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An ANN model to correlate roughness and structural performance in asphalt pavements

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HIGHLIGHTS

- Proposal of a neural network method to correlate roughness and structural capacity.
- Adoption of an LTPP-based database, including many influencing parameters.
- Comparison of various networks to analyse the method potential.
- The method can reduce traditional deflection tests (HWD, FWD) frequency for PMSs.

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ABSTRACT

In this paper, using a large database from the Long Term Pavement Performance program, the authors developed an Artificial Neural Network (ANN) to estimate the structural performance of asphalt pavements from roughness data. Considering advantages of modern high-performance survey devices in the acquisition of road pavement functional parameters, it would be of practical significance if the structural state of a pavement could be estimated from its functional conditions. To differentiate various road section conditions, several significant input parameters, related to traffic, weather, and structural aspects, have been included in the analysis. The results are very interesting and prove that the ANN represents an adequate model to evidence this relation. The papers shows the effectiveness of the adoption of a large database for the analysis of the correlation. ANN provides also better results in comparison with Linear Regression. Further, the authors trained three different ANNs to analyse the effects of modified datasets and different variables. The numerical outcomes confirm that, by using this approach, it is possible to correlate with good accuracy roughness and structural performance, allowing road agencies to actually reduce the deflection test frequency, since they are generally more costly, time consuming, and disruptive to traffic than functional surveys.

1. Introduction

Assuring good conditions to the pavement allows users to drive with acceptable comfort and safety levels. However, in order to guarantee high quality standard, road agencies have to monitor the performance parameters of the entire network frequently and to adopt the most proper maintenance operations where needed. Indeed, continuous collection of new data regarding pavement conditions is a strategical operation to update Pavement Management Systems (PMSs) and optimize network maintenance and agency funds. Pavement performance parameters are also very numerous and diversified (structural and functional parameters). Since surveys to be performed are very different and numerous, this represents a very expensive and time-consuming task. Today it is relatively economical to perform roughness or distress measurements through high-speed profilometers or laser-lightning detection systems [31,29]. However, deflection data collection by means of Falling Weight Deflectometer (FWD) or Heavy Weight Deflectometer (HWD) is slow, with high unit costs, and adverse effects on traffic due to the stop-and-go procedure [14,26].

To overpass this limitation, many researchers have tried to analyse various performance indicator (roughness, distresses, structural capacity, etc.) and to identify some useful correlation among them [3,23,32,7,11]. In this way, it would be possible to estimate the value of some indices performing other surveys,

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reducing then the frequency of the slowest and most expensive ones. The most interesting and remarkable relationship should exist between roughness measurements and the pavement structural performance. It is known that roughness and irregularities are related to deterioration of the pavement structural capacity and, if a pavement structure is not designed adequately, roughness would increase quickly [26]. Moreover, attention should be paid on overlay and maintenance operations that can alter the relationship, since they can immediately reduce roughness, without improving the pavement structural capacity significantly. However, despite some research attempts, it is not easy to analytically develop this relationship. In a report for proposing a novel index describing structural adequacy, Zhang et al. [36] combined data to visualize a possible trend between some deterioration variables (including also ride quality) and structural parameters, but they did not establish any analytical relationship between them through linear regression or other mathematical methods. The most significant contribution on the topic was provided by an FHWA report [26], in which several highway sections were studied to find a numerical relationship between International Roughness Index (IRI) and Structural Number (SN). The researchers investigated a performance data set from the Long Term Pavement Performance (LTPP) program, but did not find any relationship neither in the parameter values nor in their change rates. They concluded that good ride quality does not mean good structural adequacy and that it is very hard to find a simple relationship between IRI and SN excluding most other factors. Bianchini and Bandini [6] suggested a Neuro-Fuzzy model for prediction of pavement performance (in terms of Pavement Serviceability Index) in Minnesota asphalt pavement roads, considering deflection and distress data, with acceptable results, but the study did not analyse directly the correlation between roughness and SN.

In this paper, the authors propose a different approach to attest the relationship existing between roughness and structural performance on asphalt pavement. In detail, analysing and combining a large set of data from the LTPP program, the authors have trained an Artificial Neural Network (ANN) to find an analytical and reliable correlation between roughness and structural capacity. Roughness has been measured using IRI, while the structural performance of the pavement has been evaluated through the effective SN (SN_{eff}). According to the procedure proposed in the AASHTO Guide [1], SN_{eff} has been calculated from deflection measurements. The ANN has been trained using a large data set of input parameters, to differentiate various scenarios and take into account numerous relevant aspects, such as traffic, weather, and structural conditions. In the paper, for more clarity, various networks are presented, considering several data samples and different groups of sections. For all the networks, training results and numerical validations are provided. In general, the numerical outcomes are useful to analytically demonstrate the connection between structural performance and roughness and the ANN resulted an adequate method for studying the problem, with better results than a classical linear regression approach.

2. Theoretical notes on ANNs

ANNs are recent computational models defined in analogy with the biological characteristics to simulate the decision process in the brain. They are useful to approximate and estimate unknown functions depending on various and numerous input values. One of the main characteristics of this approach is that it represents a way to solve very complex and nonlinear problems using only very simple mathematical operations [25,18]. In particular, ANN can be considered as a "black-box" approach, since the results are produced with no regards to the causal relationships between input and output [28]. The method potentiality is fully exploited when adopted for big data analysis and it can be used to develop generalized solutions to problems using large set of example data [15]. Like the brain, the ANN is made up of various interconnected neurons, which receive input, process the information, and produce output for other linked neurons.

