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Determining International Irregularity Index (IRI) Values Through Artificial Neural Network (ANN) Modelling

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Abstract

The quality of a pavement's level of service is generally determined by measuring the combinations of some important factors which affect the speed, travel time, freedom to maneuver, user comfort and convenience. In this study, a feed-forward back-propagation artificial neural network (ANN) algorithm is proposed based on the acquired International Irregularity Index (IRI) data for the highway structures, bridges and culverts, obtained through laser profilometer measurements on the surface irregularity of the bituminous hot mix roads. Analysis of ANN results were carried out through training various hidden number of neural networks for the output prediction, which is the best estimation of the surface irregularity of the roads. Results produced by artificial neural network have been compared with experimental and numerical results through extensive sets of non-training experimental data. As the comparison of results with ANN study having average absolute mean relative errors as 12.68% for bridges and 12.90% for culverts provided very accurate results, the model proposed could be used to obtain the surface irregularity of the roads by avoiding heavy duty of collecting numerous field data. The results obtained through ANN model were found more accurate than the results produced by numerical models.

Keywords: International Irregularity Index; Laser Profilometer; Artificial Neural Networks; Numerical Analysis

1. INTRODUCTION

The road network is known as an indicator of the level of development among countries. The project of a road network starts from planning and covers the design, construction and maintenance of the road throughout its service life. The pavement management system is a systematic approach that realizes these processes in the broadest sense. The performance of the highways put into service is quite high in the early days. However, it decreases due to factors such as traffic and climate conditions. These deteriorated roads affect the economy of the countries directly or indirectly. That is, if maintenance and repair are carried out before the pavement performance decreases to a certain level, the performance can be brought and kept to the desired level at a low cost. However, if no maintenance and repair work are carried out, the life of the road will end in a relatively short period of time [1].

As the budget allocated for the maintenance and repair of roads in many countries is quite limited, maintenance work should be carried out in a timely manner by determining the priority within the existing budget. In this way the pavement performance might be kept at a reasonable low cost and possible short time ending of road life is prevented. From this point of view, selection of improvement strategies is a crucial necessity to determine the most appropriate work program for the analyzed roads.

This obviously requires the resulting superstructure system to be applicable and stable at every stage with regard to economical, accurate and precise determining of the surface irregularities, slip resistance, and driving comfort [2]. The quality of a pavement's level of service, in this sense, is generally determined by measuring the combinations of some important factors which affect the speed, travel time, freedom of maneuver, and convenience [3].

For this purpose, performance prediction models have been developed to plan the required resource needs for the coming years by analyzing the deterioration level of the road surface. Solor̀zano et.al. showed that it is possible to develop IRI performance models using the IRI data of the main network of Spain, the RCE (State Road Network), even if the pavement structure is completely unknown and information about the time of the maintenance and rehabilitation activities were conducted is not provided. They, with this type of data, employed probabilistic models, more specifically, Markov chains, by means of transition probability matrices to provide an adequate solution for modelling the IRI evolution of the roads [4].

As many observations have shown, the lifespan of a superstructure designed to be 20 years can only be 10-12 years, and sometimes less, without maintenance and repair [5]. Accordingly, it is necessary to carry out planned and programmed maintenance and repairs in certain periods in order to benefit from a superstructure as it should.

A pavement management system is carried out in stages. Proper evaluation of road networks to be investigated should be evaluated at the first stage of the pavement management system. Following, the obtained data should be analyzed to determine the current condition of the road based on the factors affecting the performance of the road surface. As the final stage, the work program must be determined and selected as the most convenient strategy of the pavement management system. Through all these processes, the main objective is to acquire the improvement program that reveals when involvement should be made to make sure that the pavement performance will be kept at the desired level as much as possible in a most economical and sustainable way [6].

While the Superstructure Management System (MSM) did not include any performance prediction factor at the beginning for the initial condition assessments, later, on the other hand, a simple performance prediction model was developed based only on one factor, such as the age of the pavement. Different performance predictions are carried out using some combined data on variables such as climate conditions and traffic load in the currently implemented models [7].

Highway and transportation engineers study and investigate the surface irregularity of the roads for the different highways leading to many experimental studies [8]. In addition of the fact that it is not easy to obtain data from the field, experimental studies are costly. Therefore, numerical and different approximation methods are alternative methods for further analyses as they are less costly than the other methods. Pérez-Acebo et all developed deterministic IRI performance model based on the data available regarding the variables of thickness of bituminous materials, age of the pavement, the Annual Average Daily Traffic and type of the pavement. Their study revealed the fact that flexible and semi-rigid pavements have completely different behavior and they must be considered separately as their behavior depending on the distinguishing variables they have [9].

