Prediction of Pavement Performance through Neuro-Fuzzy Reasoning

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Abstract: *Government agencies and consulting companies in charge of pavement management face the challenge of maintaining pavements in serviceable conditions throughout their life from the functional and structural standpoints. For this, the assessment and prediction of the pavement conditions are crucial. This study proposes a neuro-fuzzy model to predict the performance of flexible pavements using the parameters routinely collected by agencies to characterize the condition of an existing pavement. These parameters are generally obtained by performing falling weight deflectometer tests and monitoring the development of distresses on the pavement surface. The proposed hybrid model for predicting pavement performance was characterized by multilayer, feedforward neural networks that led the reasoning process of the IF-THEN fuzzy rules. The results of the neuro-fuzzy model were superior to those of the linear regression model in terms of accuracy in the approximation. The proposed neuro-fuzzy model showed good generalization capability, and the evaluation of the model performance produced satisfactory results, demonstrating the efficiency and potential of these new mathematical modeling techniques.*

1 INTRODUCTION

Maintaining an in-service pavement structure in acceptable conditions from the structural and functional points of view depends on many factors, which are often not explicit and change in time. Although maintenance strategies may be influenced by human experience, data interpretation procedures, and policies of the pavement management agency, these maintenance strategies are largely supported on the implementation of the so-called pavement management system (PMS). A PMS is based on the complete inventory of the pavement network and includes information about the pavements such as type, location and size of sections, number of traffic lanes, route designations, functional classification, and section conditions (i.e., type of distresses, roughness, and deflections). In addition, a PMS applies analytical tools or statistical methods to assist agencies in the decision-making procedure to maintain pavements in serviceable and functional conditions throughout their life. The development of such tools that are capable of describing and predicting pavement performance accurately is critical for agencies, in particular for planning at the network level, and is the focus of this article.

Predicting the performance of a pavement structure is a very important but difficult process and is strongly connected to the assessment of the pavement condition and serviceability level. Pavement databases, including information on past and current pavement conditions, may be employed to forecast the future state of the pavement network. Agencies aiming for an efficient pavement management, every so often (usually every 2 years), collect nondestructive deflection testing (NDT) data using the falling weight deflectometer (FWD). Pavement evaluation programs also include distress surveys to monitor the behavior of the structure and its interaction with traffic load and environmental changes.

In the literature, many studies (e.g., Shahin, 1994; Zhang et al., 2003) have underlined the importance of assessment programs that include FWD testing and distress surveys to determine the pavement structural conditions. In fact, the analysis of the information obtained from these programs is generally used to predict

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the change in the load bearing capacity of the pavement structure. Among others, Van Gurp et al. (1989) established a proper plan for structural maintenance based on the analysis of FWD deflection measurements, pavement condition from visual surveys, core analyses, age and structure of the pavement, traffic carried to date, and expected traffic. Their predicting model was built on a statistical procedure that finds the relationship between residual structural life and deflection parameters.

The study of Park and Kim (2003) predicted flexible pavement remaining life through empirical equations based on FWD data and considered sets of deflections due to different loads. Its peculiarity was in the application of Miner's law and in assuming a linear cumulative relationship between damage and traffic over the pavement structure. The Markov chain process related to prediction of pavement overall condition was applied by Li et al. (1996) and Yang et al. (2006); the stochastic approach applied to pavement performance was also investigated by Butt et al. (1992), Vennalaganti et al. (1994), Hong and Wang (2003), and others.

The objective of this research is to develop a model to predict more effectively the performance of flexible pavements through the application of a neuro-fuzzy approach. Many studies on neural networks specifically applied to design, performance, and structural assessment of pavements are reported in the literature (e.g., Eldin and Senouci, 1995; Saltan et al., 2002; Choi et al., 2004; Mei et al., 2004; Loizos and Karlaftis, 2006). Artificial neural networks represent an excellent tool for dealing with the complexity of the pavement structure and the inherent non-linearity of the measured data. Neural networks are characterized by their large flexibility and adaptability to the system and the information available in describing it. Expressing a complex system through neural networks has proven to be successful in overcoming many of the limitations of classical methods such as finite element and the traditional statistical analyses (Prozzi and Madanat, 2003; Yang et al., 2006). With the inclusion of the fuzzy reasoning into the neural network paradigm, this study proposes an attractive alternative from the practical and theoretical standpoints to predict pavement performance. As supported by the literature (e.g., Funahashi, 1989; Hornik et al., 1989; Poggio and Girosi, 1990; Adeli and Hung, 1993a; Klir and Yuan, 1995; Adeli and Karim, 2000; Samant and Adeli, 2001; Karim and Adeli, 2002; Jiang and Adeli, 2003, 2008; Adeli and Jiang, 2003, 2006), the implementation of a neuro-fuzzy model is an appropriate strategy to handle parameters characterized by various types of uncertainty, like the parameters that determine the pavement performance and serviceability.

The proposed model aims to quantify the change in the level of serviceability of a pavement structure in the medium-term of 5 years, which is a time range commonly used in PMS planning. However, the model is flexible enough to be implemented for different time ranges. The parameters implemented in the proposed neuro-fuzzy model are those that characterize the conditions of an existing pavement that is fully operational. The combination of neural networks and fuzzy reasoning aims to extract implicit knowledge contained in the data and recognize the inherent "patterns" governing the variables selected as system descriptors, which in this case are the pavement distresses, FWD data, and observed pavement performance, and their statistical distributions.

2 PAVEMENT PERFORMANCE

The term performance refers to the structural and functional responses of the pavement to the actions of the elements or factors that induce modifications to its original structure. These elements comprise traffic using the pavement, environmental conditions of the site, and materials composing the pavement structure itself. With time, the combined influence of these factors changes the serviceability condition of the pavement. The pavement performance and the change in the serviceability offered to the traveling public are important elements that agencies managing pavement networks need to take into consideration in the development of their infrastructure maintenance strategies.