Many papers presented application of ANNs in different areas of civil engineering with good results. Among all, ANNs were adopted for structural, construction, environmental, geotechnical and infrastructure engineering. Adeli [2] reviewed the ANN state of the art in the 90′s. Concerning the infrastructures, Ceylan et al. [10] presented a recent survey on ANN application in pavement engineering. Eldin and Senouci [13] proposed an ANN for rating highway pavement conditions, while Terzi [30] presented a model for predicting PSI considering distresses. Roberts and Attoh-Okine [27] used different kinds of ANNs to produce prediction of pavement performance in terms of IRI, while Kirbaş and Karaşahin [20] compared ANN to regression analysis and multiadaptive regression slides for determining pavement performance models in terms of PCI. Attoh-Okine [5] adopted an ANN model to evaluate pavement conditions from distresses grouping different relevant pavement condition variables, while Owusu-Ababia [22] suggested a procedure to estimate evolution of crackings. Plati et al. [24] adopted an ANN to evaluate pavement structural condition from FWD data. La Torre et al. [21] tried to predict roughness on highway pavements by means of ANN, but this technique can be also adopted for crack recognition [35]. Other interesting approaches in infrastructure engineering were proposed for the analysis of the factors influencing the compaction phase [4], for the evaluation of the driver's visual perception [8], for maintenance cost estimation and prioritization [16,9,33], for pavement friction management of airport runways [17], and for the aging analysis of asphalt binders [34].

Multilayer Feed-forward Neural Network (MFNN) is the most widely used type of ANN. An MFNN is characterized by three kinds of layers of interconnected neurons: input, hidden, and output layers (Fig. 1a). Each neuron processes the received inputs and, according to a properly defined activation function, produces an output (Fig. 1b) that is transmitted to neurons in the following layer through specific connections defining the network topology. Each connection is associated to a specific weight (w_i) that amplifies or reduces the input. For the single neuron, the relationship existing between inputs (x_i) and output (y_i) is defined using a specific transfer function that usually has the logistic sigmoidal shape (Eq. (1), Fig. 1c).

$$f(I) = \frac{1}{1 + e^{-I}} \tag{1}$$

where $I = \Sigma\, w_i\, x_i$ is the sum of the weighted inputs x_i produced by the previous neurons.

In a "supervised approach" – such as MFNN -, given a large set of input and output data, the training procedure consists in the modulation of the various weights to produce acceptable outputs. The results should be very similar to the output provided for training. Usually, the training phase is performed using a back propagation model [19,12] that allows the network to adjust the weights in a reverse direction, distributing the error among the various neurons and minimizing it after each iteration. Levenberg-Marquardt is the most used training algorithm and, generally, the error is evaluated in terms of Mean Square Error (MSE). If a set of N records is considered MSE can be evaluated using Eq. (2).

$$MSE = \frac{1}{N}\sum_{i=0}^{n}(e_i)^2 = \frac{1}{N}\sum_{i=0}^{n}(t_i - p_i)^2 \tag{2}$$

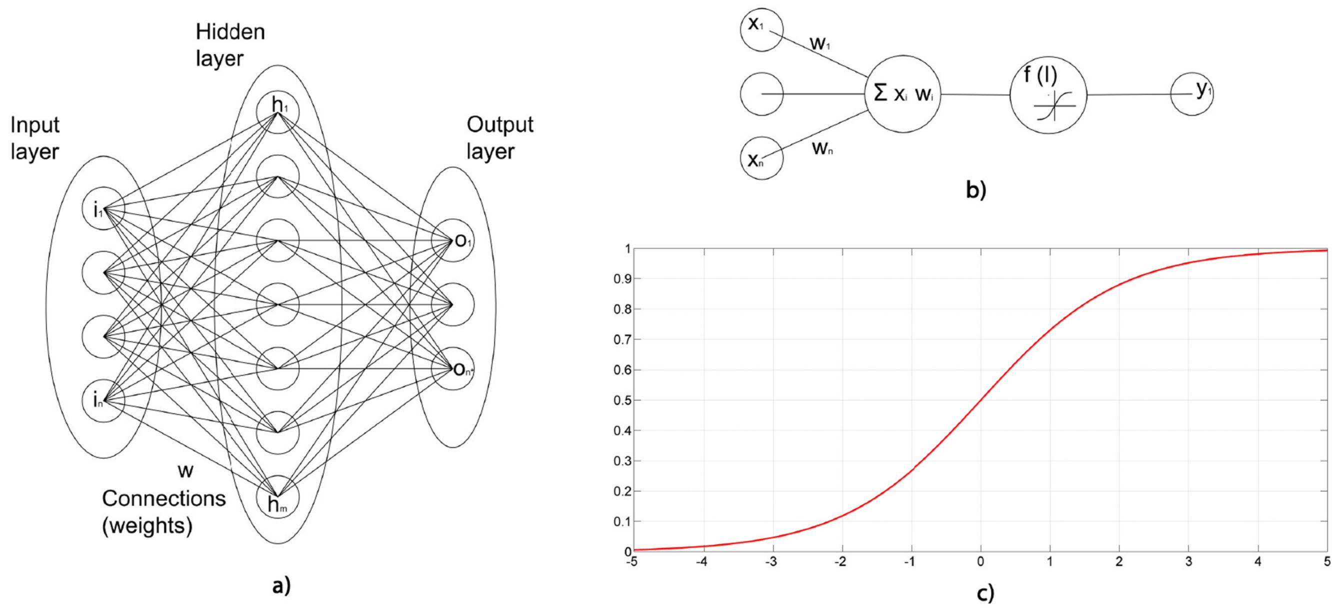

Fig. 1. a) Layers of a MLP ANN and network topology. b) Perceptron structure. c) Sigmoidal transfer function.

where e_i is the error for each set of input, t_i is the expected output, and p_i represents the output provided by the network.