Zeng at. all [10] suggested an imaging-based DNN (Deep Neural Network) model through 2-dimensional pavement images as an alternative to vibration-based models for the identification of IRI values of the pavement.

Some of the research focused on limited experimental measurements to show the capability of the neural network technique in modelling surface irregularity phenomena of the roads [11]. Some research presented that the number and distribution of the training data are linked to the performance of the network when estimating the surface irregularity of the roads under different conditions [12].

Erkmen et al. [13] investigated the effect of engineering structures on surface irregularity by examining the interaction of the surface irregularity of the highway superstructure during and after the approaches to the engineering structures. In this context, International Irregularity Index (IRI) data obtained within the borders of the General Directorate of Highways in Turkey (KGM)-18th Regional (Kars) Directorate were used. They compared and assessed the effect of roadway structures on the irregularity of the asphalt structure through the analytical and statistical evaluation.

This study focuses on the prediction of the surface irregularity of the roads through experimental data and numerical model approach. Hence, an Artificial Neural Network (ANN) model was developed for the prediction of the surface irregularity of the roads with the data obtained from General Directorate of Highways in Turkey. Similar data used by Erkmen at all (2023) for analytical calculations were employed to set up the ANN model for the predictions of IRI values. The measurements were carried out and averaged for every 10m-long of the related highway sections by using Dynatest brand laser profilometer measurement device with serial number of 5051-4-278. It should be pointed out that the readings are obtained for the road sections before and after the engineering structures of bridges and culverts for the intervals of two sections of 150 meters up to 300 meters. In other words, roads were divided into 150m-long 4 different parts before and after the engineering structures, 26 bridges and 177 culverts, so that up to 300m road sections, hence 600m in total, were taken into consideration to collect the data. Furthermore, the IRI values for bridges and culverts were also obtained and averaged.

Artificial neural networks (ANN) are nonlinear mapping systems whose structure is based on principles inspired by the biological nervous systems of humans. An artificial neural network consists of large number of simple processors linked by weighted connections and provides a fundamentally different approach to forecasting modelling than numerical solution methods. This technique has been applied in many disciplines of science and has produced preliminary results in the many areas of modelling and investigations. Some of the authors considered the problem of accuracy in the surface irregularity of the roads by employing artificial neural network (ANN) models [14], [15], [16], [17].

Wu et al. [18] provides a comprehensive analysis of the patterns in predicting pavement roughness using artificial intelligence algorithms categorized into machine learning and deep learning by emphasizing the similarities and differences among them. They state that the influence of different maintenance behaviors on the long-term performance of pavement should be studied to clarify the pertinence of maintenance measures as far as the maintenance data is concerned.

Fakhri and Dezfoulian [19] suggested a method for pavement structural evaluation to assess pavement layers condition and identify needed rehabilitations. They developed a relationship between deflection bowl parameters derived from Falling Weight Deflectometer (FWD) and two pavement performance indices, International Roughness Index (IRI) and Pavement Surface Evaluation and Rating index (PASER). Artificial Neural Network (ANN) and regression models are used for this purpose. Their study revealed the fact that ANN models had superiority over non-intelligent regression models.

2. MATERIALS AND METHODS

Neuron is a basic processor in artificial neural networks. Each neuron has one output that is based on the situation of the neuron activation, and can receive many inputs from other neurons. With this sense, artificial neurons can be modelled as a multi-input nonlinear process with weighted interconnections.

The back-propagation algorithm the focus of the recent studies on modelling, is the most suitable method for training multi-layer feed-forward networks. The algorithm of training a back-propagation network is developed by using different literatures [20], [21], [22], [23], [24], [25], [26] and summarized as follows:

1. *Present a training pattern and propagate it through the network to obtain the outputs*

2. *Initialization:* Initialize all weights to small random values and threshold values: set all weights and threshold to small random values. Usually, the training sets are normalized to values between –0.1 and 0.9 during processing.

3. *The net input to the j^{th} node in the hidden layer*

$$net_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j \tag{1}$$

where *"i"* is the input node, *"j"* is the hidden layer node, *"x"* is the input, *"w_{ij}"* is the weights value connection from the *"i^{th}"* input node to the *"j^{th}"* hidden layer node and *"θ_j"* the threshold between the input and hidden layers.

4. *The output of the "j^{th}" node in the hidden layer:*

$$h_j = f_h\left(\sum_{i=1}^{n} w_{ij} x_i - \theta_j\right) \tag{2}$$

$$f_h(x) = \frac{1}{1+e^{-\lambda_h x}} \tag{3}$$

where *"h_j"* is the vector of hidden-layer neurons, *"$f_h(x)$"* is a logistic sigmoid activation function from input layer to hidden layer, *"λ_h"* is the variable which controls the slope of the sigmoidal function.