From the experimental results of the AASHO Road Test (Carey and Irick, 1960, 1962), the pavement serviceability was expressed in terms of the present serviceability index (PSI). The original definition of the PSI was based on individual observations and on "the judgment of an observer as to the current ability of a pavement to serve the traffic it is meant to serve" (Carey and Irick, 1962) by applying a quantitative scale ranging from 5 (excellent road) to 0 (impossible road). Subsequent studies (e.g., Uzan and Lytton, 1982; Hall and Muñoz, 1999; Prozzi and Madanat, 2003) proposed other formulations of the present serviceability index that included parameters related to the conditions of the pavement surface. The study of Hall and Muñoz (1999) provided an expression to estimate PSI values from the current status of the pavement measured through the international roughness index (IRI). The IRI is a standard roughness measurement calculated from the records of a specific type of road meter installed on vehicles or trailers (Sayers and Karamihas, 1998). Hall and Muñoz (1999) formulated the following equation to estimate

the PSI from IRI measurements (given in m/km) for flexible pavements:

$$PSI = 5 - 0.2397 X^4 + 1.771 X^3 - 1.4045 X^2 - 1.5803 X \tag{1}$$

where $X = \log(1 + SV)$, and SV is the slope variance calculated as $SV = 2.2704(IRI)^2$.

Therefore, the pavement performance can be quantified by the PSI, which consequently represents the output of the forecasting model developed in this study. The reason supporting this choice resides in the two types of information contained in the definition of the index. The PSI comprises information regarding both the structural and functional capabilities of the pavement. The serviceability is affected by the distresses appearing on the pavement surface due to the deficiency of the structure in supporting the load for which it was designed, and thus, its functionality is compromised because the structure is not able to offer an adequate riding surface.

3 THE PROBLEM OF PERFORMANCE PREDICTION REINTERPRETED THROUGH NEURO-FUZZY MODELING

The factors causing the decrease in the serviceability level are multiple and include the traffic using the structure, climatic changes (e.g., freeze-thaw cycles, rainfalls, etc.), materials constituting the pavement, and construction practices. Besides traffic, which may be considered as the explicit cause of deterioration, the influence of the other factors is only measured indirectly. It is not possible to define unique parameters that explicitly quantify the effects of these factors.

These considerations lead to the conclusion that the factors and variables influencing the performance of the pavement structure and the interactions among them constitute a complex system (Mantegna and Stanley, 1999). This is a system that cannot be represented by objective and deterministic mathematical laws; in fact, only specific numerical analyses may be able to provide an approximate description of the system. In this perspective, neuro-fuzzy models can be employed to obtain "the best" description of an environment that is solely explained by data and nondeterministic cause-effect rules. Because the neuro-fuzzy procedure is essentially data driven, the extracted knowledge offers a different vision of the system structured over field observations. Furthermore, the knowledge mining of neuro-fuzzy models overcomes the limitation imposed by the lack of a deterministic model to describe the pavement condition.

The variability of the pavement response to an applied impulse load, represented by deflection basin parameters, and the distresses affecting the pavement structure allow the evaluation of the structural and functional characteristics of flexible pavements. Processing these factors through a neuro-fuzzy prediction model can extract an embedded knowledge from the numerical data that is not immediately obvious due to the implicit form of the relations among variables. In this way, a neuro-fuzzy model can provide one of the possible representations of the pavement complex system.

4 METHODOLOGY

The method developed in this study to predict pavement performance is based on a hybrid modeling tool named neuro-fuzzy model, created by combining neural networks and fuzzy models. This hybrid numerical analysis offers one of the possible interpretations of the underlying relations among the variables identified as relevant for the assessment of the pavement conditions. The neuro-fuzzy model tends to overcome the shortcomings of these modeling methods in the problem-solving procedure (Nauck et al., 1997). Neural networks may handle some of the limitations inherent to fuzzy reasoning and vice versa. Neural networks are considered universal approximators (Hornik et al., 1989; Poggio and Girosi, 1990); they have good generalization and learning capabilities and the ability of extracting knowledge from data (Jiang and Adeli, 2005). In addition, neural networks represent a data-driven modeling system with robustness and high accuracy (Haykin, 1999). However, they carry some disadvantages such as the difficulty of introducing prior knowledge in the network itself.

In contrast, fuzzy theories are able to express explicit knowledge of the system and are the direct way, via fuzzy IF-THEN rules, to deal with uncertainty and concepts expressed through natural language (Sarma and Adeli, 2000a, 2000b; Chao, 2007; Nomura et al., 2007; Stathopoulos et al., 2008; Carden and Brownjohn, 2008; Jin and Doloi, 2009). Moreover, robustness and universal approximation capability characterize these models. Besides these aspects, the main issue is whether the logic is explicit or implicit in the reasoning process. Fuzzy theories are always able to express an inference process because the logical structure is manifested through IF-THEN rules; on the other hand, rules cannot be expressed if the logic is not identified *a priori*. Instead, neural networks self-organize the approximate mapping by learning and, consequently, they are applicable within the unidentified logical structure (Takagi and Hayashi, 1991). Another problem

includes the design of the membership function that may be derived from a partition of the learning data through neural network techniques (Takagi and Hayashi, 1991; Ross, 2004).

A neuro-fuzzy approach is the adequate choice for predicting performance of flexible pavements from pavement condition data. This selection is justified in part by the large amount of available input data to be processed. In this case, a data-driven approach offers a means to uncover the intimate relations among inputs, thus avoiding heuristic searches of these relations and the IF-THEN rules.

5 NEURO-FUZZY MODEL FORMULATION

The neuro-fuzzy model adopted in this study to predict flexible pavement performance is called neural network (NN)-driven fuzzy reasoning. This model was originally developed by Takagi and Hayashi (1991) with the purpose of detecting chemical components in seawater. The NN-driven fuzzy reasoning combines fuzzy models and neural networks in a homogeneous architecture where the latter guide the interpretation of the fuzzy IF-THEN rules. The basic idea is to use the fuzzy theory to perform the reasoning part and the neural networks to determine the numerical components of the membership functions through an adaptive process extracted from the data.

5.1 Artificial neural networks

A characteristic of the connectionist paradigm is the learning process, from which the network derives its capability to generalize and produce coherent outputs from inputs never processed during the training phase. With learning, the free parameters (i.e., the synaptic weights) are adjusted through a process of stimulation by the environment in which the network is embedded. In the supervised learning procedure, pairs of input and corresponding desired output are offered to the network, which will adjust the synaptic weights to map each input to its related output based on the error between the outputs (desired and produced). This adjustment is carried out in an iterative fashion based on the error, also called cost function, which depends on the values of the neuron weights and may be visualized as a multidimensional error surface. For the network to improve its performance, the error has to move down over the surface toward a point of global minimum, avoiding getting relegated on points of local minimum that do not represent a situation of good performance. Several methods exist for training of the neural network such as the simple backpropagation (BP) (Hung and Adeli,

1993), counter-propagation (Adeli and Park, 1995; Sirca and Adeli, 2001; Dharia and Adeli, 2003), and adaptive conjugate gradient neural networks (Adeli and Hung, 1993b, 1994). The choice of method is led by the level of performance that the network needs to achieve, the type of data to analyze, and the number of neurons forming the network.

