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Modelling the effects of flexible pavement distresses in the long-term pavement performance database on performance

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Highlights

- HMA pavement modeling with LTPP data
- Comparison of nonlinear regression analysis, MARS, and ANN approaches
- Developing the relationship between IRI and ten types of pavement distress
- Modelling performances are very close to each other

Abstract

Evaluating flexible pavement performance is mandatory for managing transport infrastructure. This study focuses on modeling the relationships between international roughness index (IRI) and a total of 10 types of pavement distress, including alligator, block, wheel path length, wheel path longitudinal, non-wheel path longitudinal, transverse crackings, patches, bleeding, raveling areas, and pumping. The data recorded under the Long-Term Pavement Performance was used to develop the models. Data sets covering General Pavement Studies from seven states of the United States were used in modeling. The study used modeling approaches, including nonlinear regression analysis, multivariate adaptive regression splines, and artificial neural networks (ANN), in which IRI was the dependent variable and pavement distress was the independent variable. In the developed models, 0.516, 0.623, and 0.684 regression coefficients values were obtained for nonlinear regression analysis, multivariate adaptive regression splines, and artificial neural networks approaches, respectively. The analysis results have determined that the artificial neural networks technique performs more successfully than the other techniques. The statistical error analyses of the root mean square error, Nash-Sutcliffe coefficient of efficiency, mean absolute error, and normalized root mean square error also showed that the same modeling approach performs more successfully. With these data generated from a universally used database, it has been determined once again that ANN is the most efficient mathematical approach in modeling the relationships between surface distresses and IRI.

Keywords: *International Roughness Index, Pavement Distress, Long-Term Pavement Performance, Distress Effect*

Information

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1. Introduction

Roads are one of the essential parts of a provincial's infrastructure for economic and social growth. Roads are necessary because they link different parts of the country together and make it easier for people and goods to move around. Every year, governments spend billions of dollars developing new roads and repairing and maintaining existing ones. Roads become more valuable as a country grows, especially if there are no other ways to get around, like railways or canals. The increase in annual expenses shows that coordinated efforts are needed to get the most out of these investments [1, 2].

The effectiveness and efficiency of several civil engineering structures mainly depend on their administration. This ensures that such constructions have a long lifespan, serve their intended purpose, and incur the lowest possible cost. A Pavement Management System (PMS) is a collection of planned and directed activities or procedures that maximize the Return on Investment (ROI) relative to the available budget [3].

The PMS is a structure for managing and maintaining roads based on statistical and mathematical methods. In the 1970s, when there were many more roads to keep track of, the idea of "pavement management" began. PMS was first described at the workshop organized in 1980 as a system that finds the best solutions at different

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levels of management and keeps pavements in a good state for use. For many years, many authorities, especially The American Association of State Highway and Transportation (AASHTO) and the Federal Highway Administration (FHWA), have been trying to establish and develop PMS in road networks of different scales [4, 5].

The pavement performance is an essential component of any PMS. The measurement, evaluation and prediction of performance are crucial in managing pavements. The term "deterioration" describes the reduction in the performance level of pavements over time. Road pavements will inevitably deteriorate over time due to axle loads transferred from vehicles, environmental effects, materials used and manufacturing quality. These various parameters contribute to the complexity of the operation. Using performance models, the status of the road at any given time can be approximately predicted [6, 7].

The predicted performance plays a significant role at both the management levels (network and project). The entire facility can be planned using performance models to justify the budget and resources. The planning and timing of maintenance work for specific projects depend on when a section falls out of service. This may be predicted with precision using performance models. In addition to the performance and interplay between the infrastructure facility and its user, formulating an acceptable transportation policy and evaluating its economic benefits depend on the performance and interaction [7].

The pavement's roughness can be considered a simple way to measure road users' satisfaction level and a significant indicator in determining the level of performance. It measures the road surface, ride quality, and comfort of drivers and passengers. Increases in pavement roughness are associated with higher fuel consumption, higher costs for car maintenance and repairs, higher emissions of greenhouse gases, and reduced vehicle efficiency. It might cause traffic safety problems that cost millions of dollars annually to repair. The International Roughness Index (IRI) is a universally accepted parameter to quantify pavement roughness, measured with automated, multifunctional measuring devices or tools [8, 9].

Similar studies recorded in the literature can be summarized as follows. Al-Omari and Darter [10] investigated the correlations amongst them IRI, present serviceability rating (PSR), and several pavement distress types, including rutting, deformations, potholes, and cracks. The Long Term Pavement Performance (LTPP) database data were used in their study. Mactutis et al. [11] studied the relationship between distress and roughness using WesTrack Project data. In this study, a correlation was found between the IRI and the initial IRI of the pavement, the extent of fatigue cracking and the average rut depth. Reportedly, the initial IRI has a significant impact on roughness. Fatigue cracks are very sensitive to roughness, but ruts are not so sharp. Dewan and Smith [12] investigated how pavement distress can be used to calculate vehicle operating costs (VOC) directly. They collected data from the California LTPP sites to establish a relationship between IRI and pavement distress. The correlation was determined on the basis of 39 observations at 15.2 m intervals along a 152.4 m test section. However, Lin et al. [13] studied the capability to estimate IRI from pavement distress collected from pavement videos and photos of a camera sited on an Automated Road Analyzer (ARAN) vehicle. 125 road sections, each section 1-kilometer-long of Taiwan's provincial highways and country roads, were surveyed for data collection. This investigation discovered and examined relationships between 10 different distress types. In addition, some analyzes were made in the study on using IRI to measure the correlation between pavement distress severities and types. Aultman-Hall et al. [14] analyzed the correlations between IRI, cracking, and rutting. This research aimed to determine whether these correlations were able for IRI, the more easily measurable variable, to be substituted for the others. The findings showed that although there are statistically significant correlations between cracking, rutting and IRI, these correlations are insufficient for IRI to substitute pavement conditions.

