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MODELING THE ROUGHNESS PROGRESSION ON KANSAS PORTLAND CEMENT CONCRETE (PCC) PAVEMENTS

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16 Abstract

Long-term prediction of the performance and durability of pavement represents a critical and vital issue in the pavement surface type selection process by the Kansas Department of Transportation (KDOT) using the life-cycle-cost analysis. Accurate prediction of roughness progression on Portland Cement Concrete (PCC) pavements is very important since the current model used by KDOT is based on the pavement serviceability guidelines (1993 AASHTO Design Guide). In this study, dynamic Artificial Neural Network (ANN) and statistical analysis approaches were used to develop reliable and accurate time-dependent roughness (International Roughness Index, IRI) prediction models for the newly constructed Kansas Jointed Plain Concrete Pavements (JPCP). To achieve this objective, data used in the model development process include construction and materials data as well as other inventory items, such as, traffic and climatic related data, which reflect the section-specific local conditions in Kansas.

Utilizing a two-stage training approach, a three-layer (19-10-1) time-dependent ANN-based roughness prediction model was developed. It was able to project the time-dependant roughness behavior with a reasonably high coefficient of determination, $R^2 = 0.90$ (ANN-based model) and $R^2 = 0.73$ (SAS-based model). The sensitivity analysis performed herein quantified, to some degree, the impact of various key input parameters on the PCC pavement roughness profile. To further validate the developed ANN-based model, it was used to predict IRI values for years 2001 ($R^2 = 0.80$) and 2002 ($R^2 = 0.74$) data. Using multiple regression analysis technique, a statistical-based model was developed and then used to project the 20-year and 30-year IRI values.

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KANSAS DEPARTMENT OF TRANSPORTATION
TOPEKA, KANSAS

KANSAS STATE UNIVERSITY
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PREFACE

The Kansas Department of Transportation's (KDOT) Kansas Transportation Research and New-Developments (K-TRAN) Research Program funded this research project. It is an ongoing, cooperative and comprehensive research program addressing transportation needs of the state of Kansas utilizing academic and research resources from KDOT, Kansas State University and the University of Kansas. Transportation professionals in KDOT and the universities jointly develop the projects included in the research program.

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ABSTRACT

Long-term prediction of the performance and durability of pavement represents a critical and vital issue in the life-cycle-cost analysis used in the Kansas Department of Transportation's (KDOT) pavement surface-type selection process. Accurate prediction of roughness progression on Portland cement concrete (PCC) pavements is very important since the current model used by KDOT is based on the pavement serviceability guidelines (1993 AASHTO Design Guide). In this study, dynamic artificial neural network (ANN) and statistical analysis approaches were used to develop reliable and accurate time-dependent roughness (International Roughness Index, IRI) prediction models for the newly constructed Kansas Jointed Plain Concrete Pavements (JPCP). To achieve this objective, data used in the model development process include construction and materials data as well as other inventory items such as traffic and climatic related data, which reflect the section-specific local conditions in Kansas.

Utilizing a two-stage training approach, a three-layer (19-10-1) time-dependent ANN-based roughness prediction model was developed. It was able to project the time-dependant roughness behavior with a reasonably high coefficient of determination, R^2 = 0.90 (ANN-based model) and R^2 = 0.73 (SAS-based model). The sensitivity analysis performed herein quantified, to some degree, the impact of various key input parameters on the PCC pavement roughness profile. To further validate the developed ANN-based model, it was used to predict IRI values for years 2001 (R^2 = 0.80) and 2002 (R^2 = 0.74) data. Using a multiple regression analysis technique, a statistical-based model was developed and then used to project the 20-year and 30-year IRI values.

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Chapter 1

Introduction

1.1 Background

Performance evaluation of pavements should be on a well-planned basis and be an integral part of the overall pavement management system. Accurate prediction of pavement performance over longer periods of time represents a critical issue in the Pavement Management System (PMS) of the Kansas Department of Transportation (KDOT). The success of pavement design is largely dependent on subsequent construction, maintenance, and rehabilitation. Portland Cement Concrete pavements provide adequate service for only up to 10 or 12 years, and sometimes less, without major maintenance or rehabilitation (Byrum et al., 1997). It is quite feasible to provide an initial service life of 20 or 25 years performance. Consequently, many agencies have recognized the need to link together explicitly the activities of planning, designing, constructing, and maintaining pavements.

This research aims at developing reliable and accurate time-dependent roughness prediction models for newly constructed Jointed Plain Concrete Pavements (JPCP) in Kansas. The developed models employ quantified relationships to predict subsequent pavement performance for a given project and have the ability to relate measured input variables to the level of expected performance. Usage of these predictive models will allow KDOT's geotechnical/pavement unit to obtain reliable and accurate predictions of the future condition of the pavement based on measured engineering parameters. In particular, these performance models will allow the geotechnical/pavement unit to project and simulate the performance of pavement structures using various construction design strategies.

1.2 Research Objectives

The broad objective of the study is to develop rational, practical, easy-to-implement, reliable, and accurate time-dependent performance projection/prediction models for newly constructed Kansas rigid pavements (Jointed Plain Concrete Pavements, JPCP) using dynamic Artificial Neural Network (ANN) and statistical analysis approaches. Inputs for model development take into consideration various parameters related to pavement design inputs, concrete paving material used, prevailing traffic loadings, construction quality, subgrade soil properties, and prevailing climatic conditions.

1.3 Problem Statement

For decades KDOT has developed rehabilitation, resurfacing, and reconstruction strategies for flexible, composite, and rigid pavements. The pavement surface type selection process in the KDOT for alternate strategies uses Life-Cycle-Cost (LCC) analysis. Many factors affect pavement behavior or performance. Research on pavement performance has failed to produce a definitive relationship of distress outputs and pavement performance (Hass et al., 1994). Defining the need for these relationships is a first priority research need.