5.2 The NN-driven fuzzy reasoning model

The four main parts of the NN-driven fuzzy reasoning model of Takagi and Hayashi (1991) perform the following functions: (a) determination of the number of inference rules, (b) identification of the IF-part of the rules, (c) identification of the THEN-part of the rules, and (d) determination of the final value or output. The block diagram in Figure 1 illustrates the position and function of the four numerical parts of the model.

5.2.1 Part a: Determination of the number of inference rules. This part consists of determining the number of fuzzy inference rules and the subsequent combination of the data belonging to each rule. A classical clustering procedure can be employed. The number of clusters coincides with the number of rules because the rules are determined based on data values. This portion defines which inputs are included in each single rule (cluster), whose total number has been determined through the *k*-means clustering algorithm (MathWorks, Inc., 2007).

5.2.2 Part b: Identification of the IF-part of the rules. This phase establishes the membership function pertinent to each rule with the application of a neural network. The network representing the membership function is trained with the output derived from the clustering phase. The output produced by this network consists of an *s*-dimensional weight vector in which each component represents the membership of the input to the *s* clusters. The supervised learning process teaches the network to assign to the partitioned input the degree of membership to the *i*th cluster derived from Part a. After the learning phase, the neural network is able to infer the degree of membership (R^s) of each element belonging to the *s*th group. Formally, the membership function of the relation R^s is defined as

$$\mu_{A^s}(x_i) = \hat{w}_i^s, \quad \text{with} \quad i = 1, 2, \ldots, n \qquad (2)$$

where *n* is the number of elements, and $\hat{w}_i^s \in [0, 1]$ represents the membership degree of the element x_i to the cluster A^s.

5.2.3 Part c: Identification of the THEN-part of the rules. This part includes the use of neural networks to

determine the link between the output and the inputs previously partitioned in Part a. The THEN-part of the model is in charge of concluding the final value of the output. This is a representation of the fuzzy modeling form of "IF $x \in A^s$ THEN $y = u(x)$," where x is an input vector, A^s is the fuzzy set of the sth partitioned rule space, and $u(x)$ is the inference function represented in this case by a neural network associated with the sth partition. This approach presumes that what is inferred at each rule is simply expressed in the input–output links embedded in the numerical data. In fact, the number of neural networks created in this phase is equal to the number of clusters (s) determined in Part a. A supervised learning process trains each network employing the input–output pairs that belong to the respective sth cluster.

5.2.4 Part d: Combiner. This module combines the values obtained from the membership function (s-dimensional weight vector) and the values from the neural networks of the THEN-part of the rules to determine the final value y_i^* that the neuro-fuzzy model aims to approximate:

$$y_i^* = \frac{\sum_{s=1}^{r} \mu_{A^s}(x_i) \cdot \overline{u_s(x_i)}}{\sum_{s=1}^{r} \mu_{A^s}(x_i)} \quad \text{with } i = 1, 2, \ldots, n \quad (3)$$

where $\mu_{A^s}(x_i)$ is the s-dimensional vector with the membership of the input x_i to the relation R^s calculated from

the network of Part b; and $\overline{u_s(x_i)}$ is an inferred value obtained from the neural networks of Part c.

To evaluate the right number of iterations and avoid over-learning of the networks defined in Part c, Takagi and Hayashi (1991) recommended choosing the number of iterations in the network training phase based on the lowest value of the index I^s given by

$$I^s = \left[\frac{n_c}{(n_t)^s + n_c} \sum_{i=1}^{(n_t)^s} \{y_i - \overline{u_s(x_i)}\}^2 \right]$$
$$+ \left[\frac{(n_t)^s}{(n_t)^s + n_c} \sum_{j=1}^{n_c} \{y_j - \overline{u_s(x_j)} \cdot \mu_{A^s}(x_j)\}^2 \right]$$
$$(4)$$

where n_c is the cardinality of the checking data set; and $(n_t)^s$ is the training data set belonging to the sth cluster previously defined during the design of the neural networks. The index I^s was used during the training for a qualitative assessment of the performance of the networks included in Part c. The quantitative assessment was performed through the evaluation of the mean square error (mse).

The IF-THEN rules represented by this model express the following reasoning. IF the input set belongs to s clusters at different levels (depicted by the membership function values), THEN the output is a weighted average that includes the affiliation of the input set to each one of the s clusters. As mentioned previously, Figure 1 shows the block diagram that represents the reasoning.
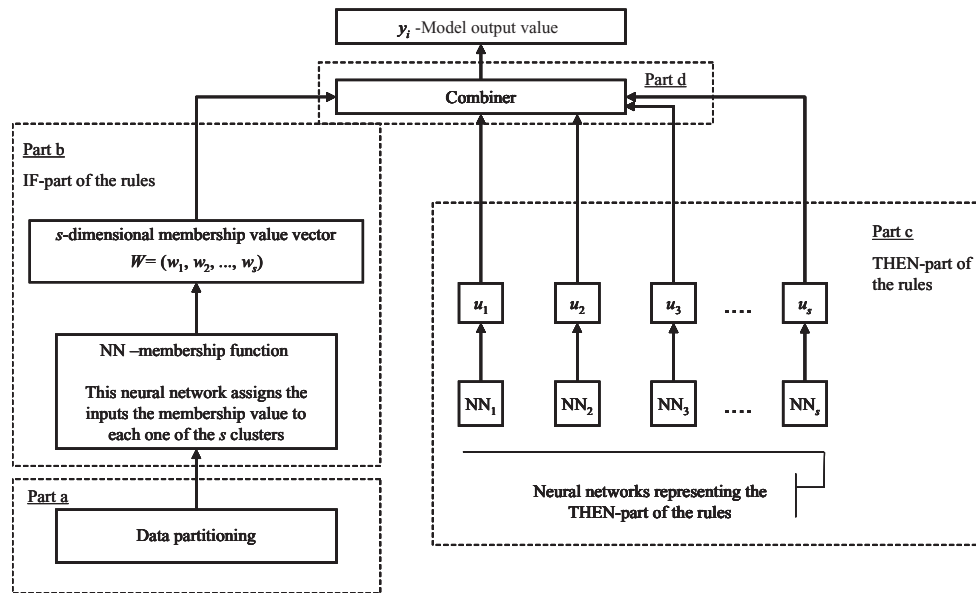
Fig. 1. Diagram of the neural network (NN)-driven fuzzy reasoning model.

