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# Predicting asphalt pavement crack initiation following rehabilitation treatments

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## ABSTRACT

Prolongation of the service life of pavements requires efficient prediction of the performance of their structural condition and particularly the occurrence and propagation of cracking of the asphalt layer. Although pavement performance prediction has been extensively investigated in the past, models for predicting the cracking probability and for quantifying impacts of associated explanatory factors following pavement treatment, have not been adequately investigated in the past. In this paper the probability of alligator crack initiation following pavement treatments is modeled with the use of genetically optimized Neural Networks. The proposed methodological approach represents the actual (observed) relationships between of probability of crack initiation and the various design, traffic and weather factors as well as the different rehabilitation strategies. Data from the Long Term Pavement Performance (LTPP) Data Base and the Specific Pavement Study 5 (SPS-5) are used for model development. Results indicate that the proposed approach results in accurately predicting the probability of crack initiation following treatment; furthermore it provided information on the relationship between external factors and cracking probability that can help pavement managers in developing appropriate rehabilitation strategies.

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## 1. Introduction

Monitoring and maintaining pavements in a serviceable condition, throughout the lifetime of a highway system, is the cornerstone of Pavement Management Systems (PMS). To enhance the performance of PMS, successful prediction of pavement performance and particularly of the occurrence and propagation of cracking, is of primary importance. Indeed, the way in which future serviceability is affected by material deterioration and wear factors, in addition to improvements resulting from pavement treatments, are critical to the effectiveness of a Pavement Management System (PMS) (Roberts and Attoh-Okine, 1998; Anwaar et al., 2013). Repeated traffic loads lead to the formation of pavement deterioration patterns consisting of many-sided, sharp-angled pieces, known as alligator cracking. Once initiated, cracking rapidly propagates both in severity and extent, allowing water to penetrate the pavement, weakening the unbound layers and consequently accelerating the rate of pavement deterioration (Owusu-Ababio, 1998). Predicting when and in what form patterns will probably occur is also important for determining optimal pavement maintenance strategies.

Literature on pavement cracking prediction is extensive, with different methodologies applied for that purpose, such as linear regression, survival analysis and advanced computational intelligence approaches (Wang et al., 2005; Ker et al., 2008;

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Ceylan et al., 2011; Mariani et al., 2012). Regression techniques have been found inefficient for accurately predicting crack performance in the presence of the multitude of contributory factors, material nonlinearity, and uncertainty involved in the cracking process (Haider and Karim, 2009). Artificial Neural Networks (ANN) have been systematically used in pavement management: Bosurgi and Trifirò (2005) reviewed research on ANNs applications in pavement management and identified areas such as condition assessment, deterioration modeling and performance prediction, project and intervention selection, prioritization, optimization and accident prediction. Owusu-Ababio (1998) investigated several ANN model architectures for predicting flexible pavement cracking. Lou et al. (2001) developed a back-propagation neural network (BPNN) model to forecast the short-term time variation of cracking initiation for Florida's highway network; the BPNN model results were compared to those of a commonly used autoregressive model and the BPNN model was seen to be certainly more accurate than the autoregressive model. Ceylan et al. (2013) applied ANN, attempting to increase accuracy in pavement back-calculation results and Sun and Hudson (2005) proposed an ANN based probabilistic framework for pavement fatigue cracking prediction for characterizing damage distribution under mixed traffic loading. Haider and Karim (2009) compared the ability of ANN and recurrent Markov chains to model crack performance, using the Florida Department of Transportation's pavement condition data. Bianchini and Bandini (2010) implemented neuro-fuzzy models to the change in the pavement serviceability related to the traffic increment based on the current conditions of the structure and considering the climatic or environmental factors.

Despite this interest, potential models for prediction of the cracking probability and quantification of the impact of associated explanatory factors have not been adequately investigated in the past. For example, even the recent FHWA report "Impact of Design Features on Pavement Response and Performance in Rehabilitated Flexible and Rigid Pavements" (FHWA, 2011) only offers a cross-classification approach for identifying appropriate treatments to pavements but does not attempt to predict the impact of these treatments or pavement design parameters to cracking. Furthermore, work on rehabilitation strategies has focused resource allocation schemes and prioritization issues, while it has relatively disregarded the importance of evaluating rehabilitation strategies on the grounds of pavement serviceability (Bosurgi and Trifirò, 2005). In addition, research based on ANN has rarely used the explanatory abilities of this method; this has significant implications on the usefulness of proposed models as a managerial tool, despite their well-documented usefulness in research. The traditional lack of explanatory power in ANN significantly hinders their use as tools to explain relationships between cracking and various external factors; therefore, this affects the ability of pavement managers to develop informed rehabilitation strategies.

In this paper the problem of modeling the risk of alligator crack initiation is treated using genetically optimized Neural Network models focusing on the influence of different rehabilitation strategies. The proposed methodological approach targets on transparently representing the observed relationships between risk of crack initiation and the various design, traffic and weather factors as well as the different rehabilitation strategies, using influence measures, tailor-made for ANN. Data from the Long Term Pavement Performance (LTPP) Data Base and the Specific Pavement Study 5: Rehabilitation of AC pavements (SPS-5) are used. The remainder of the paper is structured as follows: Section 2 outlines the ANN scheme used in this work for developing crack predictions models. Data used are presented in Section 3 and model results are offered and discussed in Section 4. Section 5 contains the conclusions of the paper.

## 2. Neural network pavement performance prediction scheme

Multilayer Feed-forward Perceptrons (MLPs) has been proven to be efficient in treating transportation problems (Karlaftis and Vlahogianni, 2011). MLP can be considered as a generalization of single-layer Perceptrons. The existence of a hidden layer consisting of a set of processing units is responsible for introducing non-linearity to the network (Principe et al., 1999).

A MLP with one hidden layer and a logistic output activation function provides an output value  $y_p$  of the  $p$ -th data example of the form (Principe et al., 1999):

$$y_p = \frac{1}{1 + e^{-s_j}}, \quad (1)$$

$$s_j = \sum_k w_{kj} h_k + \theta_j \quad (2)$$

where  $w_{kj}$  is the connection weight between the  $k_{th}$  neuron in the hidden layer and the  $j_{th}$  neuron in the output layer and  $\theta_j$  is the bias term. The term  $h_k$  presents the output of the hidden neuron and is given by:  $h_k = \frac{1}{1 + e^{-s_k}}$ , with  $s_k = \sum_i w_{ik} x_i - \theta_i$ , where  $w_{ik}$  is the connection weight between the  $k_{th}$  neuron in the hidden layer and the  $i_{th}$  input variable.  $\theta_i$  is the bias term. The output of the MLP for a discrete choice model can be described by:

$$\tilde{p}_i = \sum_j \gamma_j s_{j,i} \quad (3)$$

$$\sum_{j=1} \gamma_j = 1, \gamma_j \geq 0 \quad (4)$$

where probability  $\tilde{p}_i$  is the weighted average of the logsigmoid function for neurons bounded between 0 and 1.

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