The new construction program for pavements in Kansas is in the range of $150 to $200 million (Hancock, 2000). Therefore, accuracy of the pavement performance prediction model is essential to minimize funds expended on these pavements. A significant portion of these funds is usually spent on pavement related activities such as rehabilitation, resurfacing, and new construction. Identifying and selecting strategies that can potentially perform better than others could provide a high benefit return. Rational pavement performance prediction and projection models are needed so that funds expended on pavement rehabilitation, resurfacing, and new construction can be minimized.

1.4 Literature Review

In the past, many studies have been conducted in order to develop performance (i.e., pavement distress and roughness) prediction models for the newly constructed Jointed Plain Concrete Pavements (JPCP). Some progress is being made on the development of increasingly sophisticated analytical tools for modeling the long-term pavement behavior. The pavement performance evaluation procedure generally involves a study of the functional behavior of a section or length of pavement structure. This is important to in pavement design, rehabilitation, and management tasks. The objective of the earlier studies on performance prediction and analysis models involved in predicting PCC pavement distress indices (Yu et al., 1997; Hoerner et al., 1999) was primarily an improvement of the key distress indicator and roughness prediction models used in the prototype Performance-Related Specifications (PRS) for Jointed Plain Concrete Pavement (JPCP). Using version 2.0 of the PaveSpec PRS demonstration software, Yu et al. (1997) and Hoerner et al. (1999) established that the prototype PRS was improved. As a result, the PavSpec PRS demonstration software was upgraded to Version 3.0 (Hoerner et al., 2000).

In the case of the development of Performance-Related Specifications for JPCP, the specific data elements required by distress indicator models were summarized. Depending on the required data elements, such models predicted the development of joint spalling, faulting, slab cracking, and pavement smoothness over time. The existing literature documented this approach (Byrum et al., 1997; Hoerner et al., 1999; Owusu-Antwi et al., 1997; Simpson et al., 1994).

Similarly, using a local Microsoft Access database, Titus-Glover et al. (1999) developed improved pavement distress and roughness prediction models that incorporate mechanistic principles but that are still practical for use by State highway agencies. Likewise, Yu et al. (1997) used the ORACLE database management system to evaluate the performance of 303 in service concrete pavement sections located throughout North America.

Because price adjustments are directly dependent on the future pavement performance predicted through mathematical prediction models, it is important to have confidence in the validity or accuracy of these models. In recent years, State Highway Agencies (SHAs) have expressed concern over whether the prediction models would accurately predict the pavement performance associated with their agency's specific designs, materials, subgrades, traffic, and climatic conditions. This important question must be adequately addressed, or it will inhibit the implementation of the model in Kansas. Therefore, the focus of this study is to develop new performance models that reflect the local conditions.

Current efforts should be concentrated on the development of enhanced and improved pavement models to predict the time-dependent pavement roughness profiles, since many of the existing models contain substantial limitations. In this study, the dynamic Artificial Neural Network (ANN) and statistical analysis approaches were utilized to establish an efficient, rational, and practical, easy-to-implement, time-dependent roughness prediction model for the newly constructed JPCP in Kansas.

Chapter 2

Project Identification and Data Collection

2.1 Selection of Projects

Twenty-three projects on state, US and Interstate routes in Kansas were selected in this study as shown in Table 2.1. All data types for 23 constructed projects (total 102 of 1-mile sections) for newly built jointed plain concrete pavements (JPCP) on I-35, I-70, I-435, K-15, K-96, US-50, US-56, US-75, and US-77 were collected from the Kansas Department of Transportation (KDOT) historical pavement database. Each project has a different construction date. The oldest project was constructed in 1993, while the newest project was constructed in 1998. All the PCC pavement sections considered are Jointed Plain Concrete Pavements (JPCP) with 4.6 m (15 ft.) joint spacing, doweled joints and tied shoulder. The projects vary in length from 1.6 km (1 mile) to 32 km (20 miles). The JPCP slab thicknesses vary from 229 mm (9 in.) to 292 mm (11.5 in.). The number of ESALs (Equivalent Single Axle Loads) in a year is calculated by the following: the AADT (Average Annual Daily Traffic) is multiplied by the percentage of trucks and then multiplied by the average-ESALs-per-truck factor, which is in turn multiplied by the number of days in a year. A truck factor of 1.7 for rigid pavements was used. The database for each section included annual roughness values measured during each year after construction. The last available roughness IRI data was for year 2003. Longitudinal profile measurements were done on right and left wheel paths with a South Dakota-type Profilometer. From these profile data, the International Roughness Index (IRI) values were calculated with the RoadRuf software developed by the University of Michigan Transportation Research Institute. The IRI value used in this study represents only the right wheel-path readings.

TABLE 2.1: Selected Portland Cement Concrete (PCC) Projects

No.	Project K Number	County	Lane	Route	Construction Year	Begin County Milepost	End County Milepost
1	K-2633-01	Lyon	East	I-35	1995	10.9	16.7
2	K-2633-01	Lyon	West	I-35	1995	10.9	16.7
3	K-3596-01	Franklin	East	I-35	1996	0	3.2
4	K-3596-02	Franklin	East	I-35	1996	3.2	9
5	K-4088-02	Johnson	East	I-35	1997	13	16
6	K-4088-02	Johnson	West	I-35	1997	13	16
7	K-2446-01	Shawnee	North	I-70	1993	11.7	15
8	K-3344-01	Shawnee	South	I-70	1994	9	10
9	K-2447-01	Wyandotte	North	I-70	1994	15.6	17.1
10	K-2447-01	Wyandotte	South	I-70	1994	15.6	17.1
11	K-3637-01	Johnson	West	I-435	1997	0	3.3
12	K-4058-03	Harvey	Undivided	US-50	1996	28.7	35.6
13	K-3216-02	Chase	Undivided	US-50	1998	0	9
14	K-3217-02	Chase	Undivided	US-50	1998	9	19
15	K-4422-02	Ford	Undivided	US-56	1997	12.2	16
16	K-3251-01	Jackson	East	US-75	1996	8	12
17	K-3251-01	Jackson	East	US-75	1996	12	17.3
18	K-3251-01	Jackson	West	US-75	1997	8	12
19	K-3251-01	Jackson	West	US-75	1997	12	17.3
20	K-4341-01	Shawnee	East	US-75	1997	20	22
21	K-4341-01	Shawnee	West	US-5	1997	20	22
22	K-3684-01	Sedgwick	West	K-5	1998	0	5.7
23	K-4460-01	Sedgwick	North	K-96	1997	3.9	14.7