Besides, Hozayen and Alrukaibi [15] presented a methodology for establishing acceptance criteria determining the performance levels to manage pavements. In their studies, they conducted performance tests on rural roads to learn more about surface roughness and pavement distresses. The overall length of this road is 572 kilometres; it has been divided into three segments 390 kilometres, 139 kilometres, and 43 kilometres. The results showed a regression relationship between raveling and roughness for the three roadway segments, with the coefficient of determination (R2) varying from 0.946 to 0.962. Prasad et al. [16] created a model correlating PMGSY road pavement distress with roughness in India. Data concerning pavement distress were obtained at regular intervals of 50 meters. Bump Integrator, calibrated using MERLIN, was used to collect roughness data. Based on the data obtained in the field, a regression equation was created with the IRI and the visual distresses. The maximum value of the determination coefficient (R2) was 0.66. Also, Meegoda and Gao [17] studied the GPS test section roughness data given in the LTPP database over time to create a model that estimates how pavement roughness would change as the pavement ages. They created and normalized a computable correlation between IRI progression, traffic loads transferred to the pavement, structure number, and climatic area. They created a scale of one to five performance levels to quantify the degree of deterioration of asphalt pavements.

Kirbas et al. [18] investigated the correlation between pavement distress and roughness in flexible pavements. It has been shown that a specific amount of surface distress affects the IRI. A mathematical modeling analysis of the correlations between IRI and 32 distresses with 13 surface distress types, and severities was implemented in their models. The modeling techniques included linear regression, multivariate adaptive regression splines (MARS), and artificial neural networks (ANN). It has been confirmed that the ANN technique is the most accurate. Also, Kirbas et al. [19], in another study, created a pavement performance estimation model that estimates the performance of hot mix asphalt (HMA)-coated provincial roads and state highways under the authority of the General Directorate of Highways (KGM) over the next several years. An empirical equation expressing the relationship between PCI and IRI is also proposed in the study.

Reviewing the literature, Chandra et al. [20], Sandra and Sarkar [21], Mubaraki [22], H Joni et al. [23], Yu Qiao et al. [24] and many more researchers seem to have developed mathematical models that determine the relationships between IRI and surface distress. It is understood that many modeling approaches, such as linear and nonlinear regression models, ANN, fuzzy logic, and MARS, are used to develop models in research. Notably, studies have frequently investigated the relationship between IRI and seven types of deterioration, including potholes, raveling, rutting, cracking, patching, corrugation, and depression. In the models generated, performances up to 0.986 were obtained as the determination coefficient (R2).

The LTPP database collects climate, traffic and performance data on over 2500 road sections. Data entries into this database are made randomly due to the field operators' work plans. While some data can be entered annually, others are entered in the study plans every 2 or 3 years. In addition, overlapping data stacks seasonally is quite troublesome. In this study, special efforts were made to ensure that the data collection dates for each surface disturbance and IRI data evaluated were close to each other. The data stack was prepared carefully, considering the date and significance of each data used in modelling and the climate situation at the time of measurement. In this way, a data set suitable for modelling was obtained. In the literature, it is clearly seen that the similarity values are low in studies that utilize the LTPP database, but the dataset is not created with similar precision. In addition, as seen in other studies of the authors of this study, the ANN method has once again been proven to be the most suitable technique for investigating the relationships between surface distortions and IRI.

There are many studies in the literature that investigate the effects of distress that negatively affect driving comfort on IRI and model the relationships. Also, it is seen that there are limited studies that evaluate the types of distress by considering the severity levels such as low, medium and high. Kumar et al. [6], Prasad et al. [16], Meegoda and Gao [17], and similar studies do not consider the severity levels of pavement distress types. On the other hand, it is understood that one or two types of modeling techniques are frequently evaluated in the investigation of relationships. It is noteworthy that in Shrestha and Khadka [9], Al-Omari and Darter [10], Qiao et al. [24] and similar studies, only one or two techniques were used to investigate the similarities between pavement deterioration and IRI. In terms of the modeling techniques evaluated, there are hardly any studies using three or more methods. With many studies conducted today, it has become clear which parameters affect the estimation of the service level provided by pavements to road users. It is now understood that the research topic focused on is the correct selection of the modeling approach to be used in developing relationships. For this reason, using many techniques in researching relationships and bringing their comparative results to the literature will undoubtedly provide convenience to researchers in solving the problems. Within the scope of this study, the relationships between IRI and a total of 22 independent variables at different severity levels were investigated in 10 various distresses, alligator cracking, block cracking, wheel path longitudinal cracking, non-wheel path longitudinal cracking, transverse cracking, patches area, bleeding area, raveling area, pumping and bleeding, and wheel path length crack, and 6 of them were low, medium and high severity levels, using LTPP data. Three techniques, Nonlinear Regression Analysis, MARS and ANN, were used to investigate the relationships. The working principle established in the study can be seen in the flowchart in Figure 1.

