# ARTIFICIAL INTELLIGENCE APPLICATIONS IN THE BACKCALCULATION OF THE MECHANICAL PROPERTIES OF FLEXIBLE PAVEMENTS

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***ABSTRACT***
*Nondestructive testing (NDT) is widely accepted technique used for the calculation of the mechanical properties of flexible pavements. Falling Weight Deflectometer (FWD) is the most preferred technique in all NDT methods. Basically, FWD measures time-domain deflections emerging by the applied impulse load, and the deflections are used for the calculation of mechanical pavement properties with a backcalculation tool. In the previous studies, traditional optimization algorithms were mostly treated in backcalculation tools; nevertheless, artificial intelligence (AI) techniques, such as neural networks, were utilized in the models developed recently. In this study, the applicability of AI techniques on backcaulating the mechanical properties of flexible pavements is considered as well as an example backcalculation problem is solved and discussed with this way of calculation. In this context, it is aimed for pavement engineers focusing on maintenance and rehabilitation strategies that to present a different viewpoint.*

***Keywords:*** *NDT, backcalculation, flexible pavements, pavement analysis.*

## INTRODUCTION

Throughout the desing life of a road pavement, some necessary conditions should be considered, namely, the evaluation of remaining life of pavement and assortment of reasonable repairing and renovation policy. In other words, highway engineers demend flexible, rapid, and reliable way to clarify the physical condition of considered pavement section. If the pavement's structural condition would like to be analyzed in nondestructive way, nondestructive testing (NDT) methods are the only way due to their fast application and nondestructive abilities.

NDT methods may be primarily classified as deflection basin methods and surface wave methods. The previous methods are basically based on the measurement of surface deflections emerging by the applied load as well as on establishing a correlation among these values and the stiffness of each layer. Noticeably, the quantity of surface deflection depends on loading circumstances (type, magnitude, contact area, and duration), location of measurement, and layer characteristics (thickness, mass, and stiffness). For that reason, discrepancies among NDT devices derive from the variations in loading conditions and measurement locations. The Dynaflect road rater, falling weight deflectometer (FWD), and rolling weight deflectometer (RWD) methods are commonly used as typical deflection basin testing techniques. [1-2].

On the contrary, the Rayleigh waves excited by applied load and propagating through the pavement surface can be recorded by the surface wave tests. Afterward, this permits the travel time between consecutive receivers to be calculated for different excitation frequencies by recorded wavelength data. Such method is also referred to as spectral analysis of surface waves (SASW) and depends on the phase velocities and the excitation frequencies [3].

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The acknowledgement of material features, namely material stiffness of each pavement layer, is crucial in conducting pavement design using mechanistic approaches. Theoretical models (such as layered elastic theory and finite element method) use stiffness properties of pavement layers to calculate resulting strains. In order to obtain the structural condition (in terms of elastic stiffness) of a pavement structure using measured surface deflections, it is necessary to characterize the inverse mapping of theoretical pavement response model. Such numerical models involving parameter identification routines are generally referred to as pavement backcalculation methods [4].

In general, backcalculation techniques can be grouped into three basic categories, namely, static, dynamic, and adaptive. Adaptive methods are acknowledged as neural networks and neuro-fuzzy systems in presented studies. In adaptive processes, no pavement response model is directly utilized, and they simulate the inverse mapping by learning the target behavior via known input-output data patterns [5-9]. As the names imply, static and dynamic methods are categorized by the type of loading, and utilize conventional pavement response models. Hence, they employ two calculation directions, namely forward and backward. In the forward direction of analysis, deflections are computed for given traffic loads and pavement structure. In the backward pass of computation, calculated values are compared with deflection values measured by NDT device, and new mechanical properties are determined by a parameter identification routine. These optimization steps are conducted until the differences between calculated and measured deflections stay under a certain error criterion. It should be mentioned that, the inverse process can be performed by several techniques, such as the least-squares, the gradient descent method, database search, and genetic algorithm [2,10-12].

