Development of the non-destructive monitoring methods of the pavement conditions via artificial neural networks

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Abstract. Non-structural parameters like surface defects and ride quality were frequently used, as a practical index for the rehabilitation selection process. The key purpose of this study was the assessment of using artificial network technology as a support for decision-makers about paving maintenance concerning the structural condition compared to the conventional, time-consuming, effort, and costly methods. The structural model was established based on the deflections from the FWD, (asphalt and base) layers thickness, surface temperature, precipitation rate, AADTT, traffic volume of class 9 and base layer type. The data used in building the developed ANN model is related to a previous study of flexible pavement structures on the M4 highway in the Russian highways network during the five years 2013-2017. The ANN model was built, trained, and tested by the Matlab program. The focus was on calculating roughness, fatigue, and rutting values as they are the most common pavement distress on site. We used the logistic model equations, developed by the Federal Highway Administration's Long-Term pavement Performance (LTPP) to calculate the three pavement distress that will be used as output variables while training the ANN model. The ANN model presented a high performance in predicting the three pavement distress (fatigue, roughness, and rutting) where the R-squared value was equal (1, 0.999, and 1), respectively for the forecasting sections.

1. Introduction
A lot of government highway departments have used various methods to preserve or enhance the surface performance of highway pavements with comprehensive sealing layers, thin asphalt overlays, and several types of surface curing over their service life. Such interventions supply temporary maintenance for the surface performance, but they do not provide the solution for any structural defects correlated to the pavements. As a result, the general performance of the pavement continues to deteriorate due to the structural distortion of the pavement layers and the subgrade, while the surface curing was regularly introduced [1].

Evaluation of pavement condition is a significant phase in the pavement management system (PMS) because it helps preserve and increase the operational life of current pavements [2]. Highway departments used non-structural variables such as surface distress and ride quality as a functional indicator in the choice of treatment. The structural capacity of the pavement determines the highway's ability to resist traffic loads and avoid severe deterioration [3].

Understanding the pavements structural state helps to make the right decision on the type of treatment that delays the pavement deterioration cycle. A pavement's deterioration cycle reflects the...
behavior of a non-linear mechanism that can be characterized by varying deterioration levels at several stages of pavement operational life. If the rate of deterioration is identified, the real state of the pavement may be defined more precisely at any time. Unfortunately, a mathematical solution to this issue is unlikely since there are no models that could be so accurate that they reflect the actual deterioration cycle of the pavement. To obtain an approximate estimation of the pavement condition deterioration rate, the differences between the pavement condition assessments over the various operational periods can be used [1]. Figure 1 represents the pavement deterioration process during its operating period.

![Figure 1. The pavement deterioration process over time.](image)

Using non-destructive testing is a significant technique for the assessment of pavement structures and is recognized as an effective method for assessing the structural state of pavements in use [4,5]. The falling weight deflectometer (FWD) is commonly known as an efficient in understanding the pavement's structural status and helping to make the correct decision about the treatment form, which decreases the pavement's deterioration rate [6]. The applied dynamic weight is transferred to the pavement surface in the FWD test, and deflections are recorded with high precision by specially built sensors. The utilized load generates an impact load over the surface layer of the pavement with contact time is 25–30 ms, which identity with a wheel speed of 50 mph [7].

The amount of impact load, period, and loading zone are regulated in such a direction that it correlates closely with the real loading by a standard truck on the roadway during operation [8]. The maximum load is regulated by variation of the falling level, the dropping mass, and the constant of spring. The implemented load could change from 4.45 to 156 kN [9,10]. The loading pulses are usually of a half-sine form, and the load affects a circular diameter of 0.3 m. Surface deflections are obtained and registered by seven or more sensors at different distances from the loading center [11–13]. The obtained deflection values can be used to estimate the effect of the pavement elastic modulus on the stress value [14,15]. The main benefit of this approach is that it matches nearly the real loading in the service life of the pavement. Another advantage is that traffic does not stop during the test operation. A schema of the FWD test is shown in (Figure 2).

