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Neural Networks Modeling of Stress Growth in Asphalt Overlays due to Load and Thermal Effects during Reflection Cracking

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Abstract

Although several techniques have been introduced to reduce reflective cracking, one of the primary forms of distress in hot-mix asphalt (HMA) overlays of flexible and rigid pavements, the underlying mechanism and causes of reflective cracking are not yet well understood. Fracture mechanics is used to understand the stable and progressive crack growth that often occurs in engineering components under varying applied stress. The stress intensity factor (SIF) is its basis and describes the stress state at the crack tip. This can be used with the appropriate material properties to calculate the rate at which the crack will propagate in a linear elastic manner. Unfortunately, the SIF is difficult to compute or measure, particularly if the crack is situated in a complex three-dimensional (3D) geometry or subjected to a non-simple stress state. In this study, the neural networks (NN) methodology is successfully used to model the SIF as cracks grow upward through a HMA overlay as a result of both load and thermal effects with and without reinforcing interlayers. Nearly 100,000 runs of a finite-element program were conducted to calculate the SIFs at the tip of the reflection crack for a wide variety of crack lengths and pavement structures. The coefficient of determination (R2) of all the developed NN models except one was above 0.99. Owing to the rapid prediction of SIFs using developed NN models, the overall computer run time for a 20-year reflection cracking prediction of a typical overlay was significantly reduced.

Keywords

finite element, fracture mechanics, HMA overlay, neural networks, prediction model, reflective cracking

Disciplines

Civil and Environmental Engineering | Construction Engineering and Management

Comments

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Neural Networks Modeling of Stress Growth in Asphalt Overlays due to Load and Thermal Effects during Reflection Cracking

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Abstract: Although, several techniques have been introduced to reduce reflective cracking, one of the primary forms of distress in hot-mix asphalt (HMA) overlays of flexible and rigid pavements, the underlying mechanism and causes of reflective cracking is not yet well understood. Fracture mechanics is used to understand the stable and progressive crack growth that often occurs in engineering components under varying applied stress. The stress intensity factor (SIF) is its basis and describes the stress state at the crack tip. This can be used with the appropriate material properties to calculate the rate at which the crack will propagate in a linear elastic manner. Unfortunately, the SIF is difficult to compute or measure, particularly if the crack is situated in a complex three-dimensional geometry or subjected to a non-simple stress state. In this study, the Neural Networks (NN) methodology is successfully used to model the SIF as cracks grow upward through a HMA overlay due to both load and thermal effects with and without reinforcing interlayers. Nearly 100,000 runs of a finite element program were conducted to calculate the SIFs at the tip of the reflection crack for a wide variety of crack lengths and pavement structures. The coefficient of determination (R^2) of all the developed NN models except one was above 0.99. Due to rapid prediction of SIFs using developed NN models, the overall computer run time for a twenty-year reflection cracking prediction of a typical overlay was significantly reduced.

CE Database subject headings: Reflective cracking; HMA overlay; Neural Networks; Prediction Model; Fracture Mechanics; Finite Element.

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Introduction

Background

Flexible pavements or hot-mix asphalt (HMA) pavements, are a major component associated with the construction of highway facilities and, at present, constitute approximately 94 percent of surfaced roadways in the United States (NAPA, 2001). Other major pavement types include rigid, or Portland cement concrete (PCC) pavements, and composite pavements consisting of a PCC pavement overlaid with an HMA pavement (Huang, 1993).

A common technique used by many transportation agencies for preventive maintenance and/or rehabilitation of both flexible and composite pavements, is simply to construct a thin Hot-Mix Asphalt (HMA) overlay (Finn and Monismith, 1984). This approach is designed to protect the existing surface against water intrusion, reduce roughness, restore skid resistance, increase structural capacity, and improve the overall ride quality to the traveling public (Roberts et al., 1996). However, many HMA overlays prematurely exhibit a cracking pattern similar to that in the old underlying pavement. The cracking in the new overlay surface is due to the inability of the overlay to withstand shear and tensile stresses created by movements concentrated around preexisting cracks in the underlying pavement. This movement may be due to traffic loading causing differential deflections at cracks in the underlying pavement layers, expansion or contraction of subgrade soils, expansion or contraction of the pavement itself due to changes in temperature, or combinations of these phenomena. Pavement movement, induced by any of the above causes, creates shear and/or tensile stresses in the new overlay. When these stresses become greater than the shear or tensile strength of the HMA, a crack develops in the new overlay. This propagation of an existing cracking pattern from the old pavement into and through a new overlay is known as *reflective cracking* (Cleveland et al., 2002).

Reflective cracks through HMA overlays have been an international problem for decades. Although reflection cracks do not generally reduce the structural capacity of a pavement, subsequent ingress of moisture and the effects of the natural environment and traffic can lead to the premature distress and even failure of the pavement.

Some treatments have shown significant delays in the appearance and reductions in the amount and severity of reflective cracks. One frequently used solution is to install an interlayer between the old and new pavements as shown in Figure 1. To control or delay reflection cracking, many crack interlayer countermeasures have been investigated in the laboratory and the field experimental roads (Monismith and Coetzee, 1980; Kim and Buttlar, 2002; Bozkurt, 2003; Button and Lytton, 1987; Al-Qadi et al., 2004). For characterizing interlayer products, it is better to distinguish between asphalt based interlayer materials (e. g. stress-absorbing membrane interlayer [SAMI], sand asphalt) and other types of interlayer products such as reinforcing fiberglass, grids, and fabrics.