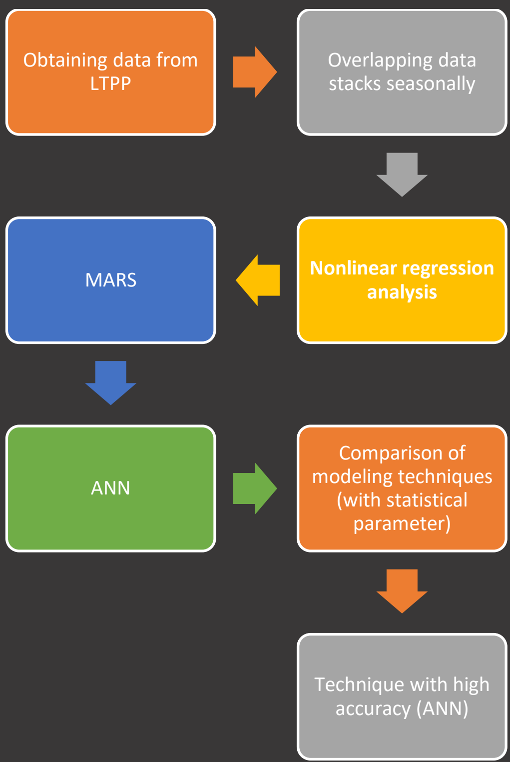

Figure 1. Flowchart of the study

2. Introduction

2.1. Long term pavement performance (LTPP)

The LTPP programme, which has collected data from more than 2581 road segments in the United States and Canada over the past 33 years, is the largest pavement performance research programme. The goal of the LTPP programme is to monitor the performance of pavements in these sections over the long term. The data collected includes information about construction, pavement structure, material quality, maintenance and rehabilitation activities, pavement conditions, pavement loading, and environmental conditions. The LTPP database was developed to record the pavement's characteristics, condition, maintenance activities and reconstruction projects over some time. Each road in the database has a section number indicating where it is located, what material it is made of and how thick the structure is.

Utilizing the LTPP database by the Federal Highway Administration (FHWA) is the principal means for amassing and scrutinizing pavement-related information within the United States and Canada. The LTPP program exhibits a broad reach, enabling the assessment of a pavement's extended-term effectiveness in diverse loading and environmental circumstances. Its objective involves identifying how loading, environment, material characteristics, fluctuations, construction quality, and maintenance levels influence the deterioration and functionality of pavements. Furthermore, it endeavours to enhance design methodologies and strategies and formulate equations that facilitate the rehabilitation of existing and newly constructed pavements [25, 26].

The LTPP database is designed so that users can easily access data from many modules, e.g. inventory, maintenance, monitoring, remediation, materials testing, transport and climate. Within the LTPP program, two distinct categories of experiments are incorporated: general pavement studies (GPS) and specific pavement studies (SPS). These experiments encompass different research approaches and objectives to investigate and analyze various aspects of pavements comprehensively. The general pavement studies (GPS) entail a broader scope, aiming to understand and evaluate pavements' overall performance and behavior under diverse conditions. In contrast, specific pavement studies (SPS) concentrate on more focused research inquiries, targeting particular aspects or phenomena within pavement systems; by combining GPS and SPS, the LTPP program endeavours to provide a comprehensive understanding of pavements, encompassing their overall performance and specific factors and phenomena that influence their functionality and deterioration.

Access to the LTPP data is available through both online and offline means. Starting from March 2003, the online LTPP data have been accessible via the http://www.infopave.com website. This study uses data from the LTTP InfoPave website [26].

2.2. Data collection

The LTPP database is this study's main data source, containing data up to 2023. The LTPP database's accuracy is acceptable and has been used in several studies. The LTPP data set consists of a classified collection of information from different types of pavement. The data collection includes comprehensive details on the types of pavement, the environment, traffic, maintenance, and rehabilitation. Therefore, LTPP sites located in Arizona, Florida, Minnesota, Mississippi, North Carolina, Oklahoma, and Tennessee from seven states of the United States have been selected to obtain the necessary data according to specific criteria [26].

The LTPP InfoPave website's 'Data' tab was used to obtain the data. A filtering tool allows the selection of only the relevant data. Data was selected, then extracted into a Microsoft Excel file that could be downloaded. In this study, the extracted Excel file for both the IRI and distress tables had the same fields, such as State_Code, SHRP_ID, Survey_Date, and Construction_Number. In this study, the distress data used were obtained from the LTPP table MON_DIS_AC_REV, and IRI data from the LTPP table MON_HSS_PROFILE_SECTION, respectively, and downloaded from the LTPP InfoPave website.

This research selected asphalt concrete pavement on a granular base (GPS-1) and asphalt concrete pavement on a bound base (GPS-2) test sections because these are commonly constructed pavement types. 102 LTPP test sections were selected from GPS–1 and GPS–2, as shown in Table 1. We consider only asphalt concrete (AC) pavements that did not undergo maintenance or rehabilitation at the measurement time. The data collection step was then started. The performance of pavements captured in the LTPP database can be influenced by numerous factors, which can be categorized into four primary domains: structure, climate, traffic, and performance. However, this study selected some factors considered the most important to pavement performance problems, especially the IRI and pavement distress.

Table 1. Presents the final number of test sections in each LTPP state for GPS-1 and GPS-2 pavements

State Code	State Name	Section Total
4	Arizona	17
12	Florida	20
27	Minnesota	13
28	Mississippi	13
37	North Carolina	16
40	Oklahoma	10
47	Tennessee	13
	Total Sections	102

The primary aim of this study is to construct empirical models capable of predicting the behavior of flexible pavements in granular base sections. A multitude of internal and external factors can influence the formulation of the pavement performance model. When constructing or evaluating pavements, it is crucial to take these factors into account to anticipate the long-term functional and structural conditions of the pavement.

