANN**				**$MAPE_k$**
		E_{AC} (psi)	**E_{Ri} (psi)**	**D_0**	**D_{12}**	**D_{24}**	**D_{36}**	
1	13.2	1631300	2845	5.53	4.85	4.18	3.53	11.21
2	13.2	1812526	6483	4.38	3.78	3.21	2.67	31.35
3	13.2	262704	12905	9.21	6.04	4.16	2.85	19.46
4	13.2	1827618	11299	3.7	3.12	2.6	2.12	43.85
5	13.2	1268395	13473	4.2	3.42	2.75	2.18	39.43
6	13.2	204105	9525	11.63	7.59	5.2	3.55	31.30
7	13.2	564211	1464	10.91	9.13	7.53	6.05	63.14
8	13.2	1098294	12039	4.71	3.81	3.06	2.4	32.62
9	13.2	1915439	13142	3.43	2.88	2.39	1.94	48.29
10	13.2	1930128	9824	3.77	3.21	2.69	2.22	42.03
11	13.2	323650	10851	8.86	6.19	4.45	3.16	15.16
12	13.2	1941480	10661	3.66	3.11	2.6	2.14	43.91
13	13.2	1914762	6099	4.32	3.75	3.19	2.67	31.81
14	13.2	975898	9521	5.42	4.41	3.55	2.8	21.94
15	13.2	1602558	3225	5.47	4.78	4.1	3.46	12.65

As can be clearly seen that 1st agent in the population has the minimum *MAPE* value which means that it produces the closest deflections with the sample section. In ensuing iterations, GSA-ANN algorithm attempts to decrease the difference between deflection basins in order to increase the closeness of layer moduli through the GSA's searching capability. For Iteration-1 *fitness_best*, *solution_best* and *cost* arrays are updated as following:

Table 16 *fitness_best*, *solution_best* and *cost* arrays for Iteration-1

Iteration-1	
Variable	**Assigned Array**
fitness_best	[11.21]
solution_best	[1,631,300 2,845]
$cost_k$	[11.21]

To mobilize the agents in the population, their masses and applied forces to each other are essential to be calculated first. Using the fitness values of each agent, masses are computed and then gravitational constant are decreased linearly using the current iteration number. In conclusion, new positions and velocities which are going to be used for the next iteration are updated through the acceleration for each dimension. Obtained results for M_k, a_{kj}, V_{kj} and X_{kj} are presented in the following tabular form:

Table 17 Updated Variables of GSA-ANN Algorithm for Iteration-1

Iteration-1				G_1 = 990,050			
Agent	M_k	a_{kj}		V_{kj}		X_{kj}	
1	0.114126	-141334	5866	-141334	5866	1489966	8711
2	0.06933	-200161	11715	-200161	11715	1612365	10374
3	0.095775	176915	-8730	176915	-8730	439618	4175
4	0.041507	-244365	-20455	-244365	-20455	1583253	2375
5	0.05134	-13721	-2256	-13721	-2256	1254674	11218
6	0.069429	518626	3742	518626	3742	722731	13267
7	-0.0014	240940	6828	240940	6828	805151	8292
8	0.066488	135518	-3806	135518	-3806	1233812	8232
9	0.031644	-440833	-42776	-440833	-42776	1474606	13646
10	0.045571	-424787	-7571	-424787	-7571	1505341	2252
11	0.105349	316670	-787	316670	-787	640320	10064
12	0.041377	-471177	-6237	-471177	-6237	1470302	4424
13	0.068294	-316678	29241	-316678	29241	1598084	7303
14	0.090259	111874	-256	111874	-256	1087772	9265
15	0.110916	-4400	5637	-4400	5637	1598158	8862

Immediately after updating new positions, Iteration-2 starts by combining thickness of AC layer with new positions. Next, they are provided to ANN model to estimate new deflections. Positions in the second iteration and associated deflections are presented along with the obtained error rates in Table 18.

Table 18 Calculated Deflections and Obtained Errors for Iteration-2

Iteration-2								
Agent	t_{AC} **(in.)**	X_{kj}		**Calculated Deflections by ANN**				$MAPE_k$
		E_{AC} **(psi)**	E_{Ri} **(psi)**	D_0	D_{12}	D_{24}	D_{36}	
1	13.2	1489966	8711	4.49	3.79	3.15	2.57	31.89
2	13.2	1612365	10374	4.07	3.42	2.84	2.31	38.55
3	13.2	439618	4175	10.27	8.12	6.38	4.91	42.30
4	13.2	1583253	2375	5.78	5.08	4.39	3.72	7.23
5	13.2	1254674	11218	4.51	3.71	3.02	2.4	34.03
6	13.2	722731	13267	5.57	4.28	3.3	2.5	25.35
7	13.2	805151	8292	6.25	5.04	4.03	3.15	11.07
8	13.2	1233812	8232	5.04	4.21	3.47	2.8	24.68
9	13.2	1474606	13646	3.88	3.19	2.6	2.07	43.21
10	13.2	1505341	2252	6	5.27	4.54	3.84	5.57
11	13.2	640320	10064	6.55	5.09	3.95	3	11.17
12	13.2	1470302	4424	5.4	4.67	3.96	3.3	15.25
13	13.2	1598084	7303	4.55	3.88	3.26	2.69	29.86
14	13.2	1087772	9265	5.18	4.26	3.46	2.76	24.26
15	13.2	1598158	8862	4.3	3.65	3.03	2.48	34.49

In the second iteration, 10th agent in the population has the minimum error rate which means that the algorithm found a better agent whose deflection basin fits better than the best agent in the previous iteration. Therefore, *fitness_best*, *solution_best* and *cost* arrays are updated as follows:

Table 19 *fitness_best*, *solution_best* and *cost* arrays for Iteration-2

Iteration-2	
Variable	**Assigned Array**
fitness_best	[5.57]
solution_best	[1,505,341 2,252]
$cost_k$	$\begin{bmatrix} 11.21 \\ 5.57 \end{bmatrix}$

By following the calculation of gravitational constant, G_2 for Iteration-2, M_k, a_{kj}, V_{kj} and X_{kj} are updated, respectively. Corresponding values are shown in the following tabular form:

Table 20 Updated Variables of GSA-ANN Algorithm for Iteration-2

Iteration-2				$\boldsymbol{G_1}$ = 980,199			
Agent	$\boldsymbol{M_k}$	$\boldsymbol{a_{kj}}$		$\boldsymbol{V_{kj}}$		$\boldsymbol{X_{kj}}$	
1	0.041419	-61455	-18390	-102468	-17812	1387498	-9102
2	0.016089	-567538	-22402	-631093	-12754	981272	-2380
3	0.001804	468141	3974	583788	2447	1023407	6622
4	0.135273	-314669	19228	-548511	15882	1034742	18257
5	0.033283	44072	-9003	31232	-10505	1285906	713
6	0.066344	405889	-7113	643361	-3766	1366092	9501
7	0.120693	140855	-213	198796	3314	1003947	11606
8	0.068875	29685	-1183	133207	-3858	1367019	4375
9	-0.00164	-116719	-33590	-451455	-40160	1023151	-26514
10	0.141616	-236941	18251	-551559	11032	953782	13284
11	0.120282	477884	-2181	713388	-2607	1353708	7457
12	0.10478	-58134	1672	-108041	-2568	1362261	1857
13	0.049159	-444867	-2481	-660702	-1412	937383	5892
14	0.070473	194803	-1627	246630	-1834	1334402	7431
15	0.031555	-382936	-64597	-383870	-60378	1214288	-51515

Iterations continue by updating and checking the boundary conditions of positions. At the end of the last iterations results are printed to the screen. Since it is not possible to show each stage of iterations, overall results are presented. As denoted at the beginning of the algorithm, *maxIterationNumber* is regarded as 50 so that the obtained *fitness_best* and *solution_best* values at the end of the iterations are presented in Table 21. This means that backcalculated layer moduli are 887,786 psi (6118 MPa) for E_{AC} and 5,434 psi (37.4 MPa) for E_{Ri} which show good approximation with corresponding deflection basin of 0.27 *MAPE* value.

Table 21 Solution of the Problem at the End of Iteration-50

Iteration-50	
Variable	**Assigned Array**
fitness_best	[0.27]
solution_best	[887,786 5,434]

The performance of GSA-ANN algorithm can be evaluated through the comparison of backcalculated and actual layer moduli values in Table 10. According to this comparison presented in Table 22, GSA-ANN estimates layer moduli less than 1% error which is satisfactory for backcalculation problems.

Table 22 Comparison of Actual and Backcalculated Moduli

Variable	**Actual Value**		**Backcalculated Value**		**MAPE (%)**
	(MPa)	**(psi)**	**(MPa)**	**(psi)**	
E_{AC}	6130	889,744	6117	887,786	0.22
$E_{Rİ}$	35	5,393	37	5,434	0.75

cost is the 50 by 1 array of recorded *fitness_best* results for each iteration. It is performed to show how GSA-ANN algorithm comes through the solution of the problem. The array is plotted by presenting the *fitness_best* versus *iteration* values as illustrates in Figure 40. Moreover, movement of agents in the search space is observed that approximating to the global solution are presented thorough the randomly selected iterations as depicted in Figure 41.

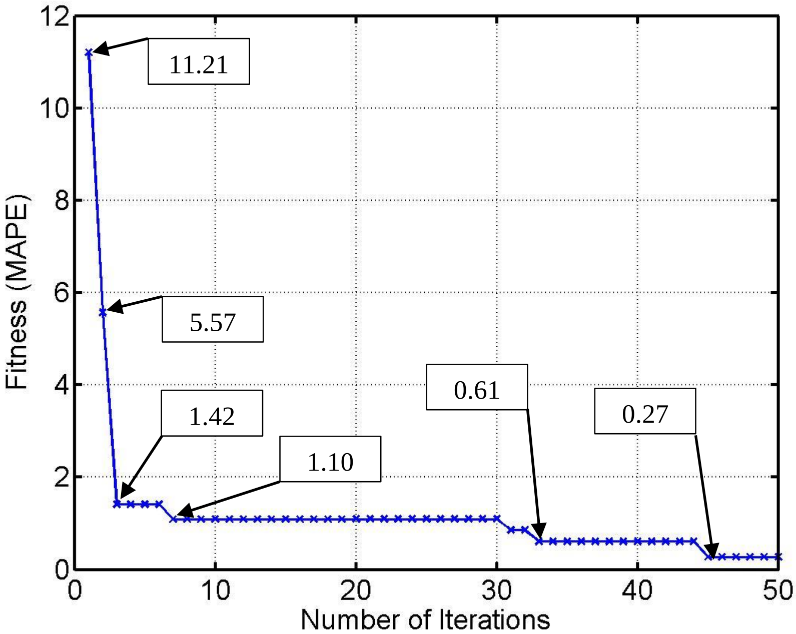


Figure 40 Plot of *cost* array

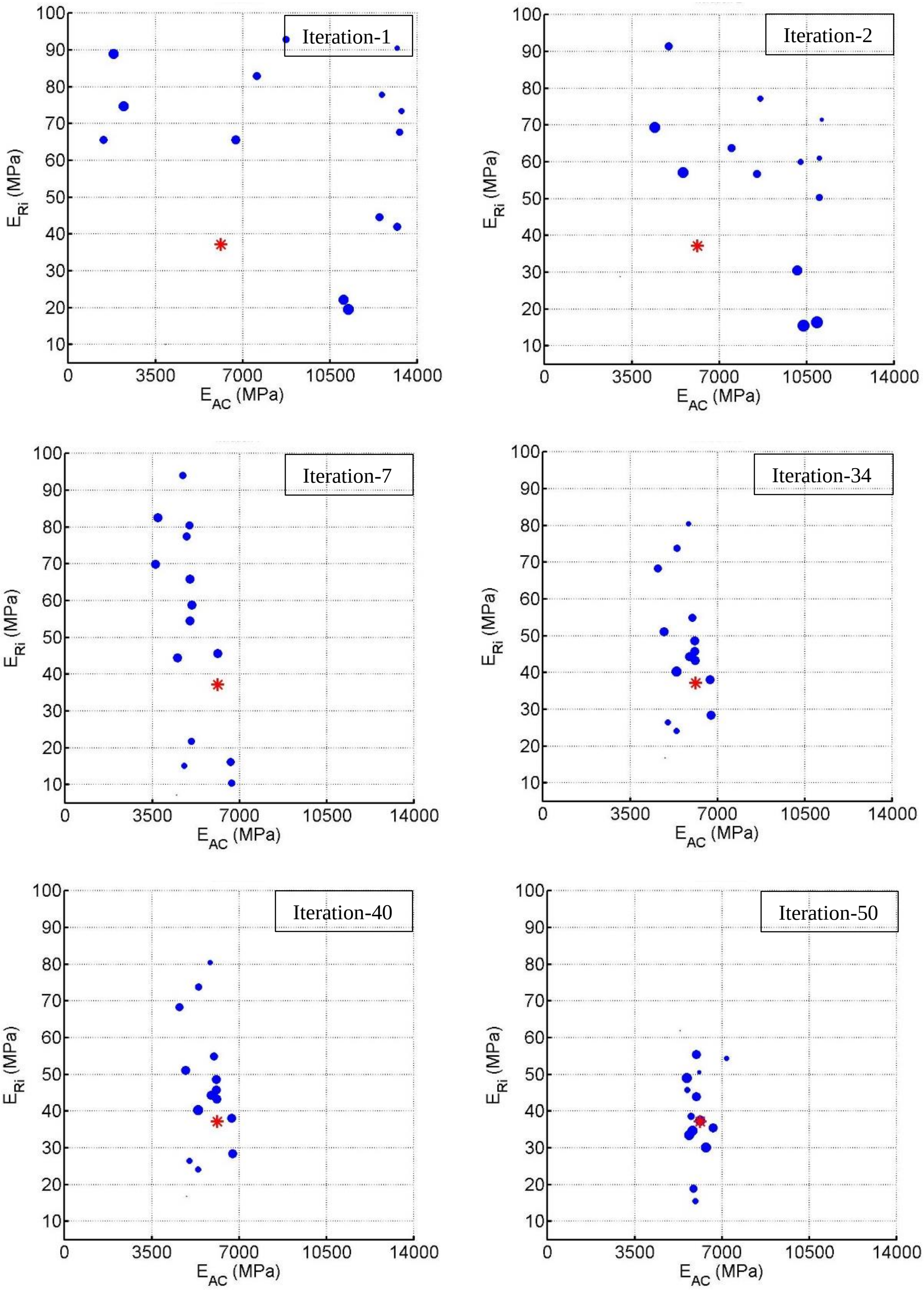


Figure 41 Positions of the Agents in the Search Space through the Iterations

CHAPTER 4

PERFORMANCE EVALUATION OF GSA-ANN METHOD

4.1 Introduction

Proposed GSA-ANN backcalculation method needs to be validated to indicate how effectively it works in pavement layer backcalculation problems. This chapter focuses on the verification of the proposed approach through the use of two different data sources. First data set is composed of the synthetically generated pavement sections by means of ILLI-PAVE software. Prediction capability of employed ANN models are evaluated using randomly selected data from the synthetic data sets. Moreover, these data are provided to the proposed GSA-ANN backcalculation algorithm to be backcalculated as well. For the evaluation of searching ability of GSA, ANN forward response models are combined with genetic algorithm as search method which is one of the most popular metaheuristic optimization techniques. Obtained backcalculation algorithm by the use of a simple genetic algorithm (SGA) is named as SGA-ANN and it is then executed using exactly the same synthetic data backcalculated with GSA-ANN. However, these assessments are conducted with the deflection data calculated numerically with computer programs so that it is essential to execute backcalculation algorithms utilizing field deflection data measured by FWD. Therefore, for each type of flexible pavement, deflection and other required pavement data are extracted from the LTPP database and their stiffness properties are then backcalculated. In order to validate the obtained results from GSA-ANN and SGA-ANN executions, the same LTPP sections are analyzed by conventional backcalculation softwares namely EVERCALC and MODULUS.

4.2 Performance of ANN Forward Response Models

In order to evaluate the prediction performance of employed ANN models, a set of analyses are conducted. Among the thousands of data generated by ILLI-PAVE so as to train ANN models, approximately 1,000 ones for each three type of flexible pavements are randomly selected for testing purpose. By providing layer thicknesses (i.e. t_{AC}, t_{LSS} and t_{GB}) and stiffness values (i.e. E_{AC}, E_{Ri}, E_{LSS} and K_{GB}) of pavement sections to the corresponding ANN model, deflections are calculated for the uniformly spaced D_0, D_{12}, D_{24} and D_{36} sensor locations. Following that, agreement between calculated and actual deflections stored in testing data set are evaluated through the use of *MAPE* function. The comparison is illustrated by 45-degree line of equality where backcalculated and actual deflections are equal on this line.

Performance of the developed ANN models are illustrated in the way of plotting deflections for each individual sensor and pavement type, respectively. Deflections calculated with ANN are plotted versus the ILLI-PAVE solutions in the testing database. For FDP test sections, Figure 42 shows how both deflection basins are matched that the MAPE values obtained are in the range of 0.10% to 0.57%. In the same manner, differences between CFP deflection basins change from 0.19% to 0.44% MAPEs as shown in Figure 43. For FDP-LSS test sections, the error between deflections vary in the range of 0.13% to 0.34% (see Figure 44). As can be clearly seen that great majority of solutions of each section types are centered on the line of equality which indicate the success of training stages of ANN forward response models. In conclusion, ANN models for FDP, CFP and FDP-LSS sections estimate deflections accurately with a 0.3% average MAPE value. Therefore, ANN proves that its ability to calculate deflections for the sections whose layers' nonlinear nature were taken into account. It is verified that ANN can be effectively employed as a forward response model instead of ILLI-PAVE FE analysis and also ANN can individually be used as an analysis tool for flexible pavements.