Several studies and evaluations of reflective crack prevention have been conducted across the United States (US). A map showing the location of selected favorable and unfavorable paving fabric installations in the US was used in a report published by Ahlrich (1986) and cited by Cleveland et al. (2002). The map shows that the most favorable results were concentrated in the southern states. In general temperatures are more moderate and mild in southern sections of the US (Bush and Brooks, 2007).

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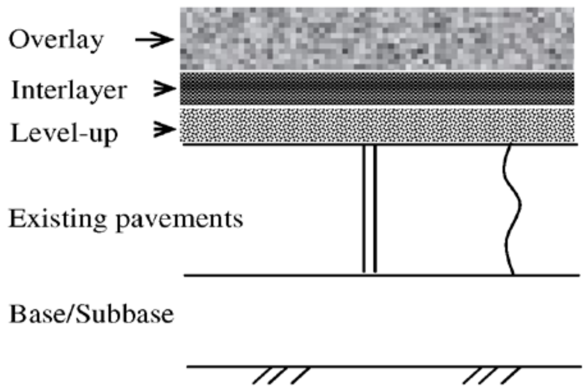

Fig. 1. Sketch of a HMA overlay system.

Mechanisms of Reflection Cracking

Lytton (1989) pointed out that, every time a load passes over a crack in the old pavement, three pulses of high stress concentrations occur at the tip of the crack, as it grows upward through the overlay (Fig. 2). The first stress pulse is a maximum shear stress pulse (shown at point A in Fig. 2). The second stress pulse is a maximum bending stress pulse (shown at point B in Fig. 2). The third stress pulse is again a maximum shear stress pulse, except that it is in the opposite direction of the first shear pulse. Also, because there is often a void beneath the old surface, the maximum shearing stress when the load is at point C is usually larger than when it is at point A. These stress pulses occur in a very short period of time, in the order of 0.05 second. At these high loading rates, the stiffness of the asphalt concrete in the overlay and in the old pavement is quite high. Each pavement movement results in a small increase in crack length in the overlay. As the number of loadings increases, the magnitude of movement increases, crack growth rate increases, and overlay reflection cracks rapidly appear at the pavement.

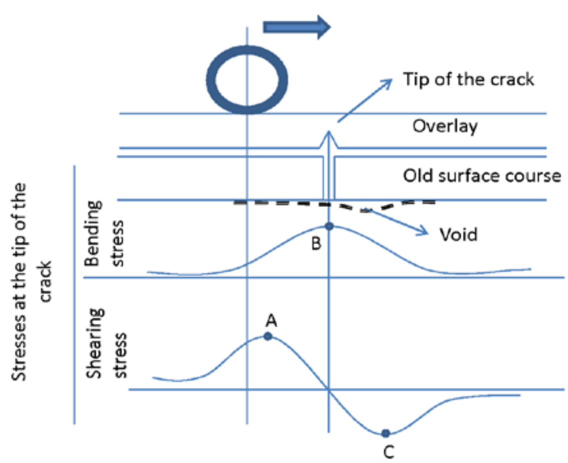

Fig. 2. Shear and bending stress induced at a crack caused by a moving wheel load (after Lytton, 1989).

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Objective and Scope

The study and the results reported in this paper are related to a National Cooperative Highway Research Program (NCHRP) project (1-41: models for predicting reflection cracking of HMA overlays) whose objective is to identify or develop mechanistic-based models for predicting reflection cracking in HMA overlays of flexible and rigid pavements and associated computational software for use in mechanistic-empirical procedures for overlay design and analysis (Tsai et al., 2010). In this study, the Neural Networks (NN) methodology is successfully used to model the stress intensity factor (SIF) as cracks grow upward through a HMA overlay due to both load and thermal effects with and without reinforcing interlayers.

Crack Modeling in HMA Pavements

The NCHRP 1-41 research project is primarily being carried out at the Texas Transportation Institute (TTI). One of the objectives of the NCHRP project is to recommend validated models for predicting the initiation, extent, and severity of reflection cracking in HMA overlays for incorporation in mechanistic-empirical procedures for overlay design and analysis. In recent years, several researchers have applied the concept of fracture mechanics into pavement design and analysis in order to account for crack development accurately. The field of fracture mechanics was developed to understand the phenomenon of fracture and crack growth in metal and/or alloy materials due to premature catastrophic failures (Broek, 1984). These concepts have been extended to crack growth in HMA in the original work guided by R. A. Schapery and R. L. Lytton at Texas A&M University in College Station, Texas.

The characterization of HMA should include the elastic, viscoelastic, plastic, fracture, and healing properties of the material. These material properties can be used with mechanistic models to predict distresses such as rutting, load-related fatigue cracking, and thermal cracking (Lytton et al., 1993). Lytton et al. (1993) provide detailed explanations of these properties and the pavement prediction models in which they are inputs.