2.2 Selection of Data Elements and Data Collection

The data was categorized and assembled into an Excel spreadsheet to prepare for the analysis using dynamic Artificial Neural Networks (ANNs) and statistical analysis (SAS program) methodology. Initially, fifty-six different potential input variables were listed. However, after data cleansing and thorough examination, the database was limited to twenty-six practical input variables. The detailed database development of the twenty-six input variables included pavement profile (initial smoothness represented by initial roughness IRI value), pavement section, pavement layer, time-series traffic, subgrade type and treatment, climatic conditions, shoulder type, concrete materials test data, and concrete mixture data. Pavement layer data included PCC slab thickness and type of base drainage, such as Portland Cement Treated Base (PCTB) and Bound Drainable Base (BDB). Time-series traffic data refers to the cumulative 80-kN (18-kip) Equivalent Single-Axle Loads (ESALs) and is used herein to represent traffic loadings. Climatic information was included in order to develop a model, which can directly account for section-specific climatic conditions. The output variable was the time-series (i.e., yearly) right wheel path roughness IRI value, which is used to quantify the long-term pavement roughness performance.

In order to find the factors that influence the pavement roughness prediction models, the independent variables (data elements) listed in Table 2.2 were considered in the analysis. The elements were divided into different groups. Table 2.2 lists the elements in each group. The climatic data was provided by the Kansas State University Weather Data Library. The historical roughness data was obtained from the KDOT Pavement Management Information System (PMIS) database.

TABLE 2.2: Data Elements Selected as Independent Variables for Portland Cement Concrete (PCC) Pavements

INVENTORY

-County code	-Route Number
-Project Number	-Begin county milepost
-End county milepost	-Project length
-Cumulative AADT (year)	-Cumulative truck factor (year)
*-Cumulative yearly ESAL values	*-Initial IRI roughness, right wheel path (in./mile)
	*-IRI roughness value at age (n) year (in./mile)

CONSTRUCTION

*-Age of pavement (year)	*-PCC slab thickness (in.)
-Base thickness (in.)	*-Plasticity index of natural subgrade soil material
*-% Subgrade material passing No.4 sieve	*-% Subgrade material passing No.200 sieve
*-Subgrade treatment:	*-Base material and treatment type
no treatment (N/A) (=0)	*Drainable base =1 ; Non-drainable base =0 :*
6" lime treated subgrade (=1)	*Cement Treated Drainable Base (CTDB)=1*
6" fly ash treated subgrade (=2)	*Edge drain=1 , No edge drain=0*
*-Unit weight of concrete (lb/ft^3)	*Bound Drainable Base (BDB)=1*
-Flexural strength of concrete (psi)	*Portland Cement Treated Base (PCTB)=0*
-Water-cement ratio	-Shoulder type (paved=1 or unpaved=0)
-Air content (%)	-Total width of outside shoulder (ft)
-Weight percentage of coarse aggregate in mix	-Shoulder thickness (in.)
-Slump (in.)	-Pavement cross-slope (1.6%)
*-Cement factor (lb/yd^3)	
-Weight percentage of fine aggregate in mix	

CLIMATE

-Cumulative annual precipitation (in.)	*-Cumulative number of days below 32 °F per year
*-Cumulative number of days above 90 °F per year	*-Cumulative number of days per year with over 0.4 in. precipitation
-Mean annual temperature (°F)	*-Average number of freeze-thaw cycles per year
*-Minimum annual temperature (°F)	-Maximum annual temperature (°F)
	-Depth of frost penetration (in.)

* independent variable used in models

Chapter 3

Factors Affecting Roughness Progression

3.1 ANN-BASED MODEL

3.1.1 Methodology (ANNs)

Artificial Neural Networks (ANNs) are mathematical models and algorithms designed to mimic the information processing and knowledge acquisition of the human brain (Basheer, 1998). ANNs are difficult to represent in a single mathematical equation and, therefore, are represented by a set of layers that constitute the network. An example of a multilayer backpropagation ANN is depicted in Figure 3.1. The basic building block of the network system is the neuron that communicates information to and from the various parts of the body. All artificial neurons interconnect with each other to form what is called an Artificial Neural Network. Other common names for ANNs are Artificial Neural Systems, Connectionism, Adaptive Systems, Adaptive Networks, Neuro-Computer, and Parallel Distribution Processor (Itani and Yacoub, 2000). In this study, ANN methodology is utilized to develop the desired neural-based roughness prediction model. ANNs are used as prediction tools capable of capturing the patterns or relation between the specific input(s) and desired output(s).