In this study, it is aimed to definitely explain flexible pavement backcalculation methods as well as to compare them in terms of modeling precision, computational expense, calculation details, and data requirements. In this context, nondestructive testing, pavement backcalculation procedures, and evaluations on backcalculation methods are given. Consequently, artificial neural networks (ANN) are employed for backcalculation of the mechanical properties of flexible pavements

**NONDESTRUCTIVE TESTING OF FLEXIBLE PAVEMENTS**

As mentioned before, NDT methods are essential for the structural evaluation of existing flexible pavements by determining the mechanical properties of pavement layers. The principle of the NDT methodology is that the structural integrity is conversely proportional with the amount of surface deflection emerged by applied load. On the other hand, geophysical methods, such as the spectral analysis of surface waves (SASW), which are dependent to pavement shear moduli calculated by Rayleigh wave velocities, are oppositions to this approach [3].

Practically, the discrepancies among deflection based NDT methods are based on variations in loading details (type, duration, and magnitude) and deflection measurement locations. In general, applied loads are divided into three categories, namely, static, steady-state vibratory, and time domain impulse. Static loading is the simplest case, which cannot behave like the actual trafic loads; thus, in current deflection basin tests, displacements are recorded along the pavement surface subjected to a steady state harmonic or a transient dynamic load [2].

Among all NDT methods, Falling Weight Deflectometer (FWD) is the most commonly used technique because of its capability to successfully simulate trafic loadings and capacity to produce larger amount of deflection data in unit time. In the time domain impulse loading, an impulse load is applied on pavement surface and deflection data is recorded in time domain. Generally, there are several sensors to measure the deflection values on different points of pavement surface. In FWD test, a falling mass is dropped on pavement surface in order to simulate the truck loading on the pavement, and transient deflections are collected by each geophone. The height is adjusted according to the desired load level. The impulse load is applied by a circular plate and a rubber seal is placed between plate and pavement surface in order to reduce the instant impact effect. As a result, peak values for each geophone are used to plot deflection basin curve.

The stress waves propagating along the surface of the pavement due to applied load are collected in wave propagation tests. By computing the travel time between adjacent receivers for different excitation frequencies, a dispersion curve is obtained through correlating phase velocities with wavelengths. As a common technique used in this kind of tests, waves are monitored and recorded by receivers, as well as time signals are transformed to the frequency domain. Thickness and stiffness of considered pavement layers are then obtained by an inversion process based on the propagation of generalized plane surface waves of the Rayleigh type. This technique is represented by SASW method [13].

## BACKCALCULATION OF FLEXIBLE PAVEMENTS

Basically, Backcalculation process is an optimization method performed to obtain inverse mapping of a known relation established by discrete or continuous data points. The backcalculation in pavement system is the procedure that involves the calculation of theoretical deflection under applied load using assumed pavement layer stiffness parameters (namely, pavement moduli). The procedure followed is that these calculated deflections are compared with measured deflections, the assumed moduli are then adjusted in an iterative procedure until the theoretical, and measured deflection basins reach an acceptable match. This implies that knowledge of the existing layer thicknesses and the behavior of the pavement materials are required.

The purpose of backcalculation is to consider the derived moduli as representative of the pavement response to load and can be used to calculate stresses and strains in the pavement structure for analyses purposes. Conventional backcalculation methods fall into two broad groups. The first approach is to employ gradient search techniques to adjust the pavement layer moduli iteratively until the theoretical and experimental deflection basins agree within a specified tolerance. An initial estimated moduli is required to start the iterative search process. The second approach is to interpolate within a database of deflection basins, generated for a prescribed pavement. Pattern searching algorithms are used to choose deflection basins in the database that most closely matches the experimental basin. The moduli of the experimental basin are then calculated through interpolation [2,14,15].

The analysis of pavement response can be conducted as either static or dynamic. Earlier studies on this problem were focused on static considerations, and the inverse relation was established by functional or statistical approaches. Nevertheless, due to the complex and dynamic behavior of the problem, they could obtain irrealistic solutions that involve considerable amount of errors. In all static approaches, forward pavement response was characterized by either layered elastic theory or finite element method (FEM) for linear or nonlinear elastic material behaviors. Additionally, the optimization processes were performed by using a parameter identification algorithm, database search algorithm, and genetic algorithm. [1,2,11,12,15].

Besides existing advantages of dynamic approach, it has several obstacles coming from the complexity and computational expense of dynamic analyses. Furthermore, in many problems, it is hard to get all necessary data required for a dynamic analysis. For these reasons, static approaches are preferred in the majority of pavement backcalculation studies, because of their simplicity and acceptable error ranges [16,17].

