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Estimation of the Depth of Flexible Pavement Layers Using Artificial Neural Network

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Abstract - Transportation infrastructure is a vital component in achieving economic growth and nations' development. Pavement structures constitute major component in the infrastructure. The purpose of the study is to provide a model that can estimate the thickness of the flexible pavement layers based on; the estimated number of 18000 lb single axle load application (W18), resilient modulus of the subgrade (Mr), modulus of elasticity of the three layers (EAC, Ebase, and Esubbase) using Artificial Neural Network (ANN). since that the developed standards by AASHTO 1993 of designing flexible pavement do not provide a direct and a simple way in estimating the thickness of the three layers of flexible pavement (asphalt concrete, base, and subbase layers). Although the American Association of State Highway and Transportation Official (AASHTO) 1993 empirical procedure is an old method and has some limitations, it has been used instead of the Mechanistic Empirical Pavement Design Method Guide (MEPDG). Since the it is simpler than the MEPDG, where the MEPDG requires a lot of data in which is not always available for different transportation agencies in most of the developing countries. The results of the ANN model show a decent prediction of the depths of flexible pavement layers, since the R2 value is 0.99 (close to 1.0) and the MSE value is 0.28 (close to zero), which indicates strong correlation, accuracy, and low inconsistency between the observed and predicted thickness of the flexible pavement layers.

Keywords: Pavement Design; Flexible Pavement; Mechanistic Empirical Pavement Design Method; AASHTO 1993 empirical method; Artificial Neural Network.

1. Introduction

Transportation infrastructure is a vital component in achieving economic growth and nations' development. As economic activities cannot take place without infrastructure. Roads constitute major component in the infrastructure. Pavement structures should be designed to withstand daily traffic loads and various environmental conditions over their design life span. pavement is a main element in constructing a highway or road, where it can cost almost 30-50 percent of the overall cost of a road construction [1].

The main purpose of pavement design is to design a pavement that can provide a road with a sufficient strength to sustain the pressure and the load that are coming from the vehicles (traffic load), for a long term with less defects as well. The road pavement is composed of superimposed multilayer with certain thicknesses and stiffness characteristics, in order to be able to sustain and transmitting the traffic load to the last layer which is the sub-grade layer without causing any failure to the roadway pavement [2]. Before 1920's, pavement design was depended on shear strength. The purpose of the design is to select the thickness of the pavement to provide resistance against shear failure. The thickness was estimated based on experience in previous construction projects without following any standard. However, with the development of science and increased traffic loads other factors came into picture and they must be evaluated in the pavement design process. Pavement performance and its serviceability has become the focus for pavement design procedures. In order to evaluate the factors that affects the performance of the pavement and quantify and measure its survivability several experiments were conducted. The American Association of State Highway and Transportation Official (AASHTO) conducted road tests between 1950 and 1960 in Ottawa, Illinois, USA. In 1961 AASHTO published a first design guide for flexible and rigid pavements. Since that time several amendments have been made in developing design methods of pavement structures and transportation agency around the world have started to use AASHTO design guides as design standards. Thus the estimation of pavement layers thickness depends on the standards instead of precious experience [2], [3].

Pavement structures can be classified into three types of pavement based on the type of the surface layer and the layers beneath it as well [4], [5] :

1. Flexible Pavement: it consists of four basics layers: asphalt concrete layer, base layer, subbase layer, and subgrade, where there will be different type of coating between each layer in the pavement as shown in Figure 1. The first three layers are the main layers for which their thicknesses should be calculated. This type of pavement is the most used type around the world, since the cost of constructing this type of pavement is low, and it is easy to repair and improved as well.

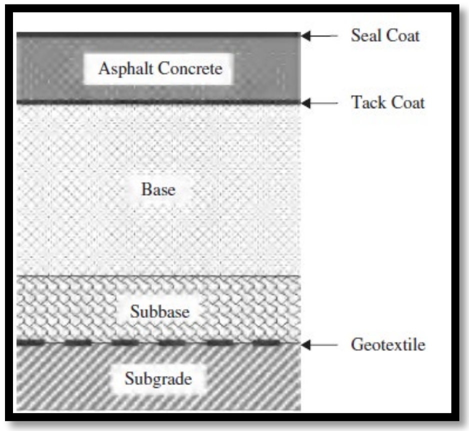


Figure 1 Flexible Pavement Structure [4], [5]

2. Rigid Pavement: consists of three layers Portland Cement Concrete, base layer and subbase layer as illustrated in Figure 2. However, this type of pavement has some disadvantages especially in the repairing or maintenance stage, where it costs high amount of money which is higher than the flexible pavement [4], [5].