The selection of independent variables is determined by considering the structure and accessibility of the LTPP data, its limitations, previous research utilizing the LTPP data, as well as engineering knowledge and expertise. Therefore, the independent variables used for this study are Alligator Cracking (Low), Alligator Cracking (Medium), Alligator Cracking (High), Block Cracking (Low), Block Cracking (Medium), Block Cracking (High), Wheel Path Longitudinal Crack (Low), Wheel Path Longitudinal Crack (Medium), Wheel Path Longitudinal Crack (High), Non-Wheel Path Longitudinal Crack (Low), Non-Wheel Path Longitudinal Crack (Medium), Non-Wheel Path Longitudinal Crack (High), Transverse Crack (Low), Transverse Crack (Medium), Transverse Crack (High), Patches (Low), Patches (Medium), Patches (High), Bleeding Area, Raveling Area, Pumping and Bleeding Length, Wheel Path Length Cracked. The designated dependent variable is the International Roughness Index (IRI).

3. Research Analysis Results

Pavement performance modeling is an essential part of the pavement management system (PMS), which aims to accurately estimate the requirement for pavement maintenance, rehabilitation, or reconstruction. These models estimate how the pavement will be in the future so that maintenance treatments can be made better, and we can see how maintenance operations might affect the future condition of the pavement. Improving the prediction accuracy of estimating methods would result in a more efficient allocation of financial resources, substantial cost savings, and the systematic selection of various maintenance treatments. Researchers have made several models that can predict how well flexible pavements will work using data from extensive experiments in different parts of the world.

The main goal of this study is to use LTPP data from seven states of the United state (Arizona, Florida, Minnesota, Mississippi, North Carolina, Oklahoma, and Tennessee) to build empirical pavement performance models. The relationship between the dependent variable IRI and the independent variable, pavement distress, was studied using regression analysis. In order to identify the best model, regression analysis used three techniques: Nonlinear Regression Analysis, MARS, and ANN.

3.1. Nonlinear regression analysis

Regression analysis is commonly used to estimate the dependent variable given the values of the independent variables. The regression function, which is a function of the independent variables, is the estimation target. Mainly, regression analysis explains how the mean value of the dependent variable changes due to changes in the independent variables. Essential goals of regression analysis include fitting the model to the data and determining the model's adequacy. The quality of the fit is evaluated, resulting in either modification of the model or adoption of the model. Regression analysis is a set of statistical approaches for determining how a dependent variable relates to one or more independent variables. There are three most common types of regression analysis, linear, multiple linear, and nonlinear regression. Most models are either linear or nonlinear. Nonlinear regression analysis is frequently applied to more complex data sets where the relationship between the dependent and independent variables is nonlinear. Linear regression models have parameters that look like they move in a straight line, while nonlinear regression models have at least one parameter that moves in a way that does not look like a straight line. In general, engineering models are nonlinear models. This is because the response of some variables is nonlinearly dependent on the implementation of some independent factors. Nonlinear regression analysis was used to develop the relationship between the international roughness index as a dependent variable and pavement distress as an independent variable, which is the main goal of this research. The Statistical Product and Service Solutions (SPSS) program develops the nonlinear regression model [3, 27].

This study used data from the General Pavement Studies (GPS-1 and GPS-2) to choose 102 test sections to be analyzed. With the help of nonlinear regression analysis modeling, the mathematical relationship between the IRI and 10 types of pavement distress was studied. There are six types of pavement distress, including Alligator Cracking, Block Cracking, Wheel Path Longitudinal Crack, Non-Wheel Path Longitudinal Crack, Transverse Crack, and Patches area with three severity levels: low, medium, and high, and four types of pavement distress have a single severity level, including Bleeding Area, Raveling Area, Pumping and Bleeding Length, Wheel Path Length Cracked. The nonlinear regression analysis was developed at a 0.05 significant level to create the model. The results of the nonlinear regression analysis are shown in Tables 2 and 3.

Table 2. ANOVA results

ANOVA			
Source	Sum of Squares	df	Mean Squares
Regression	1145.772	23	49.816
Residual	142.054	614	0.231
Corrected Total	293.451	636	

Table 3. Model summary

R	R^2	Adjusted R^2
0.718	0.516	0.497

The above result was obtained using the SPSS software and nonlinear regression analysis. Table 3 and Figure 2 summarizes the created model, including the correlation coefficient (R), determination coefficient (R2), and adjusted determination coefficient. The ANOVA table is shown in Table 2.

The dependent variable in the model is the international roughness index, while the independent variable is pavement distress. It is mathematically formulated as Equation (1).

$$IRI=\left[\begin{array}{c} 0.972\text{+Alligator Cracking (L)}\times 6.115E\text{-}5 \\ \text{+Alligator Cracking (M)}\times 0.001 \\ \text{+Alligator Cracking (H)}\times 0.001 \\ \text{+Block Cracking (L)}\times 0.001 \\ \text{+Block Cracking (M)}\times 0.002 \\ \text{+Block Cracking (H)}\times 0.001 \\ \text{+Wheel Path Longitudinal Crack (L)}\times 0.003 \\ \text{+Wheel Path Longitudinal Crack (M)}\times 0.004 \\ \text{-Wheel Path Longitudinal Crack (H)}\times 0.029 \\ \text{-Non Wheel Path Longitudinal Crack (L)}\times 0.001 \\ \text{-Non Wheel Path Longitudinal Crack (M)}\times 0.001 \\ \text{+Non Wheel Path Longitudinal Crack (H)}\times 0.001 \\ \text{+Transverse Crack (L)}\times 0.002 \\ \text{+Transverse Crack (M)}\times 0.004 \\ \text{+Transverse Crack (H)}\times 0.025 \\ \text{+Patches Area (L)}\times 0.014 \\ \text{+Patches Area (M)}\times 0.040 \\ \text{+Patches Area (H)}\times 0.009 \\ \text{+Bleeding Length}\times 0.001 \end{array}\right] \quad (1)$$

