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NEURAL NETWORKS AND NON-PARAMETRIC STATISTICAL MODELS: A COMPARATIVE ANALYSIS IN PAVEMENT CONDITION ASSESSMENT

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Abstract

Much research has concentrated on developing accurate and robust pavement condition and performance prediction models whose goals are both to assess the factors that affect pavement deterioration and to predict future pavement performance. In recent years, many authors have departed from the classical statistical approaches for model development and have worked with alternative techniques, commonly known as soft computing, that are particularly well suited for data that exhibit nonlinear properties. Based on a large European database with more than 900 test sections from 15 (European) countries, this paper complements prior research in two ways; first, it compares prediction results from three different soft computing techniques, Neural Networks, Hierarchical Tree Based Regression and Multivariate Adaptive Regression Splines, on a common database and, second, it assesses the importance of various structural, environmental and traffic characteristics on pavement condition based on these flexible computational approaches. The results show that the approaches tested provide very encouraging prediction results, especially in comparison to regression models, and that the approaches evaluate differently the factors affecting performance.

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1. Introduction

Transportation makes up almost 10% of Europe's GNP. Further, over 80% of the total transport of people and goods is provided by the road infrastructure. As such, it is obvious that a well maintained road infrastructure is an essential part of Europe's economic development. Further, poor pavement maintenance can have serious consequences on road safety and ride comfort. To this end, pavement maintenance involves substantial costs, both to the operating authorities and the user. For authorities, costs for planning maintenance, maintaining and treating pavements are very high; for users, maintenance costs are manifested through increased work-zone delays and temporary lane closures and increased safety risks associated with such closures. Given that both these costs are usually very high and that resources are scarce, pavement maintenance must be planned systematically; this is usually done through the implementation of Pavement Management Systems (PMS).

PMS are commonly used to select maintenance strategies that result in lower project life cycle costs. Integral part of these systems are pavement deterioration models that predict deterioration based on present condition, deterioration factors such as traffic, environmental and construction properties and the effects of maintenance. Interestingly, besides being the backbone of PMS, deterioration models are frequently the weak points of such systems. Inaccurate models may lead to suboptimal maintenance strategies, while well developed models may help to ensure that life-cycle cost analysis will contribute to well selected maintenance strategies that lead to prudent investment decisions.

Based on the above, it comes as little surprise that the literature contains a vast body of work regarding deterioration modeling of infrastructure facilities with a particular interest in pavements (Madanat et al. [9], Flintsch [4], Loizos et al. [8]). Most of the work has revolved around the extended linear regression framework that, although powerful and with many attractive features, should not be chosen for data that can better be approximated using non-parametric approaches. As a result, many authors have worked with a number of flexible approaches under the general term of soft computing in an effort to develop more accurate, in terms of prediction error models (a thorough review of the literature on soft computing applications in pavement and infrastructure modeling appears in Flintsch [4]; as such, interested readers should refer to that paper for a wider coverage of the available literature). From the literature it appears that most of the research interest has revolved around the development of Artificial Neural Networks (ANN) because they yield very satisfactory predictions and can straightforwardly accommodate for nonlinearities in the data (Zadeh [15], Yang et al. [14], Felker et al. [3]). But, the area of soft computing offers a number of other promising approaches that should be tested against both more traditional linear models and ANNs to establish their potential advantages and shortcomings.

The goal of this paper is to test and compare predictions from three flexible and promising soft computing techniques, ANNs, Hierarchical Tree Based Regression (HTBR) and Multivariate Adaptive Regression Splines (MARS). It should be noted that, for the comparisons to be complete and valid, all models are developed using and tested against the same data. The remainder of this paper is organized as follows; the second section describes the data set used in this work. The third section briefly reviews the three methodological approaches used in the paper and the fourth section presents the empirical findings. Finally, the fifth section summarizes the findings and offers some concluding remarks.

2. Database Development

2.1. General

The data used in this paper were collected as part of the PARIS project in the European Union (EU), considered as one of the most successful infrastructure research projects in Europe (PARIS 2000). The general objective of the PARIS project was to develop pavement deterioration models for use in pavement management systems; more specifically, the project was geared toward producing uniform data collection mechanisms and definitions, data acquisition systems and analysis methods to interpret road pavement performance in the EU, to develop a central research database for road condition data gathered in the participating countries, to develop a coherent set of pavement deterioration models, applicable for different traffic conditions, climates and materials based on data from in-service road sections and, finally, to validate the pavement deterioration models developed using a separate set of data.