As shown in Figure 3.1, main elements of an Artificial Neural Network are the input layer, hidden layer(s), output layer, and connection weights. The input layer contains the input variables, and the output layer contains the target output vector (output variable). The hidden layers are placed between the input and output layer. The computational efficiency of the network depends on its interconnection weights. The input layer containing the input nodes

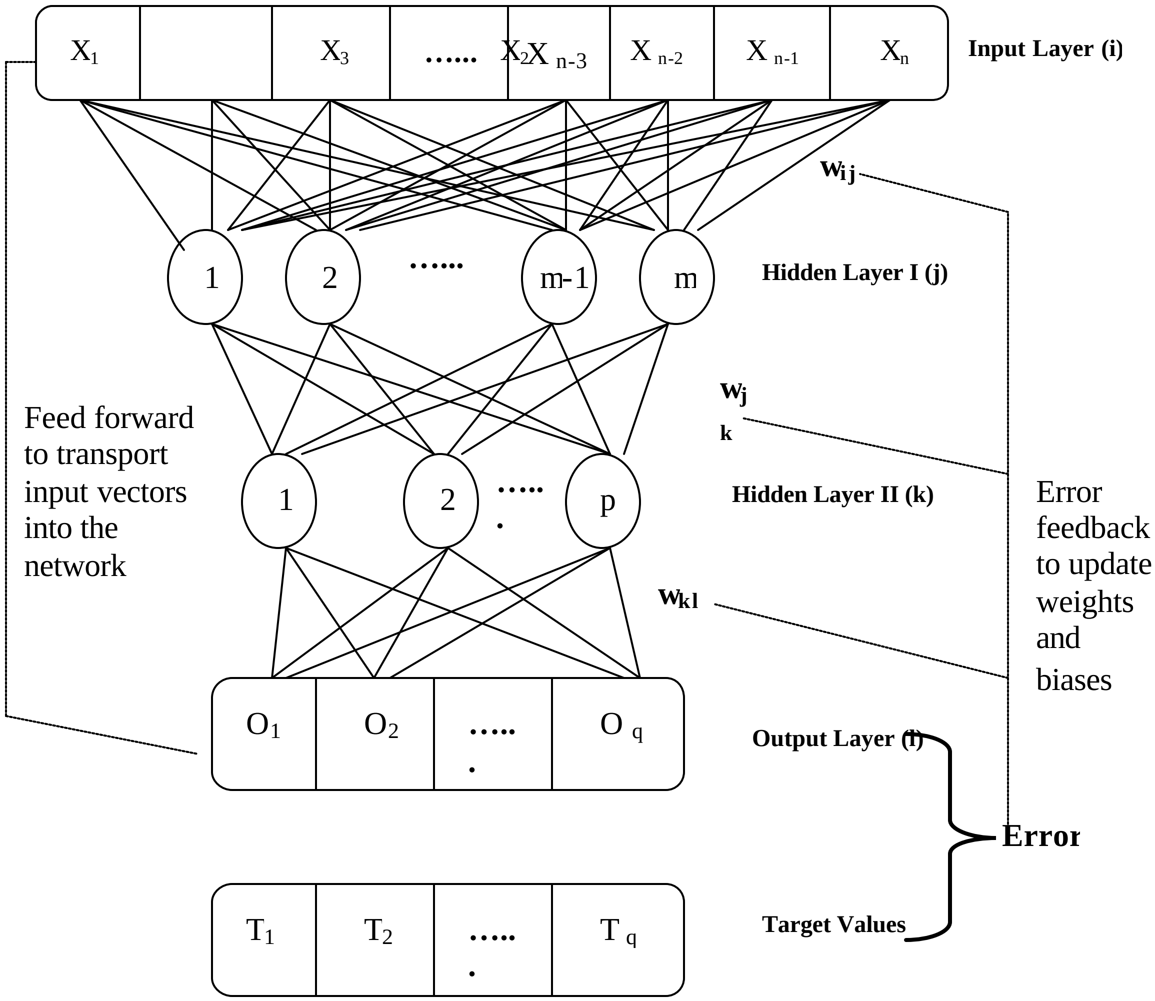

FIGURE 3.1: Schematic of the Architecture of a Typical Backpropagation ANN with Two Hidden Layers

performs no mathematical operations. It receives and processes information and forwards them to the hidden layer. The hidden layer could contain one or more layers consisting of a set of neurons that process information within the network body. Therefore, the most important operations occur in it. The hidden layer receives the processed data and then processes and feeds them forward towards an output layer. The number of hidden layers, as well as the number of neurons contained within each layer, affects dramatically the accuracy of the developed models. The output layer could contain one or more output neurons that will produce prediction for a certain output variable. Connection weights are the interconnecting links between the neurons in successive layers. Each neuron in a certain layer is connected to every single neuron in the next layer by links having an appropriate and an adjustable connection weight. No side connections are permitted in this type of network (Ali, 2000).

The three-layered (i.e., input-hidden-output layers) feed-forward error-Back Propagation Neural Network (BPNN) structure is used in this study. Back-propagating the error (i.e., the difference between the actual and computed outputs) to adjust connection weights represents the training process. Similar BPNNs have been successfully used in various civil engineering applications. Three tasks must be performed before the training of a network begins: i) make an initial choice of the neural network architecture (or network structure), ii) assign initial random values for the connection weights to calculate the output, and iii) finally, select a learning rate, which can appropriately control the adjustment rate of the connection weights. The training is accomplished by calculating the output using the assigned initial random connection weights and back-propagating the error through the hidden layer. This procedure is repeated for all training data sets until the actual and calculated outputs agree within some pre-determined tolerance.

Training is performed in order to determine the best possible values of connection weights for further use as a prediction tool (Najjar, 1999; Najjar et al., 2000).

As mentioned earlier, the nodes in a certain layer are connected to all nodes in the following layers. Each node receives signals from all other neurons located in the previous layer and integrates those signals as a weighted average. For example, input value for neuron "m" is the sum of all impinging signals multiplied by their respective weights; thus, $(input)_m$ = S(node value) x connecting weight. The input for a certain neuron might either be very large or negative. It is to be noted that this is generally not desirable. In order to avoid large or negative values and to introduce nonlinearity in the model, we make the neuron's input undergo an additional nonlinear transformation to produce an output: $(out)_m = f\,(input)_m$, where "f" is a transfer function and "$(input)_m$" is the value calculated previously. The integrated signal is transformed to activation via a transfer function such as the sigmoidal function. The sigmoidal function is a continuous activation function, designed to respond relative to the amount of excitation received. It is the most widely used function in various BPNN applications. Mathematically, it is represented by the following equation (Itani and Najjar, 2000):

$$\frac{1}{1+e^{-(input)}} \tag{1}$$

Similarly, the transformed signal is transmitted forward to the following layer. The process is performed to calculate the output of a neuron at the output layer. The produced outputs are then compared to actual (target) outputs to evaluate the error, which is used to calculate an error function. The resulting error function is used to propagate the error starting from the weights connected to the last layer (output layer), and backward to the input layers in backpropagation of error, in order to modify the weights. The procedure of forward activation of signals and the backpropagation of errors is repeatedly carried out until the error at the output side reduces to a prespecified minimum (Najjar et al., 1997; Najjar and Zhang, 2000).