5. *The net input to the "k^{th}" node in the hidden layer*

$$net_k = \sum_{j} w_{kj} x_j - \theta_k \tag{4}$$

where *k* represents the output layer, w_{kj} is the weights connection from the *"j^{th}"* hidden layer node to the k^{th} output layer, *"θ_k"* is the threshold connecting the hidden and output layers.

6. *The output of the "k^{th}" node in the output layer:*

$$y_k = f_k\left(\sum_{j} w_{kj} x_j - \theta_k\right) \tag{5}$$

$$f_k(x) = \frac{1}{1+e^{-\lambda_k x}} \tag{6}$$

where *"y_k"* is the output of output-layer neurons, *"$f_k(x)$"* is a logistic sigmoid activation function from hidden layer to output layer, λ_k variable which controls the slope of the sigmoid functional.

7. *Compute errors:* The output layer error between the target and the observed output:

$$\begin{aligned} &\delta_k = -(d_k - y_k) f_k' \\ &f_k' = y_k(1-y_k) \quad \text{for sigmoid function} \end{aligned} \tag{7}$$

where *"δ_k"* is the vector of errors for each output neuron and *"d_k" is* the target activation of output layer. *"δ_k"* depends only on the error *(d_k-y_k)* and *" f_k' "* is the local slope of the node activation function for output nodes.

The hidden layer error:

$$\begin{aligned} &\delta_j = f_h' \sum_{k=1}^{n} w_{kj} \delta_k \\ &f_h' = h_j(1-h_j) \quad \text{for sigmoid function} \end{aligned} \tag{8}$$

where *"δ_j"* is the vector of errors for each hidden layer neuron. *"δ_j"* is a weighted sum of all nodes and the local slope *" f_h' "* of the node activation function for hidden nodes.

8. *Adjust the weights and thresholds in the output layer:*

$$w_{kj}^{(t+1)} = w_{kj}^{(t)} + \alpha \delta_k h_j + \eta\left(w_{kj}^{(t)} - w_{kj}^{(t-1)}\right) \tag{9}$$

$$\theta_k^{(t+1)} = \theta_k^{(t)} + \alpha \delta_k \tag{10}$$

where *"α"* is the learning rate, *"η"* is the momentum factor and *"t"* is time period.

It should be noted that the learning rate and the momentum factor are used to allow the previous weight change to influence the weight change in this time period, *"t"*. These calculation steps repeat until the output layer error is within desired tolerance for each pattern and neuron.

The feed-forward neural network has become the most popular among the various types of neural network in different applications. The back-propagation network is most commonly used for feed forward neural network as there is a mathematically strict learning scheme to train the network and guarantee mapping between inputs and outputs. In this study, an artificial neural network modelling for prediction of the surface irregularity of the roads is performed. In addition, a feed-forward back-propagation ANN approach is used for the training and learning processes. For the solution of the

ANN algorithm, a computer program has been developed in the C language. As neural networks need a range of input and output values to be between 0.1 and 0.9 to the restriction of sigmoid function, experimental field data and required data are both normalized in order to use the values. The equation of normalization is given as follows:

$$\frac{Act.data.-Min.data}{Max.data-Min.data} \times (High\ dat - Low\ dat) + Low\ dat \qquad (11)$$

In this formula, minimum, maximum, high and low data refer to the annual minimum data value, the annual maximum data value, the maximum normalized data value (0.9), and the minimum normalized data value (0.1), respectively [27]. A three-layer feed-forward back-propagation neural network for the surface irregularity of the culverts of highways is performed as shown Figure 1. A three-layer feed-forward back-propagation neural network for the surface irregularity of the bridges of highways is performed as shown Figure 2.