It must be mentioned again that the major target of the PARIS project was to provide performance models, namely models for the initiation and propagation of pavement distress. The distress types used have been based on the results of the European Cooperation in the field of Scientific and Technical Research. The final selection of distress types to be used in the project was made by taking into account the fact that the available and collected data would be used for the development of models. For each possible distress, historical data (at least 5 years) should be available and each section should have - if possible - a complete set of data (construction, distress, traffic, deflections, etc.) in order to be suitable for analysis.

The importance of each distress was also considered, but it is practically impossible to examine the entire range of distresses in the present paper. Pothole detailed data, for example, are regularly collected by very few agencies (countries in the PARIS project); and, even in those cases, where these data are available, they come from very low volume roads for which several other critical data such as traffic, inventory and so on are not available. Basic aim of the analyses was to provide models for cracking, rutting and raveling initiation and propagation, as well as longitudinal unevenness propagation.

The pavement deterioration models produced in the project and used in this paper are based on the observed performance of a large number of test sections across Europe (Table 1). Most sections are located on the national road networks and subjected to the influence of climate and regular traffic.

2.2. The collection of data

A prime criterion for selecting the test sections used in the paper was the availability of sufficient historical distress data. The test sections for the project were selected from ongoing pavement performance studies in each country, with a minimum of two distress surveys prior to the start of the project. Using these criteria, a total number of 900 test sections were selected from ongoing pavement performance studies in eleven of the fifteen countries participating in the project. Data from four countries where local pavement performance studies were not available on a historical basis were used as the validation set. Finally, it is noted that distinction is made in the type of pavement structure used in the sections. Flexible constructions are defined as pavement constructions with one or more asphalt layers placed on the subgrade (so-called full-depth constructions). Semi-rigid constructions were defined as constructions with asphalt layers on a rigid (cemented or hydraulically bound) base with or without a granular sub-base on the subgrade.

2.3. The variables

For all test sections three types of data were collected: inventory data, data on dependent variables and data on explanatory variables. *Inventory data* are general data on the location of the test section and the type of construction (Table 2). *Dependent variables* are data on the extent and severity of the distresses to be modeled. *Explanatory variables* are external factors that are assumed to influence the performance and deterioration of the pavements.

The project, in general, developed models regarding four types of distresses: cracking, rutting, raveling and longitudinal unevenness. In this paper we demonstrate the potential use of soft computing techniques on pavement cracking propagation, a variable that has attracted considerable attention in both practice and literature. The data on explanatory variables were divided into five data groups; construction, deflection, maintenance and rehabilitation, traffic and climate (all the data and information collected appear in Tables 3-6).

3. Methodological Approaches

3.1. Soft computing

The past few years have witnessed a growing recognition of soft computing technologies that underlie the conception, design and utilization of intelligent systems. According to Zadeh [16], soft computing consists of artificial neural networks, fuzzy inference systems, genetic algorithms, approximate reasoning, derivative free optimization techniques and flexible non-parametric statistical techniques. The concept of soft computing is to offer an innovative approach for constructing computationally intelligent systems that possess humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments, and for explaining how such systems make decisions. As previously mentioned, neurocomputing (ANNs) is the best established soft computing technique for function approximation in the field of pavement deterioration (Flintsch [4], Zadeh [15], Yang et al. [14], Felker et al. [3] - interested readers should again refer to Flintsch [4] for a more detailed discussion on soft computing techniques along with their strengths and weaknesses).

Interestingly, most of the literature on pavement condition assessment has used ANNs (besides, of course, the classical statistical approaches) as the sole soft computing technique of choice without actually comparing the findings with those of other available techniques. In this paper, besides ANNs, we develop HTBR and MARS models and compare their findings. HTBR is a tree-structured non-parametric data analysis methodology while MARS is based on a divide and conquer strategy that partitions the data into separate regions each with its own regression line or hyper plane.

3.2. ANNs

Much of the attention to the field of Artificial Neural Networks (ANNs) came from the desire to produce artificial systems capable of sophisticated computations similar to those that the human brain constantly performs (Principe et al. [11]). ANN architecture, much like the human brain, is composed of simple processors called *neurons* or *nodes*, and numerous connections between them. A Neural Network consists of many processing elements that are usually organized into a sequence of layers with full or partial connections between them. Usually, an ANN consists of an input layer, where data are presented to the network, and an output layer that holds the response of the network to a given input. Frequently, to capture potential nonlinearity in the data, other intermediate layers, called *hidden layers*, are included into an

ANN. The processing in the neurons is done by an "activation function" that controls the output of each node. ANNs essentially "train" or "learn" through adaptation of their connection weights, as the hidden neurons organize themselves so that different neurons learn to recognize different features of the total input space.