Paris' Law

Fatigue is the general phenomenon of material failure due to the growth of microscopic flaws as a result of repeated loadings (Shackelford, 1992). These microcracks become more visible as the stress concentrations at the tip of the crack increase and cause further crack propagation. Paris' Law (Paris and Erdogan, 1963), as provided in Equation 1, defines the fundamental fracture law governing the rate of crack growth (commonly referred to as 'crack extension' in fracture mechanics) in a material based on linear elastic fracture mechanics.

$$\frac{dc}{dN} = A(\Delta K)^n \qquad (1)$$

where: c = crack length; N = number of load applications; dc/dN = rate of crack growth; ΔK = change of stress intensity factor during loading and unloading; A, n = fracture parameters for asphalt mixture surface.

Fracture will occur in HMA when the stress intensity factor (SIF) reaches a critical value. Fracture toughness is defined as the critical value of the stress intensity factor, K_{IC}, at the crack tip necessary to produce failure under simple uniaxial loading (Shackelford, 1992). If a material does not deform plastically at the crack tip, it is considered brittle and will have low fracture toughness. Conversely, high fracture toughness is usually associated with low strength and/or ductile materials. Asphalt concrete mixtures can be characterized as having elastic, viscoelastic, plastic, fracture, and healing material properties (Lytton et al., 1993). Therefore, HMA paving materials transition the range of brittle and ductile behavior, and the use of Paris' Law, based on linear elastic fracture mechanics, should be modified to account for the complex nature of this material.

In 1921, Griffith provided a criterion that stated that "crack propagation would occur if the energy released upon crack growth is sufficient to provide all of the energy that is required for crack growth" (Broek, 1984). In 1948, Irwin modified Griffith's Crack Theory to incorporate an energy balance analysis of crack growth (Tada et al., 2000). Tada et al. (2000) explains that, for the linear-elastic case, the elastic energy release rate, *G*, per crack tip: "may be viewed as the energy made available for the crack extension processes at the crack-tip as a result of the work from displacements of loading forces and/or reductions in strain energy in a body accompanying a unit increase in crack area".

The stress intensity factor (*K*) and the elastic energy release rate (G) are related by the following equations (Tada et al., 2000):

$$G = \frac{K^2}{E} \quad (for\ \ plain\ \ stress\ \ conditions) \tag{2}$$

$$G = \frac{K^2\left(1-\nu^2\right)}{E} \quad (for\ \ plain\ \ strain\ \ conditions) \tag{3}$$

where E = Young's modulus, and ν = Poisson's ratio. Broek (1984) provides a chapter in his textbook describing alternative methods by which the SIF can be determined. To summarize his findings, he explains that, in cases of simple geometry, analytical methods can be used, but the complexity of the boundary conditions often necessitates numerical solution of the equations. Furthermore, finite element methods (FEM) are often necessary with complex geometry and complicated stress systems. Finite element methods have the basic assumption of modeling asphalt concrete as an elastic continuum with a finite number of structural elements interconnected by nodes. The displacement of these nodes is governed by functions, either simple or complex, as prescribed by the user. The use of finite element methods to accurately compute stress fields at the crack tip is quite complex and requires the use of extensive computer resources (Cleveland et al., 2002).

Determination of Stress Intensity Factor

One of the major tasks of the NCHRP 1-41 research project is to develop and validate reflection cracking models. As a subtask, the SIF needs to be determined from bending (SIF_b), shearing (SIF_s), and thermal (SIF_T) stresses, respectively. Numerical estimation of SIFs in front of a crack tip in asphalt overlay pavement structures can currently be made via various extremely sophisticated finite element packages, such as CAPA-3D (Loizos and Scarpas, 2005). Unfortunately, their complex hardware and high execution time demands render them suitable primarily for research purposes. Two dimensional and/or axisymmetric finite element codes (such as CRACKTIP) have lower demands in terms of hardware and execution times however, it is common knowledge that the difference between plane strain conditions and the three dimensional nature of a cracked geometry and loading leads to a gross over estimation of the displacements for the same magnitude of external pressure loads. A tailor made new finite element based system: CAPAm, is specially developed for the NCHRP 1-41 project, which enables the efficient analysis of reflective cracking in asphalt overlays accounting for the three dimensional nature of the cracked pavement geometry and the loading yet, it requires no more hardware and time resources than a two dimensional finite element analysis.

In contrast to full three dimensional finite element analyses, the new system CAPAm incorporates the third dimension via a modal analysis (Figure 3). The system is based on the CAPA series of finite element codes developed at Delft University of Technology and utilized successfully for simulation of reflective cracking in various types of (un)reinforced pavements (Scarpas et al., 1993).

