

Remaining life approximation of hot mix asphalt pavement with the help of artificial neural networks

Yapay sinir ağları yardımı ile sıcak karışım asfalt kaplamaların kalan ömrünün tahmini

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Abstract

Hot Mix Asphalt pavements may require maintenance and repair as a result of deterioration due to various reasons. The remaining life of the existing pavement is not known, delaying maintenance and repair times and accelerating deterioration. In order to avoid such problems, the remaining life of road pavements can be calculated with different methods. Different prediction models can be created by determining material properties using non-destructive testing methods in calculating the remaining life of pavements. In this study, the remaining life of flexible pavements was calculated with the help of Artificial Neural Networks method. In the approximation method, the number of layers, elasticity moduli of layers, layer thicknesses, number of load repetitions were used as model inputs. The remaining life of the flexible pavement is estimated as output. Estimated results and calculated results were compared. It was observed that the remaining life estimated by the model and the remaining life calculated based on field data were closely aligned.

Keywords: Flexible pavements, Remaining life, Artificial neural network methods, Hot mix asphalt pavement.

Öz

Sıcak Karışım Asfalt kaplamalar çeşitli nedenlerden dolayı meydana gelen bozulmalar sonucunda bakım ve onarım gerektirebilmektedir. Mevcut kaplamanın kalan ömrünün bilinmemesi bakım onarım sürelerinin gecikmesine ve bozulmaların hızlanmasına sebep olmaktadır. Bu gibi sorunların önüne geçebilmek için yol kaplamalarının kalan ömürleri farklı yöntemlerle hesaplanabilmektedir. Kaplamaların kalan ömrünün hesaplanmasında tahribatsız muayene yöntemleri kullanılarak malzeme özellikleri belirlenip farklı tahmin modelleri oluşturulabilmektedir. Bu çalışmada esnek kaplamaların kalan ömrü Yapay Sinir Ağları yöntemi yardımıyla hesaplanmıştır. Yaklaşım yönteminde, tabaka sayısı, tabakaların elastisite modülleri, tabaka kalınlıkları ve yük tekrar sayısı model girdileri olarak kullanılmıştır. Esnek üstyapının kalan ömrü çıktı olarak tahmin edilmiştir. Tahmin edilen sonuçlar ile hesaplanan sonuçlar karşılaştırılmıştır. Model tarafından tahmin edilen kalan ömür ile saha verilerine dayalı olarak hesaplanan kalan ömür birbirine oldukça yakın olduğu gözlemlenmiştir.

Anahtar Kelimeler: Esnek kaplamalar, Kalan ömür, Yapay zekâ metodları, Sıcak karışım asfalt kaplama.

1 Introduction

Highways are an integral part of transportation systems. The budgets provided by governments reveal the importance of highways. In Turkey, the budget of the General Directorate of Highways, which is set at 329 billion Turkish Liras for 2025, has increased by 30% compared to the previous year [1], [2].

Serviceability and safety are one of the important issues to be considered by the road transport units of countries. Whatever the material used, flexible road pavements are subjected to wheel load and peripheral influences that cause the road to deteriorate in progress of time are shown in Figure 1. Repair and maintenance services should be provided to increase the ability to provide service, to keep security at a high level, and decelerate the degradation.

Considering the substantial investments involved, it is essential to make well-informed decisions regarding which road segments require maintenance or rehabilitation. A critical factor in this decision-making process is the precise identification of the geometric and mechanical characteristics of the pavement structure. In the evaluation of existing asphalt concrete layers, non-destructive testing (NDT) methods are

commonly employed, as they offer rapid and straightforward implementation while preserving the structural integrity of the pavement [3].



Figure 1. Deterioration of flexible road pavements.
(a): alligator crack. (b): potholes and alligator-crack.

It is essential for road engineers to ascertain the remaining life span of the asphalt concrete prior to undertaking any maintenance or remedial work, thereby establishing the scope of necessary interventions. The lifespan of an Asphalt Concrete Pavement is defined as the time interval for which its structural integrity remains intact when subjected to the effects of traffic loads and environmental factors [4].

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The Artificial Neural Networks (ANN) method can be classified as a sub-class or category within Artificial Intelligence. This method of artificial neural networks attempts to reproduce the information processed in the brain by developing mathematical relationships. When creating an artificial neural network, a set of examples is required to train and test the required algorithm with the dependent variables (DV) and independent variables (IV) consisting of dependent variables [5].

From the measured deflection values, the process of determining pavement layer elastic modulus (EM) is called "back-calculation". Roads layer EM values found as a result of the back-calculation process are indicative of the condition of the road pavement. The real importance of these values is that they give more realistic results than laboratory experiments, as they are more real values because they are performed on-site experiments. Thus, with the help of these elastic modulus values obtained, the remaining life of the road pavement can be determined and maintenance work is directed accordingly [6]. Other methods used to determine the condition of the road pavement, take a too long to prepare input data and, in particular, to perform evaluation. Creating a network is extremely difficult, especially with the finite element method. ANN eliminates this disadvantage [6].