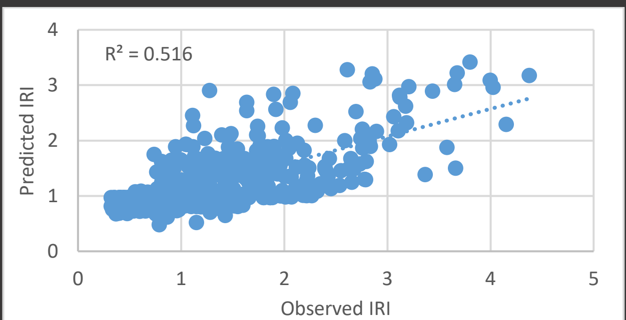

Figure 2. SPSS model prediction accuracy

3.2. Multivariate adaptive regression splines (MARS)

Multivariate Adaptive Regression Splines (MARS) is also known as the MARS method, which comes from the four letters of its name. Friedman was the first to propose this method [28]. MARS is a non-parametric technique that makes no assumptions about the basic functional relationship between dependent and independent variables. However, it develops a dynamic relationship between cause-effect variables. The MARS technique investigates the relationships between each independent variable and the dependent variable and the interactions between independent variables. It shows the effect of the interactions between all independent variables on the dependent variable. The results of the technique vary based on the number of degrees and modeling terms used [18, 28].

Consequently, it is essential to accurately select these parameters to perform the most effective model analysis. The MARS algorithm is established on the principle of linear partial function expansion with truncation. This situation is represented by Equation (2).

$$[+(X-\tau)]_+,[-(X-\tau)]_+=[q]_+,[q]_+ \quad (2)$$

Where [q]+ stands for the expression "max (0, q)", and τ stands for a knot with a single variable. The MARS algorithm investigates the relationships between each variable and the locations of knots (nodes) in all feasible partial linear representations [29]. The technique closely follows curve-fitting techniques. The MARS technique has the general form shown in Equation (3).

$$y=\beta_0+\sum_{j=1}^{P}\sum_{b=1}^{B}\left[\begin{array}{c}\beta_{bj}(+)Max\left(0,X_j-H_{bj}\right)+\\ \beta_{bj}(-)Max\left(0,H_{bj}-X_j\right)\end{array}\right] \quad (3)$$

Where P represents the independent variable, and B represents the basic function. These two univariate equations express the basic functions max (0, x− H) and max (0, H − x), and if the β coefficients are 0, just one equation is required. The H values are known as "knots." In contrast to regression analysis, this approach separates the data sets into regions by knots and can deactivate the independent variables under specific conditions and within specified limits. Therefore, it is possible to avoid the occurrence of meaningless result (estimation) values by using the independent variables with extreme values as the model inputs. This has been seen as an important advantage of the MARS approach [18, 30].

The MARS technique uses a stepwise regression process to eliminate basic functions that decrease the model's prediction performance while using a step-by-step progression procedure to investigate the model constants for these basic functions and identify the knots. The generalized cross-validation criterion (GCV) calculates the knot adjustment metric. The GCV criteria are calculated by multiplying the mean residual error by a penalty that is compensated for the variability brought on by the prediction of additional model parameters [31- 33]. GCV formula shown in Equation (4).

$$GCV=\frac{1}{n}\,\frac{\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2}{(1-P(M)/n)^2} \quad (4)$$

This study used data from the General Pavement Studies (GPS-1 and GPS-2) to choose 102 test sections to be analyzed. With the help of the Multivariate Adaptive Regression Splines (MARS) modeling approach, the mathematical relationship between the international roughness index (IRI) and 10 types of pavement distress was studied. There are six types of pavement distress, including Alligator Cracking (AC), Block Cracking(BC), Wheel Path Longitudinal Crack (WPLC), Non-Wheel Path Longitudinal Crack (NWPLC), Transverse Crack (TC), and Patches area (PA) with three severity levels: Low (L), Medium (M), and High (H), and four types of pavement distress have a single severity level, including Bleeding Area (BA), Raveling Area (RA), Pumping and Bleeding Length (PBL), Wheel Path Length Cracked (WPLC). A prediction model was developed between IRI and pavement distress. The mathematical model is shown in Equation (5).

$$IRI=\begin{bmatrix} 2.8704736 + 0.0190581 \times BF1 \\ -0.0517728 \times BF2 - 0.0019054 \times BF3 \\ -0.0042911 \times BF4 - 0.0285172 \times BF5 \\ -0.0212036 \times BF6 + 0.0020690 \times BF7 \\ +0.0073641 \times BF8 - 0.0036871 \times BF9 \\ -0.0262217 \times BF10 + 0.0130658 \times BF11 \\ -0.0137322 \times BF12 + 0.0018260 \times BF13 \\ -0.0031871 \times BF14 + 0.0339321 \times BF15 \\ -0.0136603 \times BF16 - 0.0384471 \times BF17 \\ +0.0074482 \times BF18 - 0.0216615 \times BF19 \\ +0.0061849 \times BF20 + 0.0291398 \times BF21 \\ +0.0279002 \times BF22 + 0.0247000 \times BF23 \\ +0.0010227 \times BF24 - 0.0028995 \times BF25 \\ -0.0025667 \times BF26 + 0.0033225 \times BF27 \\ +0.0123699 \times BF28 - 0.3345593 \times BF29 \\ +0.0962880 \times BF30 - 0.0231241 \times BF31 \\ +0.0056054 \times BF32 \end{bmatrix} \quad (5)$$

The mathematical model has 32 basic functions, 22 independent variables, and only one dependent variable. A GCV error of 0.215327 and a threshold of 0.0005 were used to conduct the model analysis. The model's variables are represented by basic functions (BF), which are shown in Table 4.