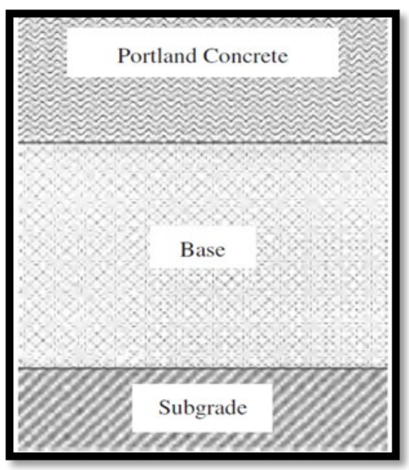


Figure 2: Rigid Pavement Structure [4], [5]

3. Composite Pavement: as shown in Figure 3 below, the Composite Pavement is used for the maintenance purposes, where an Asphalt Concrete layer is placed on the top of an existing Portland Cement Concrete layer and vice-versa.

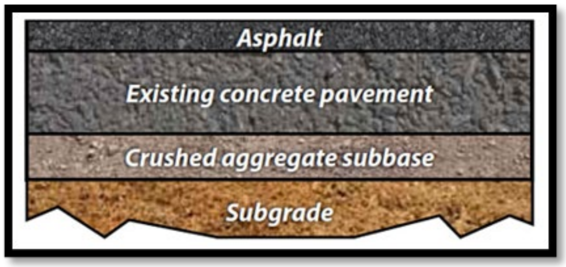


Figure 3 Structure of Composite Pavement [4],[5]

This research will focus on the design of flexible pavement because it is the most used. There are two main methods used for pavement design which are AASHTO 1993 empirical method and Mechanistic Empirical Pavement Design Method Guide (MEPDG) [7], [8]. although AASHTO 1993 empirical method is old and has some limitations and drawbacks but still it is the most used method because it is much simpler and requires less data than MEPDG methods which is more accurate, but it is more sophisticated and requires a lot of data which is not always available for different transportation agencies. The comparison between these two methods will be discussed in detail in literature review section. Wherein, this research will focus on AASHTO empirical method.

1.1 Research Problem

AASHTO empirical method uses equations that are derived from road tests that were conducted in Ottawa, Illinois between 1950 and 1960. Based on these results a Nomograph was developed to estimate the structural number of each layer and these number are used to estimate the required thickness of each layer. The problem of this Nomograph that is depends on designers' judgments there is no decisive conclusion. Each designer will have different estimates of structural numbers because of different line inclinations when using Nomograph. Therefore, different thicknesses will be resulted. Thus, the purpose of this study is to develop a mathematical model that can be used as replacement of the Nomograph in the empirical method. This mathematical model should provide a simple and direct method to calculate the structural numbers and thicknesses of pavement layers.

1.2 Objectives of the Research

The aim of this research is to develop a mathematical model using neural network analysis that can estimate the structural numbers and thicknesses of pavement layers instead of using Nomograph. The aim of the research will be obtained by following the following objectives:

- Identify the main design inputs that are needed
- Identify main factors that may affect the flexible pavement design
- Perform different design scenarios in order to construct neural network and test and validate the resulted model

2. Literature Review

This section discusses the layers of the flexible pavements and the materials and properties of each layer. In addition, it provides an overview of the 1993 empirical method and MEPDG and the conceptual differences between the two methods.

2.1 Overview of Flexible Pavement layers and materials

This subsection discusses the materials properties that are using in construction a flexible pavement layers starting from the bottom layer to the top layer.

2.1.1 Subgrade Layer

The subgrade soil layer is the foundation of the pavement of the flexible pavement, where the soil has to be strong enough to be able to carry the transmitted load from the top layers without causing any kind of deformation with taking into consideration the protection of the top layers from the extreme permanent deformation (rutting), where the strength of the sub grade soil is called as load bearing capacity [6].

In the construction of the pavement, the subgrade must be compacted and should be stable enough to sustain the dynamic loads that are coming from the top layers, having a permanent strength, easy to compact, contains fine aggregates that help to provide a well drainage behavior and having a limited settlement that is caused by the traffic load.