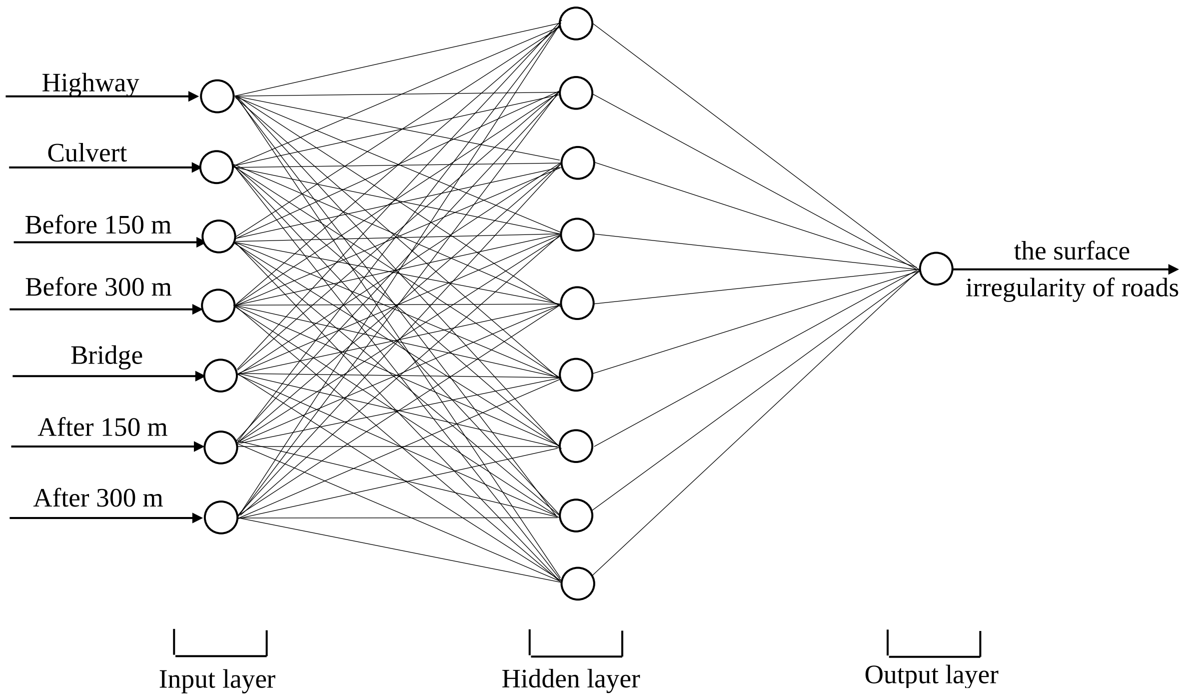

Figure 1. A three-layer feed-forward back-propagation neural network for the surface irregularity of the culverts of highways.

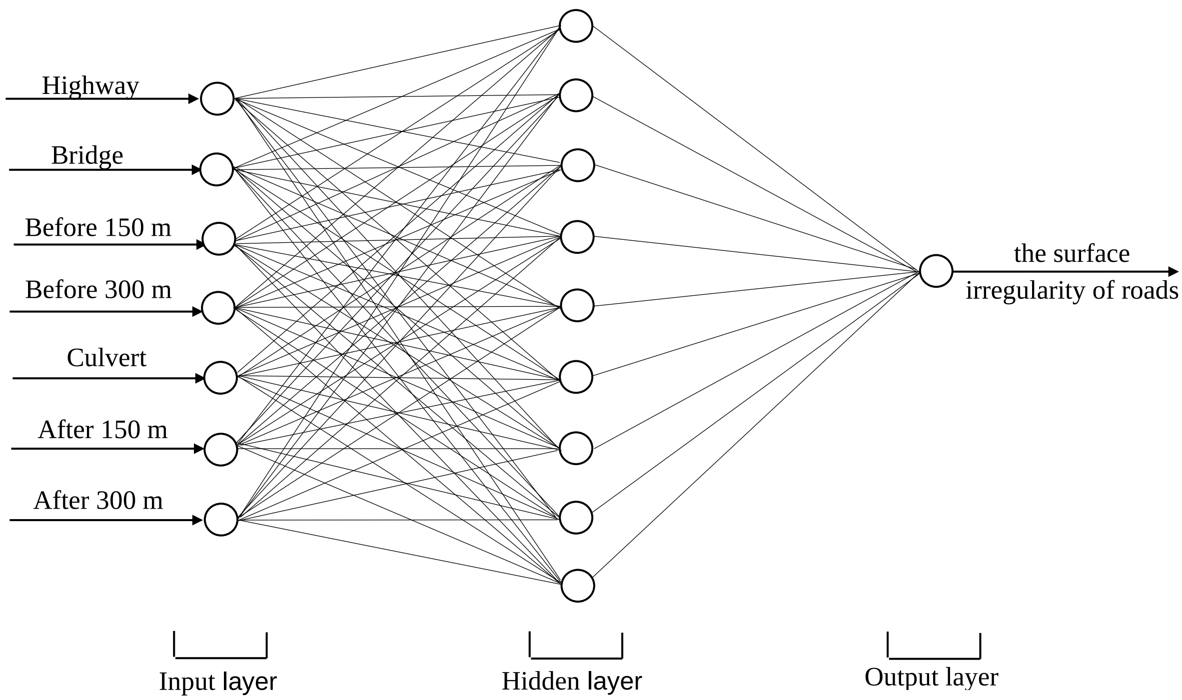

Figure 2. A three-layer feed-forward back-propagation neural network for the surface irregularity of the bridges of highways.