![Figure 2. Standard FWD test Scheme.](image)

1.1 ANN overview

ANN simulates the human mind's work, as it collects, analyzes, and uses the data entered into it to create mathematical models that help to solve complicated nonlinear problems by discovering the relationship between inputs and outputs variables [16,17]. A standard multi-layered feed-forward neural network design consisted of an enter layer, hidden layers, and output layer. The unit known as a neuron is the perfect element that used to perform the transfer operations mainly in all layers. Every neuron processes the coming inputs and generates an output according to a correctly specified
activation function. The neuron output is transmitted to the next neurons via special network connections. Every connection is linked with a specified weight (\( w_i \)) amplifying or decreasing the input. The input (\( x_i \)) output (\( Y_i \)) relation for each neuron is determined in terms of a certain transfer function that typically has a logistic sigmoidal form, as seen in Equation (1).

\[
\text{f}(I) = \frac{1}{1 + e^{-I}}
\]  

(1)

Where \( I = \sum w_i \cdot x_i \) is the sum of the weighted inputs \( x_i \) produced by the previous neurons.

The transfer job depends on the weights and biases to link information directly from inputs into outputs during the feed-forward process. At the same time, there is an error back-propagation technique that allows the neural network to adjust weights and biases from outputs into inputs through evaluating performance operations like Root Mean Square Error (RMSE) and Gradient Decline [18].

While constructing an ANN model we use an artificial database to prepare weights and biases during the training operation before applying the ANN system. To achieve the desired outcome from the training process, we follow three basic steps to create the model. The first step is to select the optimal number of layers to form the neural network provided that the numbers of layers are not less than three layers: which are input layer, the hidden layer, and the output layer. We may increase the number of hidden layers to improve the learning ability of the neural network [19]. The second step is setting the neurons number per layer. The final step involves defining transition functions and setting operational variables in the ANN model.

One of the most used algorithms in the training process is Levenberg-Marquardt, and the error rate is expressed by calculating the average error (MSE). Upon knowing the registered \( N \) set, we can use Eq (2) to calculate MSE.

\[
MSE = N^{-1} \sum_{i=1}^{n} (e_i)^2 = N^{-1} \sum_{i=1}^{n} (t_i - p_i)^2
\]

(2)

Where \( e_i \) is the error for every group of inputs, \( t_i \) is the predicted output, and \( p_i \) expresses the network output.

There are many advantages that motivate us to choose the ANN approach to solve various complex problems such as:

- Simply represent complex non-linear relationships.
- Approved models can be developed with new data from future operations in the field and benefit from them.
- Suitable for handling various small or large databases and extracting data easily.
- "Noisy" data, such as that obtained from site inspection, does not adversely affect the training operation [20].

1.2 Previous researches

Several researchers carried out different experiments to determine the condition of the pavement on the framework of their performance parameters. Many mathematical models have been implemented to characterize and determine the condition of the pavement, despite the difficulty of the measurement process to obtain the data that reflect pavement states [21].

In (2016), G. Sollazzo et al designed artificial neural networks (ANNs) models to predict the structural efficiency of asphalt pavement using roughness information. They used 13 variables as input data for the network, which have an impact on pavement performance, such as traffic parameters, structural parameters, climatic parameters, and performance parameters. Three separate ANN models were trained by the authors to assess the effect of changing databases and parameters. The results indicated that an ANN approach could be adopted to characterize pavement roughness better than other methods [22].

In (2016), Cooper and others tested models consisting of treated asphalt paving and reused asphalt slabs using the ANN approach to predict fatigue cracking and J integration of semicircular curvature.
The results showed the ability of the ANN system to predict critical stress-energy values for old-made asphalt mixtures with a low error rate [23].

In (2016) Zavrtanik et al, They studied the effect of some variables of a large number of asphalt mixtures such as sieve analysis, binder content, and maximum aggregate density on the air void content in the mixtures using the ANN system and regression analysis. By comparing the results between the two models, the preference in the process of predicting air void content for all obtained mixtures was for the ANN model [24].

In (2017) Mirabdolazimi and others developed a model to predict the rutting condition of asphalt rubber with the help of the application of artificial neural networks. The results indicated the ability of ANN to predict the default rutting values for rubber binders [25].

In 2018 Huang et al designed two models of the ANN system to increase the accuracy of forecasting rutting values. Inputs of the first model (NN3) consisted of the rutting data calculated according to the MEPDG method of the asphalt concrete layer (AC), the granular base, and the sublayer. The second model (NN20) has the same inputs in addition to seventeen variables for characterizing traffic, structure, climate, and materials. For the two models, the output variable was the value of the total pavement drainage. Then, they designed two other models with the multiple linear regression system MLR3 and MLR20 with the same inputs for the ANN models to compare the results of the two systems and find out which is better. The results demonstrated the advantage of ANN models for forecasting during the training and testing process over the MLR models [26].