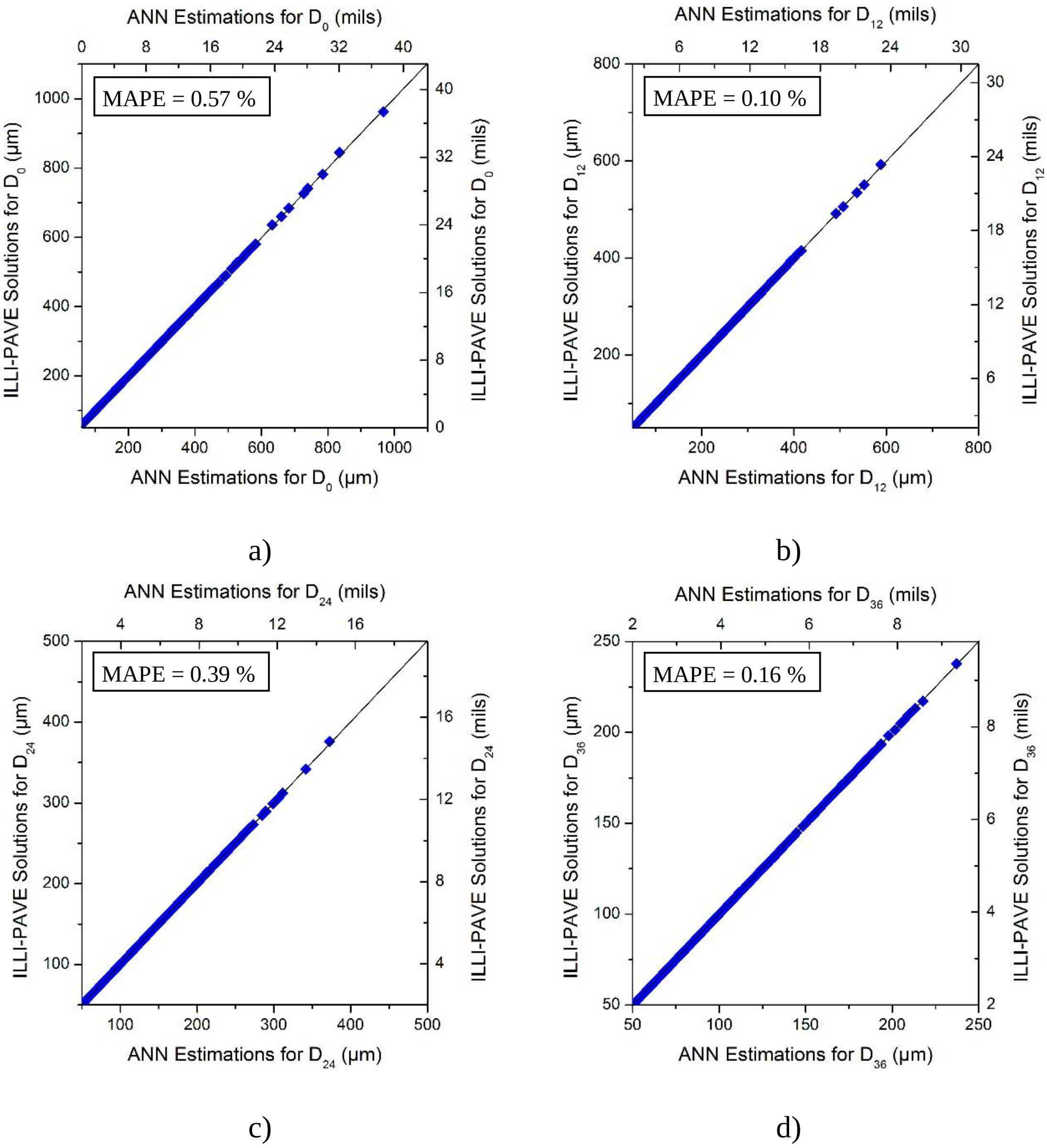


Figure 42 Comparison of ANN - ILLI-PAVE Deflections for FDP sections

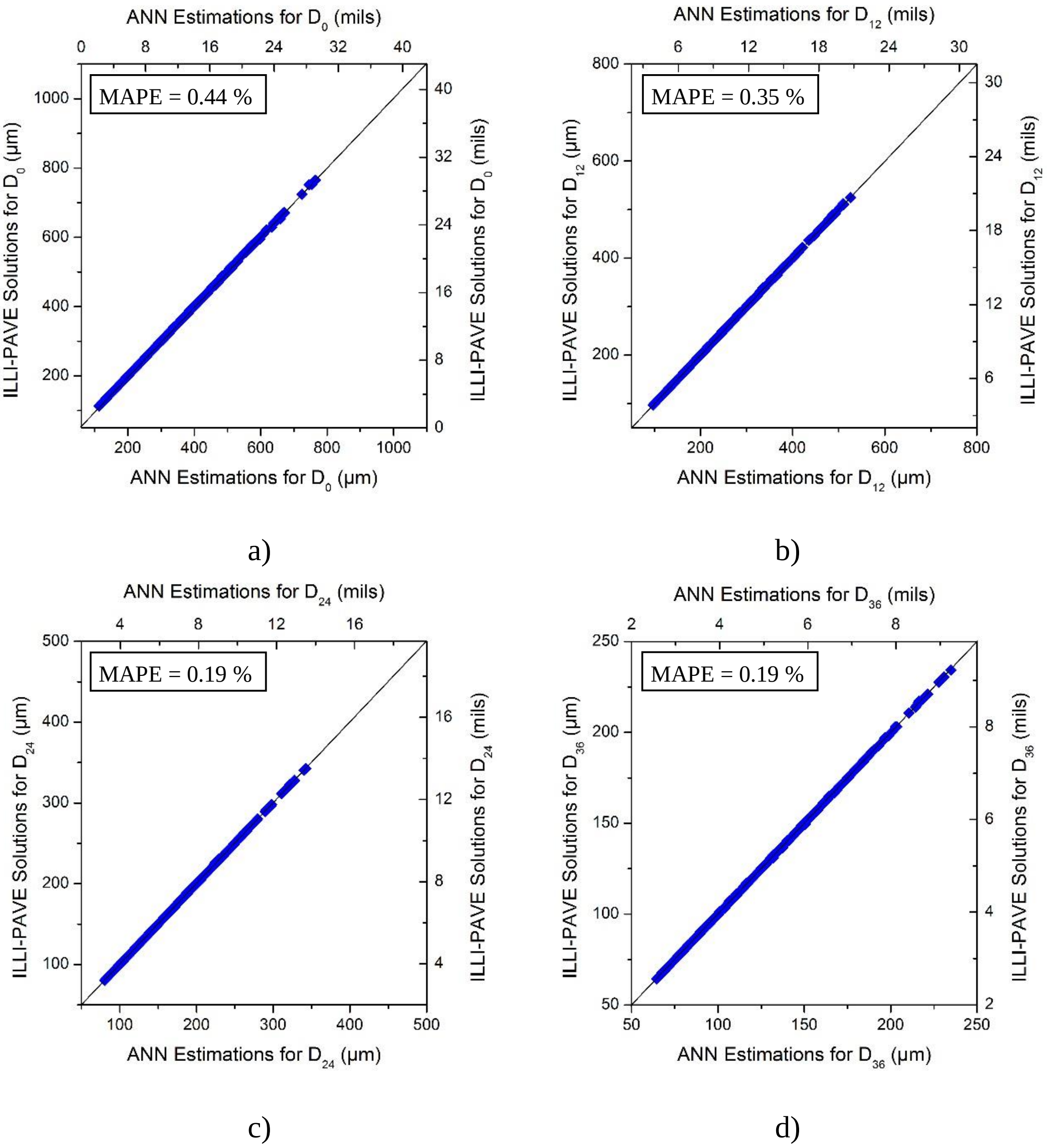
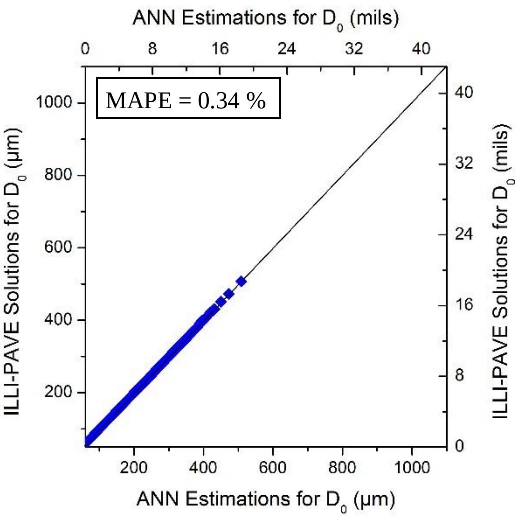


Figure 43 Comparison of ANN - ILLI-PAVE Deflections for CFP sections



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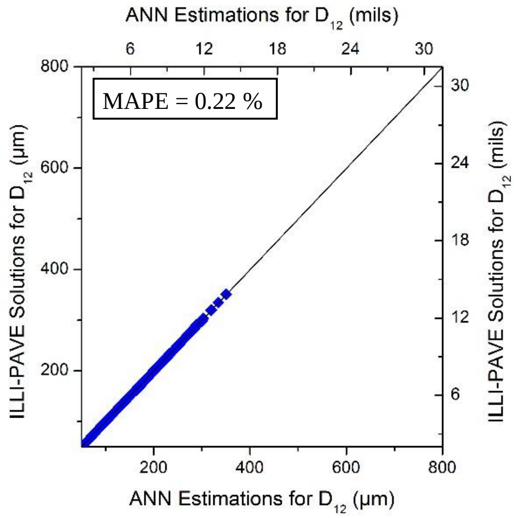

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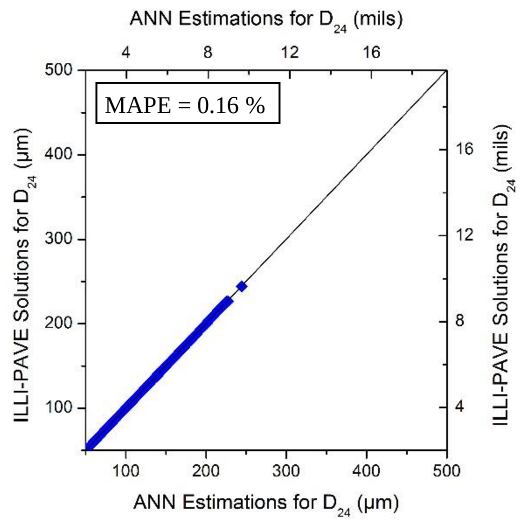
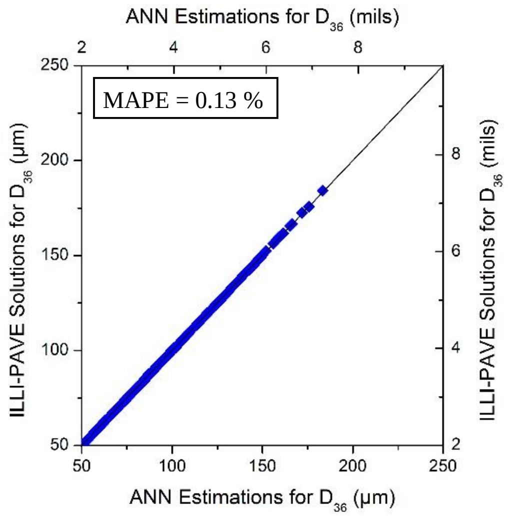


c)



d)

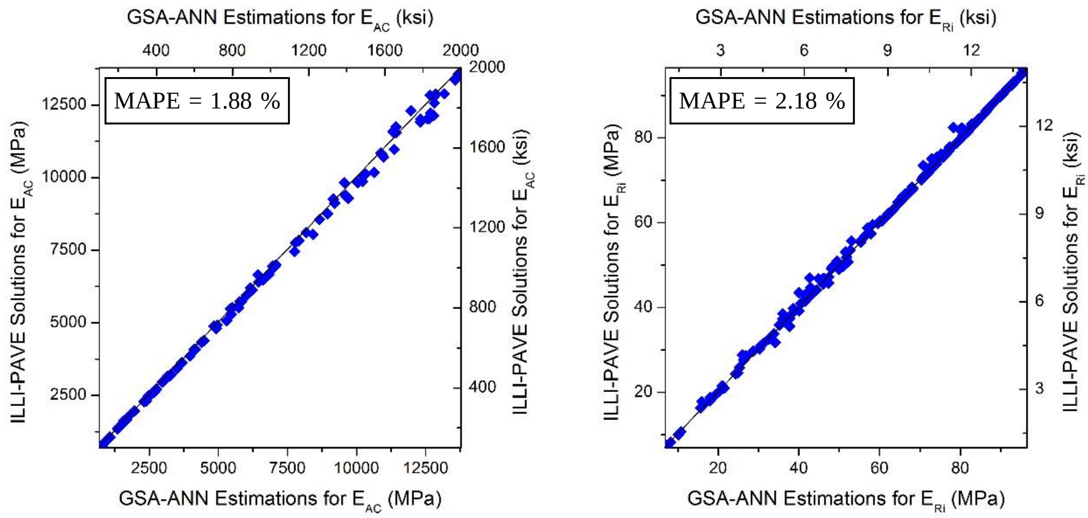
Figure 44 Comparison of ANN - ILLI-PAVE Deflections for FDP-LSS sections

4.3 Performance of GSA-ANN Algorithm for Synthetically Derived Data

Among the synthetic testing data sets including 1,000 runs of ILLI-PAVE data for each pavement type, randomly selected 100 sections are utilized to backcalculate their layer properties. In order to perform backcalculation with GSA-ANN and SGA-ANN algorithms, required values of associated parameters for each algorithm are introduced respectively. To make the solutions of both algorithms to be comparable and to maintain the consistency, it is necessary to execute the same number of function evaluation. Since the both GSA and SGA are population based methods, 50 number of agents/individuals form the population and they are evaluated for 100 times which is the selected maximum number of iterations. In GSA algorithm, *Rpower*, α and G_0 parameters are defined as 1, 0.5 and 10^8, respectively on the basis of performed experimental studies for the purpose of determining the most favorable values (Rashedi et al. 2009a). Apart from these, according to a study conducted by Reddy et al. (2004) which investigates the most effective values of GA parameters, probability of crossover and mutation are selected as 0.74 and 0.1, respectively. Consequently, performance of GSA-ANN and SGA-ANN algorithms is evaluated in terms of their ability of estimating layer moduli and reaching the optimum fitness values.

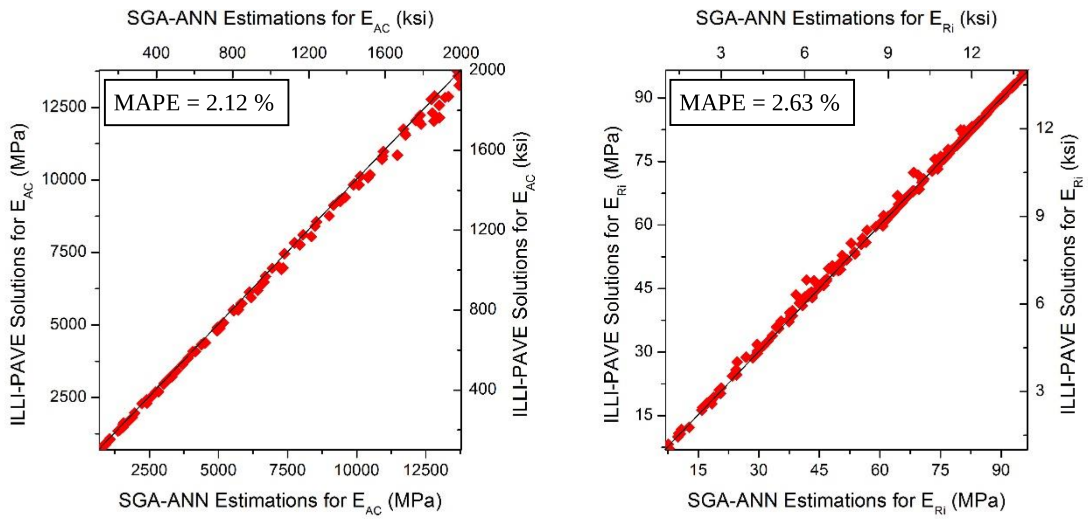
4.3.1 Performance for Full-depth Asphalt Pavements

E_{AC} and E_{Ri} values of each full-depth asphalt pavement section are backcalculated by GSA-ANN and SGA-ANN algorithms. Comparisons of estimated layer moduli with associated actual values stored in the testing data set are presented In Figures 45 and 46, respectively. Accordingly, GSA-ANN can estimate the asphalt layer moduli within MAPE value of 1.88% while SGA-ANN can produce the layer moduli within 2.12% MAPE value. Breakpoint resilient moduli for subgrade are also predicted successfully that GSA-ANN and SGA-ANN achieve 2.18% and 2.63% MAPEs, respectively. Closely locating the modulus comparison points around the line of equality proves the success of GSA-ANN approach for estimating layer moduli (Öcal and Pekcan 2014). For randomly selected two test sections, capability of reaching the optimum fitness value of backcalculation algorithms is investigated through the iterations. As illustrated in Figure 47, algorithms achieve the lowest fitness value at the initial iterations. Although GSA and SGA produce approximately the same optimum fitness values, it is observed that SGA reaches the optimum values before GSA.



a) b)

Figure 45 Performance of GSA-ANN algorithm for FDP Synthetic Data



a) b)