3. Training database

Considering the aim of the research, in order to produce a general model and have enough examples for training the ANN, there has been a need of analysing a very large data set of highway sections. For this reason, the authors decided to derive the performance and structural information from the LTPP database. The LTPP program was established as a part of the Strategic Highway Research Program (SHRP) and has been widely used as a reference database for analytical model definition and validation ([21,23,32,26]. This database contains records on structural characteristics, monitoring, maintenance, climatic features, and traffic details for over 2500 test sections located in North-American highways for more than 25 years. The analysis has been focused on asphalt concrete (AC) pavements. Maintenance and rehabilitation operations have been excluded from the dataset – i.e. measurements have been considered for each section until the first maintenance operation was performed. This was useful to simplify the research, avoiding the introduction of further unknown relationships between the parameters. Networks have been trained using various parameters (in different combinations for different networks) related to the main aspects that affect structural performance and, thus, its relationship with roughness. The authors examined records related to 342 different test sections from almost all different LTPP states. They have been analysed, averaged, and combined to produce a reliable and exhaustive data set. Traffic and climatic measurements have been averaged by the number of observation years in the database, providing a specific and stable information for each section. In detail, the authors considered 13 different parameters, listed in the following:

a) Structural parameters:
   - pavement total thickness (H) in inches, including asphalt layers and eventual subbase;
   - asphalt layer thickness (H_a) in inches;

b) Traffic parameters:
   - average of annual ESALs (Equivalent Single Axle Load) in thousands in the LTPP lane (kE);
   - average of estimated annual average daily number of trucks in the LTPP lane (Tr);

c) Climatic parameters:
   - average temperature (T_m), i.e. the mean of the annual average temperatures on the selected section in Celsius degrees;
   - standardized temperature range ($T*$), as a measurement of the temperature oscillation; this parameter has been evaluated using Eq. (3), where T_{max} and T_{min} are respectively the mean values of the annual maximum and the annual minimum temperature in Celsius degrees;

$$T^* = \frac{T_{max} - T_{min}}{T_m} \tag{3}$$

   - average number of days with average annual temperature over 32° C in a year (D_{32});
   - average number of days with average annual temperature below 0° C in a year (D_0);

d) Performance parameters:
   - time passed (Y) since the first profilometer survey in years for each section;
   - first measured IRI for each section (IRI_0) – i.e. the IRI measured at year 0 -, as starting reference value;
   - IRI value at a specific time for each section (average of left and right wheel path IRI);
   - SN_{eff} at a specific time, according to the formulation provided by the AASHTO Pavement Design Guide (1993) as a function of deflection test measurements and pavement thickness, as explained in Section 3.1;
   - average pavement surface temperature (T_t) of the section during the deflection test phase in Celsius degrees.

Table 1 provides an example of records from the data set built for this research (the "Code" column represents "State Code" and "SHRP ID" form LTPP). After value checking and data validation, the authors selected 1021 total records. When pavement performance indices (IRI and deflections) were not collected at the same time, available IRI measurements were linearly interpolated for obtaining IRI values at a specific time Y (related to FWD tests), using the closest effective profilometer results. Table 2 show the variation ranges for all the selected parameters.

Table 1
Data set example.

#	Code	Y	H	H_a	Tr	kE	T_m	T^*	D_{32}	D_0	IRI_0	IRI	T_t	SN_{eff}
1	01_1011	0,6	16	2	166	42	15,5	0,83	42	71	0,841	0,841	28,6	4,1
2	01_1011	5,9	16	2	166	42	15,5	0,83	42	71	0,841	0,961	1,9	3,8
3	01_1019	0,5	12	4	193	93	18,9	0,68	72	33	1,373	1,395	27,7	2,9
4	01_1019	2,1	12	4	193	93	18,9	0,68	72	33	1,373	1,422	41,9	2,8
5	01_1019	7,6	12	4	193	93	18,9	0,68	72	33	1,373	1,763	12,9	2,7
6	01_1021	4,3	25	3	289	127	17,6	0,74	57	43	0,962	0,994	33,0	5,9
7	01_1021	8,7	25	3	289	127	17,6	0,74	57	43	0,962	1,150	17,3	6,2
8	01_4073	0,4	19	2	356	57	15,3	0,86	40	73	0,853	0,861	24,9	5,0
9	01_4073	2,4	19	2	356	57	15,3	0,86	40	73	0,853	0,891	30,4	5,0
10	01_4126	1,8	31	12	2396	629	15,6	0,88	46	72	0,815	0,836	24,7	8,1
11	01_4126	8,2	31	12	2396	629	15,6	0,88	46	72	0,815	0,995	14,9	8,3
12	01_4155	0,3	14	4	391	48	18,7	0,70	71	31	0,946	0,951	35,7	3,5
13	01_4155	1,1	14	4	391	48	18,7	0,70	71	31	0,946	0,955	40,0	3,5
14	01_4155	1,3	14	4	391	48	18,7	0,70	71	31	0,946	0,955	16,5	3,1
15	01_4155	7,7	14	4	391	48	18,7	0,70	71	31	0,946	1,061	22,5	2,9
16	01_6012	4,4	17	5	2141	606	17,7	0,72	69	45	1,192	2,116	36,5	4,6
17	01_6012	5,3	17	5	2141	606	17,7	0,72	69	45	1,192	2,422	32,6	4,3
18	01_6012	6,1	17	5	2141	606	17,7	0,72	69	45	1,192	2,481	26,5	4,4
19	02_1002	5,0	17	3	71	21	3,4	2,35	0	172	1,705	1,897	19,8	3,2
20	02_1002	7,9	17	3	71	21	3,4	2,35	0	172	1,705	1,528	30,8	3,2
21	04_1006	1,9	15	2	1980	2334	22,0	0,82	174	16	0,759	0,944	19,4	4,4
22	04_1006	3,2	15	2	1980	2334	22,0	0,82	174	16	0,759	1,120	49,1	4,1
23	–	–	–	–	–	–	–	–	–	–	–	–	–	–