As far as the ANN analyses are concerned the network parameters were taken as the averaged IRI measurements taken along the two separate 150m long road sections of the highways both before and after the bridges and culverts for the highways. The lengths of the highways were also used as an input for the model. The outputs are the surface irregularity of the bridges and culverts respectively as illustrated in Figure 1 and Figure 2. The weights, biases and hidden node numbers are altered to minimize the error between the output values and the current data. In order to obtain the least error convergence, the configurations of the ANN are set by selecting the number of hidden layers and nodes along with the learning rate and momentum coefficient. The 745 cases of real measurements of data set related to culverts are divided into two sections. First 708 data groups (95% of all data) were used for trainings of the network and the remaining data group representing 37 cases were used for the verification of the ANN model. It should be noted that these data were randomly selected. The 130 cases of field measured data sets for bridges are also divided into two data sets. The first group consisting of 115 data set to be used for trainings of the network (88% of all data) and the other data group with 15 cases were used to validate the ANN model.

Table 1. The ANN model results for the surface irregularity of the culverts on 080-05 coded highway.

Location of the culverts on 080-05 coded highway (m)	Measured IRI Data-Averaged	ANN Model			
		ANN results	AMRE (%)	R^2	STD (%)
504	2.39	2.85	19.41	0.9623	0.03480
1440	2.25	2.33	3.64	0.9987	0.00955
2055	3.31	2.68	19.14	0.9634	0.02693
2549	1.48	1.22	17.25	0.9702	0.02391
3160	2.13	2.12	0.34	1.0000	0.00318
3537	1.56	1.80	15.50	0.9760	0.02854
3819	1.81	2.07	14.44	0.9792	0.02683
4081	1.66	1.98	19.55	0.9618	0.03501
4431	2.44	2.38	2.29	0.9995	0.00006
5088	2.15	2.54	17.95	0.9678	0.03246
5827	2.20	2.57	16.64	0.9723	0.03036
8100	5.81	4.68	19.44	0.9622	0.02741
10036	4.85	4.09	15.64	0.9755	0.02132
10472	3.58	3.94	10.07	0.9899	0.01985
11995	2.81	2.67	4.85	0.9976	0.00406
13449	1.02	0.83	18.19	0.9669	0.02542
15335	1.12	1.09	2.69	0.9993	0.00059
15645	1.18	1.07	9.13	0.9917	0.01091
15989	1.03	1.06	3.03	0.9991	0.00856
16338	1.42	1.15	19.31	0.9627	0.02720
16635	0.71	0.84	18.04	0.9674	0.03261
17058	1.41	1.14	19.20	0.9631	0.02703
17128	1.53	1.29	15.82	0.9750	0.02162
17841	1.29	1.09	15.63	0.9756	0.02131
19206	1.38	1.14	17.13	0.9707	0.02371
19843	1.08	1.17	8.42	0.9929	0.01719
20388	1.54	1.27	17.85	0.9681	0.02487
22087	0.94	1.12	19.16	0.9633	0.03439
22249	0.91	1.05	15.89	0.9748	0.02915
22973	1.10	1.30	18.56	0.9656	0.03343
24226	1.15	1.35	17.76	0.9685	0.03215
24447	1.38	1.36	1.23	0.9998	0.00175
28432	1.43	1.51	5.26	0.9972	0.01213
28669	1.64	1.51	7.77	0.9940	0.00873
28716	1.82	1.51	16.81	0.9717	0.02321
28827	2.05	1.81	11.60	0.9865	0.01486
29493	1.50	1.54	2.65	0.9993	0.00796
Average			12.90	0.9792	0.02062

Table 2. The ANN model results for the surface irregularity of the bridges on 080-03 coded highway.

Location of the bridges on 080-03 coded highway (m)	Location of the measurements on bridges	Measured IRI data-Averaged	ANN Model			
			ANN results	AMRE (%)	R^2	STD (%)
9487	after 300 m	2.32	2.78	19.65	0.9614	0.03518
20192	after 300 m	2.82	3.13	11.02	0.9879	0.02136
4691	after 300 m	1.44	1.72	19.27	0.9629	0.03458
9487	after 150 m	4.30	3.88	9.87	0.9903	0.01209
20192	after 150 m	3.36	3.82	13.84	0.9808	0.02587
4691	after 150 m	4.29	3.95	8.00	0.9936	0.00910
9487	over the bridge	4.17	4.57	9.62	0.9907	0.01912
20192	over the bridge	4.12	4.55	10.36	0.9893	0.02031
4691	over the bridge	3.80	4.48	18.01	0.9676	0.03255
9487	before 150 m	4.47	4.56	1.99	0.9996	0.00690
20192	before 150 m	4.05	4.73	16.78	0.9718	0.03059
4691	before 150 m	3.57	3.93	10.11	0.9898	0.01991
9487	before 300 m	3.52	3.15	10.49	0.9890	0.01308
20192	before 300 m	3.80	3.28	13.62	0.9814	0.01810
4691	before 300 m	3.46	2.85	17.51	0.9693	0.02432
Average				12.68	0.9817	0.02154