Figure 46 Performance of SGA-ANN algorithm for FDP Synthetic Data

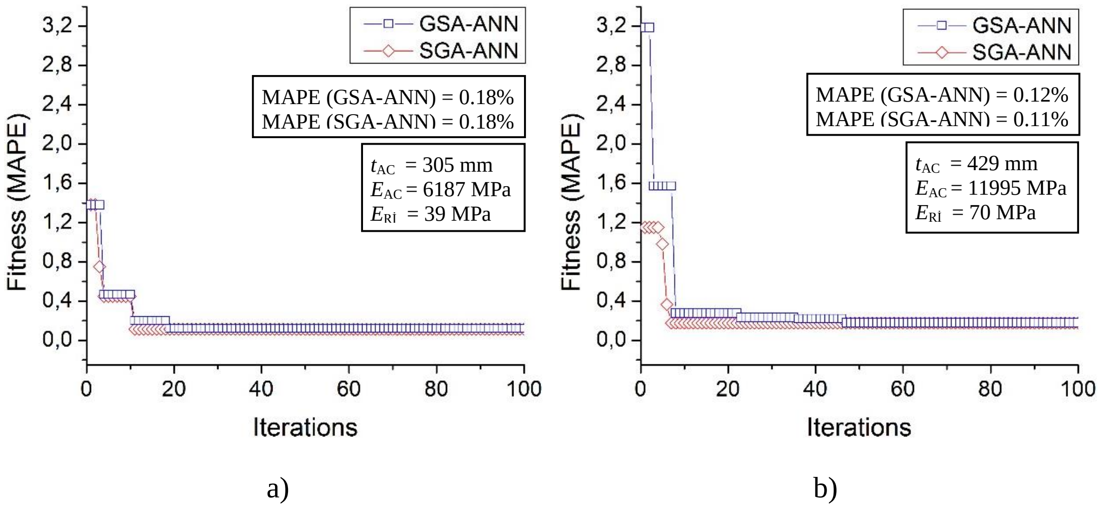


Figure 47 Progress Curves of Two Randomly Selected FDP sections for Reaching the Optimum Fitness Values

4.3.2 Performance for Conventional Flexible Pavements

The performance of GSA-ANN algorithm for backcalculation of layer moduli of CFP sections is given in Figure 48. Obtained results for each stiffness property show that E_{AC} and E_{Ri} estimations have 3.37% and 4.02% MAPEs while K_{GB} is predicted with much greater MAPE value of 21.8%. Although, GSA-ANN calculates E_{AC} and E_{Ri} of CFPs within slightly larger MAPEs than FDP solutions, these error rates are still in reasonable range. As can be seen from the Figure 49 SGA-ANN predicts each layer property with slightly higher MAPE values than the ones obtained with GSA-ANN. Results indicate that E_{AC} and E_{Ri} are estimated within the 4.36% and 6.21% MAPEs, respectively. Just as obtained with GSA-ANN performance of SGA-ANN for K_{GB} is quietly poor that 32.5% MAPE is produced. For both approaches, K_{GB} values cannot be predicted within tolerable error rates. Therefore, backcalculated K_{GB} values of granular layers are not rational to be considered in pavement maintenance and rehabilitation operations. When the solutions are investigated it is seen that abnormal predictions located away from the line of equality generally produced by the sections having thick AC layers (greater than 10 in.) and/or high stiffness values. So that the influence of applied FWD load could not be sensed by granular layers. To deal with this problem, greater level of loads should be applied to stimulate unbound granular layers by an NDT device such as heavy-weight deflectometer (HWD). Another source of error is the same deflection basin produced by different combination of layer moduli which results in erroneous prediction of stiffness values. When the performance of the algorithms on reaching to the optimum fitness values is investigated, the same trend is observed with the FDP sections that SGA finds the optimum fitness before GSA. It is also observed that optimum fitness value found by SGA is slightly lower than the value found by GSA.

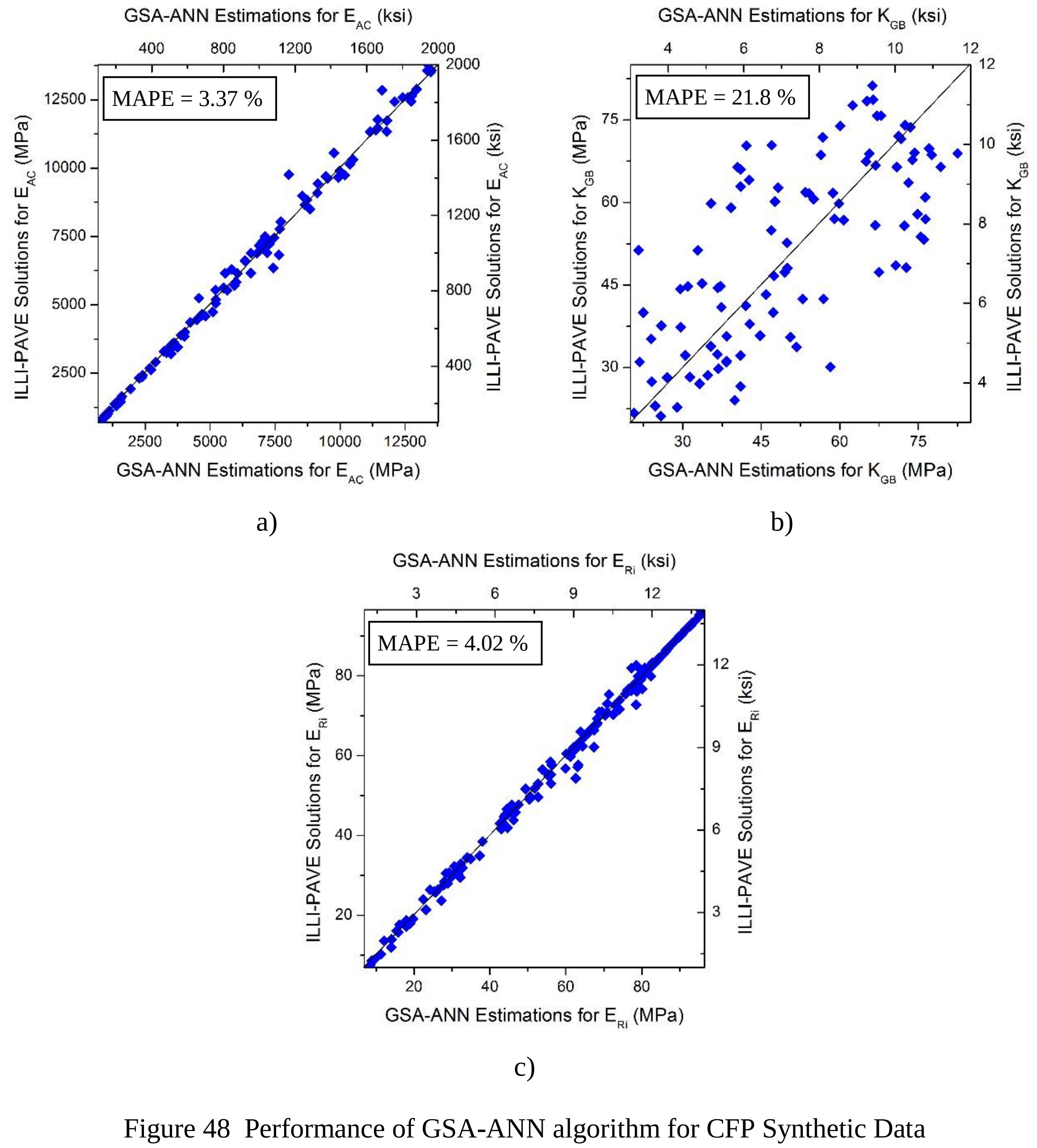


Figure 48 Performance of GSA-ANN algorithm for CFP Synthetic Data

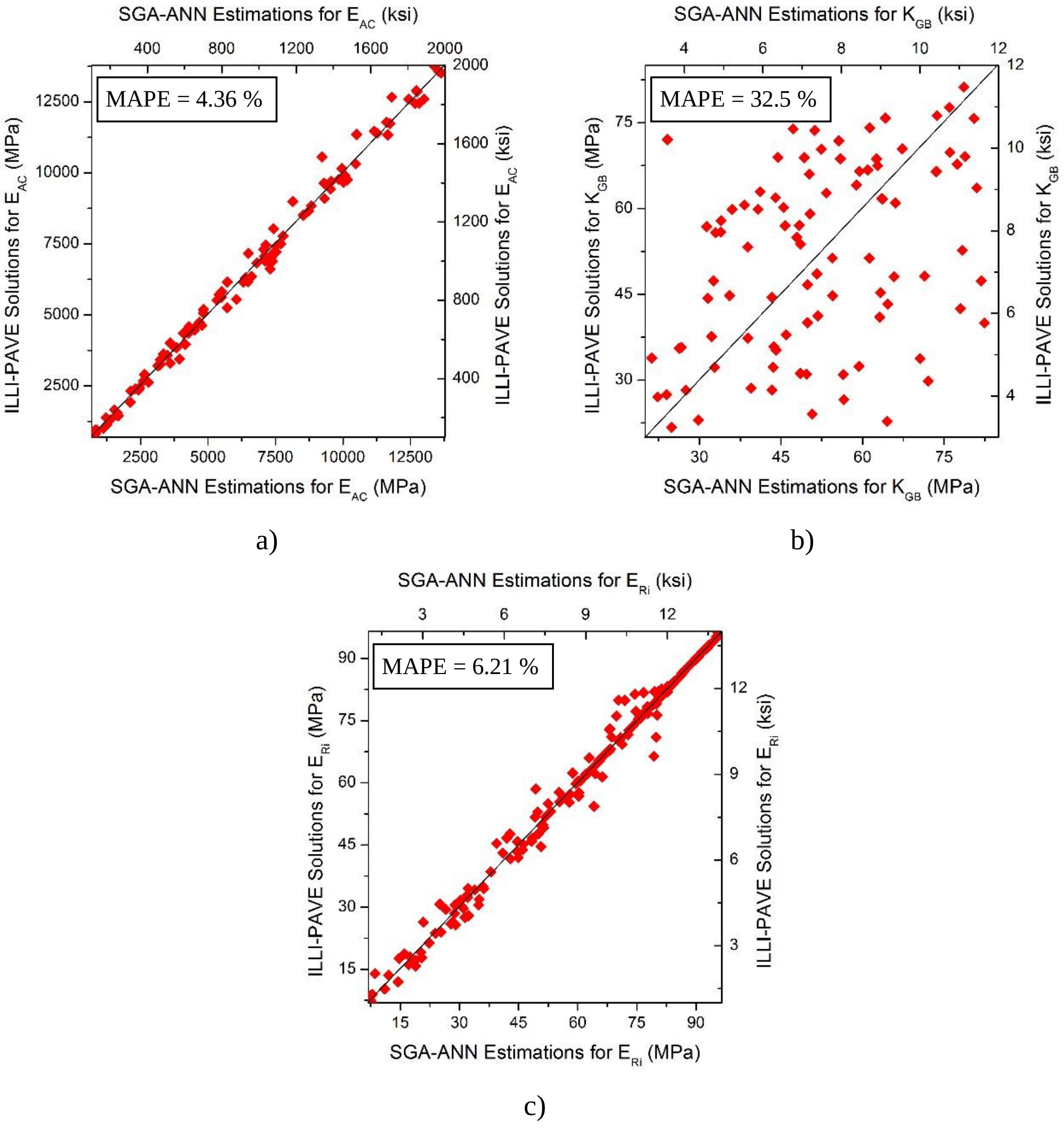
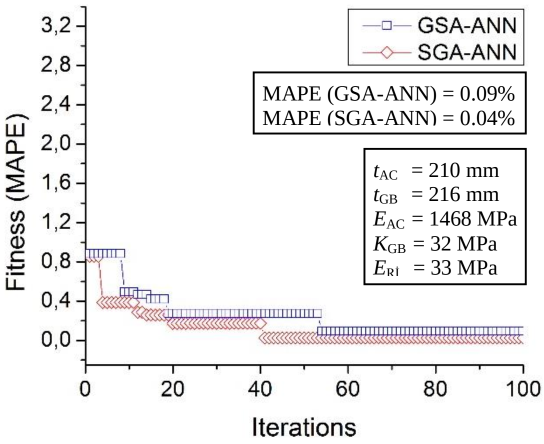
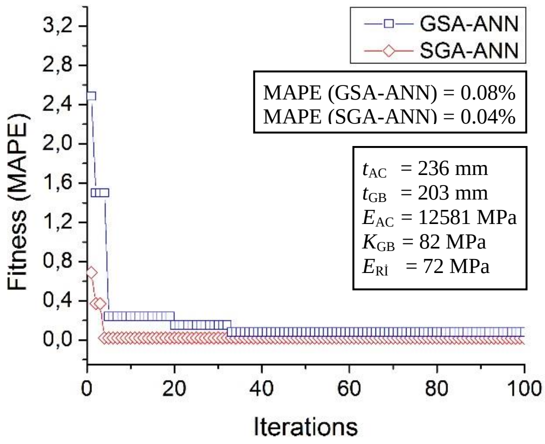


Figure 49 Performance of SGA-ANN algorithm for CFP Synthetic Data



a)



b)

Figure 50 Progress Curves of Two Randomly Selected CFP sections for Reaching the Optimum Fitness Values

4.3.3 Performance for Full-depth Asphalt Pavements on Lime Stabilized Soils

Performance of the GSA-ANN algorithm for FDP-LSS pavement layer moduli predictions is presented in Figure 51. Accordingly, algorithm estimates E_{AC} and $E_{Rİ}$ within admissible MAPE values of 3.16% and 3.41% while E_{LSS} predictions have higher error rate around 15%. On the other hand, MAPEs obtained from SGA-ANN runs indicate that the algorithm can predict the layer moduli within higher errors than GSA-ANN. It gives the estimations with 5.85%, 24.3% and 5.25% MAPEs for E_{AC}, E_{LSS} and $E_{Rİ}$, respectively (see Figure 52). When backcalculation results and ability to reaching optimum fitness are investigated, it is concluded that GSA outperforms by compared to SGA approach for FDP-LSS sections. Apart from these, elastic moduli of stabilized layer cannot be well predicted by both approaches. Higher inequalities of E_{LSS} predictions originate from the high flexural rigidity of pavements which have thick AC layers and/or higher AC layer moduli. Rigidity of surface layer is one of the most important factor influencing deflections occurred on the pavement surface.

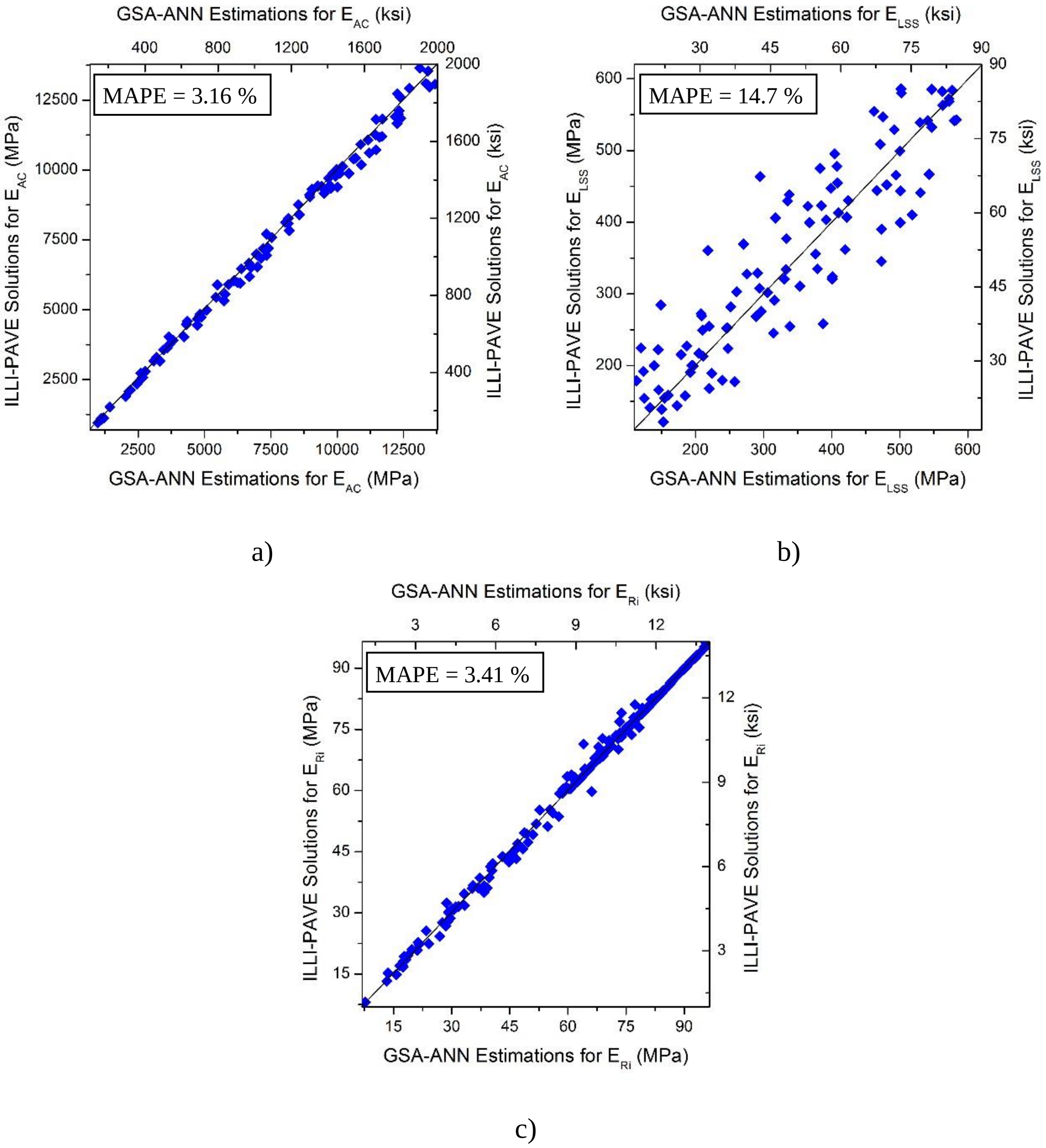
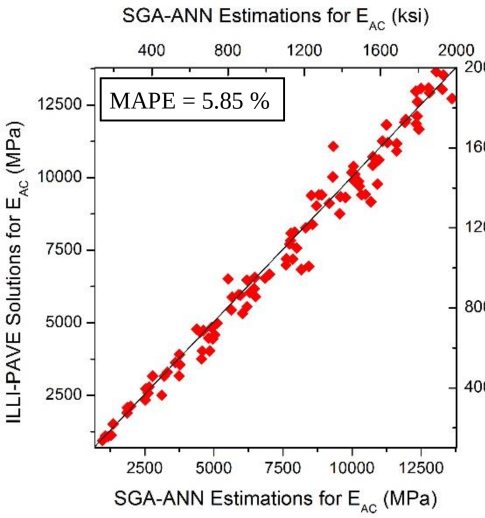
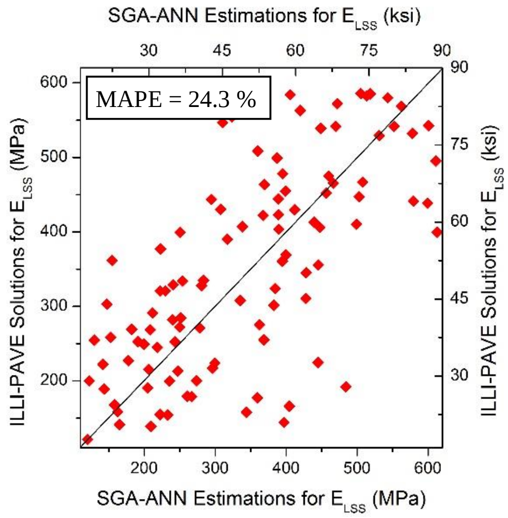