Neural Networks could reach a least-error structure by training on a number of data sets. A least-error structure is needed to produce output values that are as close to the actual values as possible. The least-error structure (maximum structure) also shows the maximum number of hidden nodes that the training was allowed to reach and the corresponding maximum number of iterations. In this study, a maximum structure of 10-6000 was obtained, indicating that the maximum allowable number of hidden nodes is specified to be 10 and an iteration of 6000 should be reached at node 10. According to Najjar and co-workers (Itani and Najjar, 2000; Najjar and Zhang, 2000), for proper ANN modeling, a two stage training approach may be needed. In the first stage, the full database is divided into training, testing, and validation sub-bases, and then the least-error-structure is determined. If accuracy measures of the least-error structure are comparable for training, testing, and validation data sets, then the second stage of training is not warranted. On the other hand, if the accuracy measures are not comparable, the least-error structure determined from stage one is then retrained on the entire database. In this study, during the first stage of training, the database containing a total of 415 data sets was divided into 225, 93, and 97 data sets for training, testing, and validation, respectively. In selecting the testing and validation data sets, it is highly recommended that data sets should be within the domain of the training data sets to prevent the developed network from extrapolating beyond the training domain.

Dynamic ANN-based training technique adopted by Najjar (1999) and Najjar & Zhang (2000) is utilized herein to model the time-dependent pavement roughness performance. This technique is utilized within the framework of the conventional feed-forward error-back propagation neural network approach. According to the feedback approach, the year (n+1) roughness IRI value, $(IRI)^{n+1}$ is determined from a number of previously determined input parameters. This logic can mathematically be represented in the following compact form:

$$\{(IRI)^{n+1}\} = ANN_{(m+1)\text{-}k\text{-}1}\{x_1, x_2, \ldots, x_m, (IRI)^n\} \tag{2}$$

where ANN denotes the neural network model that best relates a given number of inputs (m+1) [i.e., $x_1, x_2, \ldots, x_m, (IRI)^n$] to the desired output, $(IRI)^{n+1}$. Note that $\{x_1, x_2, \ldots, x_m\}$ is a vector of *(m)* parameters used herein to represent all static input parameters that are believed to affect the desired output. The *(m+1)-k-1* notation denotes the architecture of the selected network. In this case, *(m+1)* represents the *(m)* static inputs, (*k*) is the optimal number of hidden nodes as determined through the training and testing process, and (*1*) is the desired number of output, namely; the futuristic roughness IRI value [i.e., $(IRI)^{n+1}$].

3.1.2 Model Development (ANNs)

In order to filter out the most influential static input parameters, various ANN modeling trials were performed. In the final optimal network (utilizing the previously mentioned two stage training approach), the input parameter vector contained the following 19 variables:

1.	SLTH	PCC slab thickness (in.)
2.	BTYD	Drainable base (1 = Yes, 0 = No)
3.	BTYN	Non-drainable base (1 = Yes, 0 = No)
4.	UW	Concrete unit weight (lb/ft^3)
5.	CFA	Cement factor (lb/yd^3)
6.	SUBTRT_N	Non-treated subgrade (1 = Yes, 0 = No)
7.	SUBTRT_L	6 in. lime treated subgrade, LTSG (1 = Yes, 0 = No)
8.	SUBTRT_F	6 in. fly ash treated subgrade (1 = Yes, 0 = No)
9.	FSI	% of natural subgrade soil material passing No. 4 sieve
10.	TSI	% of natural subgrade soil material passing No. 200 sieve
11.	PI	Plasticity index of natural subgrade soil material

12. ESAL Cumulative yearly ESAL values
13. FTC Average number of freeze-thaw cycles per year
14. DB Cumulative total number of days below 32 °F/yr
15. DA Cumulative total number of days above 90 °F/yr
16. WET Cumulative number of days per year with over 0.4 in. precipitation
17. IIRI Initial right wheel path IRI values (in./mile)
18. AP Age of pavement (year)
19. $(IRI)^n$ IRI value at age (n) year (in./mile)

As noted earlier, the input layer includes a dynamic variable [i.e., $(IRI)^n$] that represents the IRI value at age (n) year. Accordingly, all nineteen input parameters (i.e., eighteen static and one dynamic) are used via the developed ANN-based model to predict the IRI value [i.e., $(IRI)^{n+1}$] at age (n+1) year. Note that, the initial value for (n) is zero. Based on the stage one training, the optimal network architecture was found at ten (10) hidden nodes. Accordingly, the final form of Eq. (2) can be represented by the following expanded form:

$$\{(IRI)^{n+1}\} = ANN_{19\text{-}10\text{-}1}\{SLTH, BTYD, BTYN, UW, CFA, SUBTRT\_N, SUBTRT\_L, SUBTRT\_F, FSI, TSI, PI, ESAL, FTC, DB, DA, WET, IIRI, AP, (IRI)^n\} \quad (3)$$

Based on the stage two training, the 19-10-1 ANN-based IRI prediction model yielded a coefficient of determination, R^2, of 0.90. A graphical comparison between the predicted and actual IRI values is depicted in Figure 3.2. Even though some scatter is noted in this figure, most of the data is predicted reasonably well.