The neural network model is basically formed for the surface irregularity of the culverts and bridges by using seven inputs (highways, the IRI values for culverts/bridges and the five 150m-long intervals of the highways defined before). The output on the other hand is the surface irregularity values of the culverts and bridges. As far as the hidden numbers are concerned, 5, 6 and 7 were tested. The most appropriate hidden number was found as 6 and this value was used in the analysis. In the algorithm, learning rates and momentum coefficients are taken as 0.6 for learning processes, in which 500,000 iterations were carried to obtain good fits. Furthermore, the three error measuring parameters were used to compare the performance of the various ANN configurations [28].

The performance of various ANN configurations was compared using the absolute mean relative error (AMRE), the standard deviations in the relative (STD) errors and the absolute fraction of variance (R^2). The following equations are used to acquire the related values for the assessment of the results.

$$\text{AMRE} = \frac{1}{\text{n}}\sum_{i=1}^{n} ABS(B) \tag{12}$$

$$\text{STD} = \sqrt{\frac{\sum_{i=1}^{n}\left(B-\bar{B}\right)^2}{n-1}} \tag{13}$$

$$\text{R}^2 = 1-\left[\frac{\sum_{i=1}^{n}(a_i-y_i)^2}{\sum_{i=1}^{n}(y_i)^2}\right] \tag{14}$$

where B= $(y_i - a_i)/a_i$. "y_i" is the prediction value, "a_i" is the measurement value, and "n" is the number of data available.

Table 1 and Table 2 illustrate associated prediction errors, the absolute mean relative error (AMRE), the standard deviations in the relative (STD) errors and the absolute fraction of variance (R^2) with ANN configurations for the surface irregularity of the culverts and bridges in the learning process, respectively. In calculating the roughness of the surface of bridges and culverts, the hidden layer with 6 nodes in the ANN structure gave the best results in obtaining the prediction results in Table 1 and Table 2.

Comparison of the results obtained from the ANN analysis and the real field data was carried out through employing the absolute mean relative error (AMRE), the standard deviations in the relative errors (STD) and the absolute fraction of variance (R^2). The ANN model has 12.90% of average AMRE, 0.02062 of the STD and 0.9792 of R^2 for the surface irregularity of the culverts on 080-05 coded highway for the sections of 150m length after the culverts as shown in Table 1. As for the bridges, because of the limitation on the number of available data, the ANN model is developed and tested for the whole section of the highway with 080-03 code. The ANN model, in this case, resulted in 12.68% of average the AMRE, 0.02154 of the STD and 0.9817 of R^2 for the surface irregularity of the bridges as shown in Table 2.

Comparison of the results produced by the ANN model and the field data for the surface irregularity of the culverts on highway with 080-05 code for the road sections after 150m from the culverts are given in Figure 3. In similar way, Figure 4 illustrates the comparison of the ANN model results and the measured data for the surface irregularity of the bridges of 080-03 coded highway.

As can be seen from the tables above the developed ANN model produced satisfactory results in terms of evaluation criteria for the calculation of the surface irregularity of the culverts and bridges.