The strength of the subgrade soil is measured by the resilient modulus (Mr), which measures the stiffness of the subgrade material. However, the resilient modulus is affected by the water content in the soil. High water content reduces the resilient modulus which decreases the strength of the subgrade soil [10]. As illustrated in Figure 4, the resilient modulus is the elastic model which relies on the recover strain that is caused by the repetition of the loading and unloading behavior. The resilient modulus of subgrade soil can be calculated using Equation 1. This equation can be changed, where it depends on the testing-experimental method in obtaining the resilient modulus of the subgrade (roadbed soil)[4], [6], [8].

$$M_r = \frac{\sigma_d}{\varepsilon_r} \quad (1)$$

Where:
Mr: Resilient modulus ib/in2 (psi)
σ_d: is the deviated stress
ε_r: is the recoverable strain

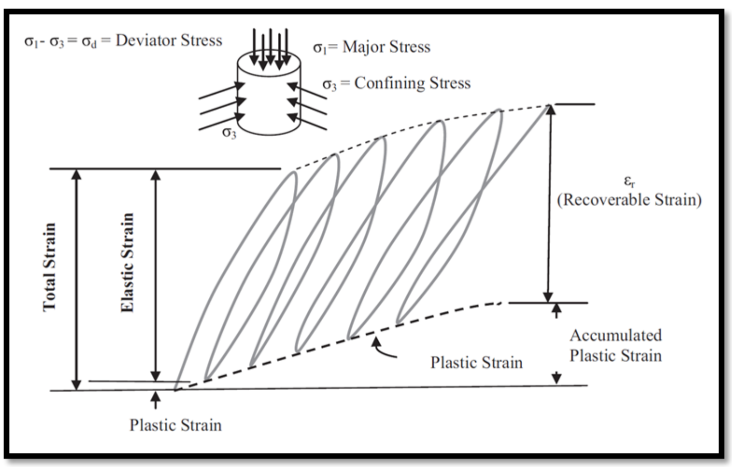


Figure 4 Resilient of Subgrade Soil [6]

2.1.2 Subbase Layer

This layer lies on the top of the subgrade soil, and it consists of granular soil, besides it may compose of manufactured aggregates or crushed rocks. The benefits of subbase layer is to provide support to the pavement, improve the load transfer across the layers, protects the subgrade soil, provides water drainage, and restrain the settlement behavior of the pavement/flexible pavement [1], [4]. The stiffness of the subbase layer can be measured by the modulus of elasticity of the layer Esub-base.

2.1.3 Base Layer

This layer lies on the top of the subbase layer and directly below the asphalt concrete layer. The difference between subbase layer and base layer, is that the subbase layer includes fine aggregates, while the base layer has higher quality materials than the subbase layer and coarse aggregates such as sand, crushed gravel, crushed slug, etc. These types of aggregates provide higher water permeability. Moreover, the base layer in the flexible pavement design has certain properties[2], [12]:

- It has higher strength (Ebase) than the subbase layer (Esub-base), since the base layer is subjected to a higher distributed load form the wheel (traffic) to the subgrade and subbase.
- It delivers a drainage system
- It provides resistance against frost

2.1.4 Asphalt Concrete Layer

The last layer which is at the surface of the pavement is the asphalt concrete layer, where this layer should sustain all the loads that are coming from the traffic, therefore its strength (EAC) must be high enough in order to be able to distribute the load to the lower layers as depicted in Figure 5, without exceeding the bearing capacity of the subgrade soil, and without causing any settlement or deformation of the subgrade soil. The asphalt concrete layer as it is noted from the name of the layer, it is mainly consisting of asphalt. This layer provides friction, drainage, strength, softness, etc.

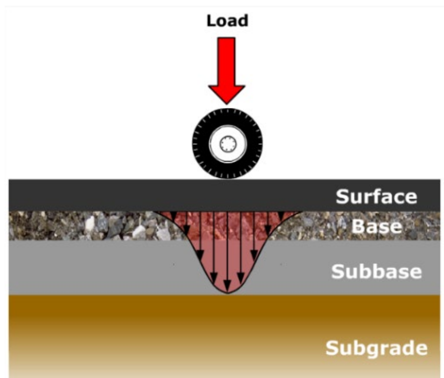


Figure 5 Traffic distributed load

2.2 Flexible Pavement design procedures

This subsection provides an overview of the main flexible design producers developed by AASHTO which are AASHTO 1993 empirical method and MEPDG and the conceptual differences between the two procedures. The design of flexible pavements depends mainly on empirical test and considers the following points:

- Traffic load
- Subgrade soil or it can be referred as roadbed soil
- Materials of the flexible pavement layers
- Performance of the flexible pavement within a time
- Drainage
- Life cycle cost
- Environment
- Reliability