3.1. Sn_{eff} calculation

In the research for the relationship between roughness and structural performance, deflection tests have been considered to evaluate the pavement structural adequacy. Directly involving the deflection values is not a proper choice, because the structural adequacy depends on many different parameters. Then, the authors have preferred to numerically describe the pavement structural performance in terms of SN. In detail, the AASHTO Guide [1] provided an accurate procedure for determining the SN_{eff} of an existing pavement using deflection test results, as a function of the total thickness of the pavement H (in inches) and the effective pavement modulus E_p (Eq. (4)).

$$SN_{eff} = 0.0045\mathrm{H}\sqrt[3]{E_p} \tag{4}$$

E_p can be calculated through an iterative procedure (Eq. (5)) considering the deflection (in inches) at center of load (d_0) corrected to 68 °F (20 °C), the pressure applied by the FWD plate in psi (p), the load plate radius in inches (a), the total thickness of the pavement in inches (H) and the subgrade resilient modulus in psi (M_R).

$$d_0 = 1.5pa\left[\left(\frac{1}{M_R\sqrt{1+\left(\frac{H}{a}\sqrt[3]{\frac{E_p}{M_R}}\right)^2}}\right)+\left(\frac{1-\frac{1}{\sqrt{1+\left(\frac{H}{a}\right)^2}}}{E_p}\right)\right] \tag{5}$$

M_R can also be evaluated using the FWD deflection results. Since at large distance from the load the deflections are due to the subgrade deformation only, it is possible to back-calculate the subgrade resilient modulus considering one deflection measurement only. In particular, if P is the applied load in pounds, d_r (in inches) is the deflection measured at a distance r (in inches) from the load, M_R can be calculated using Eq. (6).

$$M_R = \frac{0.24P}{d_r r} \tag{6}$$

In order to produce accurate results, d_r should be related to a sufficiently far geophone from the load. In practice, r is related to the radius of the stress bulb at the subgrade-pavement interface (a_r, in inches), as evidenced in Eq. (7).

$$r \geqslant 0.7a_r = 0.7\sqrt{\left[a^2+\left(H\sqrt[3]{\frac{E_p}{M_R}}\right)^2\right]} \tag{7}$$

Deflection at the center of the load vary with temperature, then d_0 has to be adjusted to a standard temperature of 68 °F (20 °C), using specific chart as function of effective temperature and of asphalt layer thickness. Fig. 2 represents different curves for the evaluation of the temperature adjusting factor, interpolated form those provided by the AASHTO Guide [1].

4. Numerical results

To evidence the relationship between IRI and SN_{eff} the authors have trained some specific ANNs. In particular, in order to underline various significant aspects, results of three different networks are presented in this paper. N_1 represents the reference network of the paper. For better studying the methodology potential, the authors have trained also networks N_2 and N_3. In particular, N_2 has been designed to evaluate results produced using a smaller and homogeneous sample, while N_3 has been considered to evalu-

Table 2
Parameter variation ranges.

#	Y	H	H_a	Tr	kE	T_m	$T*$	D_{32}	D_0	IRI_0	IRI	T_t	SN_{eff}
Min	0,0	6	1	6	1	2,4	0,3	0	0	0,575	0,000	−20,0	0,7
Max	21,9	46	20	6069	3093	25,4	4,8	174	232	3,184	4,034	56,8	14,4

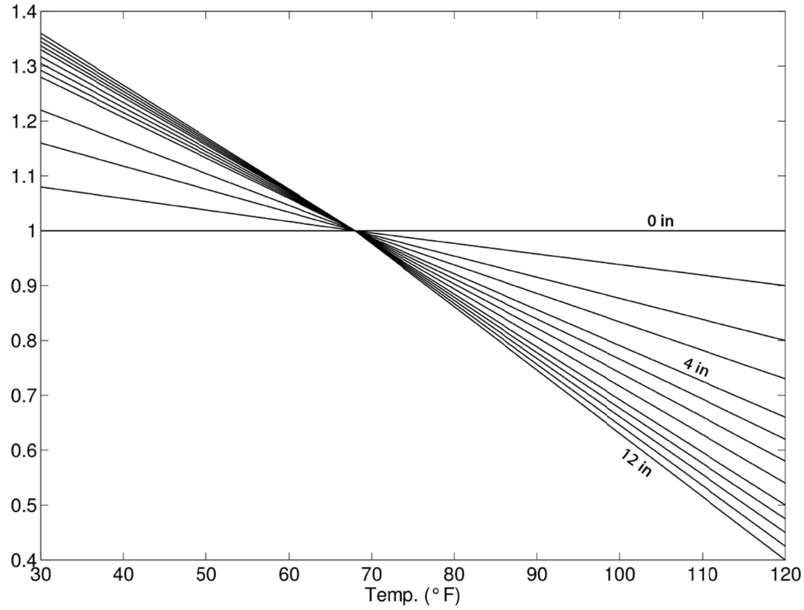

Fig. 2. Temperature adjusting factor for d_0 for granular and bituminous base.