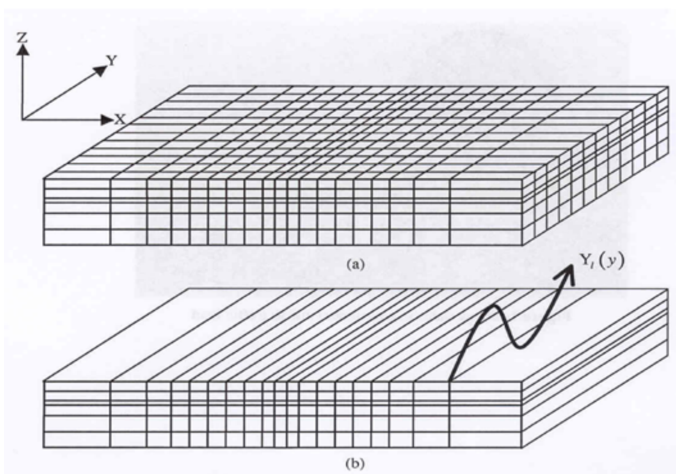

Fig. 3. A pavement section, where X is the direction of traffic: (a) 3D Finite Element Analysis; (b) Finite Element Analysis in the X-Z Direction and a Modal analysis in the Y direction.

The main focus of this study is to develop rapid NN-based models for predicting SIF_b, SIF_s, and SIF_T, respectively, in order to reduce the running time and complexity of using FEM program. An SIF database for each case was established for developing the SIF profiles with layer thickness. The primary variables affecting the SIF include traffic load (single, tandem, tridem, and quad axles), temperature, load transfer (low, medium, and high) at joints or cracks, asphalt overlay system (multiple overlay, interlayer, level-up course), and existing pavement conditions.

Seven networked personal computers were used in making multiple runs (over 105,000 such runs) to determine the SIFs for cracks at various locations when growing up through various thicknesses of overlays. Table 1 lists the overlay cases for models have been developed for predicting the SIF as a crack grows up through the overlay. So far, all of the analyses of the thermal cracking SIFs and the analyses of the single tire and dual tire load-related bending and shearing SIFs have been completed.

Table 1. Overlay cases for SIF prediction models.

Priority	Overlay Type	No. of Test Sections	Climatic Zone
1	AC/mill/AC OL	109	WF
2	JCP/AC OL	69	WF
3	AC/AC OL	59	WF
4	AC/AC OL	33	WNF
5	AC/SAMI/AC OL	26	WF
6	CRC/AC OL	21	WF
7	AC/AC OL	16	DF
8	AC/mill/AC OL	16	DNF
9	AC/SAMI/AC OL	12	WNF
10	AC/Grid/AC OL	~30	NY, Texas

There are four types of axle loads in the current MEPDG: single, tandem, tridem, and quad. For each axle load, there are more than 30 load levels. For example, single axle load ranges from 3,000 lb to 41,000 lb at 1,000 lb intervals. Considering the long computation time required to calculate SIF for each type of axle load at each load level, only one load level for each type of axle (such as 18 kips for single axle) was analyzed. Then, the SIF under other load levels was estimated based on the load ratio, which is reasonable, since the SIF is calculated in a linear elastic system. The method of analysis of tire and axle loads has been worked out using recently published data on the sizes of the tire contact patch for several truck and passenger vehicle tires. The tire patches are primarily rectangular, rather than the assumed circular tire contact patch that is used commonly in design. Empirical equations were developed in these studies that relate the tire contact area to the tire load and inflation pressure. The finite element analyses of the tire and axle load cases have been set up to treat the tire contact patches as rectangular areas with the length of the tire patch distinguishing between different load levels. This matches closely the findings of the empirical studies of the shape and size of tire patches.

Compared to fast moving traffic loads, the thermal load takes much longer. The viscoelasticity of an HMA mix and stress relaxation play significant roles in stress development at the crack/joint tip. For the thermal stress analysis, the relative stiffness of the interface between the concrete layer and the base course beneath it was accounted for. The SIFs for asphalt overlays on cracked asphalt pavements as well as on jointed concrete pavements (JCP) were computed for the cases in which there is no slip between the AC and the PCC; and full slip, partial slip and no slip between the base course and PCC slab. Also, the SIFs for asphalt overlays on cracked AC pavements in which the overlays have grid reinforcing and in which the overlay is placed on a stress-absorbing membrane interlayer (SAMI) were computed.

In addition, the analyses of the bending SIFs due to both single and dual tire loads on overlays over both asphalt and jointed concrete pavements have been completed.

Development of Neural Networks Based SIF Prediction Models

General

Literature review (Adeli, 2001; Dougherity, 1995; TR Circular, 1999) suggests that NNs and other soft computing techniques like fuzzy mathematical programming and evolutionary computing (including genetic algorithms) are increasingly used instead of the traditional methods in civil and transportation applications (Flintsch, 2003). The recent adoption and use of Neural Networks (NN) modeling techniques in the MEPDG (NCHRP, 2004) has especially placed the emphasis on the successful use of neural nets in geomechanical and pavement systems.