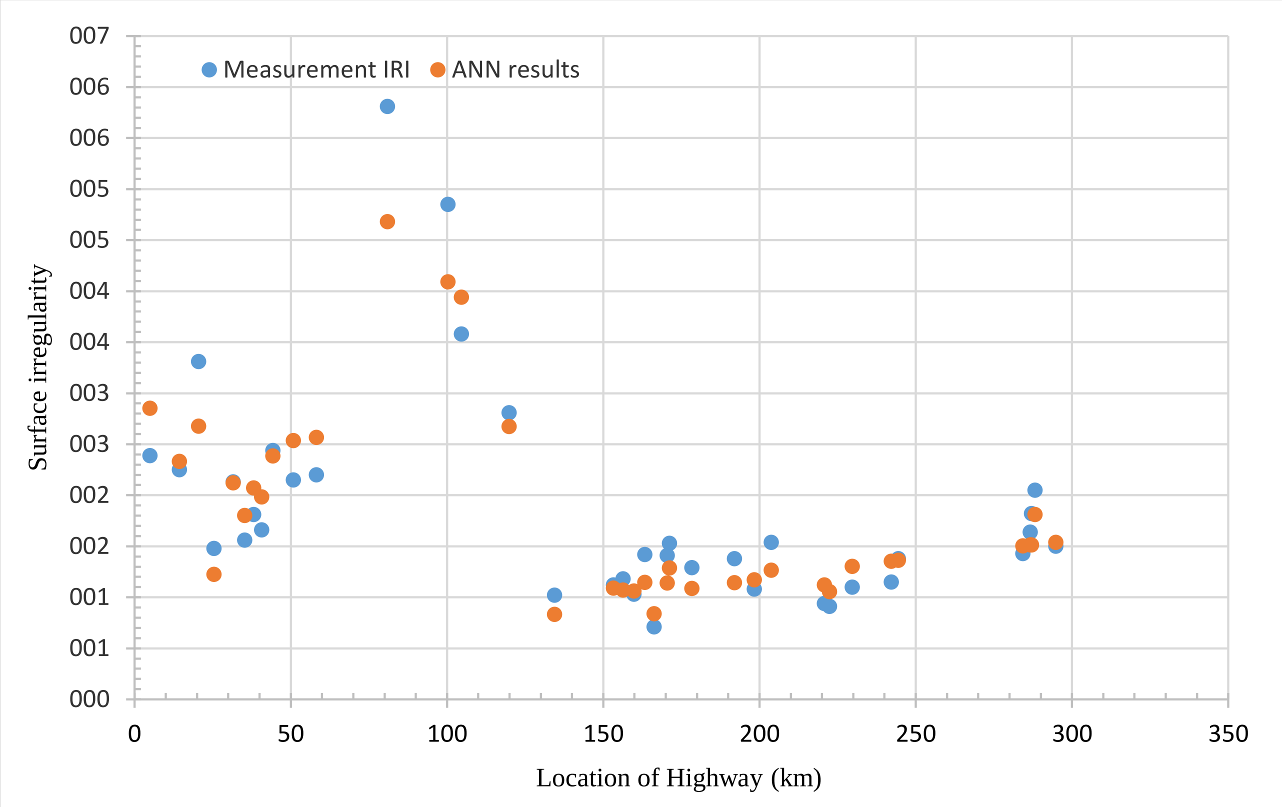

Figure 3. Comparison of the ANN model results and the measured data for the surface irregularity of the culverts on highway with the 080-05 code after 150 m on culverts.