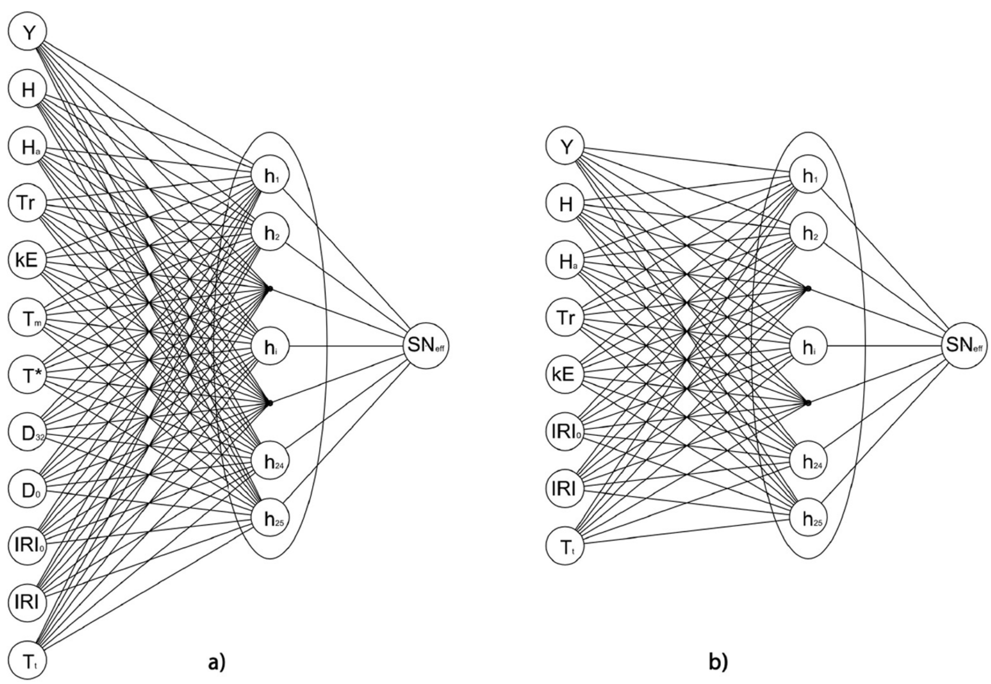

Fig. 3. Network architecture for N_1 and N_2 (a), N_3 (b).

ate changes in the accuracy due to the factors included in the network as input values.

The trained ANNs are listed in the following (for more clarity, Fig. 3 represents their network architecture):

- N_1: general network, with SN_{eff} as the target value; it includes all the available factors (12) for all the selected records (1021);
- N_2: records with similar T_m, with SN_{eff} as the target value; it was trained using only records with T_m between 15 °C and 25 °C (375 records) and all the available factors (12);
- N_3: no climatic factors, with SN_{eff} as the target value; it was trained using all the selected records (1021) using only structural, traffic, and performance factors (8); T_m, $T*$, D_{32}, and D_0 were not considered for N_3.

Each ANN contains 25 hidden neurons, and the related records were randomly divided in the training (70 %), validation (15 %), and test (15 %) groups. Trainings were performed using the Levenberg-Marquardt algorithm, measuring performance by means of MSE.

Fig. 4 represents the regression charts for N_1 for training phase (a), validation (b), test (c), and total sample (d). Fig. 5 shows the

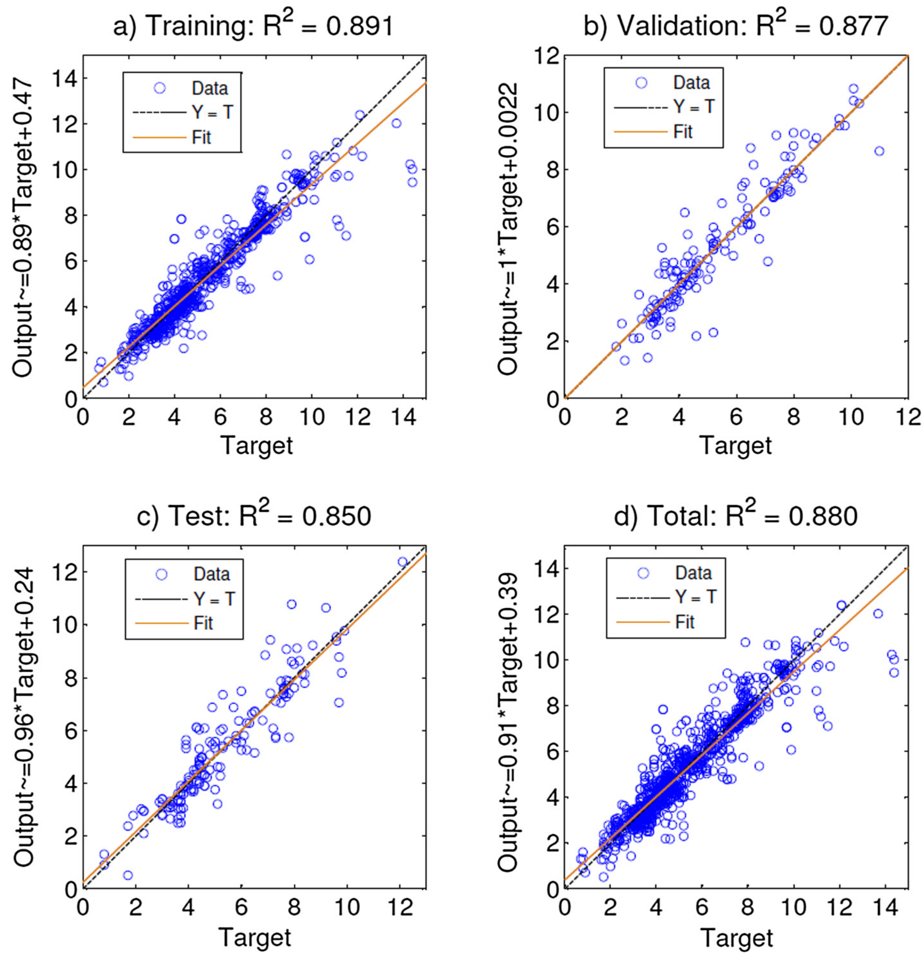

Fig. 4. Regression charts for N_1. a) Training sample; b) validation sample; c) test sample; d) total sample.