The basic element in the NN is a processing element (artificial neurons). An artificial neuron receives information (signal) from other neurons, processes it, and then relays the filtered signal to the other neurons (Tsoukalas and Uhrig, 1997). The receiving end of the neuron has incoming signals x_1, x_2 , . . ., and x_n. Each of them is assigned a weight (w_{ik}), which is given based on experience and which may change during the training process. The summation of all the weighted signal amounts yields the combined input quantity I_k. The combined input quantity I_k is then sent to a preselected transfer function (sometimes called an activation function) T, and a filtered output Y_k is generated in the outgoing end of the artificial neuron k through the mapping of the transfer function. The process can be written as the following equations:

$$I_K = \sum_{i=1}^{n} w_{ik} x_i \tag{4}$$

$$Y_K = T(I) \tag{5}$$

There are several types of transfer functions that can be used, including sigmoid, threshold, and Gaussian functions. The transfer function most often used is the sigmoid function because of its differentiability. The sigmoid function can be represented by the following equation:

$$T(I) = \frac{1}{1 + \exp(-\varphi I)} \tag{6}$$

where φ = positive scaling constant, which controls the steepness between the two asymptotic values 0 and 1 (Tsoukalas and Uhrig, 1997).

The NN performs two major functions: learning (training) and testing. This study used the backpropagation learning algorithm for the NN, which is a supervised learning algorithm in which the network is trained on a set of input–output pairs. Backpropagation ANNs are very powerful and versatile networks that can be taught a mapping from one data space to another using a representative set of patterns/examples to be learned. The term "backpropagation network" actually refers to a multi-layered, feed-forward neural network trained using an error backpropagation algorithm. The learning process performed by this algorithm is called "backpropagation learning" which is mainly an "error minimization technique" (Haykin, 1999).

In the development of backpropagation NN models, the connection weights and node biases are initially selected at random. Inputs from the mapping examples are propagated forward through each layer of the network to emerge as outputs. The errors between those outputs and the correct answers are then propagated backwards through the network and the connection weights and node biases are individually adjusted to reduce the error. After many examples (training patterns) are propagated through the network many times, the mapping function is learned with some specified error tolerance. This is called supervised learning because the network has adjusted functional mapping using the correct answers. The network is considered to be well trained when the error reaches a minimum or an allowable limit. The network performance is verified by presenting unknown testing datasets to the NN after training is completed. Backpropagation ANNs excel at data modeling with their superior function approximation (Haykin, 1999; Meier and Tutumluer, 1998, Gopalakrishnan et al., 2010).

NN Architecture

As described previously, the main focus of this study is to develop rapid NN-based models for predicting SIF_b, SIF_s, and SIF_T, respectively, in order to reduce the running time and complexity of using FEM program. An SIF database for each case was established for developing the SIF profiles with layer thickness. The primary variables affecting the SIF include traffic load (single, tandem, tridem, and quad axles), temperature, load transfer (low, medium, and high) at joints or cracks, asphalt overlay system (multiple overlay, interlayer, level-up course), and existing pavement conditions.

Nearly 100,000 runs of a finite element program were made to calculate the SIFs at the tip of the reflection crack for a wide variety of crack lengths and pavement structures. This database of SIFs was modeled with 18 separate Artificial Neural Network algorithms: 6 for thermal, 6 for bending, and 6 for shearing stresses. For the thermal load SIF calculation, a 2-D finite element program specifically for pavement thermal SIF analysis was employed. For the traffic load SIF calculation, the finite element model used a Fourier Series to represent the effects of loads acting at some lateral distance from the 2-D plane where the calculations were made (Tsai et al., 2010).

The SIF database was divided randomly into two different subsets: the training data subset and the testing data subset which consisted of 500 data points. Both datasets were normalized within the range of -2 to 2 for input values and the range of 0.1 to 0.9 for output values to satisfy the transfer function (sigmoid) range and to prevent network saturation, which could impede the network's performance. The training data subset was used to train the SIF NN prediction models and the testing data subset was used to examine the statistical accuracy of the developed NN models.

A typical four-layered, i.e., one input- two hidden–one output layer, feed forward error-back propagation NN architecture was used in this study for all SIF prediction models. To ensure efficient convergence and the desired performance of the trained network, several parameters were incorporated in the training phase. These parameters included the training rate, the momentum term, and the number of learning cycles (epochs).

The training rate is a factor that proportions the amount of adjustment applied each time the weight is updated. A small training rate might result in slower convergence and dropping into the local minima conditions in the weight-error space. A large training rate often causes the convergence behavior of the network to oscillate and possibly never converge. The use of a momentum term could carry the weight change process through one or more local minima and get it into global minima. The training rate and the momentum coefficient used in the study were 0.4 and 0.6, respectively.

A suite of NN based SIF prediction models were developed primarily under two broad categories: (a) traffic loading and (b) thermal. Under each category, there were several subcategories in terms of combinations of existing pavement type (AC or PCC), slip interface conditions (low, medium, and high), etc. Thus, the abbreviation "AC_over_AC_interlayer_slip_L", for instance, refers to AC overlay over AC pavement with 'low' slip interface condition. Several network architectures with two hidden layers were examined to determine the optimum number of hidden layer nodes through a parametric study. Overall, the training and testing mean squared errors (MSEs) decreased as the networks grew in size with increasing number of neurons in the hidden layers. For some models, best performance was achieved with 10 hidden neurons in each of the hidden layers whereas some models required 40 hidden neurons in each of the hidden layers to achieve best performance. The number of inputs varied between 8 to 10 depending on the specific case, whereas the output was always SIF (Table 2).

Table 2. Priorities and computer analysis for developing SIF prediction models.