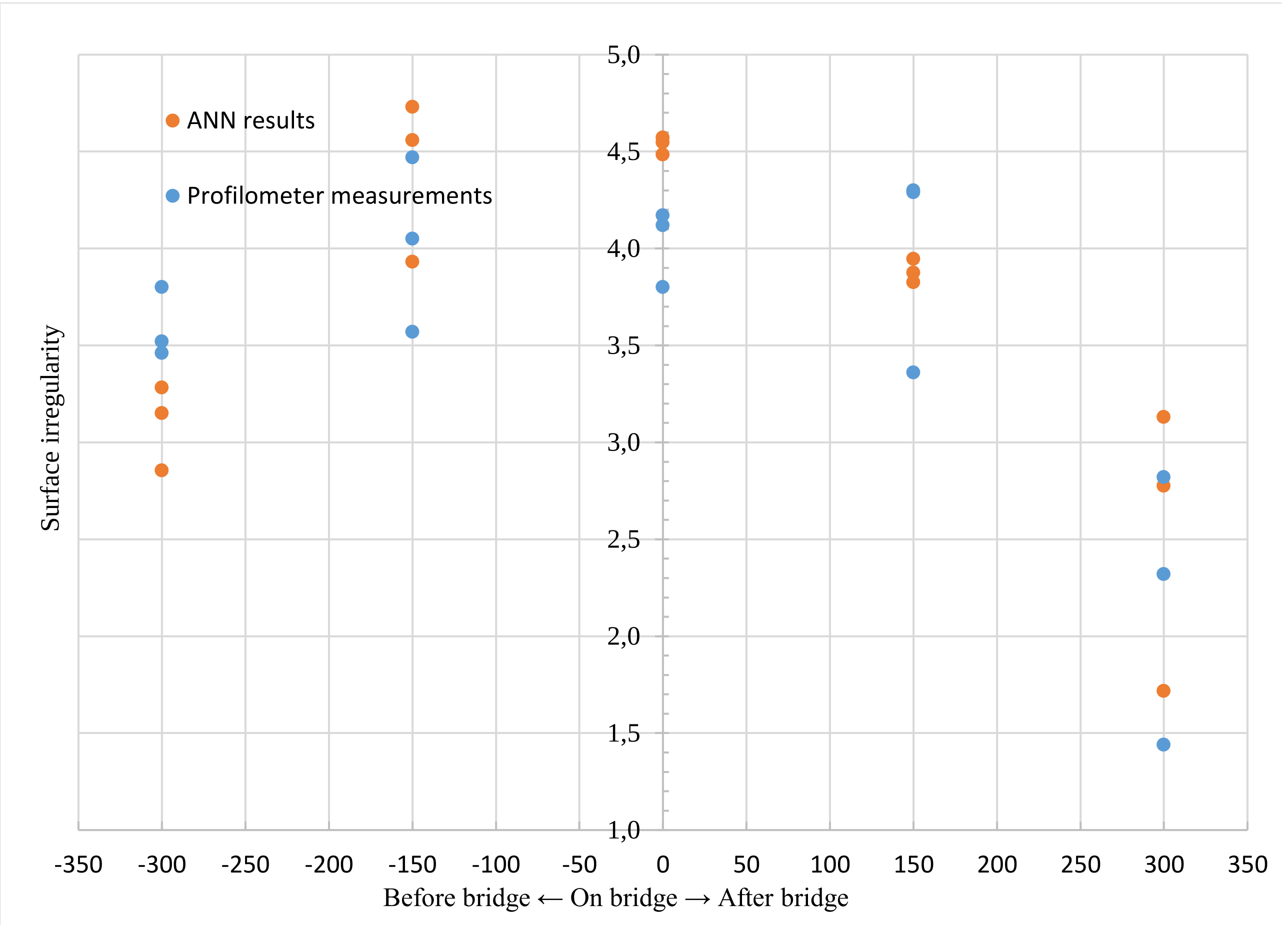

Figure 4. Comparison of the ANN model results and the measured data for the surface irregularity of the bridges for the highway with 080-03 code.

3. CONCLUSIONS

This study proposed an innovative ANN model for the calculation of surface irregularities for the bridges and culverts located in different highways based on the data obtained from General Directorate of Highways in Turkey. The findings of this study through developed ANN model led to the following concluding remarks.

- The ANN results indicate that the proposed model can be effectively used for the prediction of the surface irregularity of the bridges and culverts. The ANN approach is rather suitable for the prediction of surface irregularities of the bridges and culverts. As the proposed ANN model is based on a 6-hidden layer approach, the model effectively evaluates the importance levels of the factors and sets up the model accordingly to obtain reasonable and accurate results. Non-linear or Regression models do not provide the results with this accuracy.

- The ANN model has an average percentage value of 12.90 for AMRE, 0.02062 for STD and 0.9792 as R^2 for the surface irregularity of the culverts on highway with 080-05 code for 150m-length of the road sections from the culverts.

- The ANN model has average percentage values of 12.68 for AMRE, 0.02154 for STD and 0.9817 as R^2 for the surface irregularity of the bridges on 080-03 coded highway investigated.

- This research pointed out that ANN approach is an applicable and suitable method to predict the surface irregularities of the bridges and culverts when the related data cannot be obtained by field studies due to some physical, financial or time, professional staff and equipment related difficulties.

- This study was carried out to illustrate that artificial intelligence modelling is an effective and applicable approach to estimate the values of the highway surface irregularities based on the field data related to culverts and bridges. In this way, the effects of bridges and culverts on the IRI values of the asphalt structure of the highways to be constructed can be calculated and evaluated so that the time related applications may be put into practice as far as the maintenance programs are concerned.

- The next step of this research will be setting up new ANN models considering some important highway usage and construction parameters, such as annual average daily traffic, temperatures, heavy vehicle compositions, type of aggregates, available Marshall test results, to obtain the IRI values of the asphalt. In addition, the effect of the length and width of these constructional structures on IRI values will be investigated and modelled based on the nationwide data to be obtained from General Directorate of Highways in Turkey.

- The effectiveness of the model will also be tested by acquiring data from different regions.

NOMENCLATURE

a_i experimental value
ANN Artificial Neural Network
AMRE Absolute Mean Relative Error
d_k target activation of output layer.
h vector of hidden-layer neurons
R^2 absolute fraction of variance
STD Standard Deviation
t time period
w_{ij} weights connecting the i^{th} input node to the j^{th} hidden layer node
w_{kj} weights connecting the j^{th} hidden layer node to the k^{th} output layer
x multiple inputs
y output
y_i output value

Greek Letters

θ external threshold,
θ_j threshold between the input and hidden layers.
$f()$ logistic sigmoid activation function
$f_h()$ logistic sigmoid activation function from input layer to hidden layer
λ variable which controls the slope of the sigmoid functional
θ_k threshold connecting the hidden and output layers.
$f_k()$ logistic sigmoid activation function from hidden layer to output layer
f_k' local slope of the node activation function for output nodes
δ_k vector of errors for each output neuron
δ_j vector of errors for each hidden layer neuron.
f_h' local slope of the node activation function for hidden nodes
α learning rate
η momentum factor

Subscripts

h hidden layer
i input node, or initial condition
j hidden layer node
k output layer node
n number of the data

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