It is unambiguous that, dynamic backcalculation analysis has several advantages over static approach. First of all, it is appropriate for the inherent nature of the problem; thus, precise results could be obtained using dynamic approach. In addition, not only peak deformation values but also entire deflection record is used in the calculations of dynamic pavement response analysis. Furthermore, viscoelastic properties of AC layer can be considered in dynamic analysis efficiently. Eventually, the thickness of subgrade, which is assumed semi-infinite in static analyses, can be considered in dynamic model [2,14,16,17].

**ADAPTIVE BACKCALCULATION**
The adaptive backcalculation is essentially different from traditional techniques. Two-phased (forward and backward) structure of the conventional backcalculation approach is joined into one step using a supervised learning algorithm in adaptive technique. Namely, an adaptive system is trained by known input-output patterns, and it simulates the nonlinear mapping between input and output patterns. In Fig.1, an illustration of the adaptive learning methodology is depicted.

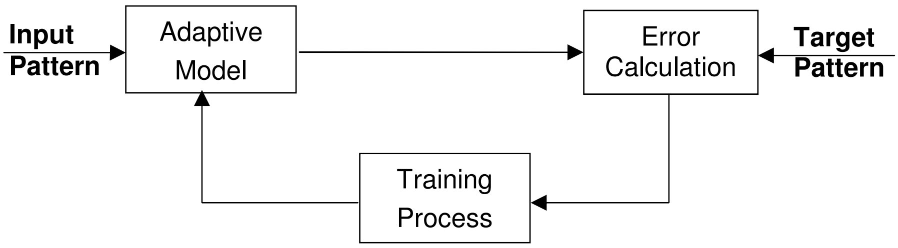


Figure 1. Typical Adaptive System

This of adaptive pavement backcalculation process was first introduced by Meier and Rix [5], who applied artificial neural networks (ANN) for the SASW test data inversion and the backcalculation of flexible pavement layer properties. Consecutively, Meier and Rix [5] confirmed the susceptibility of ANN methodology for pavement moduli backcalculation utilizing FWD data. They give a basically different approach to FWD back-calculation by using artificial ANNs. An ANN is "trained" to map deflection basins onto their corresponding pavement layer moduli. Later, they published the corresponding article comprising the dynamic aspects and the rigid bottom depth concepts [6].

Additionally, several other researches, related with ANN-based pavement backcalculation models, were performed [7-9,15,18,19]. An illustration ANN-based backcalculation model for nonlinear elastic material behavior and static loading is implyed in Fig.2. It should be noted that, ANN can only learn the mapping characterized by input-output patterns; thus, underlying material model and mechanical analysis do not have an existance in ANN-based backcalculation [18]. On the other hand, adaptive neuro-fuzzy inference (ANFIS) model iteratively determines membership functions to generate correct outputs, and simulates nonlinear input-output mapping. From this point of view, ANFIS can also be employed for analogous adaptive backcalculation process. However, ANFIS is not feasible for large number of input-output patterns and detailed input space partitionings [20].