AASHTO 1993 design method is based on empirical equations derived from the results of extensive road test conducted by AASHTO in the late 1950s and early 1960s. In 1961 AASHTO published a temporary design guide for rigid and flexible pavements. The latest design guide was published in 1993 entitled "AASHTO Guide for Design of Pavement Structures" [3]. However, this design procedure shows several limitations as these equations are developed based on one type of subgrade, single environmental condition, specific range of traffic loading and specific set of pavement material and the climate of the location at which the tests were conducted [13], [14]. With the rapid increase in traffic volumes and hence traffic loads exerted on pavement structures in addition to the advancement in material's technology, this model showed some drawbacks. Therefore, there is a need for more generic design method to overcome these limitations and drawbacks by considering all possible factors that may affect the pavement structure. Based on that AASHTO developed a mechanistic-empirical approach under the National Cooperative Highways Research Program (NCHRP) project 1-37A [15]. This procedure is called Mechanistic Empirical Pavement Design Method Guide (MEPDG) and it was completed in 2004 [15]. It is a hybrid approach which is based on mechanistic-empirical principles. This guide gone through several improvements and reviews which resulted on developing an interim edition of the MEPDG and MEPDG software in 2008 [11]. Although AASHTO 1993 empirical method is old, but it is the most widely used method today especially in developing countries. Because MEPDG is based on theories of mechanics and consists of several sophisticated models which requires different inputs than AASHTO 1993 empirical method. The major inputs for MEPDG are related to traffic loading, environmental conditions and materials characteristics in details. It requires details traffic data such as Average Annual Daily Truck Traffic for the base year, percent truck in the design direction, Percent Truck in the design lane and Operational speed of vehicles. in addition to some traffic adjustments [13]. Moreover, it incorporates detailed climatic and environmental data for the designed pavement such as Hourly air temperature Hourly precipitation, Hourly wind speed, Hourly percentage sunshine, Hourly relative humidity Groundwater table and Drainage/surface properties [13], [16]. This detailed data is not available to many transportation agencies as they don't have the enough resources to collect the required data [16], [17]. Therefore, they are still using this old method because it is simpler and less demanding. That's why this research is focusing on AASHTO 1993 empirical design because it is the most used method.

The problem with the monograph approach that it cannot provide one similar conclusion (similar thicknesses in the case of having the same pavement properties) among the designers, since each designer can have different line inclination during the nomograph approach process which will yield different results or different conclusion at the end, and with this gap the following section in the research 'Research Methodology', will concern in filling this gap by constructing a model. Worth mentioning, most of the conducted studies in flexible pavement design have constructed models to predict modulus of elasticity, the strength of the pavement, and the overlay thickness of the pavement, where there is no certain study noted that was focusing on predicting the thickness of the flexible pavement layers [18]–[21].

2.3 Overview of Artificial Neural Network and the Applications in Civil Engineering

Artificial Neural Network (ANN) is a technique that is based on the biological formation and functionality of the human's brain system that aims to predict, categorize, and estimate the specific outcomes which are based on the purpose of a study. Hence, within this process, the dynamic relations between the inputs and outputs of a study can be obtained by the ANN model. The model is splitting up into three basics layers which are called input, hidden (can be more than one layer), and output layers, where each layer has different number of nodes or neurons which are depending on the purpose of a study (inputs and outputs of the study), however the number of neurons in the hidden layer can be varied between the number of input and output neurons. Wherein the input layer includes the independent parameters of the study, while the output layer contains the dependent paraments, and the hidden layer includes the activation functions that assist in limiting the weights values within the hidden layer, where those values are locating within the connection lines between the layers as noted in Figure 11. It is worth to mention that those layers and connections lines that presents the intensity of the relations between the layers are called the architecture of artificial neural network. Besides, throughout the implementation of the ANN model, the data are divided into three datasets which are training, validation, and testing which will assist to assure that the ANN model is well trained, averting the overfitting, assessing the performing and training of the model respectively [22]–[25] .