Using a lot of data, very complex problems can be solved very accurately by using ANN. Another advantage of using ANN is that the system can be updated by adding new data [6].

Having been developed an ANN to approximate the structural performance of road from data obtained using the road performance database obtained by long-term International Roughness Index (IRI) measurements. Numerical results obtained using this approach confirm that it is possible to correlate IRI measurements and structural performance which has a high share of accuracy. It has also shown that functional research methods are generally more costly, time-consuming and harmful to traffic [7].

The degradation of the performance of asphalt pavements is expressed as a change in the original structure or function of the pavement during its actual service life due to the influence of various factors. These factors include a large number of variables such as pavement structure, traffic load, natural environment and maintenance interventions, and their interactions are complex and diverse. Therefore, characterising the relationship between the performance indicators that describe pavement behaviour and the factors that influence them is non-linear and extremely complex [8].

For the purpose of determination of the maintenance/repair time of bitumen pavement roads, it necessary to determine the level of deterioration, such as the remaining life, to achieve this, the stresses at the interfaces of the layers must be determined. After the calculation of these stresses, deflection values and layer thicknesses obtained from the falling weight deflectometer (FWD) device is considered as a parameter the ANN method and the best approach is obtained by establishing models with various algorithms [5].

Bad weather, especially floods, cause great damage to flexible road pavements. The mechanical characteristics of different roads can be negatively affected by the saturation of the pavement layers during flooding. Different NDT methods, such as FWD, can be used to display the strength of pavement layers and minimize damage while maintaining serviceability. Flexible pavement performance after flooding should be evaluated to plan the necessary maintenance/repair strategies. It has been observed that the ANN method can be used effectively [9].

2 Purpose of the study

The remaining life of the asphalt concrete was calculated with the help of Huang Comparison model by using the previously obtained layer number, layer elasticity modulus and layer thickness values [10]. According to this data, a model was created using the ANN method. Thus, for faster and safer flexible road pavement maintenance, the repair is intended to be predicted in advance.

3 Methods for remaining life for HMA pavement

Various modeling approaches have been developed to predict pavement performance more accurately. In this study, artificial neural networks (ANNs) were selected over traditional methods such as linear regression and decision trees due to their superior ability to capture nonlinear relationships and complex variable interactions. In the literature, ANN models have shown high predictive capability for both flexible and rigid pavements by incorporating diverse input variables such as traffic loading, climatic conditions, layer thicknesses, and surface distress types (e.g., cracking, rutting). For instance, Basnet et al. [11] demonstrated that ANN-based models achieved coefficient of determination (R^2) values exceeding 0.90 and reported 15–20% lower root mean square error (RMSE) compared to linear regression models. Similarly, Wu et al. [12] used a feedforward ANN model to predict short- and long-term deterioration metrics (e.g., IRI and cracking) on Louisiana's state highways, showing better generalization and lower variance errors than traditional regression models. Moreover, El-Badawy and Abaza [13] compared multiple machine learning techniques using non-destructive testing (NDT) data and found that ANN models outperformed other methods in roughness prediction, especially in contexts where high accuracy is essential for maintenance planning. These findings confirm that ANNs are robust and scalable alternatives within Pavement Management Systems (PMS), particularly in tasks involving life prediction, maintenance scheduling, and resource optimization.

ANNs are computational systems inspired by the learning and rapid decision-making mechanisms of biological neurons in the human brain. They are capable of processing data and solving complex problems through simplified and adaptable models. One of the key advantages of ANN applications—commonly employed in classification, clustering, regression, and time series prediction—is their ability to learn from data and generate solutions without requiring explicitly defined mathematical models. This characteristic makes ANNs particularly valuable in scenarios involving uncertainty, where traditional methods may be limited. Therefore, it can be concluded that artificial intelligence techniques offer significant advantages over classical approaches, especially in handling complex, nonlinear, or ambiguous problems [14].

In this context, "**data**" refers to the measured, collected, or observed values that represent the state or behavior of a system, while "**inputs**" are specific features or variables derived from the data, which are fed into the ANN to perform a learning or prediction task.

ANNs are computer-based system. Their most distinctive feature is their ability to perform learning tasks analogous to those of the human brain. The network requires a set of example cases to perform learning effectively. ANNs consist of interconnected artificial neurons, or nerve cells. Each

connection, also called a synaptic weight, holds a different numerical value. The information learned by the artificial neural network is stored in the synaptic weights of these connections. [15], [16].

The ANN framework offers a novel approach to problem-solving across a wide range of domains, providing alternatives to conventional solution strategies. Key features of ANNs include the ability to manage uncertainty, complete missing information, tolerate noise, and adapt to diverse and changing problem conditions. [16].

Process elements come together in 3 layers parallel to each other, forming a network are shown in Figure 2.