An ANN training is performed iteratively until the average sum squared error between the computed and the desired output over all the training patterns is minimized. This kind of network derives its outcome from the manner that connection weights are adjusted to reduce output errors during the learning phase (Principe et al. [11]). Output errors are calculated by comparing the desired output with the actual output. The output is obtained from forward propagation of the input through the network. Next, output errors are propagated back to the hidden and input layers, and connection weights in the network are modified to minimize a global error function. For back-propagation ANNs, the error function is usually the Generalized Delta Rule (a variation of the Least Mean Square theory), and a sigmoidal function is used as the activation function. Validation of the performance of an ANN is done using a separate set of testing data that broadly resembles the training data. Once the training and testing phases are found to be successful, the neural network model can then be put into practical applications.

3.3. HTBR

Hierarchical tree-based regression (HTBR) is a tree-structured non-parametric data analysis methodology that was first used in the 1970's in the medical and the social sciences (Steinberg and Colla [12]). An extensive review of the methods used to estimate the regression trees and their applications can be found in Breiman et al. [2]. HTBR is technically binary, because parent nodes are always split into exactly two child nodes and is recursive because the process can be repeated by treating each child node as a parent. In essence, the HTBR algorithm proceeds by iteratively asking the following two questions: (i) which of the independent variables available should be selected for the model to obtain the maximum reduction in the variability of the response (dependent variable)? and, (ii) which value of the selected independent variable (discrete or continuous) results in the maximum reduction in the variability of the response? These two steps are repeated using a numerical search procedure until a desirable end condition is met.

To formalize the treatment of HTBR, the usual Sum of Squared Error (SSE) at a node α can be written as

$$SSE_{\alpha} = \sum_{i=1}^{I} (y_{i\alpha} - \mu_{\alpha})^2, \tag{1}$$

where

$y_{i\alpha}$ = observation i of dependent variable y at node

μ_{α} = mean of I observations at node.

The observations can be split at node α on a value of the independent variable x_i resulting in two branches with corresponding nodes β and γ, containing J and K observations respectively, where $I = J + K$. The reduction in the *SSE*, *R*, resulting from the split and evaluated over all *x*'s can be written as

$$R_{all\,x} = SSE_{\alpha} - SSE_{\beta} - SSE_{\gamma}, \tag{2}$$

where SSE_{α} and SSE_{β} are defined similar to equation (1). HTBR uses numerical search procedures to maximize $R_{all\,x}$. When the data are split at an *x*, where the maximum reduction occurs, the remaining observations have a significantly smaller *SSE* than the original data. This maximization process continues iteratively at each node until either the node of a tree has met minimum population criteria (from statistical sampling theory), or minimum *SSE* criteria at a node are met.

The HTBR methodology has several attractive technical properties: it is non-parametric and does not require specification of a functional form; it does not require variables to be selected in advance, since it uses a stepwise method to determine optimal splitting rules; its results are invariant with respect to monotone transformations of the independent variables; it can handle data sets with complex (nonhomogeneous) structure; it is extremely robust to the effects of outliers; it can use any combination of categorical and qualitative (discrete) variables; and, it is not affected by multicollinearity between the independent variables.

3.4. MARS

MARS is best described by (Friedman and Roosen [6]) as a flexible procedure which models relationships that are nearly additive or involve interactions with a small number of variables. The procedure is motivated by the recursive partitioning technique governing HTBR as well as generalized additive modeling (Hastie and Tibshirani [7]), resulting in a model that is continuous with continuous derivatives (for a detailed explanation of the model fitting process see Friedman [5]).

In general, MARS was introduced by Friedman [5] as an approach of using smoothing splines to fit the relationship between a set of predictors and a dependent variable. A smoothing spline is similar to a cubic spline in which a cubic regression is fit to several preselected subsets of data (in a cubic regression between a predictor x and a dependent variable y, the regressors would include a constant, the level of x, the square of x and the cube of x). By requiring the curve segments to be continuous (so that the first and second derivatives are non-zero), one obtains a very smooth line that can capture 'shifts' in the relationship between variables. These shifts occur at locations designated as 'knots' and provide for a smooth transition between 'regimes'. The MARS algorithm searches over all possible knot locations, as well as across all variables and all interactions among all variables. It does so through the use of combinations of variables called '*basis functions*', which are similar to variable combinations created when using principal component analysis. Once MARS determines the optimal number of basis functions and knot locations, a final least-squares regression provides estimates of the fitted model on the selected basis functions.