Several conducted studies in transportation engineering, civil engineering, and pavement design have used ANN model; in terms of transportation engineering, Alqahtani [26] used ANN model to predict the health of an individual based on the transport choices and socio-economic factors in the United Arab Emirates, Gharehbaghi [27] applied ANN technique to develop an optimized Transportation Infrastructure System (TIS) that concerns with the rehabilitation process, Laffitte et al.[28] implemented ANN models to detect the noisy environment in a public transportation system, and Zhang et al. [29] utilized neural network to predict the lateral distance between private vehicle and lanes in a road. Regarding to civil engineering in general, Aisyah et al. [30] used artificial neural network to estimate the deteriorations and the service life of the compositions of a certain building, and Li and Zhao [31] implemented ANN to identify the cracks of a concrete. While concerning with pavement design, artificial neural network has been used in Elbagalati et al. [32] study to predict the resilient modulus of the subgrade (Mr) for a flexible pavement, where non-destructive test methods have been used to construct the neural network model like the rolling wheel deflectometer and failing weight deflectometer in Louisiana, USA ,where the results of those tests were used in the training part of the neural network. Additional tests were conducted in Minnesota, USA, that were used to validate the developed neural network model which which was 3 inputs (the mean of the deflections that were caused by the rear axle, standard deviation of those deflections, and the average of deflections at certain depth),1 hidden layer with 2 neurons, and 1 output which is the resilient modulus (Mr). The results of the artificial neural network model were adequate for the purpose of the study with a value of coefficient coefficient of determination 0.73. Moreover, in Yamany et al. study [33], the performance of the flexible pavement had been estimated by predicting the roughness of flexible pavement using artificial neural network (ANN) and random parameters regression technique, wherein the architecture of the developed model was 2 inputs (the age of the pavement and the Annual Average Freezing Index), 1 hidden layer with 40 neurons, and 1 output which is the roughness of the pavement, where the data used to develop this model were based on 8 different states in the U.S; Michigan, Ohio, Minnesota, Indiana, Iowa, Missouri, Illinois, and Wisconsin, and the result of the ANN model was an R2 value of 0.71 in compare to the random parameters regression which was 0.48.

At the end of the literature, it can be noted that there is lack of studies in predicting the depth of the layers in flexible pavement design (asphalt concrete layer, base layer, and sub-base layer) using artificial neural network in AASHTO 1993 approach, since there is no enough data in most of the developing countries to implement ANN in the mechanistic empirical approach.

3. Research Methodology

This section views the methodology that is adopted to construct a neural network that can be used to estimate the thickness of each layer of flexible pavement.

As mentioned in the research problem there is no direct equation can be applied to design and find the thickness of the flexible pavement layers. Instead nomograph is used to calculate the structural number of each layer SNAC, SNbase and SNsub-base. The structural number is an abstract number that express the strength a pavement structure for a given combinations of soil support layers. The percentage of the reliability is estimated using Table 1 below, the overall standard deviation is estimated as well with a value between 0.4 and 0.5 in flexible pavement.

Table 1: Recommended Level of Reliability [1], [3]

Recommended Level of Reliability		
Functional Classification	Urban	Rural
Interstate and other freeways	85-99.9	80-99.9
Other principal arterials	80-99	75-95
Collectors	80-95	75-95
Local	50-80	50-80

Also, the estimated number of 180000 lb single axle load application (W18) and the resilient modulus (Mr) of the roadbed soil (subgrade) are calculated. While for the serviceability loss (ΔPSI), it can be calculated form Equation 2 below:

$$\Delta PSI = Po - Pt \quad (2)$$

Where:

ΔPSI: the serviceability loss index, where it represents serviceability life of the flexible pavement, and it should be between 1 and 5

Po: is the initial serviceability loss

Pt: is the terminal serviceability loss

The initial and terminal serviceability losses indices can be obtained using Figure 6 below, where the initial serviceability loss in flexible pavement is 4.2 and 4.5 for the rigid pavement, while the terminal serviceability losses index is 2.0 as exhibited in Figure 7. Therefore, at the end the structural number (SN) can be estimated from Figure 7.

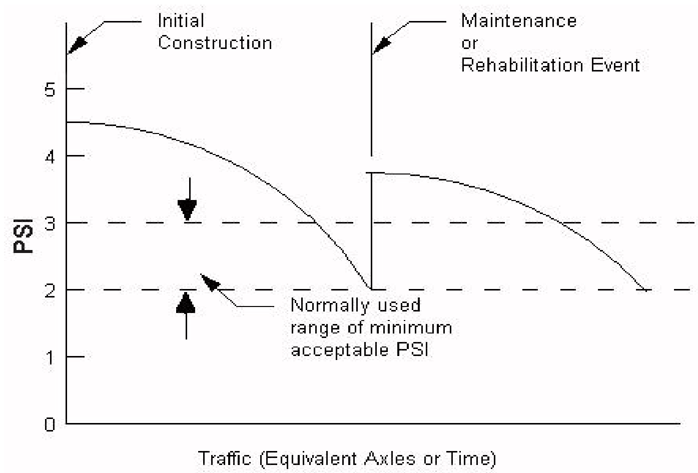


Figure 6: Serviceability Loss Index [2], [3], [11]