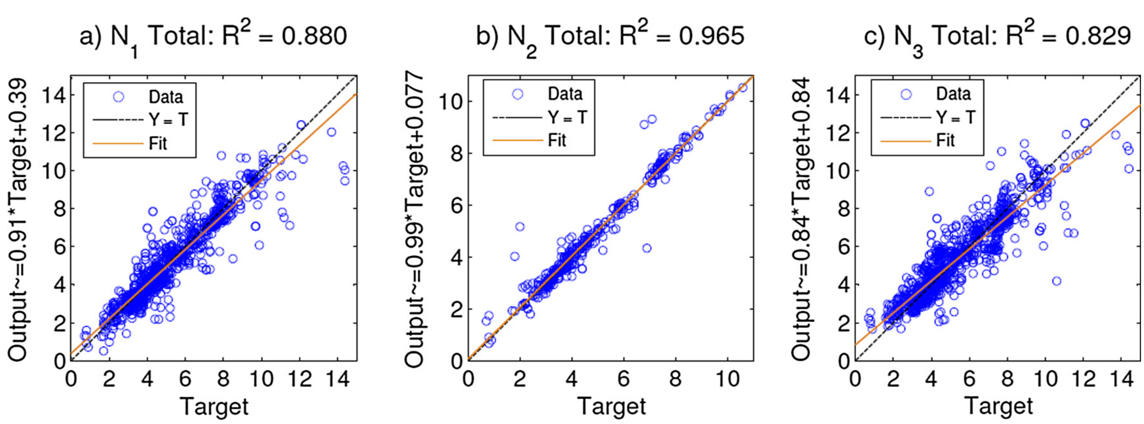

Fig. 5. Regression charts for N_1 (a), N_2 (b), and N_3 (c).

total regression chart for N_1, N_2, and N_3, while Fig. 6 provides the related error histograms. Finally, Table 3 lists all the performance results for the four ANNs.

5. Discussion

Numerical results presented in the paper are very worthwhile to validate the approach and prove the relationship between IRI and SN_{eff}. First, in order to better understand the outcomes produced by the ANN method, it is significant to represent the relationship between IRI and SN_{eff} (considering the 1021 records used for N_1 and N_3) on a regression chart (Fig. 7). As previously said, although both performance indicators should be strongly related from a theoretical point of view, nothing appears from this representation.

On the contrary, ANN approach has easily evidenced the correlation and results related to N_1 can numerically demonstrate this. As proved by the charts presented in Fig. 4, the same records combined with the other relevant parameters allowed the authors to

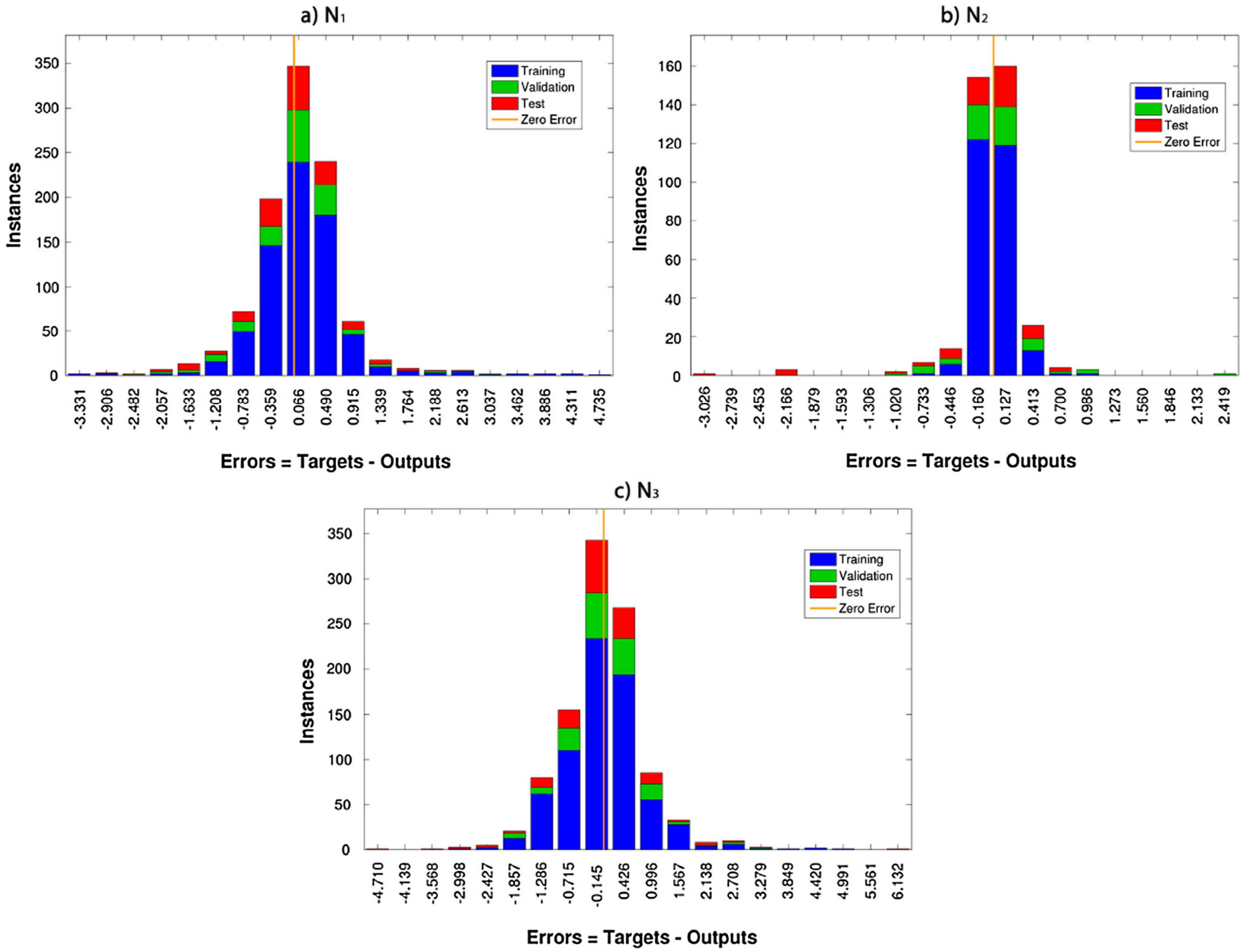

Fig. 6. Error histogram for N_1 (a), N_2 (b), and N_3 (c).