6 MODEL IMPLEMENTATION FOR PAVEMENT PERFORMANCE

The hybrid model of Takagi and Hayashi (1991) is used in this study to map from a series of inputs related to pavement conditions to a single output represented by the PSI. Besides the specific mathematical processing that each part of the model implements, the reasoning represented in the model is the future assessment of the pavement serviceability based on the current conditions and the future amount of traffic expected to use the structure. Given the pavement conditions C at time t and the anticipated traffic in the interval from t to $t + t_1$, the increment (either positive or negative) of the serviceability, expressed in terms of the PSI value, occurring between t and $t + t_1$ is predicted (Figure 2).

The PSI value was calculated with Equation (1) using IRI measurements. In a given time interval, a positive increment of serviceability (associated with a decrease in the IRI value) results generally due to rehabilitation works on the pavement section. Nevertheless, besides maintenance activities, the inherited variability or reliability of the equipment and procedures to measure IRI and the effects of temperature differentials during IRI measurements may also contribute to a positive increase in the PSI value. Quantifying the variability of IRI and PSI values due to equipment and temperature effects was not the scope of this article.

The structure of the database implemented in the neuro-fuzzy model is ruled by the time lag. The determination of the time lag t_1 and the corresponding configuration of the input and output data sets require the consideration of several important aspects. Pavement structures are designed based on a performance period, generally between 12 and 25 years. The pavement structure deteriorates during this period and at the end is expected to reach a state in which a complete reconstruction is needed if not rehabilitated during its service life. Furthermore, to enhance the applicability of this new mathematical tool by pavement management agencies, the time lag t_1 is set equal to 5 years. Based on the usual schedules of most pavement management agencies, performance predictions in a time frame of 5 years are de-

sirable. Even though the time lag of 5 years was adopted in this research, the same approach could be used to build and train neuro-fuzzy models using databases prepared for different time lags depending on specific agencies' needs (Bianchini, 2007).

6.1 The database

The MnROAD test site database was selected as the source of input and output parameters for the training and validation phases. The MnROAD test site, located near Albertville, Minnesota, is a state-run, publically funded facility developed by the Minnesota Department of Transportation (MnDOT) and the University of Minnesota. The MnROAD test track includes a 2.5-mile closed-loop, low-volume roadway (LVR) carrying a controlled 5-axle tractor semi-trailer to simulate conditions of rural roads. The pavement sections, also called cells, are in average 500 ft (152.4 m) long and 24 ft (7.32 m) wide. This study focused on the performance of conventional flexible pavements, which consist of an asphalt concrete (AC) layer underlain by layers of granular materials. The thickness of the AC layer in the MnROAD test track sections ranges from 3 to 6 inches (7.62–15.24 cm). The data collected at the MnROAD test track include distresses occurring on the pavement surface, information related to the strength of the section given by FWD testing results, and IRI measurements. The data employed in this study covered the period from 1994 to 2004.

6.2 Selection of the input variables

The inputs implemented in the neuro-fuzzy model are indicators of the structural and functional serviceability of the pavement structure. With regard to the structural serviceability, the indicators selected are linear combinations of FWD deflections. The FWD is commonly used by agencies to evaluate the structural condition of the pavement. With respect to the functional serviceability, the indicators adopted as input variables are the rut depth and the area of the pavement surface affected by alligator cracking. Although undoubtedly affecting the ride quality, these two distresses are also signs of pavement deterioration from the structural point of view.

The following seven input variables were selected for the analyses:

1. The surface curvature index (SCI), which is related to the Young modulus of the AC layer (Xu et al., 2002a, 2002b) and defined as

$$SCI = D_0 - D_{300} \qquad (5)$$

where D_0 and D_{300} are the deflections measured at the point where the load is applied and at
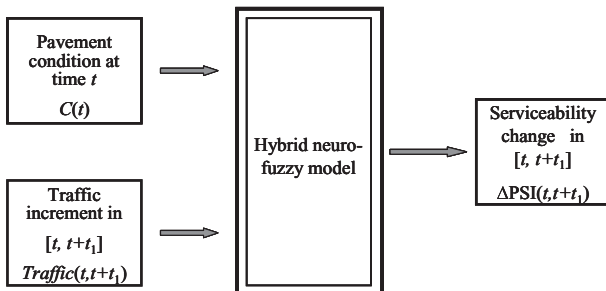

Fig. 2. Flow diagram of the reasoning process.

30.48 cm (12 in.) from it, respectively, in the FWD test.

2. D_{900}, which is the deflection measured at 91.44 cm (36 in.) from the point of load application in the FWD test and is linked to the subgrade resilient modulus (Garg and Thompson, 1999).

3. The area under the pavement profile (AUPP), which is related to the tensile stress at the bottom of the AC layer (Garg and Thompson, 1999) and is calculated as

$$\text{AUPP} = \frac{5D_0 - 2D_{300} - 2D_{600} - D_{900}}{2} \quad (6)$$

where D_{600} is the deflection measured at 60.96 cm (24 in.) from the load application point in the FWD test.

4. The rut depth, $Rut(t)$.

5. The percentage of the area of the section affected by alligator cracking with high severity, $\%Area(t)$.

6. The thickness of the asphalt layer of the pavement section, H_0.

7. The increment in the amount of traffic, $Traffic$ $(t + t_1)$, in terms of passes of the standard axle load (ESAL), measured from time t to time $t + t_1$.

Time t is not an input; it is used to identify the time frame when the measurements were taken.