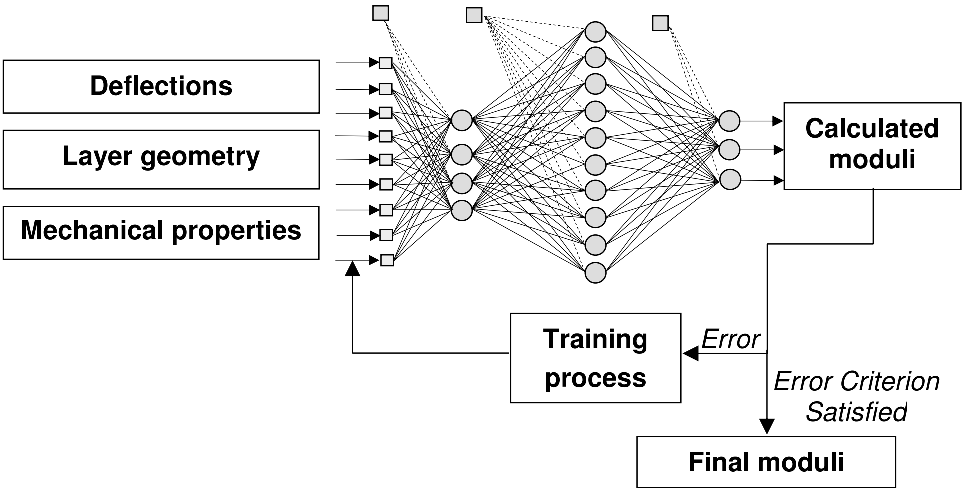


Figure 2. Illustration of ANN-based Backcalculation Procedure

## ANN-BASED BACKCALCULATION EXAMPLE

Developed ANN model utilizes FWD deflection values and layer thicknesses as input parameter, and layer moduli as output parameter. It should be noted that Poisson values are kept same for all layers as 0.35. Synthetic input-output database is developed using FEM technique with MICHBACK computer program [21]. Training and testing databases involve 1210 and 120 patterns, respectively. Table 1 shows statistical values of trainin and testing databases together.

Table 1. Descriptive statistics of the database

| Layer | Thickness (cm) | Modulus of Elasticity (MPA) |
|---|---|---|
| Asphalt | 5 - 10 | 4000 - 7000 |
| Base | 30 - 50 | 100 – 200 |
| Subgrade | ∞ | 50 – 100 |
| Mean (Asphalt) | 7.65 | 7673 |
| Mean (Base) | 40.48 | 148 |
| Mean (Subgrade) | - | 77 |
| Std Dev.(Asphalt) | 1.63 | 1205 |
| Std Dev. (Base) | 2.48 | 28 |
| Std Dev.(Subgrade) | - | 15 |

In this study, MATLAB Neural Network Toolbox is used for the development of ANN models [22]. ANN type is feedforward backpropogation multi-layer perceptron, and the learning algorithm is BFGS quasi-Newton method. Brief information on BFGS quasi-Newton algorithm is given below:

Basically, Newton's optimization method utilizes the Hessian matrix of the error energy. The Hessian matrix, $H_n$, is given by:

$$H_n = \frac{\partial^2 E w_n}{\partial {w_n}^2} \quad (1)$$

where, E is error is error vector and w is weight matrix. In this context, the adjustment (update) of synaptic weights is made by following equation:

$$\Delta w_n = -{H_n}^{-1} \delta_n \quad (2)$$

where, $\delta$ is gradient vector. However, the calculation of Hessian matrix is computationally inefficient. For that reason, quasi-Newton methods, which do not require the calculation of second derivatives, were developed by updating Hessian matrix at the each iteration of the algorithm. Quasi-Newton methods are based on the gradient concept and a quadratic error energy minimization. In quasi-Newton methods, apart from gradient descent method utilizing a linear approximation technique for weight modification, following higher order approximation equation is used for synaptic weight adjustments [23]:

$$\Delta w_n = w_{n+1} - w_n = \eta_n s_n \quad (3)$$

in which, $s_n$ is search direction vector, and $\eta_n$ is variable learning rate parameter. It should be noted that, learning-rate parameter is not a constant in this equation and enables the convergence increment along searching direction. In addition, the searching direction vector, $s_n$, is defined by:

$$s_n = -S_n \delta_n \quad (4)$$

where, $\delta_n$ is gradient vector, and $S_n$ is the adjustment matrix that makes direction vector approximate to the Newton direction. In detail, quasi-Newton methods, involve *second-order* information about the error surface without the consideration of Hessian matrix using following approximation [23]:

$$H_n \approx q_n \Delta w_n \quad (5)$$

where, $q_n$ is the curvature parameter, and computed by:

$$q_n = \delta_{n+1} - \delta_n \quad (6)$$

Discrepancies among all quasi-Newton methods come from the iterative definition of $S_n$ vector and $\eta_n$ parameter. In BFGS algorithm, adjustment matrix, $S(n)$, is obtained by following recursive equation [23]:

$$S_{n+1} = S_n + \frac{\Delta w_n \Delta w_n^{\,T}}{q_n q_n^{\,T}} - \frac{S_n q_n q_n^{\,T} S_n}{q_n^{\,T} S_n q_n} + q_n^{\,T} S_n q_n \times \left[ \frac{\Delta w_n}{\Delta w_n^{\,T} \Delta w_n} - \frac{S_n q_n}{q_n^{\,T} S_n q_n} \right] \quad (7)$$