Figure 51 Performance of GSA-ANN algorithm for FDP-LSS Synthetic Data



a)



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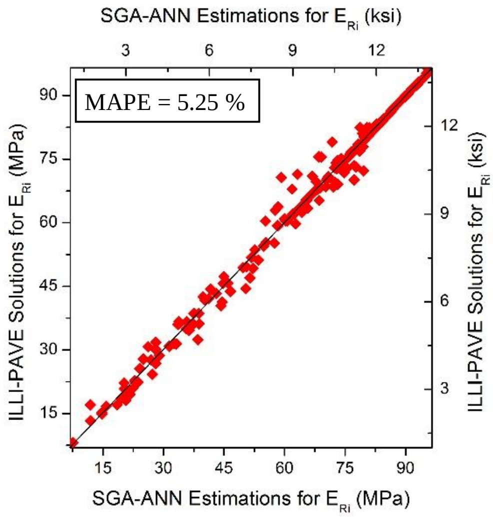
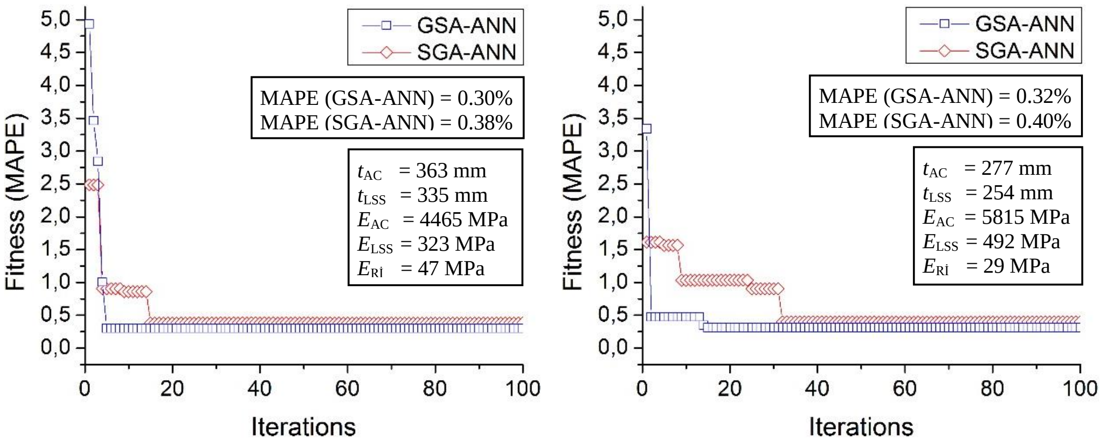


c)

Figure 52 Performance of SGA-ANN algorithm for FDP-LSS Synthetic Data



a) b)

Figure 53 Progress Curves of Two Randomly Selected FDP-LSS sections for Reaching the Optimum Fitness Values

4.4 Field Validation

Validation using only synthetically derived data is not sufficient to reveal the accomplishment of the GSA-ANN algorithm. Since the synthetic data were obtained from the numerical modelling of pavements, it is essential to verify the algorithm with the field data. Therefore, GSA-ANN model is executed for data extracted from the LTPP Program database. For each of flexible pavement types, three LTPP test sections are selected. In each section several number of FWD tests were applied that corresponding locations are named as station. Each station can be considered as a single backcalculation problem. Utilized LTPP data are accessible for download from the website: www.infopave.com. This web interface provides users the opportunity to query and to find the desired data easily.

To present the performance of GSA against SGA as a search method, SGA-ANN algorithm is also performed for the same LTPP sections. On the other hand, EVERCALC and MODULUS conventional backcalculation softwares which considers different approaches for pavement layer backcalculation are also executed to evaluate the performance of GSA-ANN algorithm.

For each of test sections, thickness of layers whose moduli values are backcalculated and corresponding deflection basins for 40 kN (9 kips) FWD loads along with the stations are extracted from the LTPP database and saved in an MS Excel file. For each type of flexible pavements, GSA-ANN algorithm is performed for a population consisting of 50 agents which are evaluated iteratively for 100 times. Other parameters of GSA: *Rpower*, α and G_0 are set to 1, 0.5 and 10^8, respectively. The same population size and iteration number are selected for SGA-ANN algorithm so as to make the analyses consistent with each other. Probability of crossover and probability of mutation are selected as 0.74 and 0.1, respectively (Reddy et al. 2004). Through the use of these input data layer properties are backcalculated and results are stored in an MS Excel file.

EVERCALC backcalculation program uses two input files namely the general file and the deflection file. The general file requests values of all the necessary input parameters from the user. Sensor configuration, radius of loading plate and units to be used in the analyses are given in the general file. Then the number of layers, corresponding moduli ranges and Poisson's ratios are defined to the software. These values are generally given as the same as the ranges used in GSA-ANN and SGA-ANN analyses to make them consistent with each other. Maximum number of iterations, deflection basin error tolerance and moduli error tolerance are chosen typically used values as 10, 1% and 1%, respectively (WSDOT 2005). The next step is to define the loads and associated deflection basins in the deflection file. Since the EVERCALC is able to calculate stress sensitivity coefficients in the case of providing deflection basins for more than one load level, 4 different load levels which are around 30, 40, 60 and 80 kN (6, 9, 11 and 15 kips) magnitudes are taken into account along with their deflection basins. After conducting analyses, backcalculated layer moduli values are stored in the same MS Excel file with GSA-ANN and SGA-ANN.

MODULUS is another conventional backcalculation software that it assumes all layers as linear elastic. The software works in MS-DOS environment and it requests from the user to define plate radius, number of sensors and corresponding locations. At the same screen, layer thicknesses, moduli ranges and Poisson's ratios are defined to the program. Unlike the EVERCALC program, MODULUS does not require any range for subgrade moduli and it only asks for an initial moduli for natural soil. On the other hand, the software enables user to define thickness for subgrade which may influence the backcalculated results. Deflection data of approximately 40 kN (9 kips) loading conditions are given to the program to perform backcalculation of layer moduli by using predefined layer properties. Finally, obtained results are recorded to the same MS Excel file with previously backcalculated moduli values using the other approaches.

All the approaches specified above are performed 10 times and an average moduli for each layer and subgrade along with the stations are plotted. For each type of flexible pavements, details of LTPP test sections, analyses and corresponding results are presented in the following sections separately.

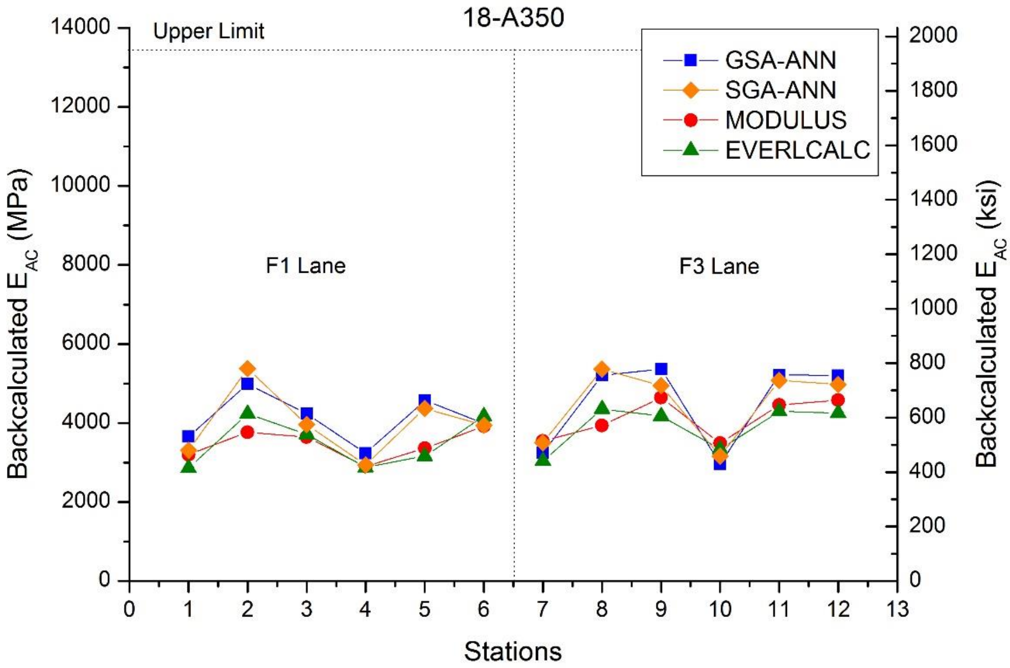
4.4.1 LTPP Full-depth Asphalt Pavement Sections

Full-depth asphalt pavements built on fine-grained subgrade are rarely encountered because of their high cost of construction and/or lack of available granular materials in the local area. In order to analyze such sections, LTPP database are investigated and locations of chosen test sections are illustrated using satellite images in Figure 57. Selected first FDP section is located in Spencer County in the State of Indiana. Sections in LTPP database are defined with the combination of two identification numbers that first one refers to the state code and the second one is the section ID specified uniquely for every LTPP section in the state. In this manner, the first section to be analyzed is named as 18-A350 where 18 is the state code and A350 is the section ID. This pavement was constructed in 1975 and it has been observed through the LTPP program specific pavement studies (SPS-3) ever since 1987. Among the several FWD tests applied to this section, deflection data measured on May 11, 1994 is extracted to perform backcalculation. When the test was started, pavement temperature was recorded as 44°C (111°F). Either flexible pavements may be built with several AC layers at one construction stage or additional AC layers may be placed on the existing asphalt pavements later on. In this context, 18-A350 section is composed of 399 mm

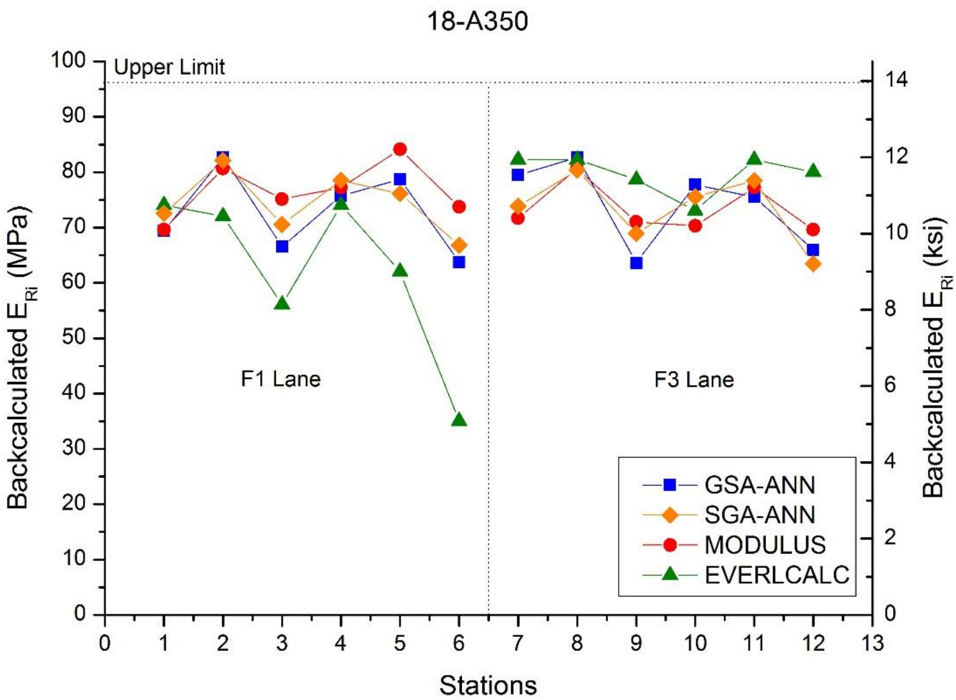
(13.6 in.) total thickness of AC layers over lean inorganic clayey fine-grained soil. The test was performed with a 7-sensored FWD device along with the 6 stations for two different lanes of the section 18-A350. Loading plate radius of an FWD configuration may differ regarding to performed test, so that it was searched for radius of 152 mm (6 in.) loading plates. Because, deflection basins in ANN models were generated under 40 kN ESAL over loading plate having 152 mm (6 in.) radius.

The second FDP section is 20-A320 which is located in Franklin County in the State of Kansas. The road including this section was constructed in 1971 and has been investigated through the LTPP Program specific pavement studies (SPS-3) ever since 1987. The backcalculated deflection data belong to the performed test on April 23, 1993 and the measured pavement temperature when the test started is 72°F (22°C). The cross section of the pavement consists total thickness of 345 mm (13.6 in) of AC layer built on lean inorganic clayey fine-grained soil. The road has two lanes that deflections were recorded in 6 stations for both lanes by means of 7-sensored FWD device. The third FDP test section is located afterwards of the 20-A320 section and named as 20-A330. The FWD test data were collected on April 23, 1993 that the pavement temperature was 59°F (15°C). The section was constructed with 335 mm (13.2 in) of AC layer above the clayey fine-grained soil. The same FWD configuration was implemented in this section and deflections were captured for 6 stations for each lane.

As explained above, FWD tests applied on the each of selected LTPP sections only have 6 stations. To observe the estimation consistency between the lanes, layer moduli are backcalculated for F1 and F3 lanes of all the FDP sections. Obtained layer moduli along with the stations for each FDP section are presented from Figure 54 to 56. SGA-ANN produces approximately the same layer moduli curve with GSA-ANN algorithm for AC layer and subgrade. As it can be seen from these figures, GSA-ANN and SGA-ANN calculations for linear elastic AC layer have the same trend with conventional backcalculation softwares despite the slight differences existing among them. Additionally, calculated layer moduli for two lanes are usually agreeable with each other. Although the same trend is observed for each analyses method except a few stations, subgrade moduli show slight variations. Generally, GSA-ANN and SGA-ANN produce lower layer moduli by compared to the other two approaches. Since the EVERCALC takes into account the nonlinearity of layers under several load levels, it is expected for GSA-ANN to produce consistent results with this software. Adherence to this, similar trend with EVERLCALC software at certain stations is observed. Because of different material model employed by EVERLCALC for fine-grained subgrades, the software may produce dissimilar layer moduli compared to GSA-ANN outputs. Nevertheless, GSA-ANN estimations for AC layer moduli are consistent with the SGA-ANN and other two programs and present admissible solutions for fine-grained subgrade moduli with traditional methods.