Including the distresses of rutting and alligator cracking in the set of variables processed in the neuro-fuzzy model complements the information provided by FWD data regarding the condition of the AC layer. The phenomenon of rutting may be induced by lack of compaction or settlement occurring in any of the pavement layers. Similarly, alligator cracking is primarily induced by fatigue in the AC layer; however, lack of support in the granular layers may also initiate a crack or system of cracks at the bottom of the AC layer. Summarizing, the following seven-dimensional vector represents the input variables to be processed by the neuro-fuzzy model:

$$[\text{SCI}(t), \text{AUPP}(t), D_{900}(t), Rut(t), \%Area(t),$$
$$H_0, Traffic(t, t + t_1)] \quad (7)$$

6.3 Selection of the output variable

Pavement performance and changes in serviceability are crucial information that agencies managing pavement networks take into consideration for developing efficient maintenance strategies. As mentioned earlier, pavement performance is often quantified using the PSI. Therefore, the change in serviceability after the structure has been subjected to the amount of traffic between t and $t + t_1$ was chosen as the single output of the forecasting model implemented in this study. The

PSI regression equation proposed by Hall and Muñoz (1999) [Equation (1)] was adopted. This equation requires IRI values as the input. The change in serviceability was expressed as the change in the PSI value. The one-dimensional vector that represents this output is

$$[\Delta\text{PSI}(t, t + t_1)] \quad (8)$$

where ΔPSI is the change in the PSI value between t and $t + t_1$.

6.4 Climatic effects

The climatic or environmental effects are implicitly embedded in the parameters used to monitor the pavement performance. After a detailed literature review (e.g., Ovik et al., 2000; Chadbourn, 2001; Palmquist et al., 2002; Stehr, 2004) and the study of the Mn-ROAD database, the need for incorporating the climatic factors in the analysis was recognized. This led to the development of a prediction model that accounts for the influence of seasonal conditions on the pavement performance parameters. Thus, climatic periods were defined based on the different responses offered by the pavement structure due to freeze-thaw cycles or changes in the degree of saturation of the granular layers when subjected to the action of the traffic or tested with the FWD device. For the MnROAD database, each year was partitioned into five seasonal periods based on the temperature approach suggested by Ovik et al. (2000). A neuro-fuzzy model was implemented for each seasonal period. The five periods are as follows:

1. Season I: this is the period of deep frost when the freezing temperature reaches the subgrade. As a consequence, the pavement deflections measured during this period are very low.

2. Season II: this period usually coincides with the first part of the spring when the temperature rises; the frost starts to disappear from the pavement structure, beginning within the aggregate base level fully saturated after melting of the ice lenses. There is an increase in the pavement deflections due to the lowered structural support.

3. Season III: this period covers usually the late spring. Thawing reaches the subgrade. This layer becomes fully saturated and its structural support decreases, inducing an increase in pavement deflections.

4. Season IV: this period usually covers the summer months and shows a rapid strength recovery because the excess of free water drains away from the granular layer, and the pavement deflections decrease rapidly.

5. Season V: this period coincides with fall. The pavement slowly recovers its full strength, and the deflections further decrease.

6.5 Data preprocessing

Preprocessing was needed to confer homogeneity to the data and improve the performance of the networks and, consequently, of the model. Based on the typology of the FWD data, a temperature adjustment was applied to the FWD deflection D_0 measured at the point of load application, as suggested by the AASHTO pavement design guide (AASHTO, 1993).

Another preprocessing was performed on the measure of the area of alligator cracking. According to the distress survey guidelines (Shahin, 1994; FHWA, 2003), alligator cracking is evaluated by low, medium, or high severity and by the affected area of the pavement surface. In a pavement section, this distress may appear with different levels of severity throughout the surface area. To consolidate into one single parameter the areas of alligator cracking occurring with different levels of severity in a given section, the deduct value approach and correction curves proposed by Shahin (1994) were adopted. This approach consists of recalculating the areas of a pavement section with severity levels of low and medium into equivalent values of the area with the high severity level. For each section, the measured area and calculated equivalent areas with high-severity alligator cracking were added, and this new area was used as the input in the analyses.

In addition, the input and output data sets were normalized to overcome the disparity of the measuring units of the various parameters and improve the network performance. To narrow the variability range of the data implemented in the prediction model, FWD deflections, rut depth, and percentage of the area affected by alligator cracking were normalized by the corresponding average values of these measurements. The increment of the amount of traffic in a 5-year interval was normalized by the designed traffic value.

7 CONSTRUCTION AND CHARACTERISTICS OF THE NEURO-FUZZY MODEL

A neuro-fuzzy model was prepared for each climatic season. The procedure to construct each neuro-fuzzy model was as follows.

Step 1: Creation of the training and validation data sets. The initial data set was divided into two sets.

The training set contained two-thirds of the initial set whereas the validation set was composed of the remaining one-third of the data. The criteria applied in the determination of the two sets were derived from the literature review of the theory and applications of neural networks (e.g., Cammarata, 1997; Kasabov, 1998; Haykin, 1999; Provenzano, 2003).

Step 2: Clustering. The conventional partitioning algorithm k-means (MathWorks, Inc., 2007) divided the training set into s clusters. The selection of the appropriate number of clusters was validated using the silhouette chart calculated by MATLAB® and the Dunn index (Balasko et al., 2002) defined as

$$DI(c) = \min_{i \in c} \left\{ \min_{j \in c, i \neq j} \left(\frac{\min_{x \in C_i, y \in C_j} [d(x, y)]}{\max_{k \in c} [\max_{x, y \in C} (d(x, y))]} \right) \right\} \quad (9)$$

where x and y are data points in cluster C, C_i, or C_j; and $d(x, y)$ is the Euclidean distance. The number of clusters coincided with the number of IF-THEN rules of the NN-driven fuzzy reasoning model. Table 1 shows the number of clusters into which all the data available were partitioned and the amount of data points that were included in the clusters for each seasonal period.

Step 3: IF-part of the rules. This step provided the definition of the neural network in charge of assigning membership values to the partitioned inputs. The initial training set, resulting from the original partition in step 1, was further divided into training and validation sets to be used in the supervised learning process of the network. Two hidden layers characterized this network; the number of neurons in the first layer was 7 and was equal to the number of inputs to process. An analysis of the mean square errors (mse) produced by the training and validation data sets allowed the determination of the appropriate number of neurons in the second hidden layer through a heuristic search. The output of this network was an s-dimensional vector containing the membership value of the input for each one of the s clusters. Different neural networks representing membership functions were created for each of the neuro-fuzzy models assigned to a particular climatic season.

Table 2 shows the characteristics of the networks in charge of assigning membership values that were implemented in the neuro-fuzzy models. The networks adopted the tangent sigmoid as transfer functions in their layers and applied the gradient descent as the training function to adjust the values of the synaptic weights. The selection of the

Table 1
Number of rules and data points for each seasonal period

Season	I		II		III			IV		V		
Rules	1	2	1	2	1	2	3	1	2	1	2	3
Rule data points	302	209	502	519	422	148	226	772	1077	176	211	39

transfer functions, learning algorithm, and other features of the networks was strictly related to the data and their variability ranges. Each of these characteristics was determined through a heuristic search evaluating which configuration was able to produce the best mapping between inputs and outputs. The networks obtained through these procedures were shown to have excellent performance and were characterized by very low values of mse, between 0.0002 and 0.0038, considered acceptable for the context in which the networks were required to operate.