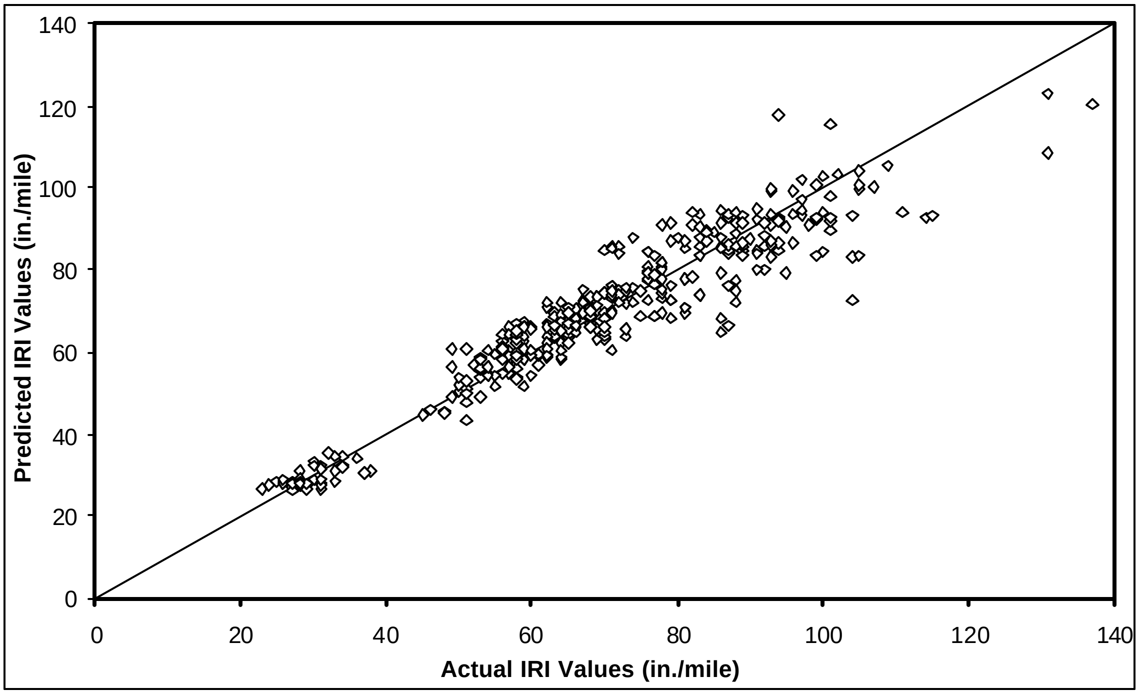

FIGURE 3.2: Comparison between Actual and Predicted IRI Values for the Developed ANN (19-10-1) Model (R^2 = 0.90)

3.1.3 Independent Validation

To further validate the developed ANN-based model, it was used to predict IRI values for years 2001 and 2002 data. This comparison between predicted and actual values for 2001 and 2002 years are respectively depicted in Figures 3.3 and 3.4. In this case, R^2 values of 0.80 and 0.74 were obtained for year 2001 and 2002 data, respectively. As expected, model prediction accuracy decreases as extrapolation time is increased.

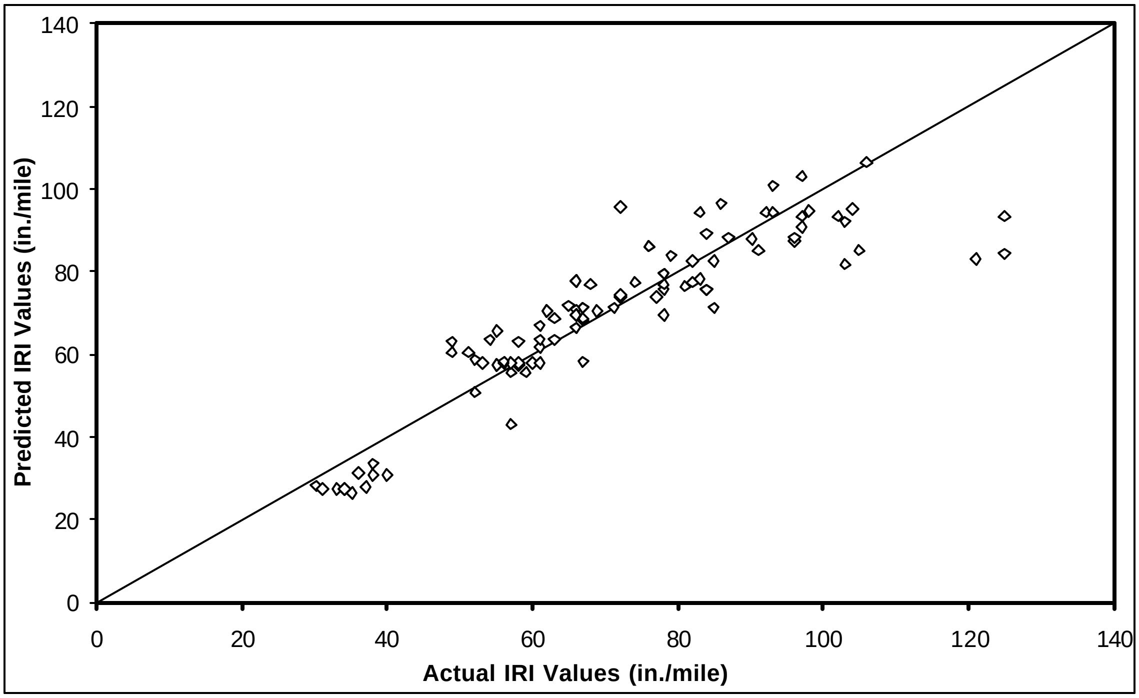

FIGURE 3.3: Predicted IRI for the Year 2001 (R^2 = 0.80)