These;

- Input Layer
- Hidden Layer
- Output layer

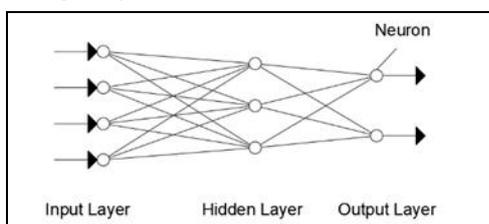


Figure 2. Display a structure of artificial neural network [17], [18].

ANN, external information is introduced through the input layer, where each neuron corresponds to a specific input variable. The number of neurons in this layer is determined by the number of features used in the model. Between the input and output layers lies the hidden layer, which plays a critical role in processing information and facilitating internal communication within the network. This layer operates independently of any external influence and enables the transformation of input data into meaningful outputs. The final results, generated through the network's internal computations, are produced at the output layer. The accuracy and efficiency of this processing largely depend on the number of neurons in the hidden layer [18].

An artificial neural network consists of three main components: neurons (artificial neural cells), connections, and a learning algorithm. The neuron is the fundamental processing unit of the network. Each neuron receives one or more input signals—depending on the factors influencing the problem—and produces an output accordingly. When interconnected through weighted connections, these neurons collectively form the structure of an artificial neural network. Layers are formed by grouping neurons that operate in the same direction or function within the same level of the architecture [17].

The input layer receives raw data from the dataset, while the output layer produces the corresponding results. In the hidden layer, on the other hand, there are neurons that make up the heart of artificial neural networks and carry out operations. Neurons across layers are typically interconnected through weighted connections, allowing data to flow through the network [19].

These connections transmit weighted signals to subsequent neurons. The neurons in the hidden layer are not only internally connected but also receive inputs from the neurons in the input layer. The strength of these connections is determined by the weights associated with them. The weighted inputs received by a hidden layer neuron are summed, and this total input is passed through an activation function. This function transforms

the input into an output value, typically within the range of 0 to 1, depending on the characteristics of the chosen activation function [19].

Hidden and output layer neurons are connected to each other, and the output layer receives weighted inputs from the neurons in the hidden layer. These signals are processed through activation functions to produce the final output. If this output value is within an acceptable range compared to the actual target value, the result is accepted. Otherwise, the discrepancy is considered an error, and a reverse process is initiated to adjust the weight coefficients, using a logic similar to the forward pass. This iterative backpropagation process continues until the error falls within an acceptable tolerance level [19].

The correct assignment of input weights in the network structure ensures accurate results. To achieve this, the network needs to be trained. Initial input weights are estimated at the beginning. By adjusting these weights through trial and error, optimal values are obtained. This process continues for all trials until the desired result is achieved [16].

If the network gives correct responses to the samples in the test set, it is considered trained. Once the network weights have been determined, their individual meanings are unknown. This is why artificial neural networks are often referred to as "black boxes". Although it is not known what the weights mean individually, it can be said that the intelligence of the network is embedded within these weights. This is because the network makes its decisions based on the inputs by using these weights, information about an event, effectively acquiring information about events through the most accurate ANN model selected for those events [16].

Using this method, the learning process is performed based on examples. The goal is to generate outputs for new inputs by identifying the relationship between input features and their corresponding outputs in case studies. It is assumed that the inputs and outputs used in the cases represent the general characteristics of the events. In order to estimate the outcome of a new case using the model, a broader solution space is explored by increasing the diversity of input variables [16].

Once the learning phase is completed, the ANN becomes ready for deployment. This stage is referred to as the inference phase. At this point, the ANN utilizes the knowledge acquired during training to generate output values corresponding to the input data. The network can also generalize and make predictions for new input values that fall within the range of the training data, effectively performing interpolation [19].

4 Remaining life of HMA pavement calculation

To calculate the remaining life of flexible pavements, certain parameters must first be determined using destructive and/or non-destructive testing (NDT) methods. Based on these parameters, critical tensile strains at the bottom of the asphalt layer and compressive strains at the interface between the base and subgrade are calculated using elastic layered pavement analysis software. KENPAVE, an empirical and mechanistic-based program, is used to perform this analysis. Subsequently, Equations (1) and (2) from Huang's models are used to estimate the pavement service life based on fatigue and deformation criteria.

4.1 Huang comparison models

The equations proposed by Huang are used to estimate the service life of a pavement before significant deterioration occurs. Two equations are presented to determine the length of

time the road can serve without problems based on the fatigue with Equation 1 and deformation with Equation 2 [10].

According to Fatigue;

$$N_f = f_1 * (\epsilon_t) - f_2 * (E_{AC}) - f_3 \quad (1)$$

Here, N_f is the maximum number of loading repetitions of fatigue cracks in the flexible pavement coating.

ϵ_t , is the maximum horizontal tensile strain under the bituminous layer. E_{AC} , the modulus of elasticity of the asphalt layer. f_1 , f_2 and f_3 are fixed coefficients usually determined from road tests and laboratory tests.

According to Deformation;

$$N_r = f_4 * (\epsilon_c) - f_5 \quad (2)$$

Here N_r is the maximum number of loading repetitions that limit deformation, ϵ_c is the pressure change on the base floor.