In (2018) H. Ziari, et al developed three models to study the rutting of Nano carbon-tube asphalt binders under the influence of temperature and loading hesitancy using artificial neural networks and regression analysis. The results of the study proved that the ANN model had better predictability of rutting values than regression models where the multiple parameter coefficient values were 0.997, 0.819, and 0.42 for the three models, respectively [27].

In (2019) Li Maoyun et al used the artificial neural networks system to construct a model that helps in the process of back-calculating the elastic modulus of pavement using the deflection data from the FWD test. When comparing the results between the ANN model and the field-measured data recorded in the long-term pavement performance, differences were small. The results showed a high accuracy during the training and testing process in predicting the modulus of elasticity for all asphalt layers [28].

1.3 Objective and scope
This study aims to develop an ANN-based model with which to know the condition of the pavement without resorting to the asphalt visual inspection process every year, which requires a lot of effort, time, and cost. It is clear that the artificial approach can be used effectively to reduce these requirements and develop a tool that helps decision-makers to interfere in real-time to maintain the most affected roads and reduce the deterioration process according to available data for the road network and available financing. To achieve this goal, The data obtained by the FWD test that was recorded in a previous study on a highway of the Russian M4 network was used to determine the condition of the pavement. The focus was on calculating roughness, fatigue, and rutting values using relationships derived from the probability density function of the logistic model, which was developed during a study of the Federal Highway Administration’s (FHWA) Long-Term Pavement Performance (LTPP) database to obtain insight of the pavement structure during the service period. The ANN model is trained and validated using an artificial database.

2. Methodology
A case study to forecast flexible pavement conditions using the ANN technique has been suggested. A variety of structural procedures have been used to design ANN models. There are generally five main steps: (1) data collection, (2) pavement distress estimation, (3) network construction, (4) network training, and (5) testing model results.
2.1 Data collection
Collecting the input variables data to construct the ANN model, which are as follows: Thickness of both the asphalt layer and the base layer, the surface temperature during the FWD test, asphalt deflection values according to FWD test sensors, precipitation rate, annual average daily truck traffic volume, the traffic volume of class 9 and base layer type (bound or unbound).

2.2 Calculating pavement defects using the logistic model.
The logistic model equations developed by the Federal Highway Administration's Long-Term Performance (LTPP) were used to calculate the three pavement distress (fatigue, roughness, and rutting) that will be used as output variables during training the ANN model.

Equations 1 and 2 show the general formula and the linear formula of the logistic model that are used to calculate the values of pavement distresses (fatigue, roughness, and rutting) separately for all sections used to construct and test the ANN model. Firstly the compensation is in the linear equation by the values of the variables that affect each distress of the pavement to obtain the value of the variable (b) as will be mentioned later, then using it in the general equation of the logistical model to obtain the values of the three distresses for all sections.

Equation (3) displays the general logistic model formulation.

\[ p(\text{event}) = \frac{1}{1 + e^{-b}} \]  

Equation (4) displays the general linear formulation for the logistic model exponent term.

\[ b = a_0 + a_1 b_1 + a_2 b_2 + \ldots + a_n b_n \]  

2.2.1 The input variables which affect the pavement fatigue to obtain the value of the variable (b) are as follows:

- \( D_1 \) is the measured deflection value in the middle of the loading plate.
- Average Annual Daily Truck Traffic volume, AADTT.
- Divide the pavement according to the base layer type to take a value (1) if it is bound and the value (0) if it is not bound.

We used the variable values derived from the logistic model for the pavement fatigue cracking mentioned in table № 1 to calculate the exponential term in equation 3.