Priorities	Total Test Sections	Computer Analyses of Stress Intensity Factors With Varying Crack Lengths		
		Thermal	Shear	Bending
1,3,4,7,8	233	1,620	25,920	4,320
2	69	14,580	25,920	4,320
5,9	38	6,480	-	-
10	~30	9,720	-	-
6	21	1,620	-	-

Results and Discussion

Six NN based SIF prediction models for thermal loading and 12 models for traffic loading were successfully developed. Table 3 displays the network architecture and the inputs used in developing the NN based SIF prediction models for thermal loading.

The "goodness-of-fit" statistics for the NN model predictions in arithmetic scale were performed using statistical parameters such as the correlation coefficient (R^2), the standard error of predicted values divided by the standard deviation of measured values (S_e/S_y), and the absolute average error (AAE). The R^2 is a measure of correlation between the predicted and the measured values and therefore, determines accuracy of the fitting model (higher R^2 equates to higher accuracy). The S_e/S_y and the AAE indicates the relative improvement in accuracy and thus a smaller value is indicative of better accuracy.

Using non-linear regression approach, the best model of thermally-induced stress intensity factors in grid-reinforced overlays that we could achieve had an R^2 value of 0.75. Using NN prediction model, the fit to the computed SIFs is nearly perfect (R-squared value of 0.9997) for a total of 2,430 sets of data. Similar results were achieved with all the cases which clearly demonstrate the success of NN based modeling approach. The trained NN models compute their results very quickly (more than 10,000 cases in less than a second) and would thus be very useful for a design approach.

Table 3. NN based SIF prediction models (thermal).

Case	Description	Architecture	Inputs
1	AC_over_AC_Interlayer_slip_L	8-40-40-1	$H_{overlay}$, $E_{overlay}$, $H_{leveling}$, $H_{existing}$, $E_{existing}$, α_{AC}, $\alpha_{existing}$, c
2	AC_over_AC_Interlayer_slip_M	8-40-40-1	$H_{overlay}$, $E_{overlay}$, $H_{leveling}$, $H_{existing}$, $E_{existing}$, α_{AC}, $\alpha_{existing}$, c
3	AC_over_AC_Interlayer_slip_H	8-40-40-1	$H_{overlay}$, $E_{overlay}$, $H_{leveling}$, $H_{existing}$, $E_{existing}$, α_{AC}, $\alpha_{existing}$, c
4	AC_SC_SC	9-40-40-1	$H_{overlay}$, $E_{overlay}$, $H_{sclayer}$, $H_{sclayer}$, $H_{existing}$ $E_{existing}$, α_{AC}, α_{SC}, c
5	AC_over_AC	7-40-40-1	$H_{overlay}$, $E_{overlay}$, $H_{existing}$, $E_{existing}$, α_{AC}, $\alpha_{existing}$, c
6	AC_over_PCC	9-40-40-1	$H_{overlay}$, $E_{overlay}$, $H_{sclayer}$, $E_{sclayer}$, $LogK_{interface}$, α_{AC}, α_{SC}, c, c_2

The prediction performance of optimized NN based SIF prediction models for cases 1 to 3 for thermal loading and three cases for traffic loading are illustrated in Figures 4 to 9 for illustration.

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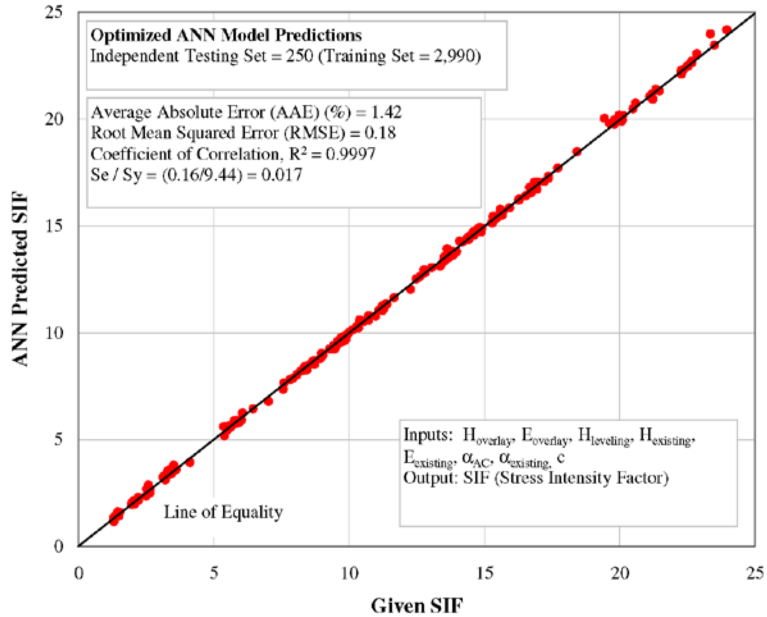

Fig. 4. Prediction performance of optimized NN model (AC_over_AC_interlayer_slip_L).