Here, the values of the coefficients (0.0796, 3.29, 0.854, $1.365 * 10^{-9}$, 4.477) are used respectively, the values are taken from the Asphalt Institute.

Table 1. Key Parameters for Estimating Remaining Life and Performance of Flexible Pavements.

Institutions	$N_f = f_1 * (\epsilon_t) - f_2 * (E_{AC}) - f_3$			$N_r = f_4 * (\epsilon_c) - f_5$		Source
	f_1	f_2	f_3	f_4	f_5	
Asphalt Institute	0.0796	3.29	0.854	-	-	[20]
Asphalt Institute	-	-	-	$1.365E^{-09}$	4.477	[21]
Shell	0.0685	5.67	2.363	-	-	[20]
Shell (50% Reliability)	-	-	-	$6.15E^{-07}$ *	4	[22]
Shell (50% Reliability)	-	-	-	$1.94E^{-07}$	4	[23]
Shell (50% Reliability)	-	-	-	$1.05E^{-07}$	4	[23]
Illinois Department of Transportation	$0.50E^{-5}$	3	-	3	-	[24]
Transport and Road Research Laboratory	$1.66E^{-10}$	4.32	-	4.32	-	[25]
University of Nottingham	-	-	-	$1.13E^{-06}$	3.571	[26]
Indian Model	$2.20E^{-04}$	3.89	-	$4.17E^{-06}$	4.534	[27]
Belgian Road Research Center	$4.92E^{-14}$	4.76	-	$3.05E^{-09}$	4.35	[28]

* $6.15E^{-07} = 6.15 * 10^{-7}$ in Table 1

Depending on the N_f , N_r values, Fatigue Life and Deformation Life are calculated with the help of the formulas given above. The critical one of these life values, that is the smaller one, is considered as the pavement's life.

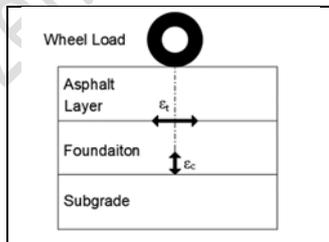


Figure 3. Flexible road pavement critical tensile and pressure strain.

Flexible road pavement damage is determined by the proportion of the wheel load applied to the pavement to the

value of wheel charge repetitions allowed. Following Equation (3) is used in the damage ratio calculation.

$$D = N / N_{f,r} \quad (3)$$

D is the damage ratio for the road pavements; N is the applied load; $N_{f,r}$ is the number of standard wheel load repetitions allowed for fatigue or deformation.

The following Equation (4) is used to calculate the remaining life.

$$RL = (1 - D) * Y \quad (4)$$

Here, RL is the remaining life, D is the damage ratio, Y is the flexible pavements design life. There are two assumptions;

- ✓ The flexible pavements design life is considered to be 20 years.
- ✓ Linear distribution is accepted for the damage ratio and the remaining life.

The dataset used in this study originates from Hazra's [29] doctoral dissertation, in which field data were collected from 16 different highway sections in Arkansas for the calibration of models predicting the remaining life of flexible pavements. This dataset was later utilized in a master's thesis by Yaseen [30] and subsequently adopted by Saltan and Alaeary [31], who applied a different approach—the Adaptive Neuro-Fuzzy Inference System (ANFIS)—to estimate the remaining service life of flexible pavements. The dataset includes key structural parameters such as the number of layers, load repetition count, elastic moduli of pavement layers, and layer thicknesses.

In order to calculate the remaining life of flexible pavements, the Casa A region was taken as an example, the KENLAYER program was used in the analysis. The parameters used in the KENLAYER were used to calculate the tensile deformation under the asphalt layer using a standard 8.2-ton single axle load with dual tires with a contact radius of 4.23 inches, a tire pressure of 80 psi and a 13.5-inch wheelbase. Huang recommends these loading parameters [10].

For the analyzes, the critical tensile strain was calculated below the asphalt layer. Tensile deformation at the base of the asphalt layer is calculated at three points, the first is the point under a single wheel center, the second is the point on the edge of the wheel and finally the midpoint between the two wheels.

HMA Poisson's ratio was taken as 0.35, 0.35 and 0.40 for foundation and subgrade layers, respectively.

After analyzing the KENLAYER program, the following results were obtained.



Figure 4. KENLAYER program result (casa a region).

- ✓ The maximum horizontal tensile strain value (ϵ_t) at the bottom of the bituminous layer was calculated as $1.17E^{-04}$.
- ✓ The maximum pressure strain value (ϵ_c) in the subgrade is calculated as $3.63E^{-04}$.
- ✓ According to fatigue, the allowable amount of the number of axle load repetitions (N_f) was calculated as $5.1E^{+06}$.
- ✓ According to the deformation, the allowable amount of the number of axle load repetitions (N_r) was calculated as $3.4E^{+06}$.
- ✓ N_f and N_r values were calculated using equations (1) and (2). Fatigue and deformation life were determined depending on N_f and N_r values. The critical one of these life values, that is the smaller one, is considered as the pavement's life.
- ✓ The damage ratio value D is calculated as 0.0902. Equation (3) is used for this calculation.
- ✓ The remaining life (RL) of the pavements was calculated as 17.32 years by using Equation (4).