Table 3
ANN performance results.

Network	Factors	Phase	Records	MSE	R^2
N_1	12	Training	715	0.565	0.891
		Validation	153	0.560	0.877
		Test	153	0.701	0.850
		Total	1021	0.585	0.880
N_2	12	Training	263	0.033	0.992
		Validation	56	0.244	0.939
		Test	56	0.551	0.862
		Total	375	0.142	0.965
N_3	8	Training	715	0.721	0.851
		Validation	153	0.723	0.837
		Test	153	1.331	0.729
		Total	1021	0.813	0.829

obtain high accuracy in the structural performance estimation through ANN. The R^2 value is always higher than 0.85 for all the three samples (training, validation, and test), with an overall value of 0.88 and a peak for the training sample of almost 0.9. This is significant to prove the existence of the sought correlation. Moreover, the effectiveness of the method is further attested considering the MSE, which varies around 0.5, assuring great accuracy and precision, as confirmed also by Fig. 6a that shows a Gaussian shape for the error distribution with average almost equal to 0. For further validation, a Linear Regression (LR) model has been performed with the same records of N_1. Fig 8 compares the regression charts provided by the two approaches. As shown in Table 4, ANN can assure better results in terms of both R^2 and MSE values. Although some of the records have been used only for testing in the ANN approach, LR provides an R^2 value 20% lower than ANN, while the MSE for LR is more than two times larger than ANN. This evi-

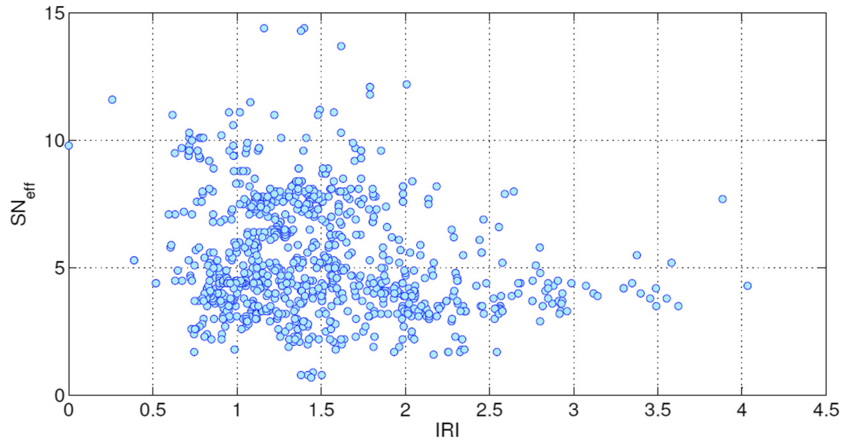

Fig. 7. Regression chart IRI/SN_{eff}.

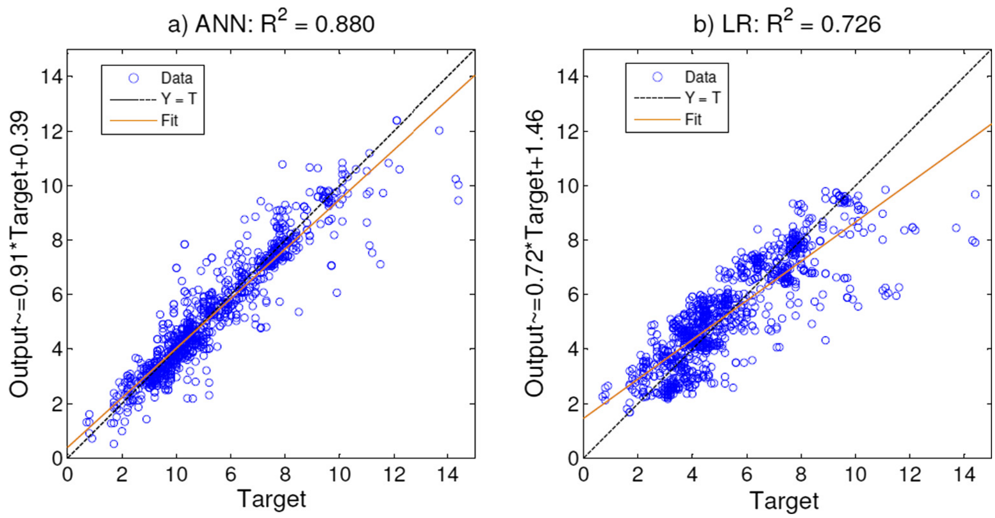

Fig. 8. ANN (a) vs LR (b) with N_1 records.

Table 4
LR vs ANN.

Model	Factors	Phase	Records	MSE	R^2
ANN	12	Training	715	0.565	0.891
		Validation	153	0.560	0.877
		Test	153	0.701	0.850
		Total	1021	0.585	0.880
LR	12	Total	1021	1.308	1.308

dences the advantages of the ANN method that can better generalize trends in noisy data and handle eventual non-linear behaviours. Then, Table 5 represents the correlation matrix of the different variables included in the analysis. Despite the obvious great influence of the total thickness on SN_{eff}, the influence of IRI is still evidenced.

Obviously, the authors believe that this is only a first step for studying the correlation between roughness and structural performance from a different perspective. Although the result is very interesting, they think it can be corrected and further improved. For simplifying future applications and evidencing advantages, limitations, and possible improvements of the method, the authors have trained networks N_2 and N_3.