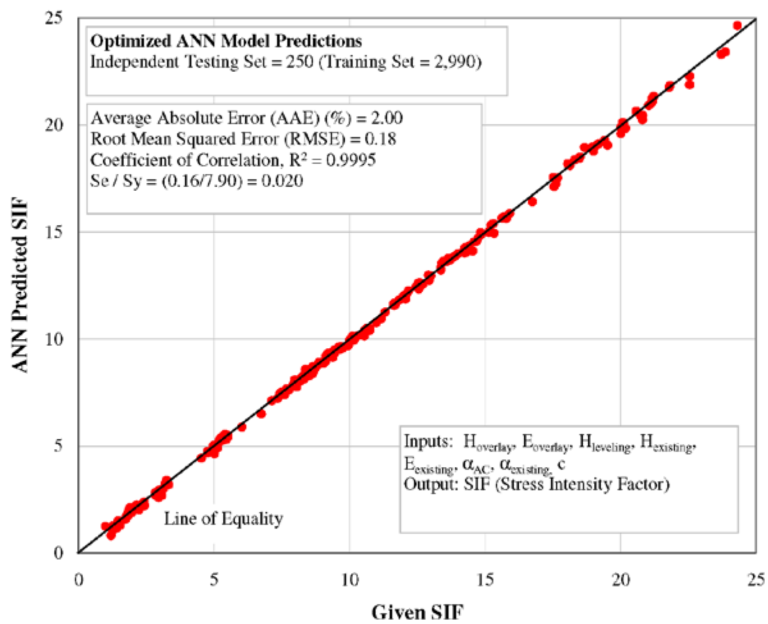

Fig. 5. Prediction performance of optimized NN model (AC_over_AC_interlayer_slip_M).

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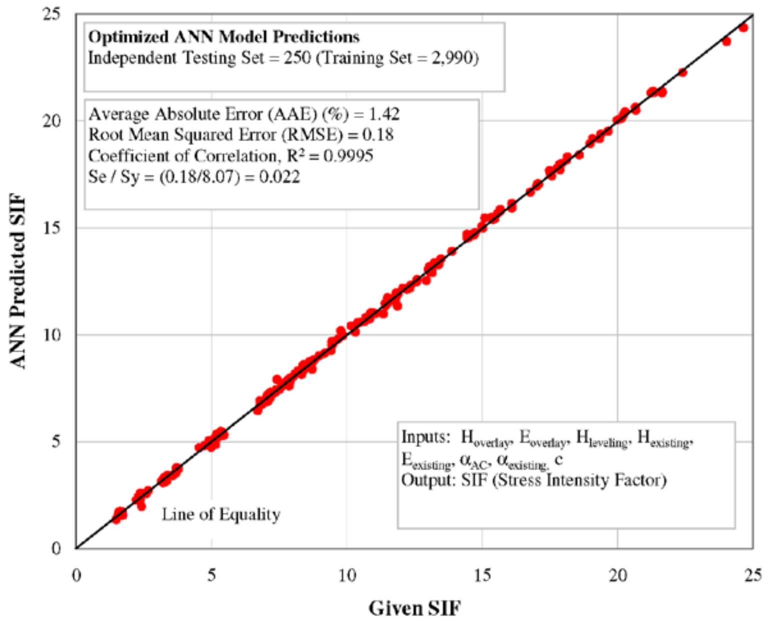

Fig. 6. Prediction performance of optimized NN model (AC_over_AC_interlayer_slip_H).

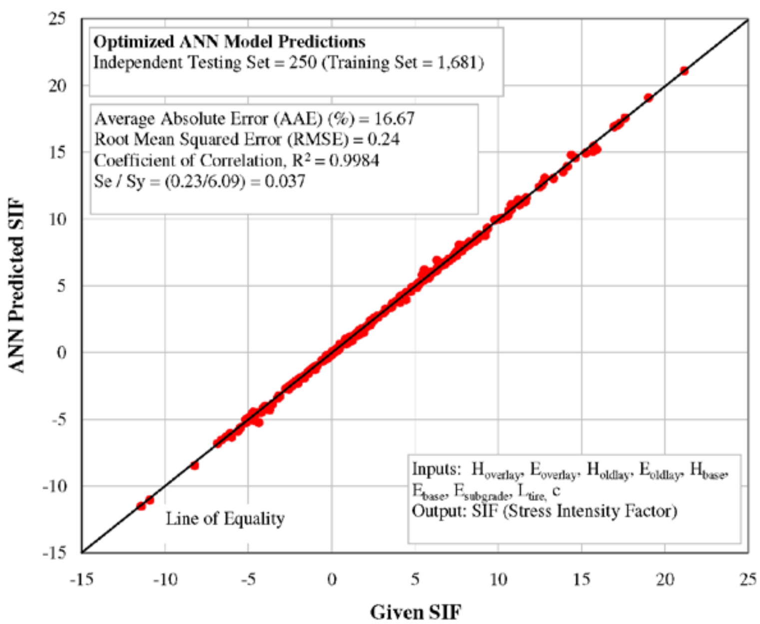

Fig. 7. Prediction performance of optimized NN model (Pure_Bending_AC_over_AC_Dual_Tire_Together).

Reference to this paper should be made as follows: Ceylan, H., Gopalakrishnan, K., and Lytton, R. (2011). "*Neural Networks Modeling of Stress Growth in Asphalt Overlays due to Load and Thermal Effects during Reflection Cracking*." ASCE Journal of Materials in Civil Engineering, Vol. 23, No. 3, pp. 221-229.