5 Artificial neural network modeling

This study aims to generate outputs using systematic solution methods based on experimentally obtained input variables in ANN models. The objective of the paper is to estimate the time at which the road pavement reaches the end of its service life, thereby reducing maintenance and repair costs. The variables used in this study to calculate the remaining life of the pavement are listed in Table 2.

Table 2. Input Parameters for the Calculation of Flexible Pavement Remaining Life.

Parameters
Layer Numbers
HMA 1 Layer Modulus of Elasticity
HMA 2 Layer Modulus of Elasticity
Base Layer Modulus of Elasticity
Subgrade Layer Modulus of Elasticity
HMA1 Layer Thickness
HMA 2 Layer Thickness
Base Layer Thickness
Actual Load

The relationship between the variables used in calculating the remaining life of asphalt pavements is highly complex and nonlinear. Based on the data obtained, ANNs appear to best capture this complexity. The success of this method in solving nonlinear problems is remarkably high [32], and this has been emphasized in many studies [33] – [39].

Although it is possible to determine the output values from the input values using ANN, the challenges encountered in this process are often overlooked. To address this issue, numerous studies have been conducted using ANN models, and various algorithms have been proposed. These algorithms are used to determine the effect of input values and their contribution to the resulting output values [40].

The ANN method can learn complex relationships from unclear imprecise data thanks to its remarkable capabilities. It can also be used to develop models and identify features that are very extremely difficult to detect. Once trained, the network can perform analysis at an expert level [10].

ANNs can learn rules by analyzing samples, make predictions through generalization, and reproduce learned behaviors by modeling operations based on these samples. They are also capable of memorizing the characteristics of data and associating previously encountered patterns with new data [41].

As shown in Figure 5, the input layer consists of multiple nodes, while the output layer contains a single node that represents the predicted value. A nonlinear activation function, typically the sigmoid function, is applied in the hidden layer to approximate the expected result, whereas a linear function is used in the output layer. There is no fixed rule for determining the number of neurons in the hidden layer; this number is generally selected through repeated calculations or trial-and-error methods [42].

One of the most important capabilities of artificial neural networks (ANNs) is their ability to learn from examples and generalize to new situations. In other words, after learning the relationship between input features and corresponding output values, the system can generate generalized solutions by producing estimated outputs for previously unseen input data [43].

Because of this, the training phase of the model consists of a sequence of processes necessary to adjust the synaptic weights and neuron thresholds in order to generalize the mapping from input data to target output values [43].

From a different perspective, the training aims to determine the values (W_1 , W_2 , b_1 and b_2) to minimize an error [44].

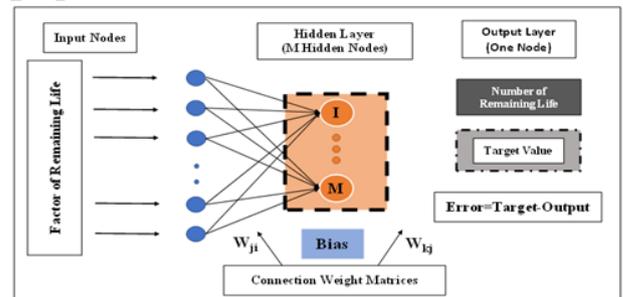


Figure 5. Structure of artificial neural network model for remaining life of a HMA pavement.

6 Development and application of ANN models

Alyuda Neuro Intelligence (Alyuda Neuro Intelligence) is used as software in this article. Alyuda Neuro Intelligence has been a frequently used software tool in the application of the ANN method over time [45].

Alyuda Neuro Intelligence is a software program designed to facilitate the prediction, classification and resolution of problems for experts. In addition to these functions, the software can also generate input data with intelligent solutions, assess the adequacy of data derived from outputs, and formulate solutions for new data in existing datasets. In this context, all stages can be completed very quickly [46].

The input layer receives the initial data, while the hidden layer(s) perform internal computations that are not visible to the user. The output layer produces the final result. The hidden layer, located between the input and output layers, operates as a black box whose internal processes cannot be accessed or altered by the user during or after training [47].

Nine significant parameters were applied in modeling. The significant parameters are layer number, BSK1, BSK2, base and subgrade layers modulus of elasticity, BSK1, BSK2 and base layers thickness, actual load. 9 variables were used in the solution and 10 neurons were used to represent priority risks to achieve the target result.

The Alyuda Neuro intelligence program offers various algorithms for automatically encoding categorical columns through data pre-processing techniques [48].