In modeling the relationship between a single predictor x_t and the dependent variable y_t, a general model can take the form

$$y_t = \sum_{k=1}^{M} a_k B_k(x_t) + \varepsilon_t, \tag{3}$$

where $B_k(x_t)$ is the kth basis function of x_t. Basis functions can be highly nonlinear transformations of x_t, but y_t is a linear-in-the-parameters function of the basis functions. Estimates of the parameters a_k are chosen by minimizing the sum of squares residuals from equation (3). The advantage of the MARS approach is in its ability to estimate the basis functions so that both the additive and the interactive effects of the predictors are allowed to determining the response variable. The MARS algorithm identifies the 'knot' locations that most reduce the sum of squared residuals. Overall, MARS excels at finding optimal variable transformations and interactions, as well as the complex data structure that often hides in high-dimensional data.

4. Model Development and Empirical Findings

As was previously mentioned, the number of cases (total sections) available to train, test and validate the network was approximately 900. To ensure the best possible performance of the models developed, the data set was divided into two groups. The training set (approximately 75% of the data) and the validation set (25% of the data) which, as can be seen from Table 1, was comprised of sections from different countries than the training set; in this way, not only are the models tested in out-of-sample conditions, but their transferability to completely different external conditions are investigated. It should be noted here that the type of cracking predicted in the present study is the propagation of the wheel-path cracking in the pavement surface.

In the case of ANN development, the training and validation sets were used to define the network topology by using the "hold out" method (Bishop [1]). This method trains various networks by minimizing the error function with respect to the training set. The networks are then compared by evaluating the error function using the validation set and the network having the smallest error with respect to the validation set that is selected. The network selected as the "best" is then made to "forget" its previous training and is retrained using the "early stopping method". With this method of training the network learns using the training set. Then, the validation set is used to assess the generalization error. It is crucial that the test set has not been used while training, so that the capacity of the network to produce results in unknown cases (generalization) can be evaluated. It must also be noted that an additional issue with neural networks is the pre-processing of inputs. In many cases standardization and/or normalization of the input data is needed before the network is trained. This is done to increase the performance of the network and decrease the training time; the input database used in this paper was constructed in such a way as to ensure that each input value was evenly distributed in the range [min, max]. The only preprocessing done to the data was to normalize them in the range $(0, 1]$ by dividing with the maximum value. This "trick" is well known to reduce the training time of a neural network and enhance its performance (Principe et al. [11], Bishop [1]).

Using the same transformations for the inputs, the HTBR and MARS models were also developed (while HTBR and MARS do not require or necessitate any transformations for the variables included in the models, we used the transformed variables in developing these models so that results among approaches could be directly compared). HTBR partitions the data into relatively homogeneous (low standard deviation) terminal nodes, and it takes the mean value observed in each node as its predicted value. In general, HTBR models can be fairly complex and detailed and therefore difficult to illustrate mathematically; nevertheless, the methodology lends itself to graphical "tree-like" representations, as shown in Figure 1.

Interpreting the tree model in Figure 1 is rather straightforward. The top of the tree, or tree root, shows that the maximum reduction in the variability in the dependent variable (*Longitudinal Cracking Propagation in the Wheel-Path*) occurs when the data are divided on the independent variable DVEH (Number of vehicles per day in direction of test section) at the value of 42,405 vehicles per day. Because this is a continuous variable, the entire sample was divided into two groups; one group, where $DVEH <= 42{,}405$ and one, where $DVEH > 42{,}405$. At the second decision node 'travelling' to the left, RAIN (average yearly rainfall) best explains the remaining variability for sections with $DVEH <= 42{,}405$ (optimal split for the rain variable occurs at 791 mm/year). It should be noted that, the farther away from the root of the tree one travels, the higher is the order of interaction. For instance, the third node 'travelling' down to the left of the tree is an interaction between the variables, *DVEH*, *RAIN*, *TH_BIT* (thickness of the bituminous layer). When completing the tree to the left - after following these three nodes - a terminal node, or leaf of the tree, is formed (Terminal node 1). For this category of pavement sections, the mean expected value for longitudinal cracking is 13.5 cm.