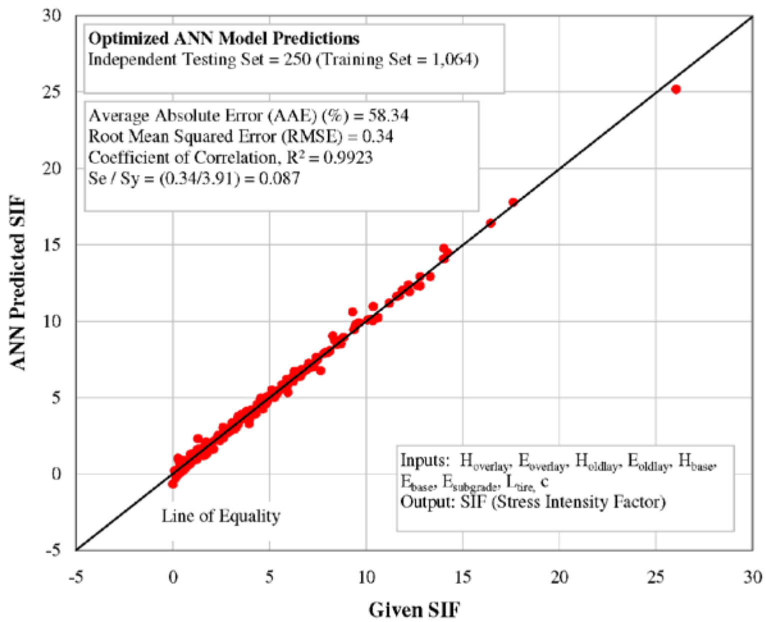

Fig. 8. Prediction performance of optimized NN model (Pure_Bending_AC_over_AC_Dual_Tire_Together_Only_Positive).

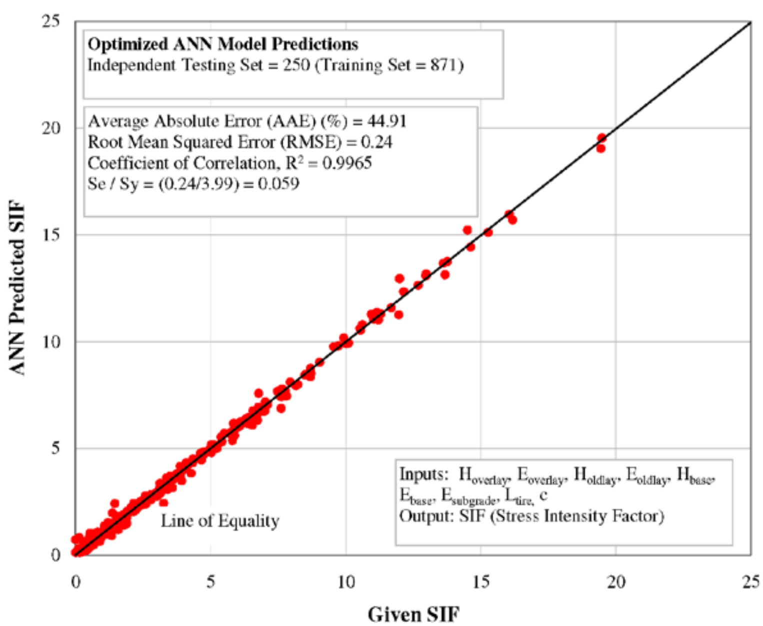

Fig. 9. Prediction performance of optimized NN model (Pure_Bending_AC_over_AC_Single_Tire_Together_Only_Positive).

Reference to this paper should be made as follows: Ceylan, H., Gopalakrishnan, K., and Lytton, R. (2011). "*Neural Networks Modeling of Stress Growth in Asphalt Overlays due to Load and Thermal Effects during Reflection Cracking*." ASCE Journal of Materials in Civil Engineering, Vol. 23, No. 3, pp. 221-229.

Conclusions

Reflection cracking is one of the primary forms of distress in hot-mix asphalt (HMA) overlays of flexible and rigid pavements. In addition to affecting ride quality, the penetration of water and foreign debris into these cracks accelerates the deterioration of the overlay and the underlying pavement, thus, reducing service life. Preliminary models for predicting the extent and severity of reflection cracking in HMA overlays have been developed. However, only limited research has been performed to evaluate and validate these models. Research is needed to address the issues associated with reflection cracking and to identify or develop mechanics-based models for use in mechanistic-empirical procedures for the analysis and design of HMA overlays. The NCHRP 1-41 research project was initiated with the objective of to identify or develop mechanics-based models for predicting reflection cracking in HMA overlays of flexible and rigid pavements and associated computational software for use in mechanistic-empirical procedures for overlay design and analysis.

As a subset of the NCHRP 1-41 project, the focus of this paper was to use the Neural Networks (NN) approach to model the stress intensity factor (SIF) as cracks grow upward through a HMA overlay due to both load and thermal effects with and without reinforcing interlayers. Several cases under both thermal loading and traffic loading were considered and the NN models significantly higher accuracy in predicting SIFs compared to non-linear regression approach.

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