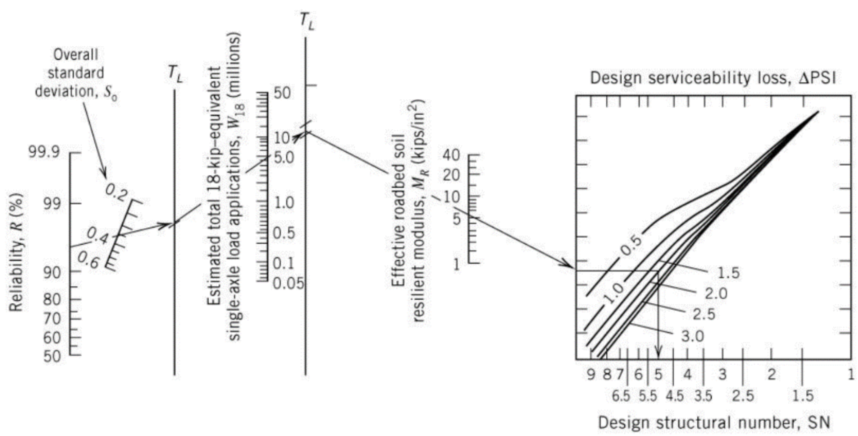


Figure 7 Obtaining the Structural Number Using the Nomograph [2], [4]

After calculating the structural number of each layer using the nomograph, the thickness of each layer can be calculated using Equation 3 as follow:

$$SN = a_1D_1 + a_2D_2m_2 + a_3D_3m_3 \tag{3}$$

Where:

a_1, a_2, a_3: structural layer coefficients for surface, base, and subbase layers respectively.

D_1, D_2, D_3: thicknesses for surface, base, and subbase layers respectively.

m_2, m_3: Drainage coefficients for base and subbase layers

The coefficients of the asphalt concrete (a1), base (a2), and subbase(a3), can be obtained from Figure 8, Figure 9 and Figure 10 respectively. While, the values of the drainage of base and subbase (m2 and m3), can be found using Table 2 below by choosing certain drainage quality and percentage of saturation [1]–[3].

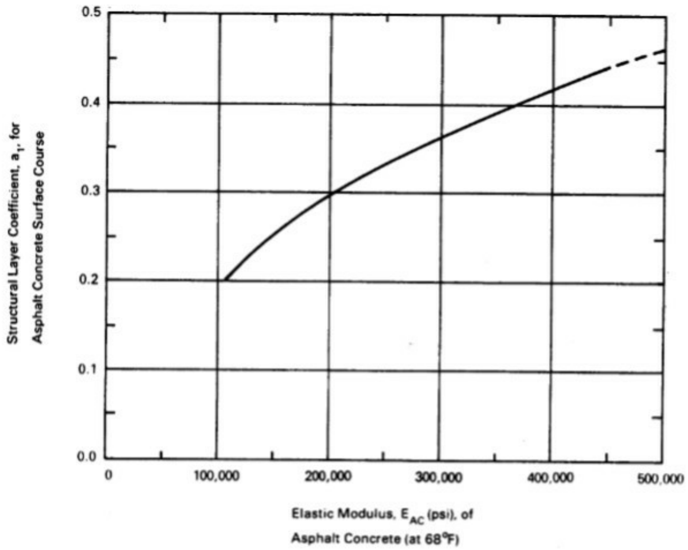


Figure 8 Estimating Structural layer coefficient of asphalt concrete layer based on elastic modulus [3]