In contrast to the CART process with its graphical representation, the MARS model gives a fairly detailed and elaborate prediction equation (actually a set of spline equations) which, in the case of pavement cracking, was formulated as follows:

$$y = 1.536 + 0.024 * BF1 - 0.188 * BF2 - 2.027 * BF3 - 4.857 * BF4$$

$$+ 3.174 * BF5 + 0.016 * BF6 + 0.074 * BF7,$$

where BF are Basis Functions and

$$BF1 = \max(0, 177.000 - TH\_BIT);$$

$$BF2 = \max(0, T\_DAY - 4.745);$$

$$BF3 = \max(0, 4.745 - T\_DAY);$$

$$BF4 = \max(0, TH\_BIT - 270.000);$$

$$BF5 = \max(0, TH\_BIT - 321.000);$$

$$BF6 = \max(0, DVEH - 15850.000) * \max(0, PAVAGE - 4.000);$$

$$BF7 = \max(0, PAVAGE - 2.000).$$

The basis functions have effects on pavement cracking only when they are positive and are zero otherwise; $\max(0, PAVAGE - 3.000)$ is interpreted as the maximum value of the two elements: 0 and $(PAVAGE - 3.000)$. Essentially, MARS takes TH_BIT, T_DAY, $DVEH$ and $PAVAGE$ and attempts to fit the best model for longitudinal pavement cracking by placing knots and choosing additive and interactive effects to minimize the sum of squared errors. The basis functions are interpreted as the additive and interactive effects of the variables relative to their knot locations; for example, the first basis function contains the $\max(0, 177.000 - TH\_BIT)$, while the sixth involves two variables and is nonlinear.

Further, in the case on the ANN development, we used a feedforward neural network with one hidden layer consisting of 15 neurons (tanh-sigmoidal node transfer function) and training was terminated after 6000 epochs. Finally, for strictly comparative purposes, we present the prediction results from the regression model originally developed in the PARIS project (PARIS [10]).

The results, as reported in Table 6, are rather interesting; as expected, all three soft computing models show fairly good performance in predicting in-sample (training set) cracking propagation with Absolute Percent Error (APE) values ranging from 9-13%. In the validation process the range of the APE values is markedly different, with the ANN model having an APE of 12% and outperforming both the HTBR and the MARS models (APE of 14% and 21%, respectively). Because the difference in results between the ANN and the HTBR models is rather small, it is feasible to use the two approaches interchangeably depending on the application and the familiarity of the analyst.

Of course, it is of interest to note the APE differences between the soft computing model approaches and the linear regression model developed which has an APE value (in the validation data set) of 37% (PARIS [10]). This APE value is quite high, especially when significantly lower values can be achieved by using other tested and accepted techniques (ANN, etc.). It must be noted here that this finding, i.e., that soft computing approaches seem to out-perform linear regression, is simply indicative and certainly not definitive. Linear regression models, for years a powerful deterioration modeling tool, have many advantages over soft computing methods as, for example, that it straightforwardly captures the cause-effect relationship between pavement deterioration and external factors and that it is easily understood and a standard option in all statistical packages. Further, in recent years, many extensions to the classical linear regression models have been developed to overcome many of the earlier limitations (normality of the dependent variable, and so on) especially when working with extended data sets. However, in this application, non-parametric approaches have performed very satisfactorily compared to classical linear regression, most probably because the data modeled display nonlinear characteristics.

Finally, it should be noted that, although the training times for the different models are very different they are not further considered, since they are not a constraining factor in this investigation; but, it is worth mentioning that the linear regression and ANN models developed required significantly higher "development" times and a large number of alternative runs before the "best" model was reached, while for the HTBR and MARS approaches this time was significantly lower. Interestingly, three graphs (Figures 2-4) were produced depicting actual versus predicted cracking values (in centimetres) for the three soft computing methods employed. As expected, Figure 2 which depicts actual versus predicted values from the ANN model estimated shows the lowest variance around the 45° line, with the HTBR and MARS results being graphically inferior, particularly for higher cracking values. It does appear from these figures that the variance of the error is larger for larger cracking propagation values. This apparent heteroskedasticity does, undoubtedly, affect prediction accuracy, particularly as it applied to larger cracking values. This is clearly an area of possible future work and model refinement.

Another interesting aspect of this analysis pertains to the selection of the "most important" variables (or variable importance factors) as reported by the three separate methodologies (Table 7 - details on the approach used for the process of variable evaluation can be found in Principe et al. [11] for ANN, Steinberg and Colla [12] for HTBR and Friedman [5] for MARS). This variable importance essentially reflects the ranking of the variables from the most to the least important with respect to cracking propagation. This implies that, based on the ANN, the thickness of the bituminous layers (*TH_BIT*) is the most important variable in predicting cracking propagation. Variable importance refers to the relative ranking of variables, with 1 indicating the most important variable in pavement cracking propagation, 2 the second most important and so on (top 10 indicated here; variables not ranked are below 10th in the importance list and their impact on pavement cracking propagation considered as low).