The regression coefficient (R^2) for this model, which measures how well it can predict, was found to be 0.623109. This model's regression coefficient is 0.623109, which indicates that 62.3% of the IRI variation can be related to the variance of pavement distress. Table 5 shows the statistical regression values of the developed model. The IRI values measured and estimated through the model are comparatively shown in Figure 3.

3.3. Artificial neural networks (ANN)

Artificial Neural Networks (ANNs), or simply neural networks, are one of the intelligent modeling approaches for processing information that may be used for analyzing the interactions among the variables. It is a generalized mathematical model that works like the human brain, which is composed of interconnected neurons of the organic nervous system [34]. In 1943, McCulloch and Pitts introduced the concept of artificial neural networks, but until 1986 when Rumelhart et al. developed the backpropagation algorithm, ANNs gained wide acceptance. ANNs are one of the most popular Artificial Intelligence (AI) approaches.

Table 4. Basic functions used in the MARS model

BF1 = max (0; TC – H – 7.0999999)
BF2 = max (0; 7.0999999 - TC – H)
BF3 = max (0; AC – M - 165.3000031)
BF4 = max (0; 165.3000031 - AC – M)
BF5 = max (0; WPLC – L - 29.8999996)
BF6 = max (0; 29.8999996 - WPLC – L)
BF7 = max (0; BC – M - 114.8000031)
BF8 = max (0; 23.2999992 – NWPLC – L)
BF9 = max (0; P&BL - 17.0000000)
BF10 = max (0; 17.0000000 - P&BL)
BF11= max (0; PA – L - 0.0000000)
BF12 = max (0; NWPLC – H - 150.3999939)
BF13 = max (0; BC – H - 0.0000000)
BF14 = max (0; 155.1999970 – BC – L)
BF15 = max (0; PA – M - 0.0000000)
BF16 = max (0; TC – M - 8.8999996)
BF17 = max (0; 8.8999996 – TC – M)
BF18 = max (0; PA – H - 0.0000000)
BF19 = max (0; WPLC – H - 0.0000000)
BF20 = max (0; 122.0000000 – AC – L)
BF21 = max (0; TC – M - 31.2999992)
BF22 = max (0; WPLC – L - 43.5999985)
BF23 = max (0; 8.5000000 – WPLC – M)
BF24 = max (0; 248.0000000 – NWPLC – M)
BF25 = max (0; WPLC - 133.6000061)
BF26 = max (0; 133.6000061 - WPLC)
BF27 = max (0; TC – L - 55.2000008)
BF28 = max (0; NWPLC – H - 115.0999985)
BF29 = max (0; WPLC - 302.7999878)
BF30 = max (0; WPLC - 294.2000122)
BF31 = max (0; TC – M - 63.9000015)
BF32 = max (0; AC – L - 31.2999992)

Table 5. IRI Prediction Model Regression Statistical Values

Regression Statistics	IRI
Mean (observed)	1.249411
Standard deviation (observed)	0.679265
Mean (predicted)	1.249411
Standard deviation (predicted)	0.536193
Mean (residual)	0.000000
Standard deviation (residual)	0.417011
R-square	0.623109

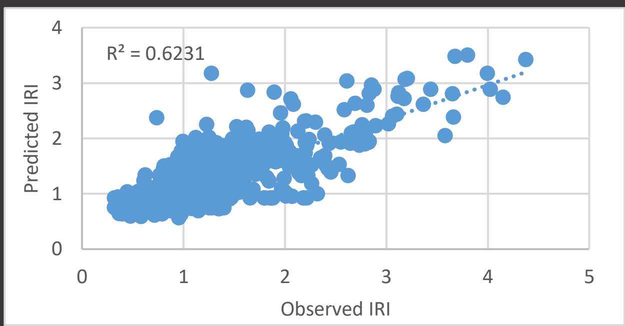

Figure 3. MARS model prediction accuracy

AI can be described as the study or process of teaching machines to learn on their own. Artificial intelligence aims to construct machines that work like the human brain and can "think." ANN models are commonly used for prediction and analysis. Even if the sample size is relatively small, models based on artificial neural networks (ANNs) can be used in complicated systems with multiple interrelated variables. It provides the necessary information by analyzing the stored data. Artificial neural networks (ANNs) copy the human brain using a computer and mathematical processing [20].

ANNs are mathematical systems made up of several neurons connected to one another and have weights assigned to them. An equation commonly referred to as a transfer function is a processing unit. This processing unit gathers and mixes data from other neurons before producing a numerical output. Process units are interconnected in a network and resemble actual neurons. Neural networks are composed of these patterns [19].

The basic structure of an ANN model is usually made up of three layers: the input layer, where known data is added to the model; the hidden layers; and the output layer, where the result of the last search is found. Each layer comprises different parts, called neurons or nodes, with a transfer function connecting it to the layer below it. The number of hidden layers is theoretically unlimited; it should be mentioned [35].