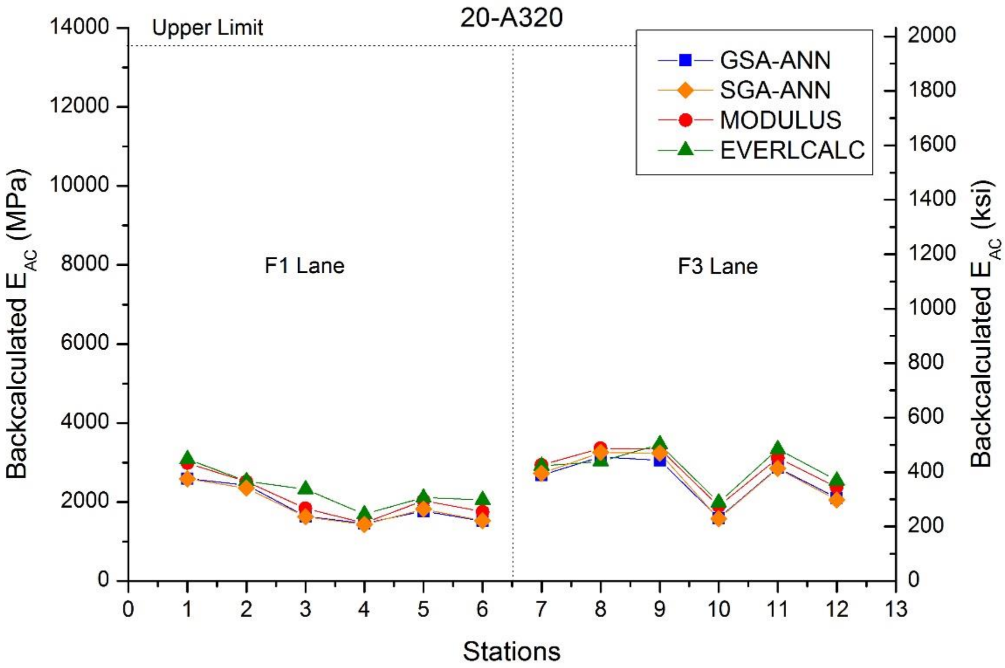


a)

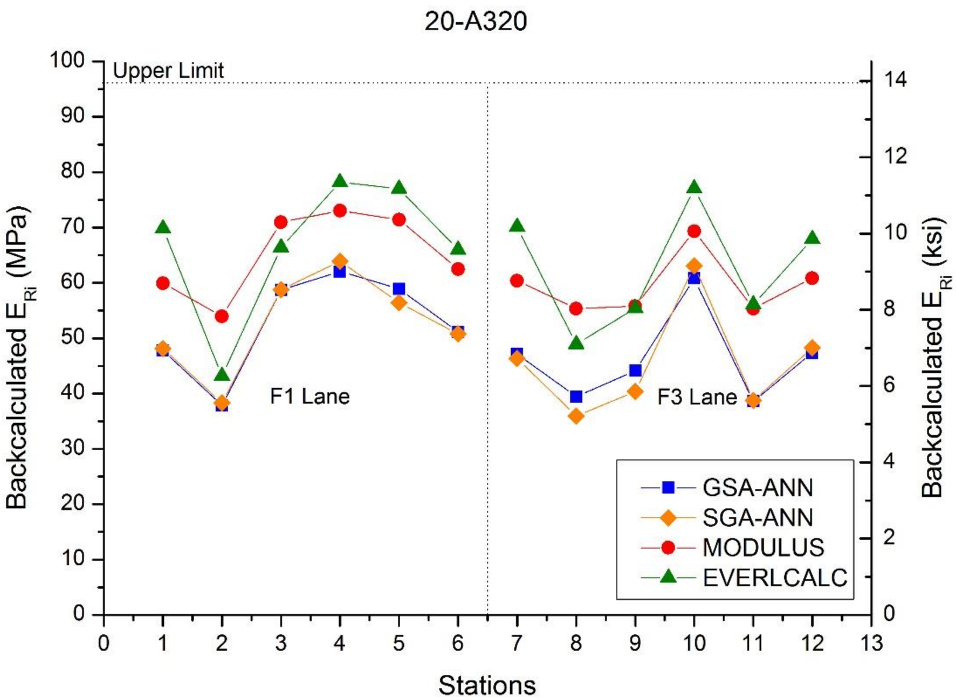


b)

Figure 54 Comparison of Layer Moduli for 18-A350 FDP Section

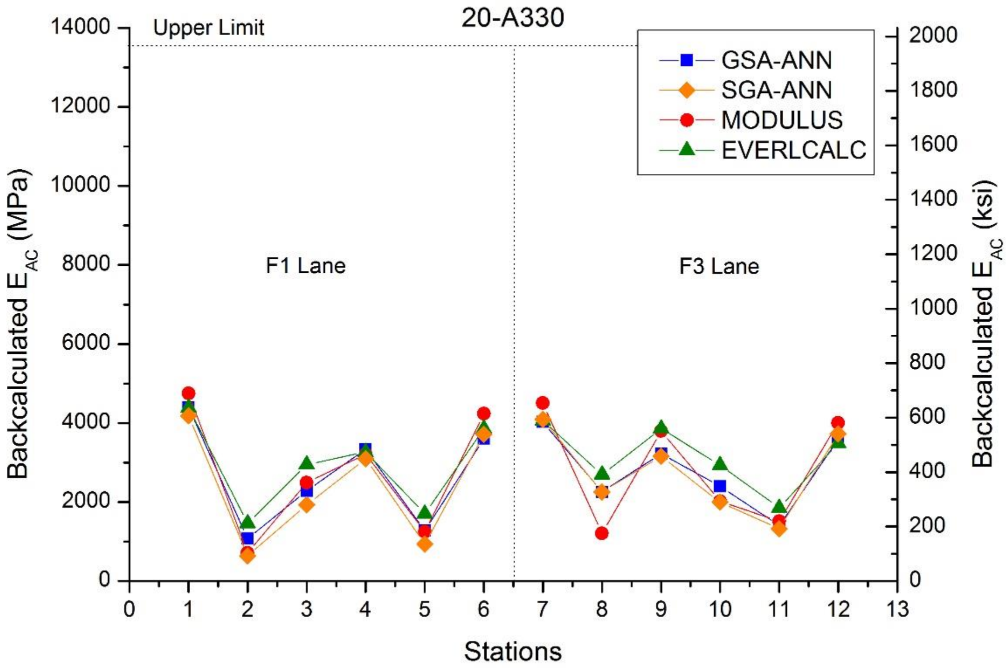


a)

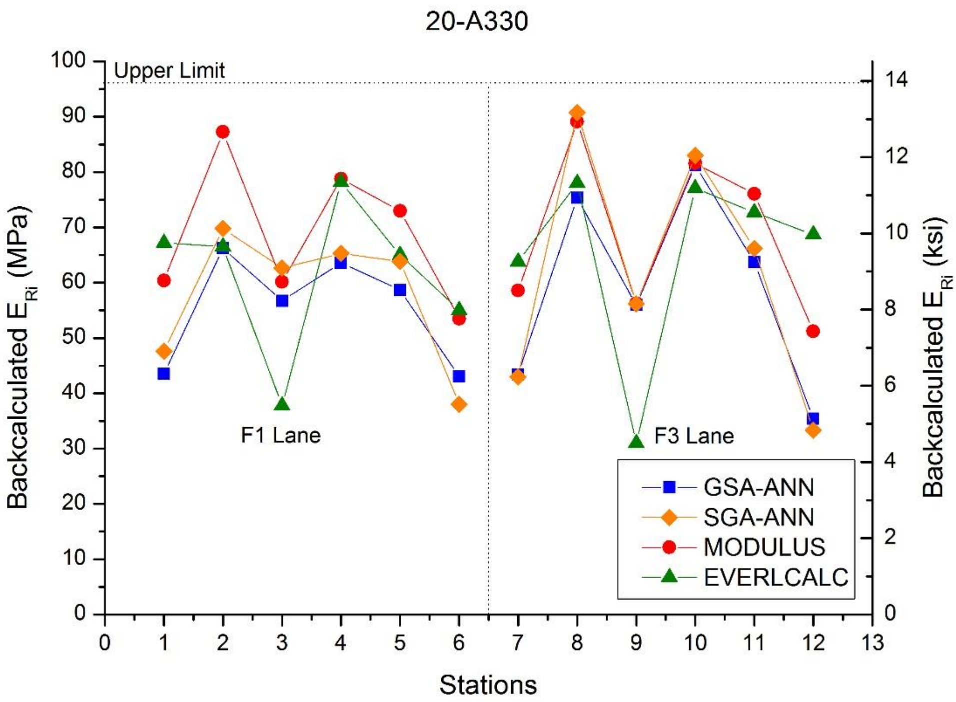


b)

Figure 55 Comparison of Layer Moduli for 20-A320 FDP Section

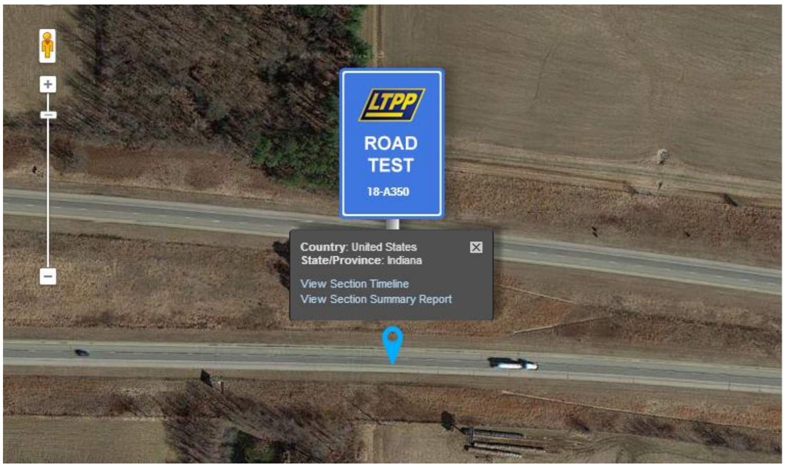


a)



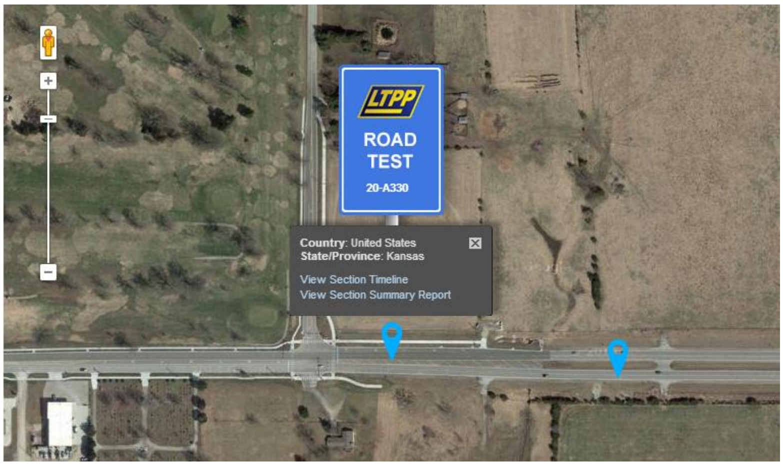
b)

Figure 56 Comparison of Layer Moduli for 20-A330 FDP Section



a) Location of 18-A350 Test Section (GPS-Lat., Long. (degree): 38.19612, -86.99742)

b) Location of 20-A320 Test Section (GPS-Lat., Long. (degree): 38.62293, -95.24045)



c) Location of 20-A330 Test Section (GPS-Lat., Long. (degree): 38.62308, -95.24844)

Figure 57 Locations of LTPP FDP Test Sections

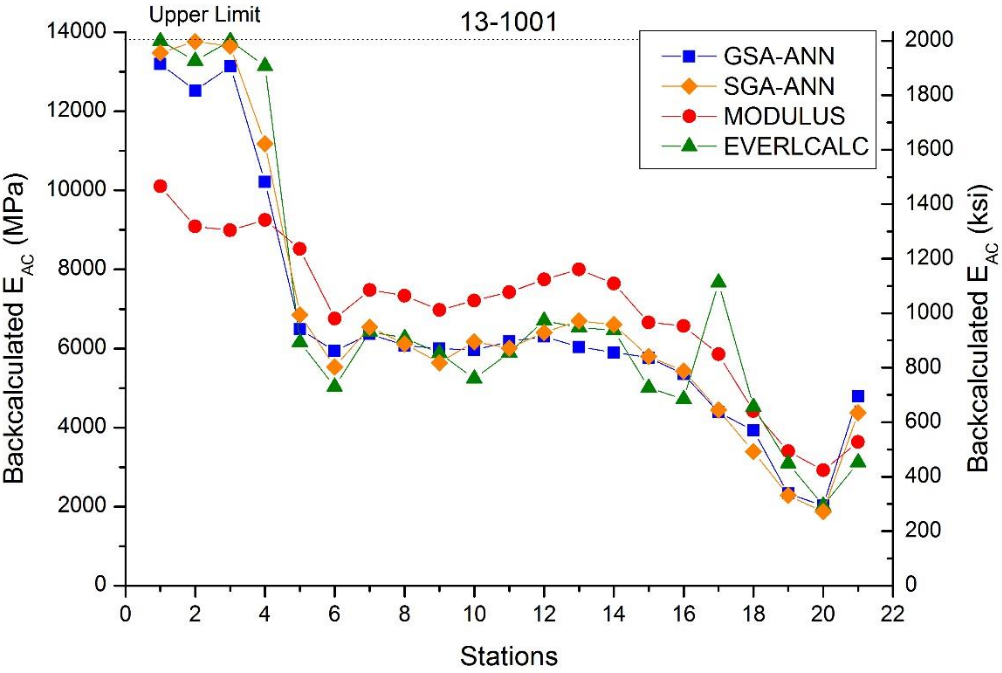
4.4.2 LTPP Conventional Flexible Pavement Sections

Conventional flexible pavements have been extensively constructed in all around the word due to their economic advantages. Building pavements with unbound granular layers reduces the total thickness of asphalt layers being constructed. Therefore, there is a large number of CFP type sections' data are readily available in LTPP database. As the results of investigations in LTPP database, three of test sections are selected from different locations in the USA and Canada. Locations of chosen test sections are illustrated using satellite images in Figure 61. The first section is situated in Walton County in the State of Georgia and it is named as 13-1001. This section was built in 1986 and it has been investigated through LTPP program general pavement studies (GPS-1) since a year later of its construction. Among the applied several FWD tests in different dates, the test was chosen which was performed on April 30, 1995 and recorded pavement temperature when the test started was approximately 38°C (100°F). Analyzed section is composed of total thickness of 211 mm (8.3 in.) of AC layer and 218 mm (8.6 in.) of crushed gravel layer which are constructed over fine-grained soil including sandy silt. FWD test were applied for two lanes of 13-1001 section along with the 21 successive stations located within approximately 150 m long road portion. Employed FWD device is configured with 7 sensors to measure deflections occurred on the pavement surface.

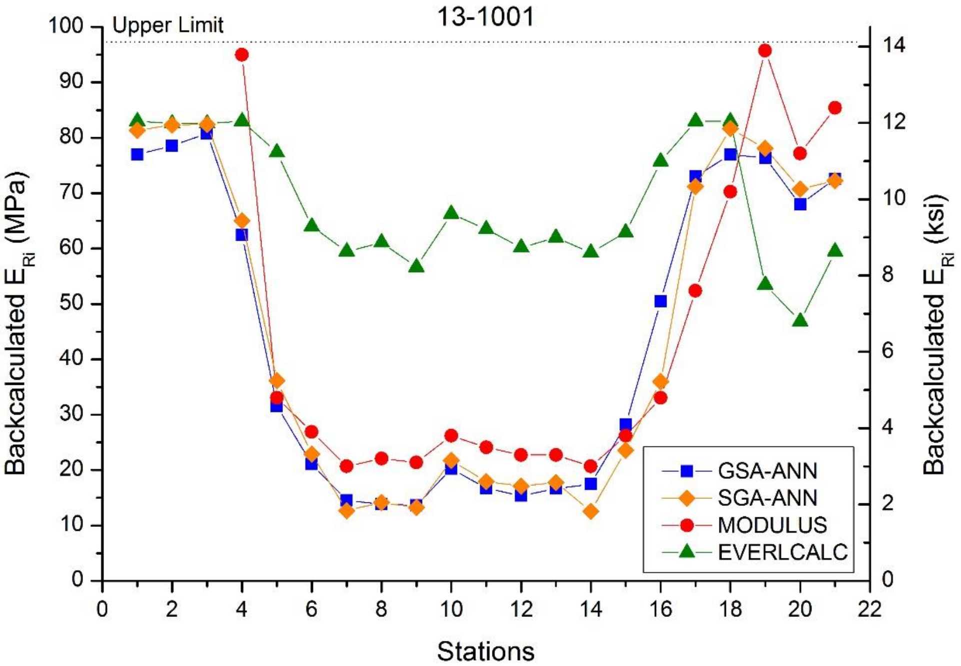
The second CFP test section is selected from the western part of USA located in Golden Valley County in the State of Montana. Defined identification number for this section is 30-8129 and it has been observed by LTPP program general pavement studies (GPS-1) since the construction year of 1988. Among the applied several FWD tests in different dates, the test is chosen which was performed on July 27, 2003 and the reported pavement temperature when the test started was approximately 28°C (82°F). The cross section of the pavement is composed of 185 mm of (7.3 in.) AC layer and 558 mm (22 in.) of crashed gravel layer placed above the gravelly lean clay with sandy soil. 9-sensored FWD device was used to measure the deflections occurred on the pavement surface. Test was performed for two lanes of the section along with the 21 successive stations located within approximately 150 m long road portion.

The third test section extracted from LTPP is situated in Canada. The unique ID number for the section is 90-6410 of which 90 refers to the ID of the Saskatchewan State and 6410 is the section ID. This pavement is relatively old comparing to the other analyzed LTPP sections that was constructed in 1968. Ever since the year of 1987, it has been investigated through LTPP program general pavement studies (GPS-1 and GPS-6B). In 2005, the section was removed from the LTPP studies. Among the FWD tests performed before the removal of the section, the test is selected which was carried out on June 14, 1990. Recorded pavement temperature was 54°F (18°C) on the test day. The section was constructed with AC layers of 147 mm (5.8 in.) and 239 mm (9.4 in.) of crushed gravel unbound layer over the fine-grained sandy silt soil. Deflection were measured with 7-sensored FWD device through the approximately 150 m long road portion including 21 stations for two lanes.

Figure 58 to 60 provide the moduli curves for CFP type LTPP test sections through the stations. Performance of GSA-ANN and SGA-ANN algorithms on granular layers are not sufficient as it was expressed in Section 4.3.2. In addition to these, MODULUS software gives elastic moduli of granular layer while GSA-ANN estimates the K_{GB} parameters in the constitutive material model. Therefore, it is not convenient to compare the outputs of the programs and it is thought that presenting granular layer moduli data does not make any contribution to this study. When the moduli curves were investigated for elastic AC layers, a general trend is observed for each of the test sections and also it is seen that GSA-ANN gives closer estimations with EVERCALC. Also, SGA-ANN produces approximately the same layer moduli curve with GSA-ANN algorithm for AC layer and subgrade. On the other hand, MODULUS AC layer moduli calculations are usually located above the other solutions. In a few stations of 13-1001, MODULUS overestimates the AC layer moduli much more than the upper limit of predefined range for subgrade, and hence these stations were not reported on the graph. Consequently, it is observed that EVERCALC solutions for subgrade moduli are generally higher than the other two approach and in some cases like in 13-1001 section, huge gaps emerge with another solutions. In conclusion, GSA-ANN gives consistent predictions with conventional softwares especially for AC layers. Predictions for unbound granular layer properties are excluded from the scope of this study because of the inadequate performance of programs.