Step 4: THEN-part of the rules. The neural networks corresponding to the THEN-part of the rules were determined in this step. As in step 3, two hidden layers characterized these networks. The first hidden layer had seven neurons as the number of inputs. The number of neurons in the second hidden layer was selected on the basis of the network performance, based on the mse. Table 3 shows the characteristics of the neural networks describing the complex system for the various seasons and a 5-year performance period. The networks were characterized by seven neurons in

Table 2
Characteristics of the neural networks for the IF-part of the rules

Characteristics	Season				
	I	II	III	IV	V
Number of neurons – 1st hidden layer	7	7	7	7	7
Number of neurons – 2nd hidden layer	6	6	7	8	9
Learning parameter	0.18	0.3	0.9	0.5	0.5
Momentum	0	0	0	0	0
mse	0.0002	0.0007	0.0038	0.0032	0.0006
Optimal number of epochs	4,500	5,000	3,500	5,500	5,000

Table 3
Characteristics of the neural networks of the THEN-part of the rules for seasons I through V

		Characteristics						
Season	Rule	Number of neurons–1st hidden layer	Number of neurons–2nd hidden layer	Learning parameter	Momentum	mse	Index (Takagi and Hayashi, 1991)	Optimal number of epochs
I	1	7	16	0.18	0.5	0.0055	83.31	7,500
I	2	7	18	0.18	0.3	0.0016	14.10	5,500
II	1	7	12	0.18	0	0.0132	68.23	8,500
II	2	7	11	0.40	0.4	0.0139	138.38	14,500
III	1	7	14	0.18	0.3	0.0128	107.83	13,000
III	2	7	14	0.18	0.3	0.0012	24.01	10,000
III	3	7	14	0.18	0.5	0.0088	95.51	13,000
IV	1	7	18	0.18	0.3	0.0082	139.12	12,500
IV	2	7	18	0.18	0.3	0.0288	81.81	18,000
V	1	7	18	0.18	0.2	0.0022	17.15	13,000
V	2	7	18	0.18	0	0.0174	63.79	9,500
V	3	7	18	0.18	0.3	0.0010	20.12	15,000

the first layer and a variable number of neurons, between 11 and 18, in the second layer. The transfer functions employed were the sigmoid function and the linear function in the first and second layers, respectively. As in step 3, the method of the gradient descent was found to produce networks with the best performance.

In addition, an analysis of the error index as defined in Equation (4) allowed the determination of the number of training epochs enforcing the generalization capability of the network. Contrarily to the error index, the mse was exclusively calculated over data in the training and validation sets belonging to the same cluster. In terms of performance, values of mse between 0.0016 and 0.0288 were considered acceptable within the context of this research.

Step 5: Assembling of the neuro-fuzzy model. The parts defined in steps 3 and 4 were connected together to produce the final numerical object to predict pavement performance. At this stage, the model did not need further training because its components (i.e., the networks) were trained when created.

8 PERFORMANCE EVALUATION OF THE NEURO-FUZZY MODEL

Five neuro-fuzzy models were created and assigned to the climatic seasons for predicting the performance within a time range of 5 years. For the evaluation of the model performance, the values of the change in serviceability produced by the neuro-fuzzy model with inputs belonging to the validation set were compared with the values calculated from actual IRI measurements using Equation (1). The coefficient of determination (R^2), the correlation charts, the square root of the mse, and the average absolute error (μ_{err}) were employed to evaluate the goodness-of-fit of the neuro-fuzzy model in predicting pavement performance.

The coefficient of determination in this research was calculated as

$$R^2 = 1 - \frac{\sum_{i=1}^{N} [\Delta\text{PSI}_{n,i,act} - \Delta\text{PSI}_{n,i,pred}]^2}{\sum_{i=1}^{N} [\Delta\text{PSI}_{n,i,act} - \overline{\Delta\text{PSI}_{n,act}}]^2} \quad (10)$$

where $\Delta\text{PSI}_{n,i,act}$ is the actual ith observed change in PSI; $\Delta\text{PSI}_{n,i,pred}$ is the ith predicted change in PSI; $\overline{\Delta\text{PSI}_{n,act}}$ is the average value of the observed change in PSI; the subscript n refers to a normalized value; and

N is the number of available observations. The square root of the mse and the average absolute error were also calculated to assess the model performance and were defined as

$$rmse = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\Delta\text{PSI}_{n,i,act} - \Delta\text{PSI}_{n,i,pred})^2} \quad (11)$$

and

$$\mu_{err} = \frac{1}{N} \sum_{i=1}^{N} |\Delta\text{PSI}_{n,i,act} - \Delta\text{PSI}_{n,i,pred}|. \quad (12)$$

The definition of an acceptable value of rmse to evaluate the performance of the neuro-fuzzy models is related to the relevance in the engineering practice of the variability of the PSI. Delatte et al. (2000) suggested that increments of ± 0.5 in the PSI value could assume a significant physical meaning in pavement management applications. However, this article set a threshold of the error in the ΔPSI value equal to 0.05; in this way, the neural networks were tailored to reach a more accurate prediction of the change in serviceability than the one needed in the practice. The threshold of 0.05 was not achieved in every model, but the ± 0.5 threshold, which is relevant from the pavement management application standpoint, was attained in each model.