Consider that there are (n) number of input variables in the input node (xi, i = 1, 2,..., n), (p) number of nodes in the hidden layer (zj, j = 1, 2,..., p), and (k) the number of output variables in the output node (ym, m = 1, 2,..., k). The ANN model can be described in Equations (6) and (7).

$$\hat{y}_m = f_y\left(\textstyle\sum_{j=1}^{p} z_j W_{kj} + b_k\right) \tag{6}$$

$$z_j = f_z\left(\textstyle\sum_{i=1}^{n} x_i W_{ji} + c_j\right) \tag{7}$$

Where the weight parameters Wkj and Wji indicate the strength of the connections between the nodes, bk, and cj are the bias functions, and fy and fz are the activation functions connected with weight parameters.

The main objective of the ANN model is to optimize the best weight parameters using a training algorithm. The backpropagation technique is most typically used for ANN training, which works by readjusting the weight parameters between the hidden and output layers to minimize output error. There is no exact procedure to determine how many hidden nodes are best, so trial-and-error methods are used to find the best number of hidden nodes. However, it was shown that better outcomes may be achieved when the number of hidden nodes is less than or equal to the number of input nodes. Several activation functions, including the sigmoid, hyperbolic tangent, and sign functions, can also learn nonlinear correlations between the input and output. In ANN modeling, the objective is to create a model that improves accuracy on the training set and then use that model on the test set [36].

In order to figure out the efficiency of ANNs, we divided the input data into three sets. The training data set has been used to compute gradients to improve network weights. The second set of data, which is used for validation, determines the best neural network training. In reality, the lowest error from the validation phase determines network weights and biases. Regularization can be performed using a validation set to prevent overfitting. After the validation stage of a network, its effectiveness is measured using the test dataset. The training, validation, and testing stages data are randomly selected using various percentages. Training, validation, and testing sets can typically use 70%, 15%, and 15% of the data, respectively [37].

The ANN approach was used in this research for prediction modeling in which pavement distress, including alligator cracking, block cracking, wheel path longitudinal crack, non-wheel path longitudinal crack, transverse crack, patches area, bleeding area, raveling area, pumping and bleeding length and wheel path length cracked were imported as input variables, and IRI was imported as the target variable. A multilayer feed-forward backpropagation network was created and trained with the Levenberg-Marquardt algorithm in MATLAB© software. The number of neurons in the hidden layer can affect the overall number of weights in an ANN model. Selecting a sufficient number of neurons in the hidden layer is important. If the hidden layer has few neurons, the ANN will have less computational resources to deal with the problem. When too many neurons are in the hidden layer, the network can learn insignificant information regarding the training set that is usually unimportant to the overall problem's behavior. Therefore, using the minimum number of neurons in the hidden layer is important.

Figure 4 shows the relationships between the predicted and calculated values using the created ANN model. In this study, the R2 value used to determine the importance of the ANN model developed is 0.684241. The results show that 68.4% of the variance in the IRI could be related to the variance of pavement distress in the developed model.

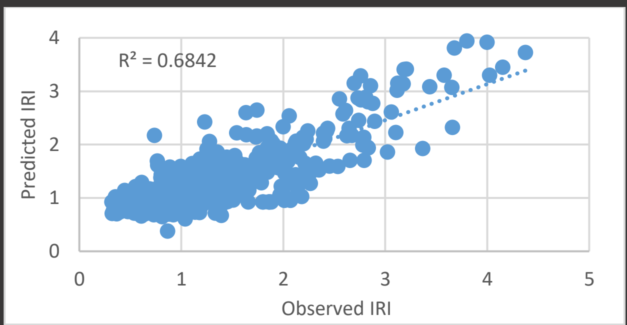

Figure 4. ANN model prediction accuracy

Table 6 shows the structural features of the ANN model developed and calibrated within the scope of the study. As the architecture of the network, there are 22 neurons expressing distress along with severity levels in the input layer and one neuron expressing IRI in the output layer. Many hidden layers and many neurons were analyzed in the calibration of the network. The highest level of performance was found in 23 neurons in a single hidden layer.

Table 6. Structural details of the ANN model

The structure of the Network used	22 inputs, 23 hidden layers, and 1 output
Percentage of the data used for training, validation, and testing	Training: 70% of the data Validation: 15% of the data Testing: 15% of the data
Type of Network	Feed Forward Back Propagation
Function used for training	Backpropagation
Transfer Function	TANSIG
Training Algorithm	Levenberg-Marquardt
Performance Function	Mean- Squared Error

4. Discussion

In the study, nonlinear regression, MARS and ANN methods were used to model the relationships between inputs and outputs. Briefly, a method progressing from simple to complex was preferred in modelling the relationships between surface distortions and IRI. Besides, nonlinear regression analysis, though relatively interpretable, has limited flexibility in capturing complex relationships between variables. MARS offer adaptability and non-parametric modeling, automatically identifying interactions without distribution assumptions, yet may suffer from increased complexity and potential over-fitting. ANNs excel in capturing intricate non-linear patterns, adaptively learning from data, but their black-box nature, tendency to over fit, and computational demands can limit interpretability and make them resource-intensive. The choice among these approaches hinges on a trade-off: nonlinear regression for interpretability, MARS for a blend of interpretability and adaptability, and ANNs for maximal predictive accuracy while accepting their complexity and computational requirements.

All three mathematical modelling techniques used in the study are solution tools frequently used in science. They have been the subject of numerous studies and scientific publications for years. When you want to examine the recent developments and usage examples of these approaches, you can look at Frost [38] for nonlinear regression, Rodriguez [39] for MARS, and Aggarwal [40] for ANN.