Interestingly, the most important variable according to the HTBR and MARS methodologies is the percentage of trucks crossing the test section. Overall, the difference in the rankings is notable. Overall, it can be inferred that the ANN approach evaluates the construction and rehabilitation variables as being the most important, while the traffic variables play the most important role in the HTBR model. This difference in findings may be attributed to the diverse ways with which these approaches select the variables to be included in the models and with which they reach the "best" final specification. Nevertheless, it must be mentioned that, although these results are quite robust (the same variables were important throughout the model development phase), they are mostly indicative and should be complemented by additional runs, model refinement and theoretical underpinnings.

5. Conclusions

Significant research in the past few years has concentrated on deterioration modeling of infrastructure facilities with a particular interest in pavements. And, although, most of the literature has worked within the extended linear regression framework many authors have worked with the so-called soft computing approaches in an effort to develop more accurate, in terms of prediction error, models, with ANNs being the models of choice. Interestingly the area of soft computing offers a number of other promising approaches that should be tested against both the traditional linear regression models and ANNs to establish their potential advantages and shortcomings. In this paper we tested three very powerful and promising soft computing techniques, ANNs, HTBR and MARS, and compared the findings and implications based on a large European database with data with over 900 sections from 15 (European) countries.

The results were interesting. All three approaches showed quite good performance in predicting cracking propagation in a separate validation data set, with APE values being 12% for ANN and 14% and 21% for HTBR and MARS. Finally, the three approaches evaluated differently the effect of independent (exogenous) factors on the dependent variable. From the results reported it can be inferred that the ANN approach evaluates the construction and rehabilitation variables as being the most important, while the traffic variables play the most important role in the HTBR model.

Finally, it is important to note that, similar to what has been reported in many other places in the literature, soft computing techniques are both very flexible in terms of a lack of model functional form constraints and their ability to model highly nonlinear data. They thus hold much promise in terms of prediction success. But, we are clearly of the opinion that, at least as a first stage in model development, results from soft computing approaches must be compared to those obtained from other methodologies; finally, publicly available and commonly accepted test bed data sets must be established that will permit different methodologies to be tested and compared based on the same data.

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Table 1. Number of RLT test sections per country

(a) Data for model development

Country	Flexible	Semi-rigid	Total
Finland	33	0	33
Sweden	296	0	296
Denmark	7	0	7
Netherlands	168	37	205
United Kingdom	15	13	28
France	12	10	22
Switzerland	31	5	36
Austria	12	0	12
Spain	3	7	10
Hungary	28	33	61
Greece	10	0	10
Total	615	105	720

(b) Data for model validation

Country	Flexible	Semi-rigid	Total
Belgium	41	25	66
Ireland	25	0	25
Portugal	45	6	51
Slovenia	54	0	54
Total	165	31	196

Table 2. Inventory information collected

Variable name	Variable description
Country	Country in which test section is located
Constr	Type of construction of test section
Lanes	Number of lanes on test site in both directions
Width	Width of the lane on which the test section is located
In Serv	Test section still in service (yes/no)
Date out	Date test section out of service

Table 3. Construction data collected

Variable name	Variable description
Pave	Type of pavement construction
Surf	Type of surface layer
Th_Bit	Total thickness of bituminous layers
Th_Rig	Total thickness of rigid layers
Th_Gra	Total thickness of granular base layer(s)
Th_Sub	Total thickness of sub-base layer(s)
Subgrade	Type of subgrade
Rig_Type	Type of rigid layer
Y_Const	Year of construction
Y_Overl	Year of latest overlay
Y_Surf	Year of latest surface layer

Table 4. Traffic data collected

Variable Name	Variable Description
Year	Year of survey
Dveh	Number of vehicles per day in direction of test section
D% Tru	Percentage of trucks in direction of test section
Lveh	Number of vehicles per day on test section
L% Tru	Percentage of trucks on test section
Esal	Number of 10 tonnes ESAL's per year on test section

Table 5. Climate data collected

Variable name	Variable description
T_Day	Average yearly day temperature
W_Day	Number of days per year with a maximum temperature above 25°C
C_Day	Number of days per year with a minimum temperature below 0°C
Freez	Freezing index
Rain	Average yearly rainfall