The performance of all models in this study was at a satisfactory level. The models were characterized by high values of R^2, and the associated correlation charts showed good qualitative distribution of the data points, which were mainly clustered around the correlation lines. In addition, the average absolute errors were considered acceptable for the physical meaning of PSI and the amount of accuracy needed in the analysis. The consideration of R^2, μ_{err} (Table 4), and the correlation

Table 4
Comparison of goodness-of-fit statistics

Season	Model	R^2	rmse	μ_{err}
I	Neuro-fuzzy	0.9872	0.0599	0.0464
	Multiple linear regression	0.8766	0.2570	0.204
II	Neuro-fuzzy	0.9604	0.1261	0.0876
	Multiple linear regression	0.8022	0.3790	0.268
III	Neuro-fuzzy	0.9697	0.1107	0.0787
	Multiple linear regression	0.9196	0.2496	0.187
IV	Neuro-fuzzy	0.8745	0.1529	0.102
	Multiple linear regression	0.8088	0.2535	0.186
V	Neuro-fuzzy	0.9349	0.1213	0.0766
	Multiple linear regression	0.8724	0.2272	0.177
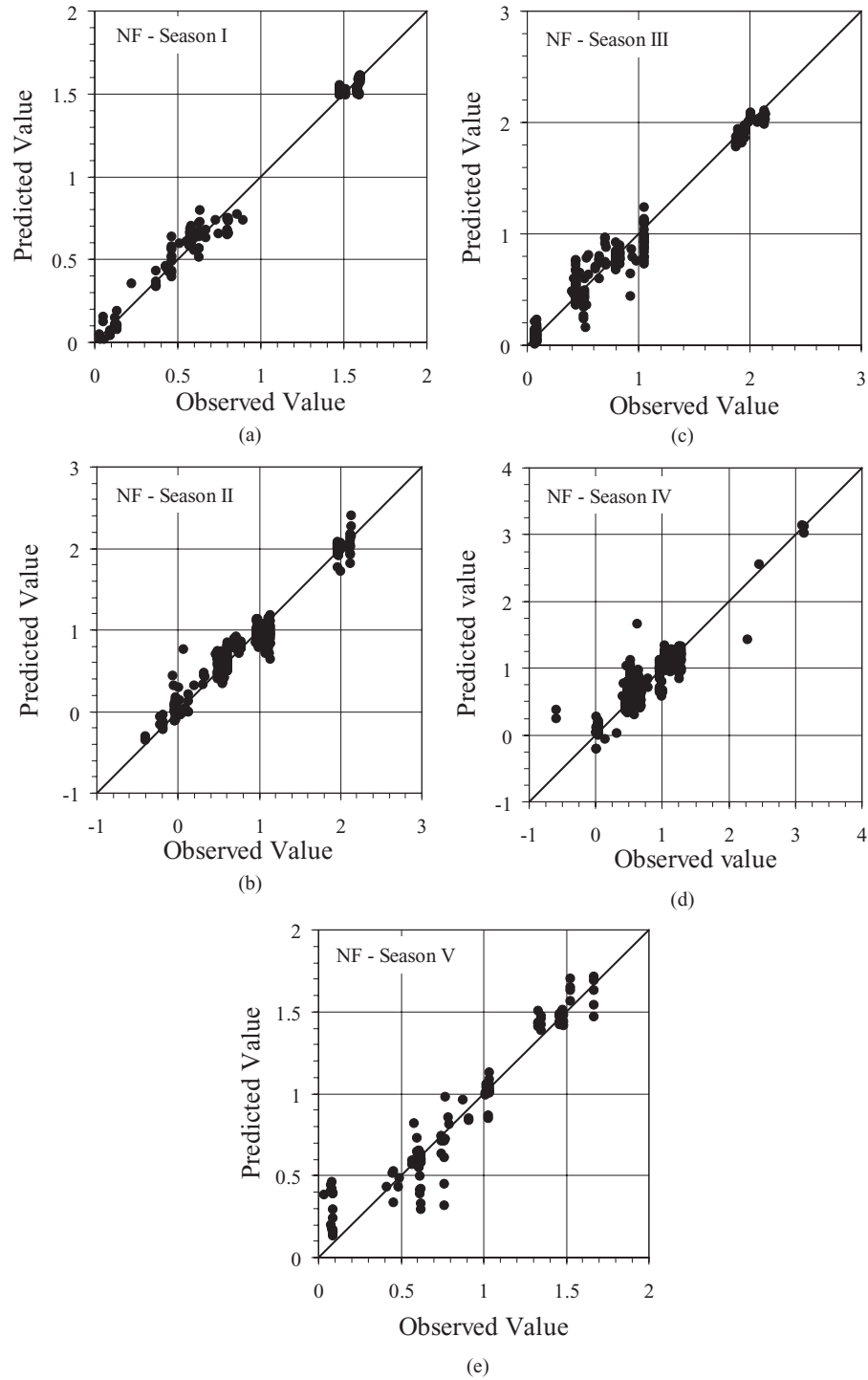
Fig. 3. Correlation charts of the neuro-fuzzy (NF) model for (a) season I, (b) season II, (c) season III, (d) season IV, and (e) season V.

charts (Figure 3) showed that the model of season I performed remarkably well; this model had the highest R^2 value (0.9872) and the lowest rmse and μ_{err} values among all the compared models. The data points

in the correlation chart for season I (Figure 3a) were smoothly clustered around the correlation line in the absence of outliers. The models associated with seasons II and V were particularly characterized by a good

Table 5
Coefficients and errors of the multiple linear regression models

	Season				
Parameter	I	II	III	IV	V
Intercept	−1.5041	3.5465	−2.2963	−1.3311	−4.4662
SCI	0.7446	0.5333	−0.0146	1.3247	0.0843
AUPP	−0.3973	−0.3919	0.1706	−1.5269	−0.6778
D_{900}	0.0057	−0.1199	−0.3897	0.8323	0.2142
Rut	−0.4262	−0.9841	−0.8708	−0.6418	−0.0981
%Area	0.0000	0.1005	0.0000	−0.1681	0.0000
H_0	1.4156	1.7356	1.8343	2.6506	2.7948
Traffic	0.9663	−4.7391	2.0508	−0.7540	2.6454
R^2	0.8766	0.8022	0.9196	0.8088	0.8724
rmse	0.2570	0.3790	0.2496	0.2535	0.2272
μ_{err}	0.204	0.268	0.187	0.186	0.177

Note: SCI, AUPP, D_{900}, *Rut*, H_0 are expressed in millimeters; *%Area* is expressed in percentage.

performance over the whole range of the serviceability change.