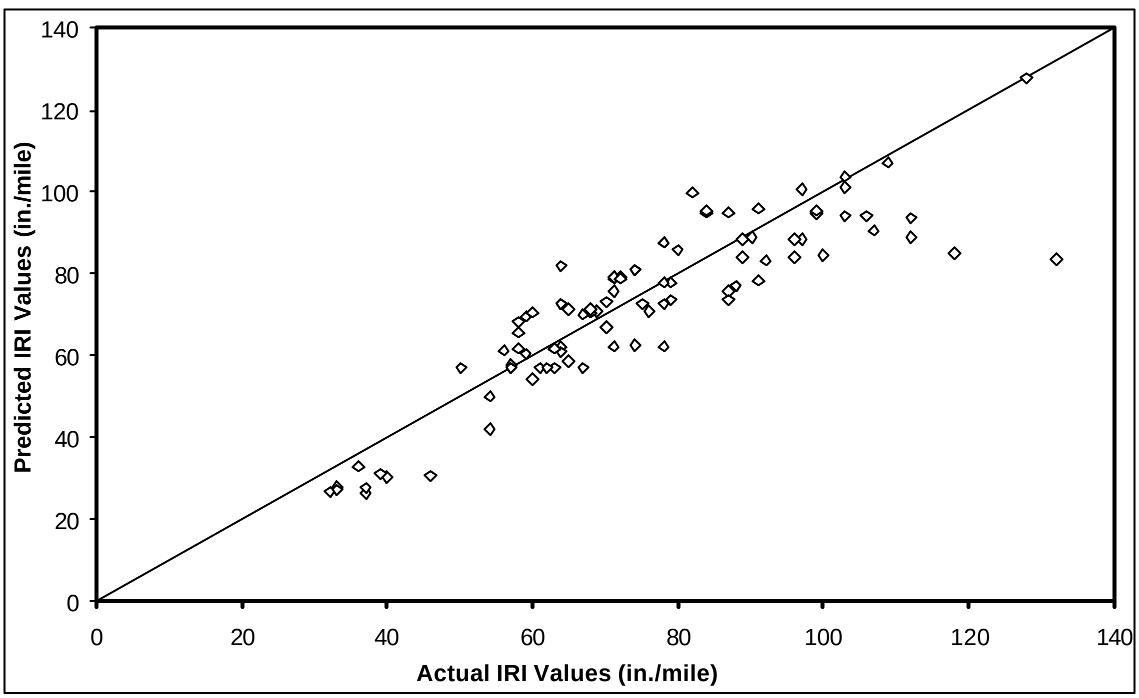

FIGURE 3.4: Predicted IRI for the Year 2002 (R^2 = 0.74)

3.1.4 ANN Sensitivity Analysis

In order to assess the impact of each independent input variable on the time-dependent IRI profile, a sensitivity analysis was performed. To accomplish this objective, a PCCP section was selected to represent the 102 sections by the average input values of all sections. Accordingly, when logically possible, each input variable was then varied within its applicable range (keeping all other input variables stationary). The time-dependent IRI profile was calculated via the developed 19-10-1 ANN-based model for a total of seven years. The seven-year span was chosen herein to represent the model's utility period. As stated earlier, this period is made up of the 5-year data used for model training and the additional 2-year data used for model validation. Selected plots for variables showing the maximum impact on IRI time-dependent profile are presented in this paper. Factors that, so far, have shown the greatest impact on the roughness are BTYD, BTYN, IIRI, SLTH, SUBTRT_N, SUBTRT_L, and SUBTRT_F. In this study, IIRI and SLTH values were varied from 30 to 90 in./mile and from 8 to 12 in., respectively.

It is noteworthy to mention that conducting the sensitivity analysis by changing one input variable over a wide range, while keeping all other input variables stationary, may not be fully valid in some cases. Additionally, trends noted herein may not be fully true if a different PCC section is used to perform the sensitivity analysis. However, similar sensitivity analysis can be performed, if desired, using the developed ANN-based IRI prediction model.

The choice of using drainable or non-drainable bases significantly influences the roughness as illustrated in Figure 3.5. This factor seems to produce the largest impact on IRI profiles, observed in this study, for Kansas JPCP pavements. Figure 3.5 demonstrates that non-drainable bases will result in PCC pavements having higher roughness. Drainable bases tend to have overall lower roughness profiles. Note that, bases that are non-drainable, are also impermeable. In this case, trapped water can cause swelling of the bases (or subgrades) and eventually leads to an uneven pavement surface. On the other hand, proper drainage will decrease the swell potential of the subgrades or bases. Numerically, for the case considered herein, the use of drainable base will decrease dramatically the roughness by 48 in./mile. In other words, after seven years of service, a drainable base tends to produce a roughness, which is about 48 in./mile lower than non-drainable base. This clearly indicates that a drainable base will help retain the smoothness longer compared to non-drainable bases.