To evaluate more objectively the modeling approaches used in this study between pavement distress and IRI, it is necessary to compare all modeling approaches by using traditional statistical comparison methods such as correlation coefficient (R), determination coefficient (R2), root mean square error (RMSE), Nash-Sutcliffe Efficiency Coefficient (NSCE), mean absolute error (MAE), and normalized root mean square error (NRMSE). Correlation coefficient in equality (8), determination coefficient in equality (9), root mean square error in equality (10), Nash-Sutcliffe Efficiency Coefficient in equality (11), mean absolute error in equality (12) , and normalized root mean square error are expressed mathematically in Equation (13).

$$R=\frac{\sum_{i=1}^{n}(X_i-\dot{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\dot{X})^2\times\sum_{i=1}^{n}(Y_i-\bar{Y})^2}} \tag{8}$$

$$R^2=\frac{\left(\sum_{i=1}^{n}(X_i-\dot{X})(Y_i-\bar{Y})\right)^2}{\sum_{i=1}^{n}(X_i-\dot{X})^2\times\sum_{i=1}^{n}(Y_i-\bar{Y})^2} \tag{9}$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{n}} \tag{10}$$

$$NSCE=1-\left[\frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{\sum_{i=1}^{n}(X_i-\dot{X})^2}\right] \tag{11}$$

$$MAE=\frac{\sum_{i=1}^{n}|X_i-Y_i|}{n} \tag{12}$$

$$NRMSE=\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i-Y_i)^2}}{X_{max}-X_{min}} \tag{13}$$

Here Xi is the observed value, Yi is the predicted value, $\dot{X}$ is the average of the observed value, $\bar{Y}$ is the average of the observed value, n is the number of samples in the data set, Xmax is the maximum observed value, and Xmin is the minimum observed value. The statistical parameter values found in the three different modeling approaches evaluated in the study are shown in Table 7.

Table 7. Comparison of the model's performance

	MARS	SPSS	ANN
R	0.789372378	0.711546953	0.827188522
R^2	0.623108751	0.506299066	0.684240851
RMSE	0.416683207	0.479350493	0.382164363
NSCE	0.623108751	0.50121841	0.682967028
MAE	0.313949559	0.351148571	0.294739697
NRMSE	0.102757879	0.118212204	0.094245218

These results indicate that the ANN model performs better than MARS and SPSS models. Similar findings were obtained in previous research, confirming that the ANN model's prediction accuracy is satisfactory [7, 8, 41]. The prediction performance of the MARS approach is also better than that of the most used SPSS approaches.

5. Conclusion

Several pavement performance prediction models have been constructed using in-service pavement databases. However, the LTPP database was used in this study because it is the world's largest pavement performance database. The LTPP program is the largest pavement performance research program, collecting data from over 2,581 pavement sections in the United States and Canada over the past 33 years and aiming to study pavement performance in these sections for a longer period of time. The LTPP program includes two types of experiments: General Pavement Studies (GPS) and Specific Pavement Studies (SPS).

The models have been developed based on the Long-Term Pavement Performance (LTPP) Database. The LTPP data were derived from GPS-1 and GPS-2 sections for seven U.S. states: Arizona, Florida, Minnesota, Mississippi, North Carolina, Oklahoma, and Tennessee. The main purpose of this study was to create pavement performance models to predict IRI from pavement distress using LTPP data.

In this study, regression analysis was performed to develop models from the data collected to study the relationship between IRI as the dependent variable and pavement distress as the independent variable. To develop the best model, regression analysis is performed using three methods Nonlinear Regression Analysis, Multivariate Adaptive Regression Splines (MARS), and Artificial Neural Networks (ANN).

The developed models have coefficients of determination (R2) equal to 0.516, 0.623, and 0.684 for nonlinear regression analysis, multivariate adaptive regression splines (MARS), and artificial neural networks (ANN), respectively. The models generated, calibrated and put into use within the scope of the study are explained in sections 3.1, 3.2 and 3.3 of the study. Finally, the results showed that the developed ANN model could predict the IRI of GPS-1 and GPS-2 pavement sections with very good accuracy and less error compared to nonlinear regression analysis and multivariate adaptive regression splines (MARS) models. The most valuable statistics error analyses, including R, R2, RMSE, NSCE, MAE, and NRMSE, were employed to compare the developed models are also supported the ANN model for better performance.

The performance levels of mathematical models are evaluated with the benchmark parameters allowed by statistics. In this study, six of these benchmark parameters were used for comparison. According to all these parameters, it is clear that the level of agreement between the prediction results of the models developed with three different techniques and the actual data is highest in the model developed with the ANN approach. This comparison is explained in chapter 4.

Due to the complex structure of fieldwork and the need for intensive labour, surface distress and IRI measurements cannot be made on very recent dates and in a recurring format every year. In addition, although some surface distress data have a negative impact on the mechanical strength of the pavement, their negative impact on surface irregularity (roughness) is limited. Even if some surface distresses are on the coating surface, their effect on discomfort remains limited since they are not on the trace of the IRI measurement. All these constraints are the main reasons prediction similarities remain at limited levels in modelling studies. As a result, the effects of each distress type and severity on IRI can be determined with precision only with similarity models created in a universe where data sets are created under idealized conditions. It is clear that until these idealized conditions are met, repeating similar studies on data produced under actual application conditions will continue to shed light on science.

Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution Statement

U. Kırbaş: Conceptualization, Data Curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing-Original Draft, Writing-Review & Editing; **F. Himat**: Data Curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing-Original Draft, Writing-Review & Editing

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