In particular, N_2 has been designed to evaluate results produced using a smaller sample made up of more similar sections. As expected, considering only records from sections with similar climatic conditions (mean temperature between 15 °C and 25 °C), the ANN can produce more precise outcomes (Fig. 5b). Although only 36 % of records used for N_1 were considered for training and testing N_2, the accuracy significantly increased: the overall R^2 value is higher than 0.96 (with a peak for training of 0.992) and the overall MSE decreased from 0.585 to 0.142. Advantages related to the adoption of homogeneous sections can be evidenced also by analysing the error histogram reported in Fig. 6b, where more than 80 % of the errors are included in the two central bins (−0.160 and 0.127). This test proves that considering more homogeneous and

Table 5
Correlation matrix.

	Y	H	H_a	Tr	kE	T_m	T^*	D_{32}	D_0	IRI_0	IRI	T_t	SN_{eff}
Y	1,000	0,073	−0,050	−0,060	−0,129	−0,006	−0,019	−0,024	0,013	−0,136	0,047	0,119	0,074
H	0,073	1,000	0,032	0,146	0,050	−0,244	0,141	−0,252	0,229	−0,218	−0,216	−0,083	0,814
H_a	−0,050	0,032	1,000	0,182	0,231	−0,207	0,090	−0,235	0,214	0,100	0,106	−0,103	0,223
Tr	−0,060	0,146	0,182	1,000	0,770	0,130	−0,133	0,017	−0,134	−0,048	−0,018	0,080	0,201
kE	−0,129	0,050	0,231	0,770	1,000	0,082	−0,088	0,004	−0,085	−0,006	0,002	0,027	0,131
T_m	−0,006	−0,244	−0,207	0,130	0,082	1,000	−0,836	0,851	−0,964	−0,092	−0,107	0,378	−0,144
T^*	−0,019	0,141	0,090	−0,133	−0,088	−0,836	1,000	−0,603	0,835	0,082	0,124	−0,341	0,054
D_{32}	−0,024	−0,252	−0,235	0,017	0,004	0,851	−0,603	1,000	−0,767	−0,040	−0,043	0,305	−0,154
D_0	0,013	0,229	0,214	−0,134	−0,085	−0,964	0,835	−0,767	1,000	0,074	0,085	−0,361	0,144
IRI_0	−0,136	−0,218	0,100	−0,048	−0,006	−0,092	0,082	−0,040	0,074	1,000	0,825	−0,068	−0,189
IRI	0,047	−0,216	0,106	−0,018	0,002	−0,107	0,124	−0,043	0,085	0,825	1,000	−0,031	−0,203
T_t	0,119	−0,083	−0,103	0,080	0,027	0,378	−0,341	0,305	−0,361	−0,068	−0,031	1,000	−0,130
SN_{eff}	0,074	0,814	0,223	0,201	0,131	−0,144	0,054	−0,154	0,144	−0,189	−0,203	−0,130	1,000

similar samples can assure very high precision and, naturally, equal results can be obtained grouping similar data in terms of structure, weather, traffic, etc. Then road agencies may feed and train their own ANNs, including data from their own road sections and surveys, obtaining very accurate and productive structural performance estimations using roughness measurements and reducing frequency of deflection tests.

Another way to improve the method and the estimation accuracy is related to the factors included in the network as input values. Results can be easily affected by number and quality of considered factors and, especially, by their connection with the studied relationship. N_3 has been defined to prove this statement. For simplicity, reverse approach has been used; then, as shown in Fig. 3b, four of the previously considered factors have been excluded (the climatic variables) with the aim of produce worse numerical outcomes. Results listed in Table 3 and Fig. 5c prove this assumption. Despite the same number of records of N_1, excluding weather variables caused a remarkable decrease of accuracy. The R^2 value fluctuates around 0.8 (an overall value of 0.829, with a reduction of almost 0.05 compared to N_1). MSE raised up to 0.813 (overall value) with almost twice value for the testing phase, in comparison with N_1. (1.331 versus 0.701). Then, since excluding relevant factors as the climatic ones produced lower precision estimations, method accuracy can be affected by the quality and the characteristics of the considered factors. Consequently, future researches can improve the method including in the analysis other significant parameters (like raining variables, subgrade stiffness, etc.) and other performance indicators (as cracking, rutting, etc.) or increasing the accuracy of the considered ones (using different and more reliable equations).

Finally, it is important to underline that this kind of prediction model should be used in similar scenarios only. Adopting the trained ANN for different contexts and larger time periods certainly affects the estimation quality, reducing the result accuracy and reliability in a very significant way.

6. Conclusion

In this paper, the authors have proposed a different approach for finally evidencing in a clear and statistically accurate way the theoretical relationship between roughness and structural performance in asphalt pavements. Using a large data set from the LTPP database, the authors have trained an ANN to numerically estimate that relationship. In detail, combining parameters concerning structural characteristics, weather, traffic, and performance features, roughness has been correlated to results of deflection tests, examined in terms of SN_{eff}. The provided results show high accuracy both in the testing and in the validation phase. For more clarity and to better highlight the model efficiency, various ANNs have been defined in this paper, considering different groups of parameters or of road sections. The numerical application assess that ANN can effectively be used as a powerful tool for estimating structural performance using roughness data, especially if compared to LR. This achievement would be useful for estimating pavement structural condition where structural surveys are not available or not conducted regularly. Obviously, although IRI-SN_{eff} correlation seems to be reliable, deflection tests must not be avoided, since structural capacity needs to be directly assessed increase the model accuracy and verify – and eventually correct – structural performance predictions. However, this paper can represent only a preliminary approach to the problem and the model may be further enhanced. Further studies should include in the data set distress ratings collected through the innovative high-performance survey devices and more precise or different climatic and traffic variables. Training various sub-networks for more similar pavement types or climatic areas can also provide more reliable and significant analytical correlation to actually improve PMSs.

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