### Table 1. The values of the coefficients used in the linear equation for calculating the state of fatigue cracking.

| Variables (\( b_i \)) | \( a_i \) | \( b_i \) = used variables. | \( a_i \) = coefficient values of the equation. | \( I_1 \) = mutual index of the used deflection value |
|-----------------------|--------|------------------------------|-----------------------------------------------|-----------------------------|
| \( I_1 \)             | 154.764|                              |                                               |                             |
| AADTT                 | -0.0005073|                             |                                               |                             |
| Pavement type         | 0.3774 |                              |                                               |                             |
| Constant              | -0.2202|                              |                                               |                             |

The variable \( I_1 \) in table 1 is determined by using equation № 5 [29].

\[ I_1 = D_1^{I_1} \]  

2.2.2 The input variables which affect the pavement roughness to obtain the value of the variable (b) are as follows:

- \( D_2 \) is the measured deflection value at distance 200mm from the center of the loading plate.
- Class 9 trucks volume, irrespective of real axle load.
• The actual life of the pavement section from construction time or from last maintenance. We used the variable values derived from the logistic model for the pavement roughness mentioned in table № 2 to calculate the exponential term in equation (3).

**Table 2.** The values of the coefficients used in the linear equation for calculating the state of pavement roughness distress.

| Variables (bi)   | $a_i$   | $b_i$= used variables. |
|------------------|---------|-------------------------|
| $I_2$            | 239.849 | $a_i$= coefficient values of the equation. |
| Current life     | -0.189  | $I_2$ = mutual index of the used deflection value. |
| Class 9 volume   | -0.0006781 |                     |
| Constant         | 0.8375  |                         |

The variable $I_2$ in table 2 is determined by using equation № 6 [29].

$$I_2 = D_1^2$$  \hspace{1cm} (6)

2.2.3 The input variables which affect the pavement rutting to obtain the value of the variable (b) are as follows

• The measured deflection value at distance 300mm from the center of the loading plate, $D_3$.
• The measured deflection value at distance 450mm from the center of the loading plate, $D_4$.
• Class 9 trucks volume, irrespective of real axle load.
• Average annual rainfall in the area (mm).

We used the variable values derived from the logistic model for the pavement rutting mentioned in table № 3 to calculate the exponential term in equation (3).

**Table 3.** The values of the coefficients used in the linear equation for calculating the state of pavement rutting distress.

| Variables (bi)   | $a_i$   | $b_i$= used variables. |
|------------------|---------|-------------------------|
| CI$_3$           | -0.01146| $a_i$= coefficient values of the equation. |
| Precipitation (mm)| -0.0005259|                     |
| Class 9 volume   | -0.0007688 |                     |
| Constant         | 2.6586  |                         |

The variable CI$_3$ in table № 3 is determined by using equation № 7 [29].

$$CI_3 = D_3 - D_4$$  \hspace{1cm} (7)

2.3 Artificial neural networks (ANNs)

The ANN network consists of conductors that provide neuron outputs to other neurons as input. The network gives a weight for every connection that reflects its relative importance by studying the data in a mathematical or computational method[30]. We used Matlab to create the ANN model and the Levenberg Marquardt algorithm was implemented to reduce error function. The program randomly divided the data into three parts as follows: 60% of the data used in the training process, 20% used them in the verification process, and the remaining 20% of the data are for testing the developed model. Log-Sigmoid Function was used as a control function to evaluate the data normalization range. The ANN model is primarily trained using the training database, and subsequently, it must be checked using the test data. After the beginning of the training process, the model adjusts the weights of each variable according to its effect on the results values. We use a variable number of hidden layers and neurons inside them to improve network performance. Each network is trained several times and the results are recorded, and then the optimum network structure is chosen by comparing the statistical
results. After completing the training phase, the competency of the trained model for this purpose was evaluated by the Square Correlation Coefficient (R2) and RMSE.

The data used in building the developed ANN model is related to a previous study of flexible pavement structures on the M4 highway in the Russian highways network. Pavement condition data for 1564 sectors were used during the five years 2013, 2014, 2015, 2016, and 2017 to build the ANN model. The numbers of sectors for the training and validation process were 940 and 312, respectively and the numbers of data used to test the suitability of the model were 312 sectors. The training process data must include the maximum and minimum values of the variables used to construct the model to achieve the desired goal. The model was set to repeat the training process for 1000 epochs using the training data to ensure the integrity of the training process without forgetting or overtraining. Figure 3 demonstrates the artificial neural network model structure.

**Figure 3.** The structure of the neural network for determining flexible pavements distress (T1, T2- the thickness of the layers of asphalt concrete and the base of the pavement, t° - surface temperature, C.L - current life, AADTT, class-9, pavement type, p-Precipitation, D1 ... D4- results of measurement of elastic deflections, under sensors-geophones).