In modeling, input and output values are normalized to the [0, 1] range using the min-max normalization algorithm prior to training [48]. The process of converting categorical variables into binary vectors is called one-of-N encoding (also known as one-hot encoding). For example, if a categorical variable has three distinct values, one-of-N encoding represents them as follows: the first category as {1, 0, 0}, the second as {0, 1, 0}, and the third as {0, 0, 1}.

In the definition of binary modeling, K means that a column with different values is encoded into a group of H binary columns. Where H is equal to the length of the binary number K represents the different value. For instance, whether the color column values are Yellow, White, Navy, Red, they will be encoded into 3 binary columns and represented as Yellow {0,0,0}, White {0,0,1}, Navy {0,1,0}, Red {0,1,1}.

In numeric modelling, N indicates that a column which has a value in different categories is coded into a numeric column with an integer value for each category. For instance, in the temperature column with the values 'Hot', 'Warm', 'Cold', 'Hot' is shown as {4}, 'Warm' as {5} and 'Cold' as {6}.

The Minimax algorithm is as follows with Equation 5:

$$T' = Tx \left\{ \frac{1}{T_{max} - T_{min}} \right\} - Tx \left\{ \frac{T_{min}}{T_{max} - T_{min}} \right\} \quad (5)$$

T_{max} and T_{min} represent the maximum and minimum values of T, while T' denotes the combined value of T. One of the most critical factors for improving learning speed and reducing error in the trained neural network is the normalization of input data.

The mathematical formulation of ANN is

$$\left\{ \begin{matrix} W_2 f_1 \\ W_1 \end{matrix} \left\{ \begin{matrix} \text{Layer Numbers} \\ \text{HMA 1 Layer Modulus of Elasticity} \\ \text{HMA 2 Layer Modulus of Elasticity} \\ \text{Base Layer Modulus of Elasticity} \\ \text{Subgrade Layer Modulus of Elasticity} \\ \text{HMA 1 Layer Thickness} \\ \text{HMA 2 Layer Thickness} \\ \text{Base Layer Thickness} \\ \text{Actual Load} \end{matrix} \right\} + [b_1] + [b_2] \right\} \quad (6)$$

In the Equation (6), the value Y represents the remaining life for HMA pavement, while W_1 and W_2 represent the weight matrix of the network, and b_1 and b_2 represent the thresholds (or bias) vectors. Since the performance of the training stage depends on the number of neurons in the hidden layer, the test was performed with a multi-combination neuron in the model. In the final layer, the value that is produced is the remaining lifetime.

The findings derived from the ANN model are rendered comprehensible by the fitness criterion. The suitability of the model result depends on the low error in the training set. The top five results from modeling are shown in Figure 6. Given the fitness criteria in Table 3, it can be seen that the best result is achieved with the 9-10-1 model.

Table 3. Fitness Evaluation Criteria for the Best Five ANN Configurations.

Network	Fitness Criteria
9-23-1	4.753065
9-9-1	7.291853
9-12-1	4.279147
9-7-1	3.77573
9-10-1	7.938952

The modeling process consists of three stages: training, validation, and testing. The results obtained during training are evaluated through the validation and testing phases. These phases are essential for assessing the effectiveness and generalization capability of the trained model. During the training phase, not all data are used; some are reserved for validation and testing to ensure objective performance evaluation. The test data are introduced only after training is complete, and performance metrics such as estimation errors are measured at this stage. In the study, a total of 32 data samples were used: 22 for training, 5 for testing, and 5 for validation. The top five performing networks are presented in Figure 6.

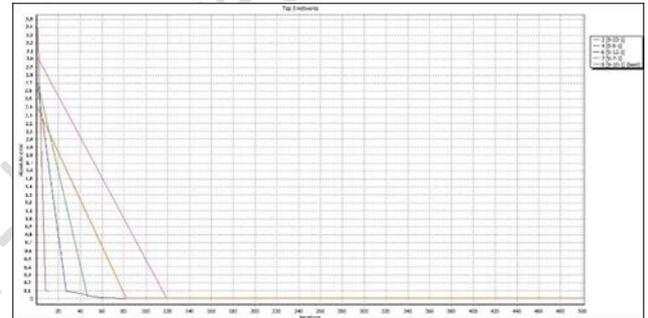


Figure 6. The top five performing networks.

7 Evaluation of ANN model

R-squared (R^2), Mean Square Error (MSE), Root Mean Square Error (RMSE) are the most important criteria for determining the ability to represent the results obtained with the ANN model. These values are calculated by the following Equations (7)-(10):

$$R^2 = r^2 \quad (7)$$

$$\text{Cor. Ratio } (r) = \frac{n(\sum \text{actual} \times \text{predicted}) - (\sum \text{actual})(\sum \text{predicted})}{\sqrt{[n \sum \text{actual}^2 - (\sum \text{actual})^2][n \sum \text{predicted}^2 - (\sum \text{predicted})^2]}} \quad (8)$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^m (t_{ai} - t_{pi})^2 \quad (9)$$

$$\text{RMSE} = \sqrt{\text{MSE}} \quad (10)$$

- t_{ai} = the i-th actual value
- t_{gi} = the i-th predicted value
- N = the number of training samples
- m = the number of parameters

8 Results

The absolute error (AE) and absolute relative error (ARE) of the target and output terms in the tested network, together with the R-squared and correlation parameters, are given in the

table below which is Table 4. The explanations of the AE and ARE are as follows:

AE (absolute error) is the absolute value of the difference between the actual value and the predicted value, indicating the success of the training work. As the amount of error obtained approaches zero, it indicates that the training is more successful [45].