On the other hand, mean squared-error (MSE) error energy function is preferred in this study for the calculation of network's performance. The formulation of MSE is as follows:

$$MSE = \frac{1}{m\,N} \sum_{k=1}^{N} \sum_{j=1}^{m} \left( y_j^k - t_j^k \right)^2 \quad (8)$$

where, m isthe number of neurons in output layer, N is number of training patterns, y is the output vector of ANN, and t is the target vector. Last point should be mentioned about developed ANN is that logistic activation function (Eq.9) is preferred in this investigation.

$$y_j(n) = \frac{1}{1 + e^{-v_j(n)}} \quad (9)$$

In addition, small parametric study is performed for the determination of ANN architecture, which is crucial for the performance of ANN. Due to the results of this trial-and-error study, optimal network arhitecture is determined as 9x10x40x3. Training graph of the optimal ANN model is given in Fig.3.

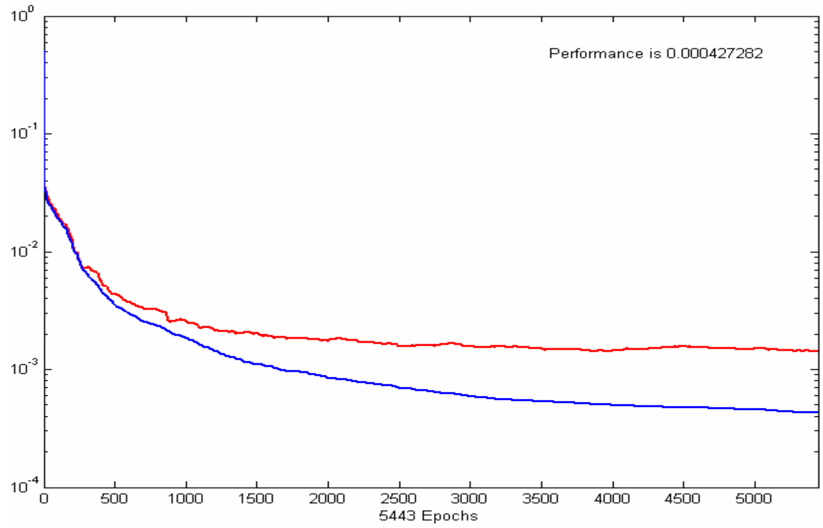


Figure 3. Learning graph of the optimal ANN

As can be seen from the learning graph the optimal epoch size is arround 2500. Furthermore, coefficient of determination is obtained for training and testing phases as 0.99 and 0.91, respectively. Consequently, Fig.4 is shown for the illustration of the best ANN-model's performance on backcalculating the mechanical pavement properties of asphalt layer.

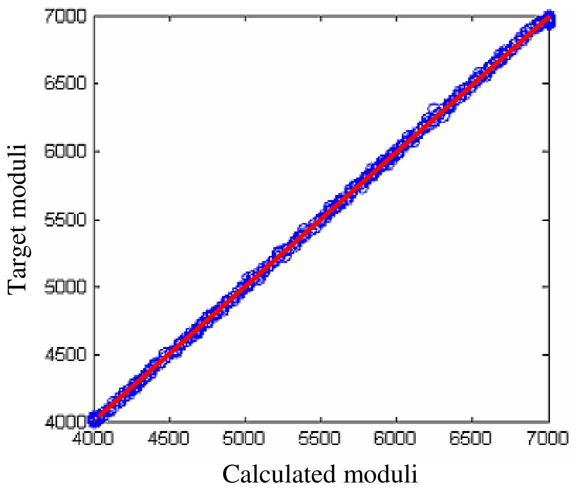


Figure 4. Scatter plot for the illustration of the ANN model's performance on asphalt layer.

**CONCLUSIONS**

In this study, backcalculation of flexible road pavements were considered in detail, and ANN technique was employed for backcalculation of the mechanical properties. Within this content, following conclusions were drawn in this study:

- With the consideration of actual traffic loads as well as the material behavior of asphalt concrete, dynamic and viscoelastic pavement response analyses give precise outcomes.
- Results of ANN-based backcalculation model is quite precise. This also verifies the outstanding learning ability of ANN methodology.
- Adaptive backcalculation methods perform real-time backcalculation analyses as a functional mapper. Nevertheless, there is no underlying mechanical background in these techniques; therefore, they must be applied carefully.

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