Outputs may differ when training a number of various neural networks to solve the same issue with the same input. This is due to change all of the specific data for training, verification, and testing operations, and change of the weight and bias values of variables and connections at every time of the training. It is necessary to train the model several times to obtain a high-quality neural network.

### 2.4 Network Training.

The `nntool` command was used in the MATLAB program to create the ANN model. The best network structure was achieved after testing several networks by changing the number of hidden layers and neurons within them and comparing the results. The optimal construction is in two hidden layers and 16 neurons with a structure of 12-16-3. A summary of the training process is shown in Figure 4.

**Figure 4.** Suggested ANN structure.
As it took 1 minute and 40 seconds for the model to stop training after it performed 500 validation checks. Performance ($1.35e^{-7}$) shows the amount of error reduction that happens throw training, gradient ($4.45e^{-5}$) illustrates the amount of diversity that happens in the error rate, $\mu$ ($1.00e^{-8}$) is the error value for each iteration and is calculated in each iteration.

3. Results
The following charts of regression in Figure 5 present the network outputs regarding training and validation goals and test groups.

![Figure 5. The regression plot of the training and testing data.](image)

There is a significant match between the ANN output and the target values, as most data lie along a 45° line. It also indicates the strength of the developed model and its ability to estimate outputs where we note that R values are approximately 1 for all training, validation, and test data.

Figure 6 shows a chart of training, validation, and test errors, as this chart allows us to know the current condition of the training operation. The performance chart for each epoch in the training operation is determined, and the performance in which the three corresponding outputs for training, validation, and testing are chosen in most points as the best results. For the next reasons the result is logical as shown in the following chart:

- The minimum mean square error occurred in the last iteration of training.
- Test data error and verification data error have similar characteristics as they notice a decrease in the validation error curve and a decrease in the test error curve at the same rate.
- There was no overlap between the three curves, especially at the best validation performance that occurred at epoch 483.
Figure 6. Training and performance chart of the created ANN model.

Model learning takes place in an open cycle, including the training, verification, and testing phases. The standard system is to set up a complete network in an open cycle, which will only be transformed into a closed cycle for multi-stage predicting after its preparation that involves all phases.

To make sure that the model can represent the correct relationship between the input variables and the targeted output after completing the training process. It was necessary to test the ability of the developed model to forecast the three pavement distress (fatigue, roughness, and rutting) that are under study for several sectors that were not used in network training. 77 sections were used to find out the confidence of the model output by entering input data of the new sectors. Then, the outputs of the ANN model and the actual values of pavement distress that were not entered for the model were compared. The used sections data represent a large range expressing various pavement conditions to indicate the strength of the model. Table 4 shows data for some of the sectors used in the forecasting process.

Figure 7 (a-b-c) represents the linear relationship between the expected pavement distress values through the artificial neural network model and the actual values of the selected sections to test the predictability of the model. We found that most points lie on a line whose slope is approximately 45 degrees, where the R-squared value was equal (1.09999 and 1) for the three pavement distress (fatigue, roughness, and rutting), respectively, indicating a small error in the prediction of the target values.
**Figure 7.** The results of estimating the pavement distress from the deflection values of FWD (a, b, c — showing the relation between the predicted value of pavement distress using artificial neural network model and the actual values).
4. Conclusion
The study aimed to develop a model that follows the approach of artificial neural networks to predict the condition of the pavement structure by knowing the values of the distress under study (roughness, fatigue, and damage). Distress was studied under the influence of the following parameters: (asphalt concrete layer thickness and pavement base, t” - surface temperature, CL - current life, AADTT, class-9, pavement type, p-precipitation, D1 ... D4 - results of deviations measurement Flexible from FWD test).

The study showed the possibility of relying on the results of the modified ANN model instead of the equations derived from the probability density function of the logistic model, which was developed during a study of the Federal Highway Administration’s (FHWA) Long-Term Pavement Performance (LTPP) database to obtain insight of the pavement condition during the service period.

The strength of the developed model reflects its ability to represent a wide range of pavement distress with high accuracy.

The ANN model presented a high performance in predicting the three pavement distress (fatigue, roughness, and rutting) where the $R^2$ value was equal (1.09999, and 1), respectively for the forecasting sections.

This research has helped in the possibility of using ANN modeling to assess the current pavement condition using FWD test measurements and employing it in maintenance operations management.

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