ARE (Absolute Relative Error) is the absolute value of a coefficient obtained by dividing the difference between the actual value and the predicted value by the actual value, indicating the success of the training work [45].

The remaining life for HMA pavement was approximated using the ANN models. The Equation (11), (12) used in the model error calculations are presented below [47].

$$AE = |actual - predicted| \quad (11)$$

$$ARE = \left| \frac{actual - predicted}{actual} \right| \quad (12)$$

Table 4. Evaluation of the Tested ANN Model Using AE, ARE, R-squared, and Correlation Coefficients

	Target	Output	AE	ARE
Mean	18.133952	18.143245	0.118787	0.006928
Std. Dev.	1.85587	1.852484	0.098964	0.006377
Min.	11.708229	12.0102	0.024054	0.001229
Max.	19.80675	19.705716	0.538379	0.028831
Correlation	(0.99542)			
R-Squared	(0.99086)			

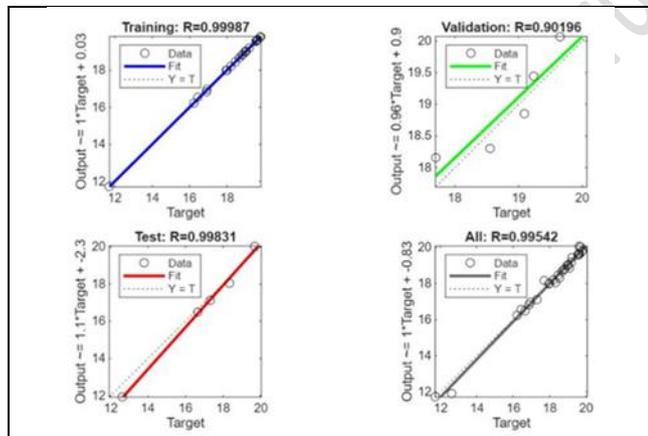


Figure 7. Graphical Representation of the Relationship Between Predicted and Actual Values of ANN model.

Correlation (r) is a statistical coefficient between the predicted values obtained as a result of modeling and the actual values. The value (r) shows that the positive linear relationship strengths as it approaches 1, the negative linear relationship strengths as it approaches -1, while the linear relationship weakens as it approaches 0 [44].

R-squared is a statistical ratio. This calculation is used to determine the model's accuracy. This comparison is made by comparing the simplest model accuracy using the mean of all target values with the model prediction accuracy. This determined value is expected to be close to 1. It shows that the power of the model increases as it approaches a value of this

ratio and weakens as it moves away from 1. Negative values indicate much weaker models [44].

Table 5 shows the correlation coefficient, R-squared, MSE, and RMSE values for the training, validation, and test phases of the ANN model. The fact that the correlation and R-squared values are close to 1 and the MSE and RMSE values are close to 0 prove the strength of the model. Under the light of this information, it shows that this method is suitable for calculating the remaining life of asphalt pavements.

Table 5. Statistical evaluation results of the ANN model.

Model	Correlation	R-Squared	MSE	RMSE
Training	0.99987	0.99974	0.0009	0.03
Validation	0.90196	0.81353	0.1107	0.33
Test	0.99831	0.99662	0.1539	0.39

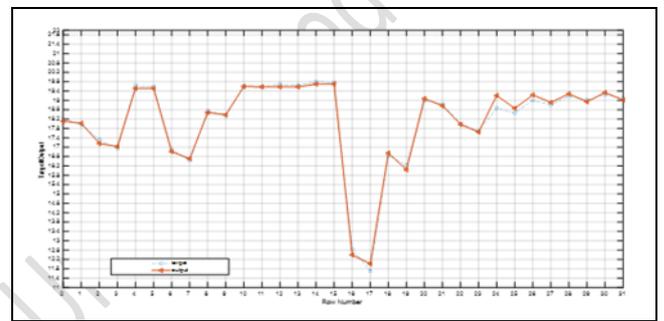


Figure 8. Affair of target-output valuation for remaining life of HMA pavement.

As illustrated in Figure 8, the data presented correspond to target and predicted values for the remaining life of the HMA pavement analyzed in this study. As shown in the graph, the predicted values closely match the target values, indicating a high level of model accuracy.

Table 6. Significance percentage of parameters in calculating remaining life.