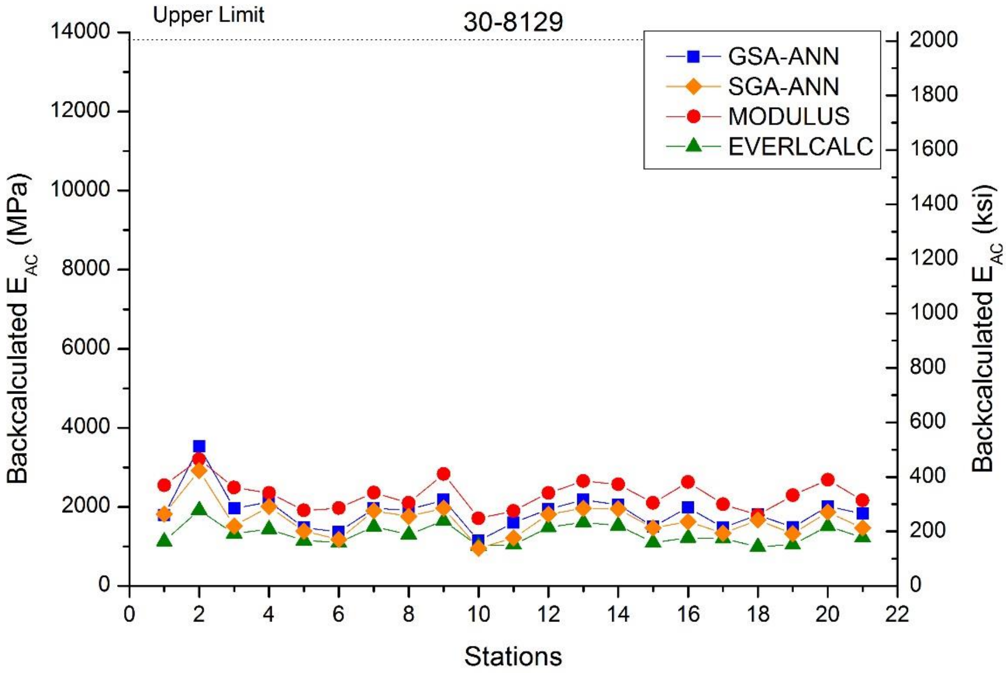


a)

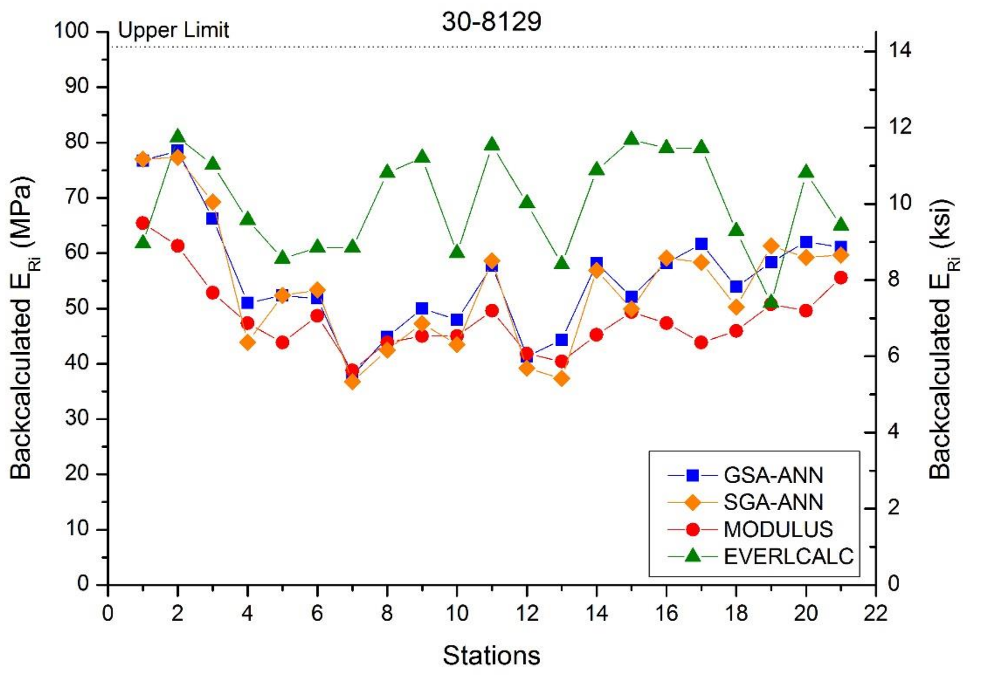


b)

Figure 58 Comparison of Layer Moduli 13-1001 CFP Section

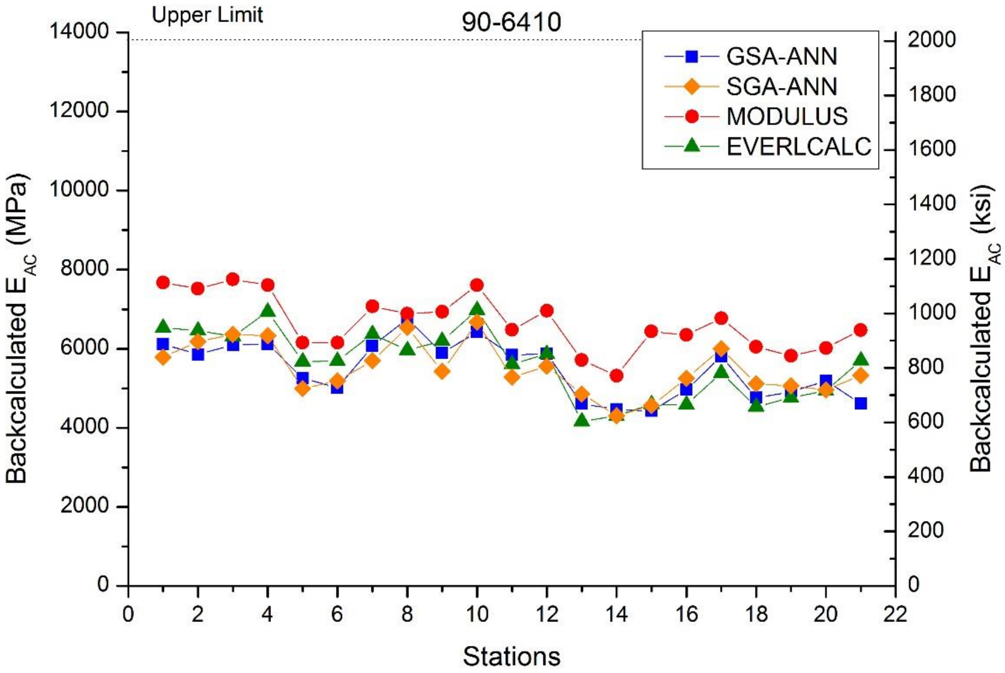


a)

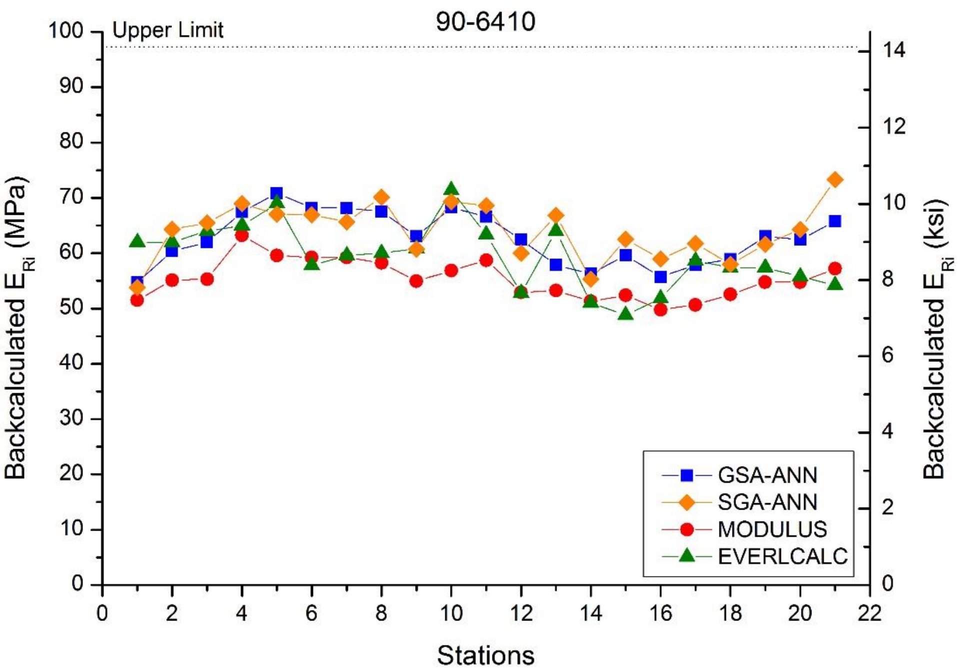


b)

Figure 59 Comparison of Layer Moduli for 30-8129 CFP Section

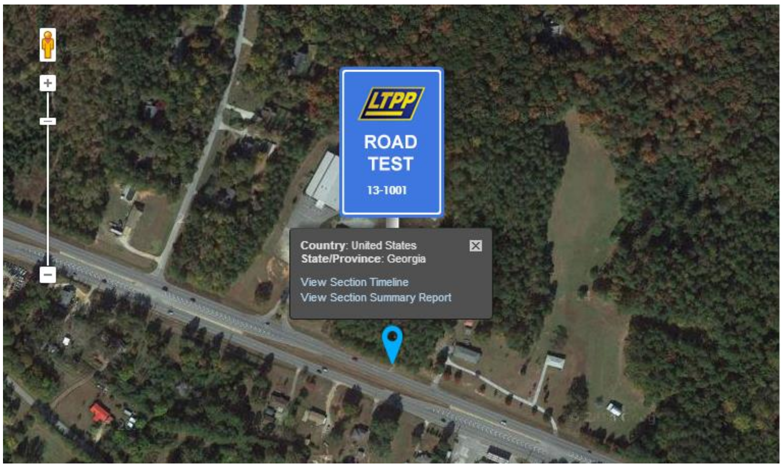


a)

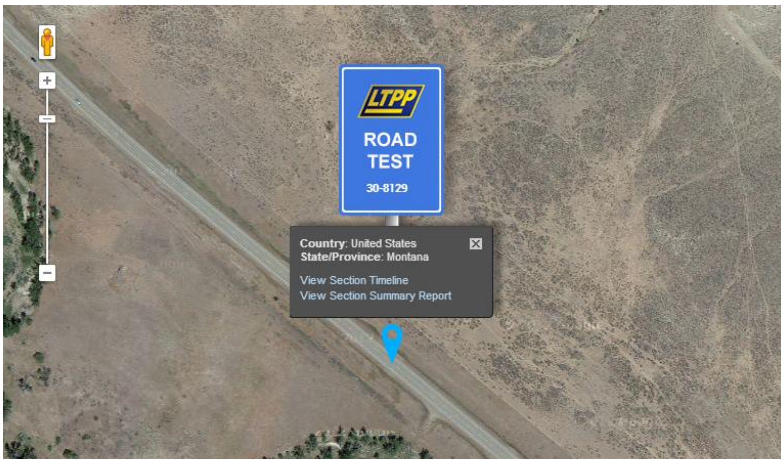


b)

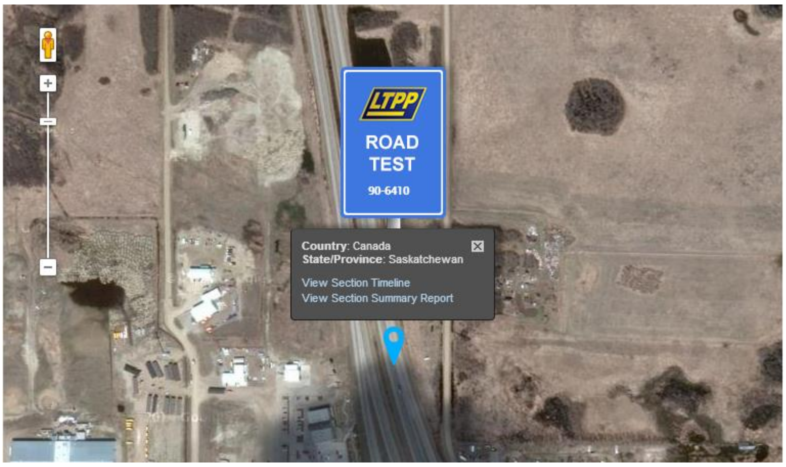
Figure 60 Comparison of Layer Moduli for 90-6410 CFP Section



a) Location of 13-1001 Test Section (GPS-Lat., Long. (degree): 33.8075, -83.79003)



b) Location of 30-8129 Test Section (GPS-Lat., Long. (degree): 46.30759, -109.12174)



c) Location of 90-6410 Test Section (GPS-Lat., Long. (degree): 52.05876, -106.59993)

Figure 61 Locations of LTPP CFP Test Sections

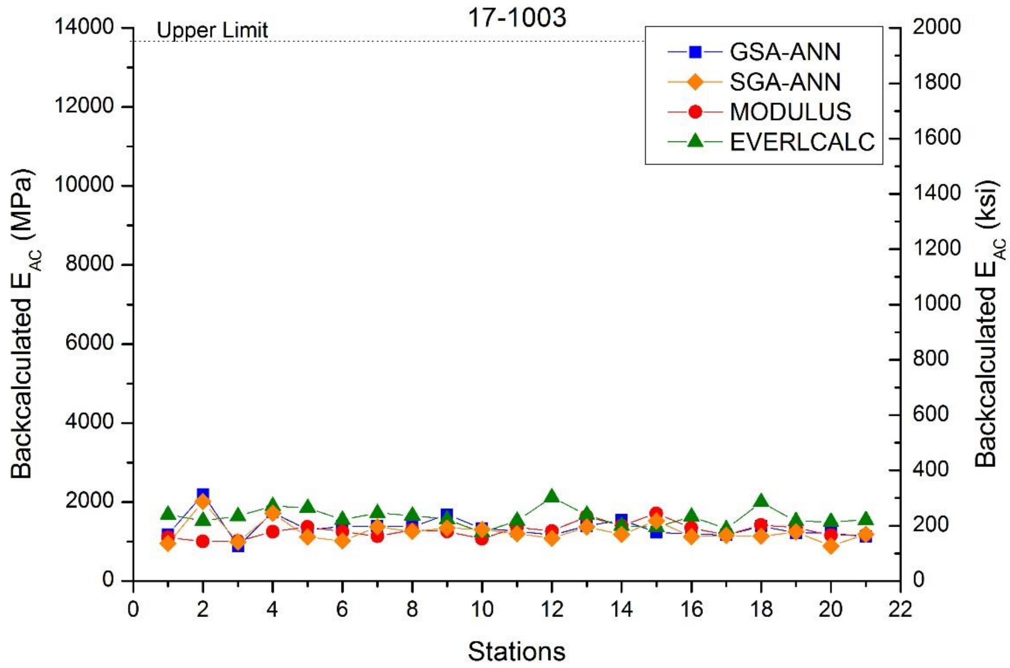
4.4.3 LTPP Full-depth Asphalt Pavement Sections on Lime Stabilized Soils

Sometimes, it is essential to improve the natural soil quality to build pavements over the subgrade. One of the materials used for the purpose of improvement is lime. Previous studies proves the necessity of regarding lime stabilized soils as an independent layer in pavement analyses (Pekcan 2010). Since the strength of untreated fine-grained subgrade soils may not be sufficient to resist the applied loads, lime stabilization is a common approach for improvement. Several full-depth asphalt pavement sections on lime stabilized soils which is a popular approach in USA are available in LTPP database. Locations of chosen test sections are illustrated using satellite images in Figure 68. The first FDP-LSS section analyzed is located in Clinton County in the State of Illinois and identified as 17-1003. The pavement was constructed in 1986, and ever since the year of 1987 it has been observed through the LTPP Program general pavement studies (GPS-1). The FWD test data belong to this section were collected on August 31, 2004 and the pavement temperature was around 31°C (88°F). The test section in question consists of a total thickness of 310 mm (12.2 in.) AC layers which include a number of thinner successive AC layers and 305 mm (12 in.) lime stabilized soil layer constructed over the fine-grained sandy clayey soil. FWD tests were performed with 9-sensored device along with the approximately 150 m long road portion which includes 21 test stations.