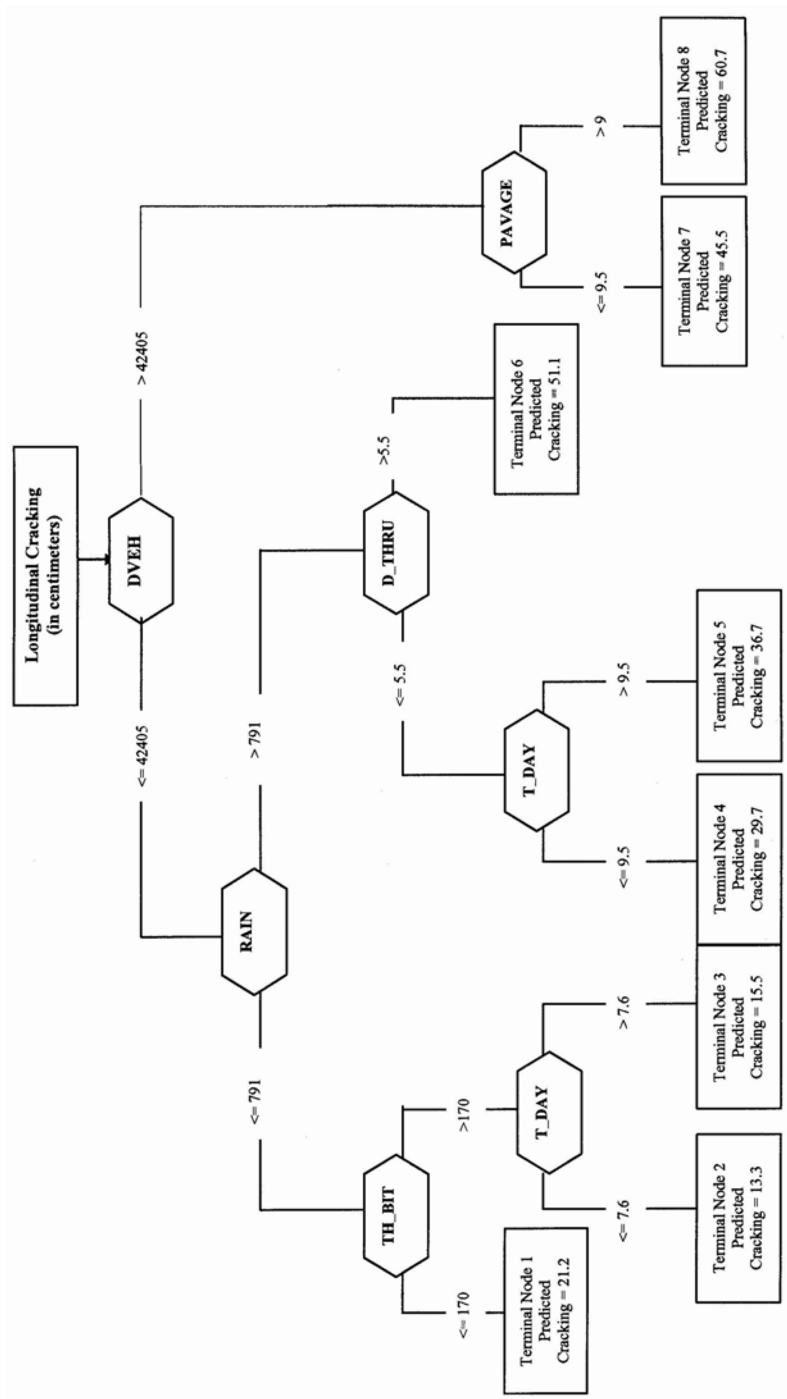
Table 6. Performance comparison between different methodological approaches (pavement cracking propagation)

	Absolute Percent Error (APE)		
Method	Training set	Validation set	Training time (sec)
Regression	31	37	<3
ANN	9	12	205
HTBR	10	14	11
MARS	13	21	23

Table 7. Variable importance assessment

	Methodology[1]		
Variable name	ANN	HTBR	MARS
Construction and rehabilitation variables			
Pave	10		
Surf			10
Th_Bit	1	3	2
Th_Rig			
Th_Gra	2	6	3
Th_Sub		4	6
Subgrade			
Rig_Type			
Y_Const (Age)	7	7	5
Y_Overl	8	10	
Y_Surf			
Traffic variables			
Dveh		8	
D% Tru	3	1	1
Lveh			
L% Tru	5		8
Esal		2	
Climate variables			
T_Day	4	9	4
W_Day	6		7
C_Day			
Freez	9		9
Rain		5	

[1]Variable importance refers to the relative ranking of variables, with 1 indicating the most important variable in pavement cracking propagation, 2 the second most important and so on (top 10 indicated here).