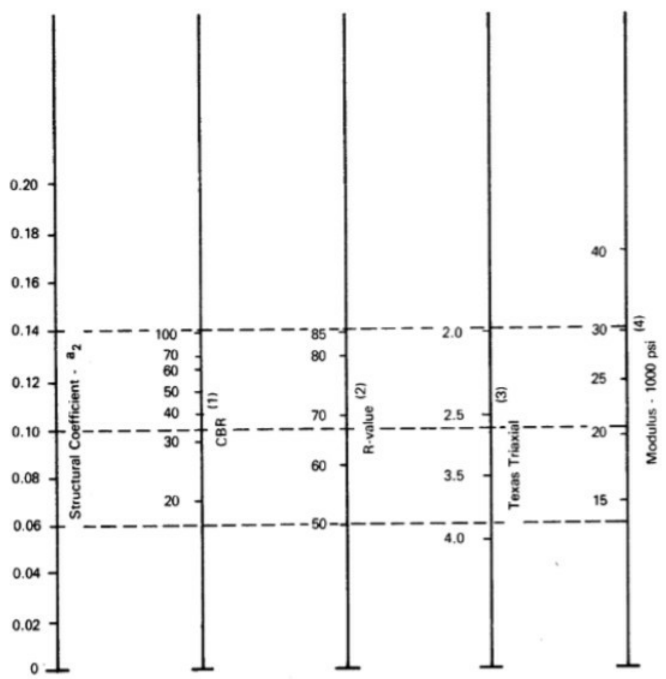
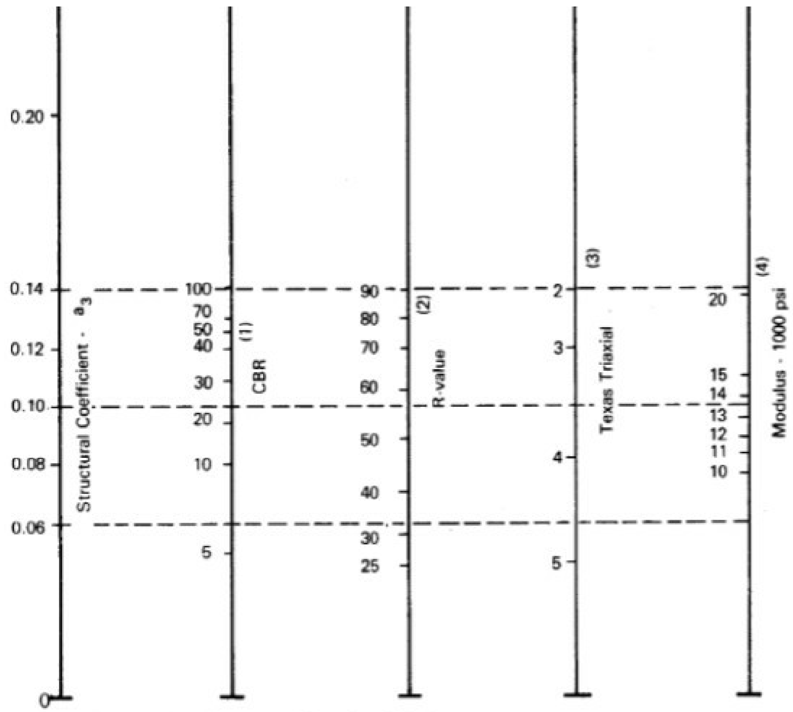


Figure 9 Estimating Structural Layer Coefficient of Base Layer Based on Elastic Modulus [3]



(1) Scale derived from correlations from Illinois.

(2) Scale derived from correlations obtained from The Asphalt Institute, California, New Mexico and Wyoming.

(3) Scale derived from correlations obtained from Texas.

(4) Scale derived on NCHRP project *(3)*.

Figure 10 Estimating Structural Layer Coefficient of Sub-Base Layer Based on Elastic Modulus [3]

The drainage coefficients can be obtained from table 2 below.

Table 2: Drainage Coefficient with Different Drainage Quality [1], [3]

Percent of Time Layer Is Approaching Saturation

Drainage Quality*	<1%	1–5%	5–25%	>25%	
Excellent	1.40–1.35	1.35–1.30	1.30–1.20	1.2	
Good	1.35–1.25	1.25–1.15	1.15–1.00	1	
Fair	1.25–1.15	1.15–1.05	1.00–0.80	0.8	
Poor	1.15–1.05	1.05–0.80	0.80–0.60	0.6	
Very Poor	1.05–0.95	0.95–0.75	0.75–0.40	0.4	

The empirical method is used to estimate the thicknesses of flexible pavement layers for different scenarios and the results of these scenarios are used to construct, test and validate a neural network model using MATLAB R2019a Software Software that can be used after as a replacement of the nomograph.

Hence, data of 480 observations of the estimated number of 18000lb single axle load application (W18), resilient modulus of the subgrade (Mr) in psi, modulus of elasticity of the asphalt concrete (EAC), base layer (Ebase) and sub-base layer (Esub-base) in psi, and depth of these three layers; asphalt concrete layer (AC), base layer, and sub-base layer are used to create the artificial neural network model in the study in order to estimate the depth of the three layers, where the results and detailed architecture of the ANN model will be elaborated in the following section.