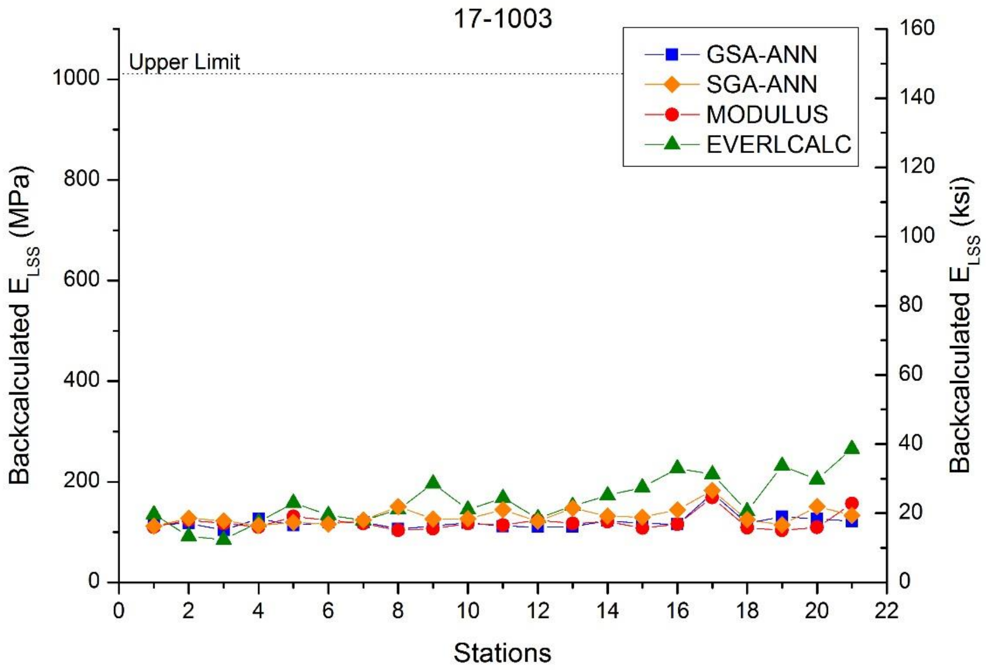
The second FDP-LSS section is also located in Clinton County in the State of Illinois and specified as 17-A320. This section was constructed afterwards the previously defined 17-1003 section in 1986 and it has been observed since 1987 within the scope of LTPP program specific pavement studies (SPS-3). The selected FWD test was performed on September 1, 2004 and the corresponding pavement temperature was about 38°C (100°F). The cross section of the pavement includes 315 mm (12.4 in.) of AC layer and 305 mm (12 in.) of lime stabilized soil layer constructed over the fine-grained sandy clayey soil. The FWD device captured the deflection data with 9-sensored configuration throughout the test direction. The length of the test portion of the road is about 150 m and it consists of 12 experimental stations.

The third and the last section analyzed is located in Buchanan County in State of Iowa and it is defined as 19-1044. The section was constructed in 1971, and ever since the year of 1987, it has been investigated along with the LTPP program general pavement studies (GPS-1). The data belong to this section was measured on April 4, 2002 and the pavement temperature was recorded as 15°C (59°F). Because the pavement was constructed long time ago, it has been subjected to overlaying operations that AC layer thickness increases during the service life of pavements. The latest condition was considered in this section of which composed of 506 mm (19.9 in.) of AC layer and 254 mm (10 in.) of lime stabilized soil built over the sandy lean clayey subgrade. FWD tests were performed with 9-sensored device along with the approximately 150 m long road including 21 test stations.

Backcalculated layer moduli of FDP-LSS sections of LTPP database are illustrated from Figure 62 to 67. As can be clearly seen that, for all the sections, GSA-ANN prediction for linear elastic layers (AC and LSS layer) are consistent with the other two backcalculation programs. Similar to FDP and CFP comparison results, SGA-ANN gives the best approximation to the GSA-ANN algorithm. Especially, there are substantial conformity among the E_{AC} estimations while E_{LSS} predictions show slight differences that both layer moduli are estimated around the lower limit of associated modulus ranges by each backcalculation approach. In section 17-1003, modulus of stabilized layer is calculated higher than the other approaches as much as half of the stations. Apart from these, for the most of the stations, backcalculated subgrade moduli by GSA-ANN show a good trend with other programs’ results, in particular EVERCALC solutions. Generally GSA-ANN calculated subgrade moduli are found to be lower than the other programs. Since the proposed model considers the subgrade nonlinear and employs the bilinear arithmetic model solutions, the gap between the results may be originated from the assumed linearity of subgrade by MODULUS software. Nevertheless, estimations of GSA-ANN for subgrade moduli is commonly agreeable with the nonlinear solutions of EVERCALC. GSA-ANN works in conformity with the other two backcalculation programs for full-depth asphalt pavements constructed over lime stabilized soils.



a)



b)

Figure 62 Comparison of Surface and Base Layer Moduli for 17-1003 FDP_LSS Section

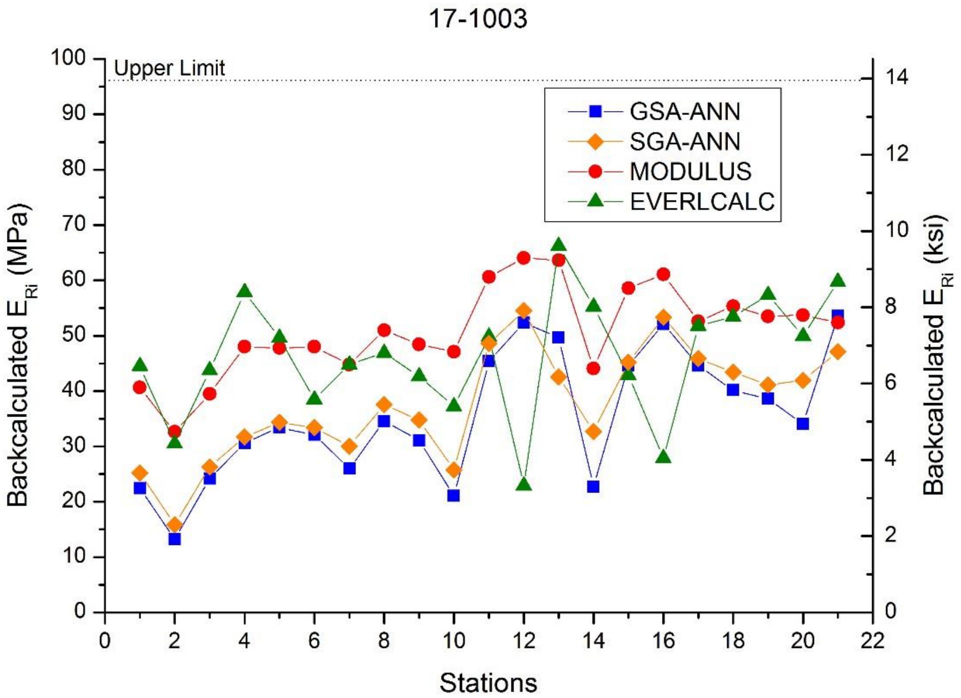
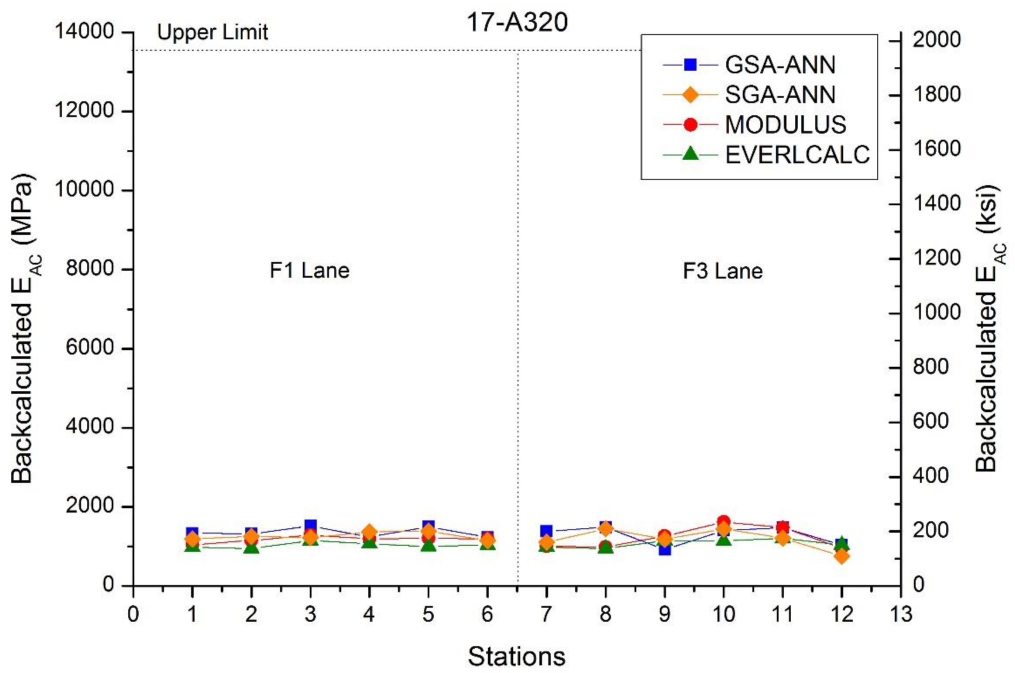
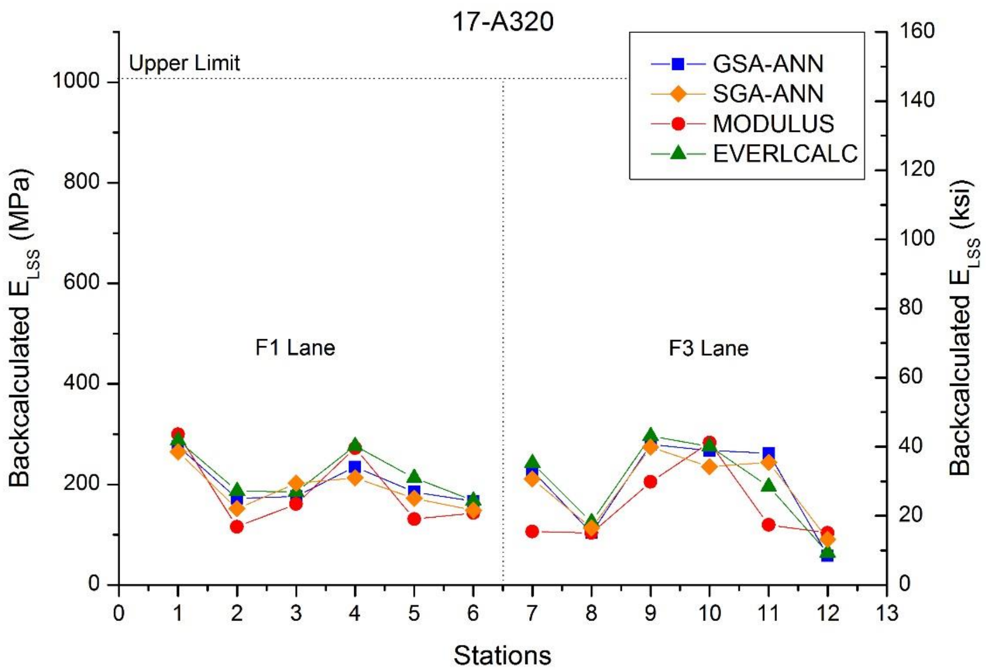


Figure 63 Comparison of Subgrade Moduli for 17-1003 FDP_LSS Section



a)



b)

Figure 64 Comparison of Surface and Base Layer Moduli for 17-A320 FDP_LSS Section

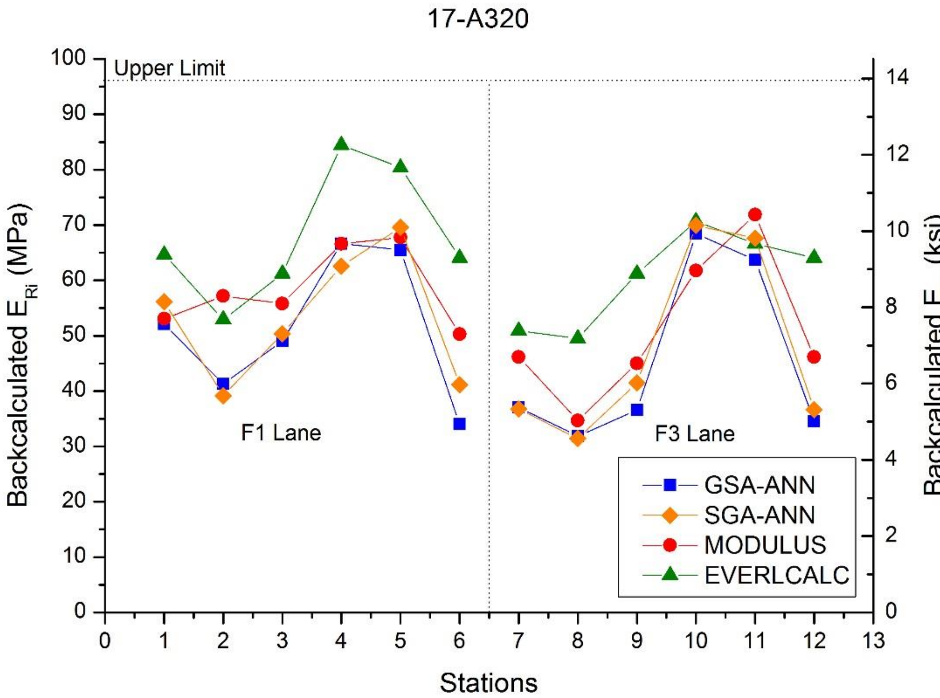
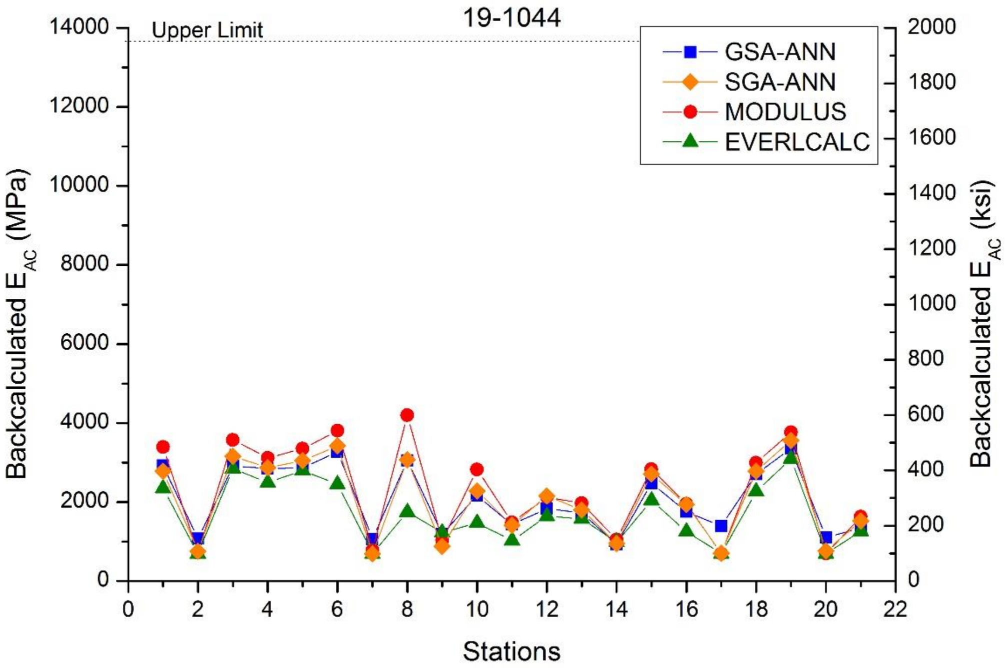
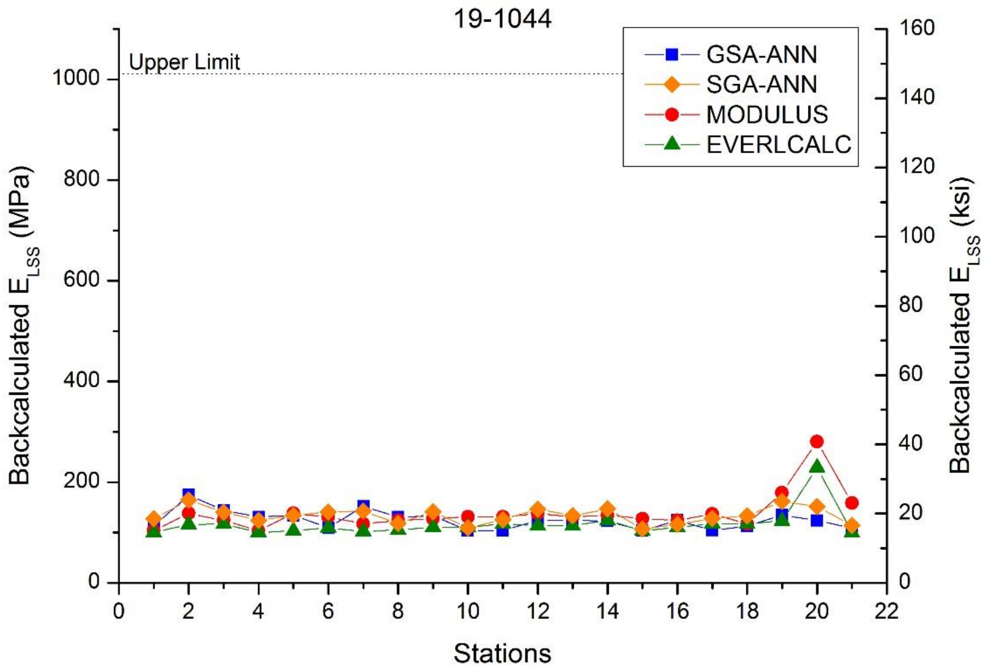


Figure 65 Comparison of Subgrade Moduli for 17-A320 FDP_LSS Section



a)



b)

Figure 66 Comparison of Surface and Base Layer Moduli for 19-1044 FDP_LSS Section