9 COMPARISON WITH A MULTIPLE LINEAR REGRESSION MODEL

To evaluate their performance, the neuro-fuzzy models were also compared with the results obtained using the classical statistical model of a linear regression analysis. Multiple-variable linear regression models were constructed for each climatic season. Table 4 compares R^2, rmse, and μ_{err} produced by the neuro-fuzzy and the linear regression models. Table 5 contains the parameters of the multiple linear regression models for each season. Figure 4 shows the correlation line charts associated with the linear regression models. The analysis of the R^2 values and the correlation line charts validated the excellent performance of the neuro-fuzzy models. The neuro-fuzzy models exhibited significantly higher values of R^2 and lower values of rmse and μ_{err} compared with the multiple linear regression models. The R^2 values of the neuro-fuzzy models were 5–20% higher than those calculated for the multiple linear regression models for the corresponding climatic seasons. In terms of the calculated errors, the neuro-fuzzy models had rmse values that were 40–77% smaller than those of the multiple linear regression models. Similarly, the μ_{err} values of the neuro-fuzzy models were 45–77% smaller than those of the multiple linear regression models. Additionally, the correlation charts, representing the performance of the linear regression models, displayed a greater data scattering around the line of the perfect match.

The study of the individual contributions of the input variables to the output represented by the change in

pavement serviceability was not included in the scope of this article. The input parameters were selected based on the sensitivity analysis performed in previous studies by Garg and Thompson (1999) and Xu et al. (2002a, 2002b).

10 CONCLUSIONS

The proposed neuro-fuzzy model provided a good representation of the complex system of the pavement performance. In fact, the model was capable of predicting 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. The proposed neuro-fuzzy model implemented parameters that characterize the conditions of the in-service pavement and are routinely collected by pavement management agencies. Historical data consisting of parameters that describe the pavement condition, the traffic increment, and the associated change in the serviceability level were used for training and validation of the neural networks.

Five neuro-fuzzy models were created, one per each identified climatic season. The performance evaluation tested each model's ability to approximate the mapping between pavement conditions, traffic increment, and change in pavement serviceability. The goodness-of-fit process was based on the analysis of the coefficients of determination (R^2) together with the correlation charts; it also included the calculation and analysis of the average error (μ_{err}) and the rmse. It was demonstrated that the five neuro-fuzzy models had good approximation and generalization capabilities when processing new data.
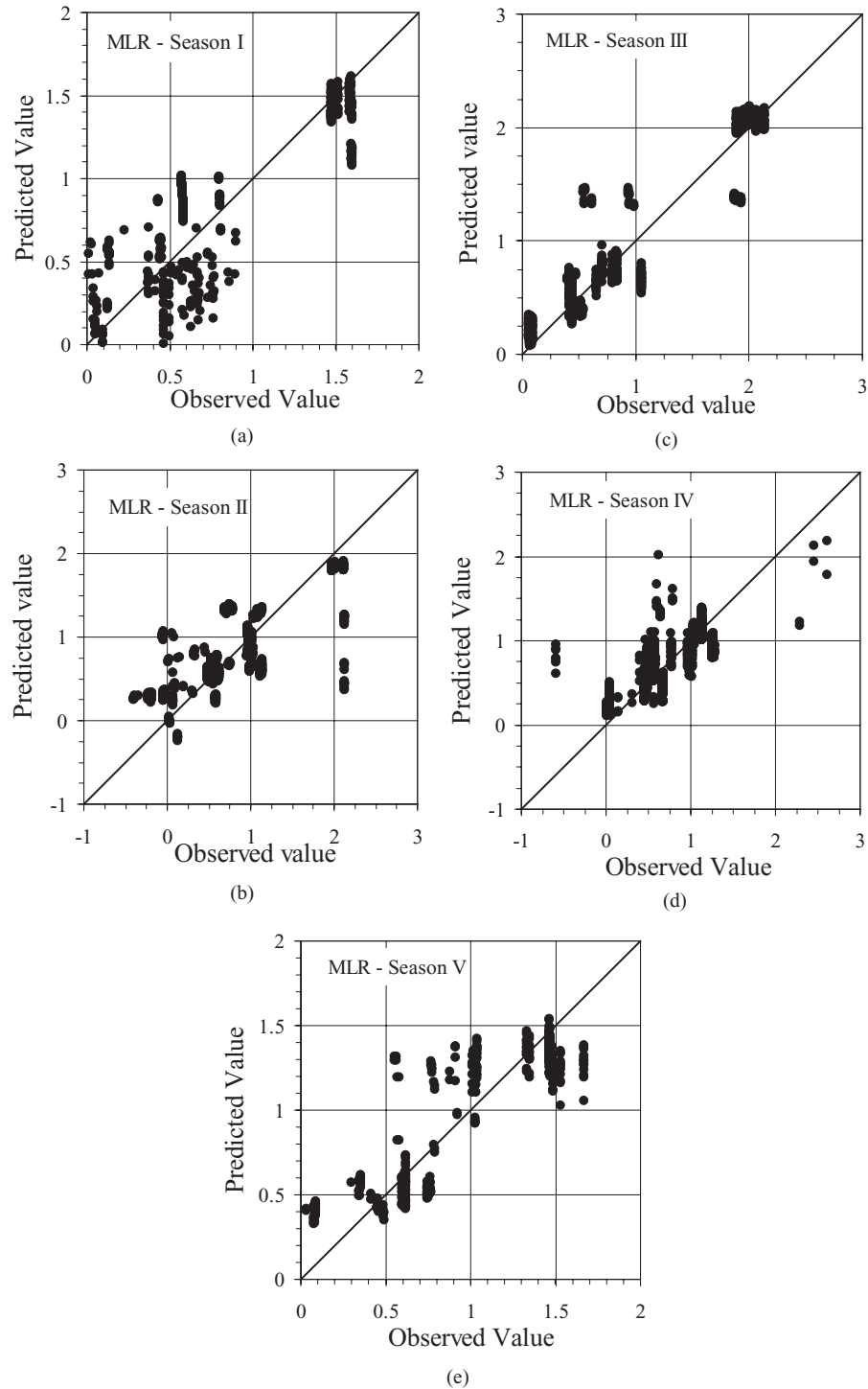
Fig. 4. Multiple linear regression correlation charts for (a) season I, (b) season II, (c) season III, (d) season IV, and (e) season V.

The performance of the neuro-fuzzy models was compared with that of the classical statistical linear regression models for each climatic season. The R^2 of the multiple linear regression models were definitely lower than those produced by the neuro-fuzzy models, and the correlation charts exhibited high scattering of the data around the lines of the perfect match. In conclusion, the neuro-fuzzy models outperformed the linear regression models. The comparison of the neuro-fuzzy models with the linear models showed the

capability of the new mathematical approach implemented in this study in describing nonlinear, complex systems, such as the pavement structure. This study also stresses the importance of performing *a priori* thorough analyses of the independent variables used as the input and their influence on the determination of the final output.

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