4. Results And Discussion

As stated earlier, the 3 layers' depths (AC, base, and sub-base layers) of the flexible pavement will be predicted based on 5 variables (W18, Mr, EAC, Ebase, Esub-base). Thus, those 5 variables will be as an input in the input layer in the neural network model (5 neurons), while the three layers' depths will be as an output in the output layer with 3 neurons or nodes as noted in Figure 11. Regarding the hidden layer of the created ANN model, where due to the lack of having specific formula or theory to select number of neurons, as referred to various researches, rule of thumb is implemented and 4 neurons have been selected which are between number of neurons in the output and input layers. In concerns with the activation function in the hidden layer, tan-sigmoidal function (Equation 4) is selected.

$$\text{Tan-Sigmoidal Function} = \frac{2}{1+(e^{-x})} - 1 \quad (4)$$

This function can aid to decrease the values of the weights within the connections lines and shorten those values between +1 and -1, wherein those weights can be changed throughout the neural network functionality in order to decrease possible errors of the model [34]. Hence, feed forward back propagations will be implemented to adjust those weights, wherein this type of process is considered as a type of a neural network model.

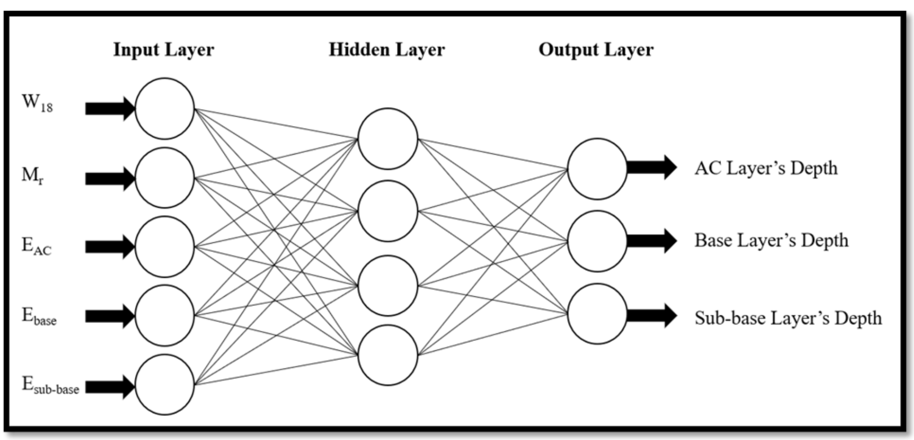


Figure 11 Architecture of the ANN Model

Furthermore, as mentioned in the literature review section, as part of the process of ANN model, the data are divided into three parts; training, validation, and testing datasets, where in order to assure that the model is well trained, validated, and tested, 60 % (288) of the data will be in the training dataset, 96 of the data (20%) will be in the validation and testing data sets.

The results of the neural network model and the performance of the model can be assessed based on the resulted R2 and the Mean Squared Error (MSE) values of the model. R2 value, is used to measure the correlations between the observed and predicted layers' depths. A high value of R2 (close to 1.0) indicates the strong correlation between the observed and predicted

layers' depths of the flexible pavement. The MSE value, is used to measure the accuracy of the model's predictions. Low MSE values (close to zero) reflects the decent predictions of the ANN model and the accuracy of the model.
The resulted R2 value of the three datasets (training, validation, and testing data sets) are :0.99644, 0.99614, 0.99714 and 0.99655 respectively. These high R2 values reflects that the ANN model fits the data. The correlation between the observed and predicted layers' depths is very strong, and the ANN model can explain 99% of the variation in the layers' depths. On the other hand, the resulted MSE value of the ANN model is 0.28 which is low and indicates that the model has good predictions accuracy.

5. Conclusion

Over the years the transportations sector has been developed, and with this development the road pavement has been developed as well. Wherein there are three types of the pavement which are flexible pavement, rigid pavement, and composite pavement. The focus of the study is on the flexible pavement.

The purpose of this study is to construct an artificial neural network (ANN) model that can predict the depths or the thicknesses of the flexible pavement layers in inches (asphalt, base and sub-base layers) based on five input variables namely, resilient modulus of subgrade (Mr), the estimated number of 18000lb single axle load application (W18), asphalt modulus of elasticity (EAC), base modulus of elasticity (Ebase) and sub-base modulus of elasticity (Esub-base). The model is created based on the AASHTO 1993 standards approach instead of the Mechanistic Empirical Pavement Design Method Guide (MEPDG). Because it requires a lot of information that have to be observed over periods of time, and most of the developing countries lack of such information.

With the aid of MATLAB R2019a Software, the neural network model has been developed referring to data of 480 observations of the mentioned variables previously. The results of the neural reflect an accurate and good estimation of the thickness of the flexible pavement. High R^2 and low MSE values indicate the strong correlation and the low inconsistency between the observed and estimated thickness of the flexible pavement.

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