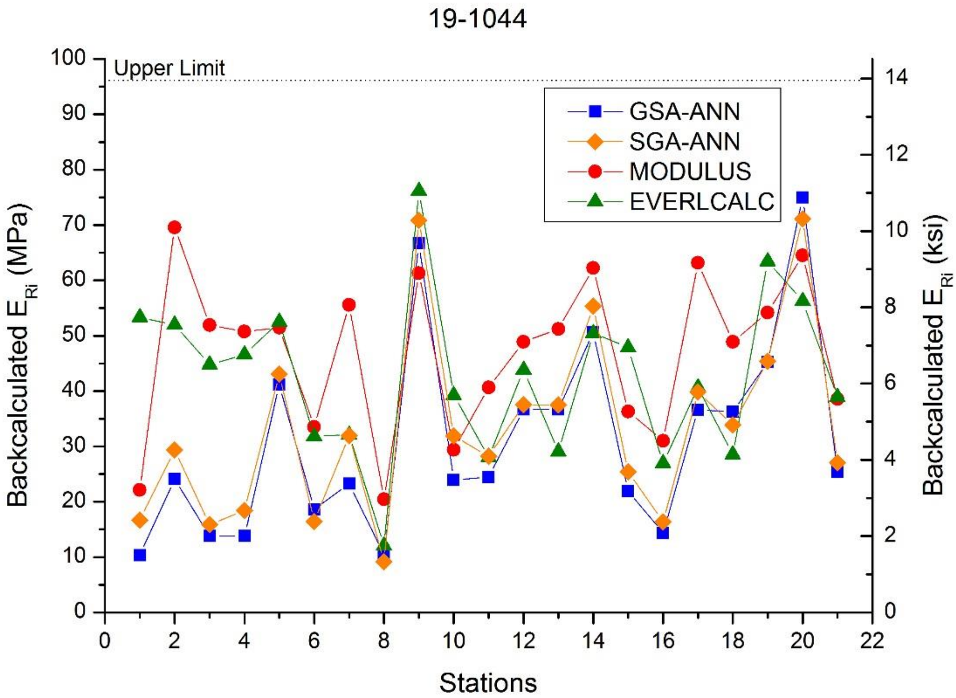
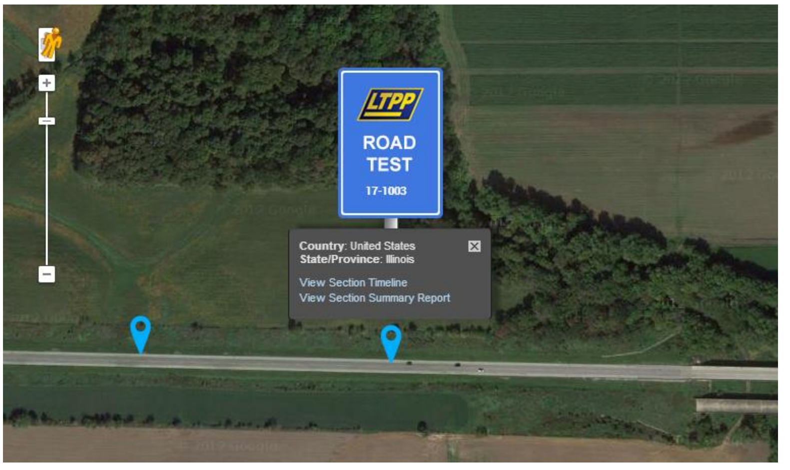
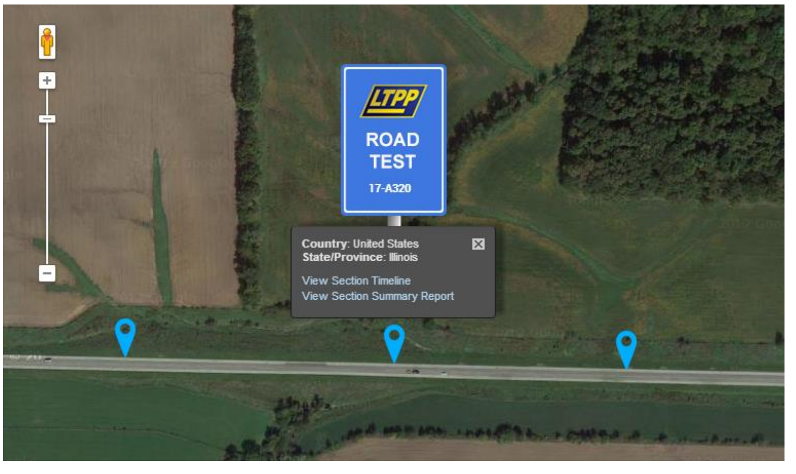


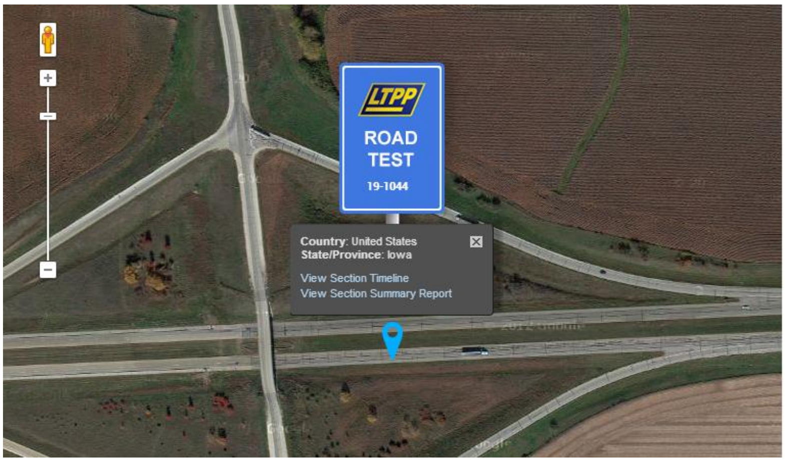
Figure 67 Comparison of Subgrade Moduli for 19-1044 FDP_LSS Section



a) Location of 17-1003 Test Section (GPS-Lat., Long. (degree): 38.61603, -89.63421)



b) Location of 17-A320 Test Section (GPS-Lat., Long. (degree): 38.61616, -89.63927)



c) Location of 19-1044 Test Section (GPS-Lat., Long. (degree): 42.46363, -91.64574)

Figure 68 Locations of LTPP FDP-LSS Test Sections

CHAPTER 5

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

Transportation agencies evaluate structural capacity of in-service pavements to accurately decide about the rehabilitation and maintenance operations. Nondestructive pavement testing and evaluation tools play a significant role while making such assessments. Among various testing devices, the most commonly used one is Falling Weight Deflectometer (FWD), which measures the surface deflections under imposed loading conditions. Through the use of FWD deflections, layer moduli of pavements can be inversely determined using intelligent search schemes. This process is called as backcalculation and it is composed of two main parts which are forward response modelling of deflections and employing a search method. In pavement backcalculation, it is aimed to match FWD deflections with forward response model deflections repetitively by adjusting layer moduli in each iteration. Regarded material behavior in forward analyses is one of the overriding factors on the accuracy of calculated deflections. Generally, forward models use elastic layered theory of which assumes that all the layers exhibit linearly elastic, however subgrade and base/subbase layers have stress dependent nonlinear nature. For the purpose of obtaining more accurate deflections, it is required to take into account the nonlinear behavior of these geomaterials. Finite element method (FEM) can be considered as the most appropriate approach for advanced structural modeling of pavements owing to its capability of handling complex geometries and nonlinearity of geomaterials by means of constitutive material models. However, inherent nature of FEM analyses increases the runtime of the backcalculation algorithm. Since the backcalculation operations work iteratively, it requires a great number of analyses to be performed successively so that a forward response approach is needed which gives fast and accurate deflections. In this context, artificial neural networks (ANNs) can be used as an analyses tool which can produce fast and accurate results through the use of FE solutions. Search method is the second significant part of a backcalculation operation that input properties of forward response model are investigated using a search method. It determines the most appropriate values by considering the difference between forwardly calculated and measured FWD deflections. For this purpose, several different optimization algorithms can be employed.

In this study, a backcalculation algorithm namely GSA-ANN is proposed for backcalculation of flexible pavements. As a forward response engine, previously developed ANN models were used (Pekcan 2010). While generating these models input and output data of the ILLI-PAVE FEM based pavement design and analysis software were used so that nonlinearity of pavement geomaterials were considered. By making use of the ability of ANNs in establishing the nonlinear relationship between input and output properties of a system, a fast and robust approach was employed. However, the accuracy of the ANN estimations are also related with the provided input properties to the ANN models. Proposed algorithm uses a newly developed metaheuristic optimization technique namely gravitational search algorithm (GSA) to select most appropriate input properties of ANN models. This method was developed by inspiring the Newton's law of universal gravitation and second law of motion (Rashedi et al. 2009a). The ability of GSA in searching the global solutions in defined search space was combined with the employed ANN model to form the GSA-ANN backcalculation approach. Forward ANN models take layer moduli and thicknesses to produce deflections at certain radial locations. Therefore, GSA was adapted to find best values of input parameters of ANN models by searching within the predefined ranges of layer moduli.

Proposed GSA-ANN algorithm was developed in MATLAB computing environment. Entire algorithm was developed on the basis of GSA which contains within itself ANN forward response models. In this manner, GSA code was developed by adapting the parameters of the algorithm to the pavement layer backcalculation problem. Then, ANN forward response models were embedded to the objective function part of the GSA. In order to start the algorithm, GSA-ANN requests from the user necessary input properties such as type of pavement, directory of FWD data in the computer and GSA parameters. After providing all the values of parameters to the algorithm, GSA generates an initial population consisting a certain number of possible layer moduli of the pavement section in question. Then they are provided together with layer thickness to the ANN models in order to calculate deflections. Mean absolute percentage error (MAPE) function was employed as the objective function which evaluates the difference between calculated and FWD deflections. GSA aims to minimize the MAPEs by searching much approximate layer moduli to the actual values throughout the iterations. According to obtained values of the objective function, GSA updates the layer moduli for the next iteration. This process continues iteratively until reaching the termination criteria which was selected as maximum number of iterations in this study. At the end, the layer properties of pavement section which produces the closest deflection basins to the actual ones is reported as the backcalculated layer moduli of the section.

In an attempt to validate developed GSA-ANN backcalculation model, it is required to conduct a number of analyses through the use of different data sources. Firstly, synthetically derived data generated ILLI-PAVE software were employed for evaluation of forward ANN models and GSA-ANN backcalculation algorithm. Moreover, to check the performance of GSA while searching layer moduli, another metaheuristic search method namely simple genetic algorithm (SGA) was combined with the same ANN forward response models. Obtained algorithm was named as SGA-ANN and it was also evaluated using the same synthetic data with GSA-ANN. Accordingly, the results of both algorithms were compared to present the effectiveness of GSA against a powerful search method. However, validation of GSA-ANN method by synthetically derived data is not sufficient to present the effectiveness of the method. In this context, field data were utilized which are extracted from the Long-

Term Pavement Performance (LTPP) Program databases. Three of LTPP sections located all around the USA and Canada were selected and analyzed for each type of pavement type. These sections' layer properties were backcalculated with GSA-ANN and SGA-ANN. Moreover, for further validation of the algorithm, the same LTPP sections were backcalculated with two conventional backcalculation softwares: EVERCALC and MODULUS. Finally, layer moduli values backcalculated by each approach were compared and obtained results were presented to show effectiveness of developed GSA-ANN model.

5.2 Conclusions

In this thesis, a backcalculation algorithm was developed which adequately characterizes pavement geomaterials and eliminates the computational complexity of pavement layer backcalculation problems. The main objective of this study was to examine the use of hybrid soft computing methods in backcalculating nonlinear pavement layer properties. In this context, performance of the proposed approach was investigated by using synthetically derived deflection data and field data to show its effectiveness in pavement layer backcalculation. According to the findings of the study, the following conclusions are obtained.

Utilized ANN models for forward response analyses could predict surface deflections of full-depth asphalt pavements on natural and lime stabilized soils and conventional flexible pavements very close to that of calculated deflections obtained through ILLI-PAVE FE program. Superior performances of ANN models indicate that they could be employed as surrogate forward response models of FE analyses. By this way, ANN enables fast, precise and realistic deflections of those computed with ILLI-PAVE software and also it reduces the required analyses time of pavement layer backcalculation problems.

According to the results of verification with synthetically derived FWD data, proposed approach could produce the AC layer modulus and fine-grained subgrade resilient modulus, E_{AC} and E_{Ri} in a good agreement with the actual moduli values of synthetic sections. In FDP sections, MAPE of layer moduli predictions were calculated to be around 2% while the ones for FDP-LSS and CFP predictions were generally found to be less than 4%. In general, MAPEs show excellent performance of GSA-ANN algorithm. However, proposed method underperforms for unbound granular and lime stabilized layers moduli estimations that some predictions of these layers (particularly unbound granular layer) were observed to be out of the reasonable limits, i.e., MAPEs may exceed more than 20%. When the results were investigated, it is seen that abnormal predictions were produced in the sections with thin asphalt layer or when the asphalt layer has high stiffness value. Therefore, the impact of the applied FWD load could not be propagated enough to the layers located below.

Through the use of the same synthetic data, the performance of SGA-ANN algorithm was also evaluated. According to obtained results, SGA-ANN could successfully predict the AC layer moduli and subgrade moduli of FDP sections within low MAPEs which are around 2%. However, the algorithm showed slightly worse performance than GSA-ANN for CFP and FDP-LSS sections that it produced approximately 5% MAPEs for each type. When the curves for reaching optimum fitness values were investigated a general trend was observed that SGA could finds the optimum fitness values before GSA finds. It is also observed that there is no significant difference between obtained fitness values for randomly selected test sections. The use of metaheuristic optimization methods in pavement backcalculation is a relatively new approach and GSA was utilized first time in a pavement layer backcalculation study. Regarding the findings and comparison with SGA-ANN solutions, GSA proves its effectiveness for synthetically derived data over SGA search approach. On the other hand, use of GSA and ANN together shows reliability and versatility of the hybrid soft computing methods in pavement backcalculation.

By considering the necessity of using field data to verify GSA-ANN model, three test sections were selected from the LTPP database for each of FDP, CFP and FDP-LSS type pavements. In order to examine how consistent results are produced by GSA-ANN model, SGA-ANN and two well-accepted conventional backcalculation softwares were utilized for solving the same LTPP sections. According to analyses results of all the pavement types, GSA-ANN produced AC layer modulus, E_{AC} in conformity with the other two programs such that each one considers the asphalt layer as linearly elastic. Observed good trend and close modulus values show the accomplishment of the GSA-ANN model in estimating elastic modulus of asphalt layers. Another layer considered as linear elastic by all the approaches is lime stabilized one. Because of the weak asphalt and lime stabilized layers selected FDP-LSS sections generally have higher deflection values. Therefore predictions become closer to the lower limit of the defined ranges but all the approaches produce consistent stabilized layer moduli with each other.

Apart from these, E_{Ri} predictions of GSA-ANN, SGA-ANN and EVERCALC were expected to give approximate solutions due to their nonlinear analysis capability. By considering the results of investigations, the same trend was observed for most of the stations. However, quietly large gaps were observed between the solutions. EVERCALC calculated higher E_{Ri} values for the sections having weak AC layers and it produced more close estimations for medium strength AC layers in CFPs. Although the consistency reached between each approach for subgrade moduli, values slightly differ that MODULUS interpretations usually located above the others. Excessive predictions of MODULUS come from the assumed linear elastic behavior of subgrade.

Another issue is the predefined ranges of layer moduli which were also taken into account in developing ANN models are somewhat restricted for certain sections encountered in LTPP databases. So that layer moduli ranges should cover larger values to use GSA-ANN algorithm for large scale applications.

Comparison of unbound granular layer modulus was not incorporated in this study. As stated in Chapter 4, performance of GSA-ANN in estimating K_{GB} parameter was not sufficient through the use of synthetic FWD data. As expected, significant differences occurred between GSA-ANN, SGA-ANN and EVERCALC predictions. Also, MODULUS estimations were not regarded because the software produces elastic modulus. In comparisons, K_{GB} parameter of material models were considered. Therefore, comparison of unbound granular layer stiffness property lies beyond the scope of this thesis.

5.3 Recommendations

GSA-ANN backcalculation method proved to work effectively when the primary objectives of this study are considered. In order to increase the performance of the proposed method and to widen its applicability, the followings are recommended to be studied in the future studies:

- GSA-ANN results may hit the upper limits of predefined ranges of ANN based surrogate models, which indicates the higher stiffness of the sections. To handle such cases, ranges of layer moduli should be extended to make GSA-ANN to be more applicable for various sections. Moreover, other pavement types can be embedded to the proposed model by training additional ANN models for flexible pavements having more than three layers.
- Further works need to be done to better characterize the unbound granular layer of conventional flexible pavements. An innovative approach is essential for backcalculating granular layer stiffness properties. In order to better describe this layer, higher FWD loads can be used in the field.
- In this study, material characterization was carried a step further against the traditional elastic layered approaches, i.e., the stress dependent behavior of unbound base and fine-grained subgrade soils are taken into account. However, the behavior of surface layer was assumed as linear elastic although it has viscoelastic nature. As the FWD has dynamic nature, the viscoelastic behavior of asphalt materials should be considered for more accurate backcalculation models.
- Temperature directly influence the stiffness properties of asphalt layers. For some field data, GSA-ANN produced extreme modulus values for AC layer. In order to address such cases, temperature should be taken into account in finite element analyses, which is possible if a viscoelastic constitutive material behavior is considered.
- In recent FWD studies, thickness of pavement layers are obtained through the use of ground penetrating radar and/or coring operations in the field. To

eliminate this need thickness estimations should be investigated using the developed approach.

- Since the backcalculated layer moduli calculated using different softwares show huge variations, laboratory analyses may be conducted on the samples obtained from the field. This can further increase the reliability of GSA-ANN solutions.
- Deflections are directly influenced by the conditions when/where the test is applied. Cracks may cause the abnormal deflections on the surface. In addition, variations in reported layer thicknesses may cause GSA-ANN to produce erratic solutions. Therefore, FWD tests on damage free pavements or newly constructed pavements may produce more meaningful backcalculated layer moduli values. Another way to tackle such a problem is to continuously monitor the pavements using FWD device.

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