Longitudinal Cracking (in centimeters)
DVEH
<= 42405
> 42405
RAIN
<= 791
> 791
TH_BIT
<= 170
>170
Terminal Node 1 Predicted Cracking = 21.2
T_DAY
<= 7.6
> 7.6
Terminal Node 2 Predicted Cracking = 13.3
Terminal Node 3 Predicted Cracking = 15.5
D_THRU
<= 5.5
>5.5
T_DAY
<= 9.5
> 9.5
Terminal Node 4 Predicted Cracking = 29.7
Terminal Node 5 Predicted Cracking = 36.7
Terminal Node 6 Predicted Cracking = 51.1
PAVAGE
<= 9.5
> 9
Terminal Node 7 Predicted Cracking = 45.5
Terminal Node 8 Predicted Cracking = 60.7

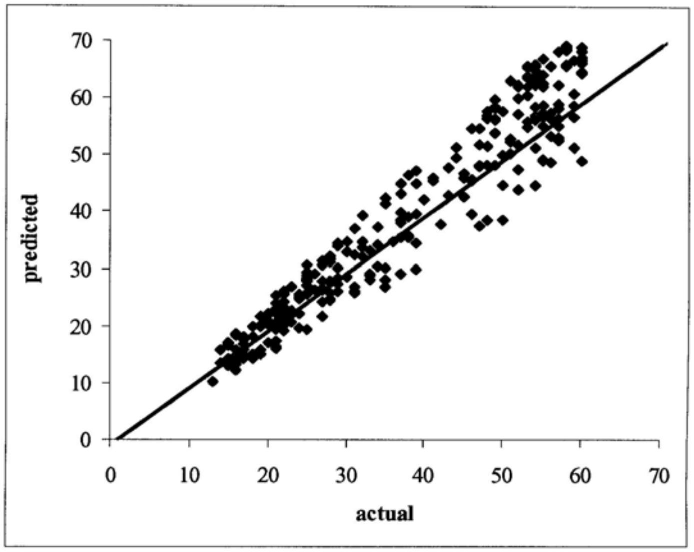


Figure 2. Actual versus predicted values for the ANN model developed.

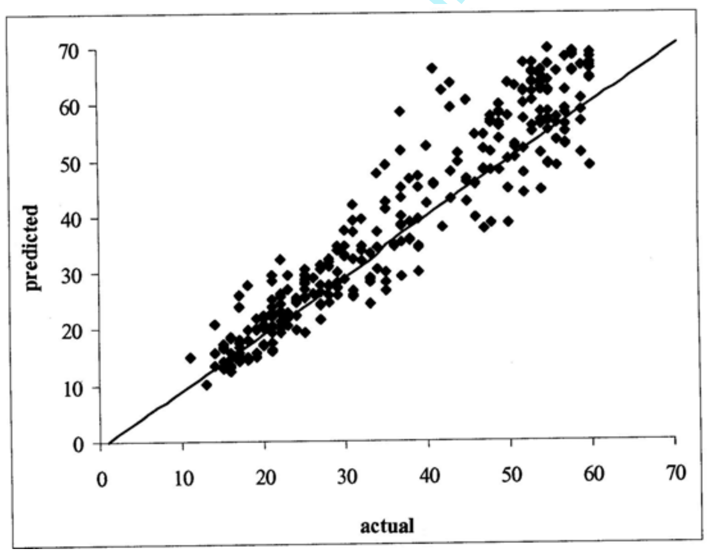


Figure 3. Actual versus predicted values for the HTBR model developed.

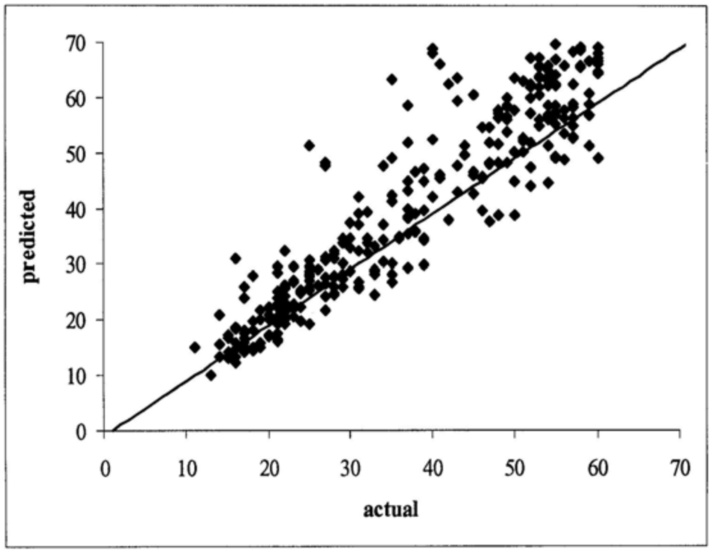


Figure 4. Actual versus predicted values for the MARS model developed.

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