Input Column Name	Importance %
HMA1 Layer Thickness	44.63
Actual Load	31.34
Base Layer Thickness	7.74
Base Layer Modulus of Elasticity	7.31
HMA 2 Layer Thickness	5.23
HMA 2 Layer Modulus of Elasticity	2.15
HMA 1 Layer Modulus of Elasticity	1.13
Subgrade Layer Modulus of Elasticity	0.34
Layer Numbers	0.14

The results show that in Table 6, five important properties, namely HMA1 Layer Thickness, Actual Load, Base Layer Thickness, Base Layer Modulus of Elasticity, HMA2 Layer Thickness, are very effective in predicting remaining life.

In accordance with the recommendation to compare the results with similar studies in the literature, the findings obtained in this study were compared with relevant literature data. Table 7 summarizes the results of studies employing different modeling approaches. As seen in the table, the results of the ANN model developed in this study are largely consistent with those reported in the literature, which supports the validity of the proposed approach.

Table 7. Comparison of ANN model results with findings from previous studies.

Remaining Life Prediction(year)			
Item No	Calculated Data	Yaseen Thesis Prediction Data [30]	ANN Model Prediction
1	18.23	18.20	18.22
2	17.98	18.10	17.97
3	17.34	15.80	17.32
4	16.96	15.80	16.94
5	19.65	19.60	19.65
6	19.64	19.60	19.60
7	16.90	16.40	16.89
8	16.45	16.40	16.44
9	18.56	18.40	18.55
10	18.35	18.40	18.34
11	19.56	19.60	19.62
12	19.60	19.60	19.56
13	19.82	19.80	19.70
14	16.68	15.90	19.65
15	19.88	19.90	19.81
16	19.78	23.10	19.78
17	12.70	10.50	12.63
18	11.76	11.80	11.71
19	16.64	16.60	16.65
20	16.22	16.20	16.23
21	19.00	19.00	19.00
22	18.83	18.80	18.84
23	18.02	18.90	18.01
24	17.70	17.70	17.69
25	18.46	18.50	18.67
26	18.49	18.50	18.46
27	19.00	19.00	19.00
28	18.81	18.80	18.81
29	19.20	19.20	19.19
30	19.03	19.00	19.03
31	19.24	19.20	19.24
32	19.09	19.10	19.09

9 Conclusions

In this study, two different loads were applied to each of the flexible road pavements determined in 16 different regions of Arkansas. As a result of the applied loads, the critical tensile and compressive strain in flexible pavement pavements were determined with the help of the KENLAYER program. Using the obtained strains, the remaining life calculation was made with the Huang comparison model. The remaining lives obtained with the Huang Model were calculated and compared with the ANN model. In the ANN model, the number of layers, actual load, elasticity moduli (for two asphalt pavements layers, the subgrade, and the base layer), and layer thickness (for the two-asphalt pavement layers and the base layer) were used as inputs, while the remaining life was obtained as the output. The model was constructed using 32 input parameters. 22 samples were used for training, 5 for validation and 5 for testing. The correlation coefficient obtained from the model is 0.99542, while the R^2 value is 0.99086.

As noted, the data used in this study were obtained from a single region and consist of only 32 observations, which may limit the generalizability and representativeness of the model across different geographical areas and pavement structures. Despite this limitation, the primary aim of the study was to explore the applicability and potential of the ANN approach in predicting the remaining life of flexible pavements using the available dataset.

It is also recognized that the small dataset size increases the risk of overfitting. While performance metrics such as R^2 and MSE, along with validation testing, were utilized to assess model accuracy, further investigation is required to evaluate the model's robustness under varying conditions. Future research should involve more extensive and diverse datasets from multiple regions in order to enhance both the reliability and generalizability of the developed model.

Consequently, the proposed ANN model yielded favorable results in estimating the remaining life of flexible pavements. In future applications, this model can be integrated into the national road network in Turkey to optimize maintenance and rehabilitation planning through early deterioration detection, potentially reducing long-term infrastructure costs. Turkey's General Directorate of Highways (KGM) currently operates a Pavement Management System (PMS) integrated with Geographic Information Systems (GIS), which facilitates the structured collection and analysis of pavement data. According to the 2024 PMS Guideline [49], key variables such as pavement types, layer thicknesses, surface distress types (e.g., cracking, rutting), traffic loads, and historical maintenance activities are systematically collected and spatially referenced using GIS technologies. This data infrastructure provides a reliable foundation for training and validating ANN models. A proposed implementation scenario would involve piloting the model on selected road sections with complete datasets, followed by nationwide deployment upon successful validation.

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11 Author contribution statement

Author 1 and Author 2 jointly contributed to the conceptual development and design of the study. Author 2 was responsible for designing ANN model, including the network architecture and algorithmic structure. Author 1 provided and organized the dataset used for training and evaluation of the model. In addition, Author 1 conducted the literature review and drafted the initial manuscript. Author 2 processed and analyzed the model outputs, and contributed to the interpretation and presentation of the results. Both authors reviewed and approved the final version of the manuscript.

12 Ethics Committee Approval and Conflict of Interest Statement

"There is no need to obtain an ethics committee approval in the article prepared".

"There is no conflict of interest with any person/institution in the article prepared".

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