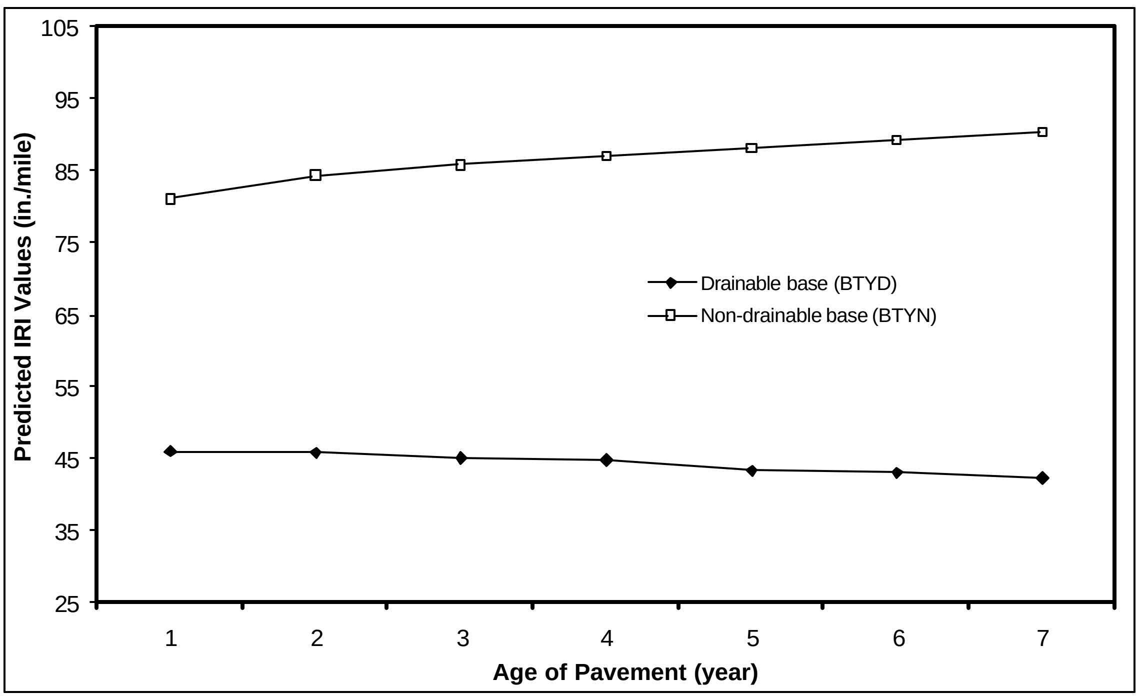

FIGURE 3.5: Predicted IRI Values for Drainable and Non-drainable Base

Figure 3.6 illustrates the influence of initial IRI on the time-dependent future roughness. The initial IRI is the IRI measured during the first year after construction. As indicated in Figure 3.6, the same profiles seem to progressively become smoother with time as vehicles travel over them. Generally, as the pavement section is opened to traffic, its "smoothing" effect tends to slow the progression of roughness. Note that, poorly finished pavements may have high initial IRI values (Hancock, 2000). In these situations, at early age, traffic loading represented herein by ESAL's tends to produce smoother pavements due to "smoothing" of the pavement surface irregularities. Consequently, this may lead to a sudden decrease in the IRI profile. This sudden drop may also happen due to the stabilization of: i) the subgrade soil moisture content and ii) the non-uniform consolidation of the subgrade during the early years of pavement life (Hancock, 2000; Akhter, 2001). Eventually, all pavements will have positive rates of roughness progression.

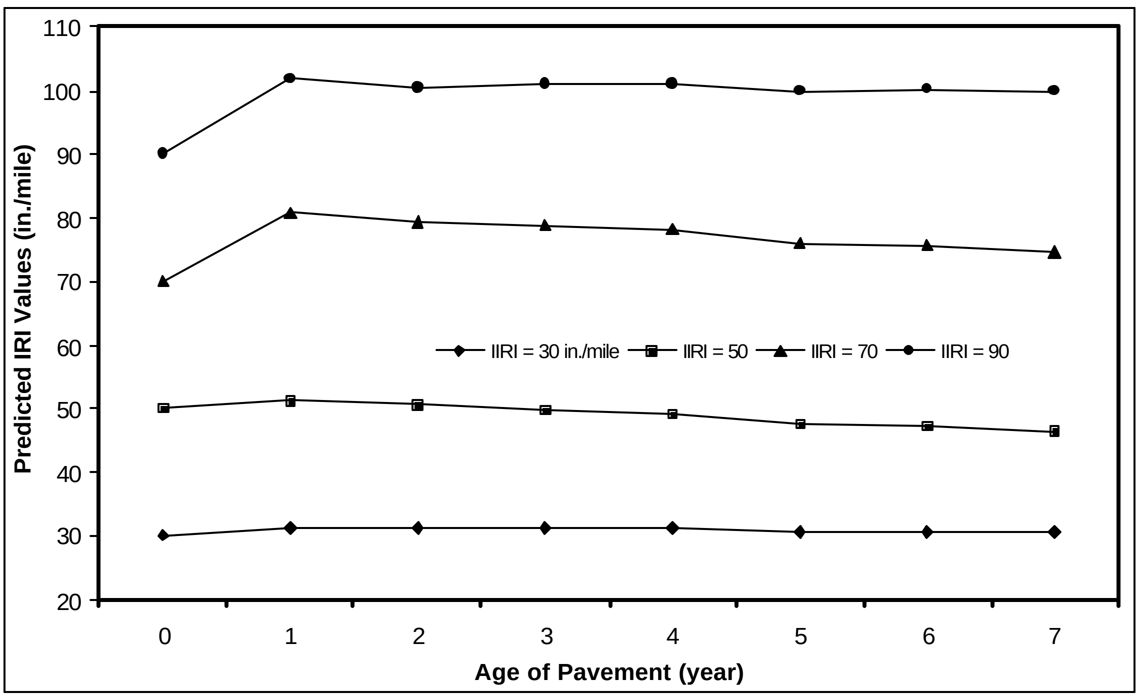

FIGURE 3.6: Predicted IRI Values for Different Initial IRI Values

Figure 3.7 shows the effect of PCC slab thickness on the roughness. As it can be noted, PCC slab thickness has a notable effect on roughness profiles. As it can be observed in this case, thicker PCC slabs are generally associated with higher initial IRI values. On the other hand, higher IRI progression is noted on thinner slabs compare to those noted on thicker PCC slabs. In other words, subjecting all slabs to the same traffic loading will cause thinner slabs to experience higher progression in their IRI profile. This can clearly be noted when comparing the IRI profile of the 8-inch slab with the profile shown for the 12- inch slab. For this reason, thicker slabs will generally sustain their initial IRI values for longer periods compare to thinner slabs. Therefore, an increase in slab thickness will typically yield a reduction in IRI progression. This observation is in full agreement with our expectation.

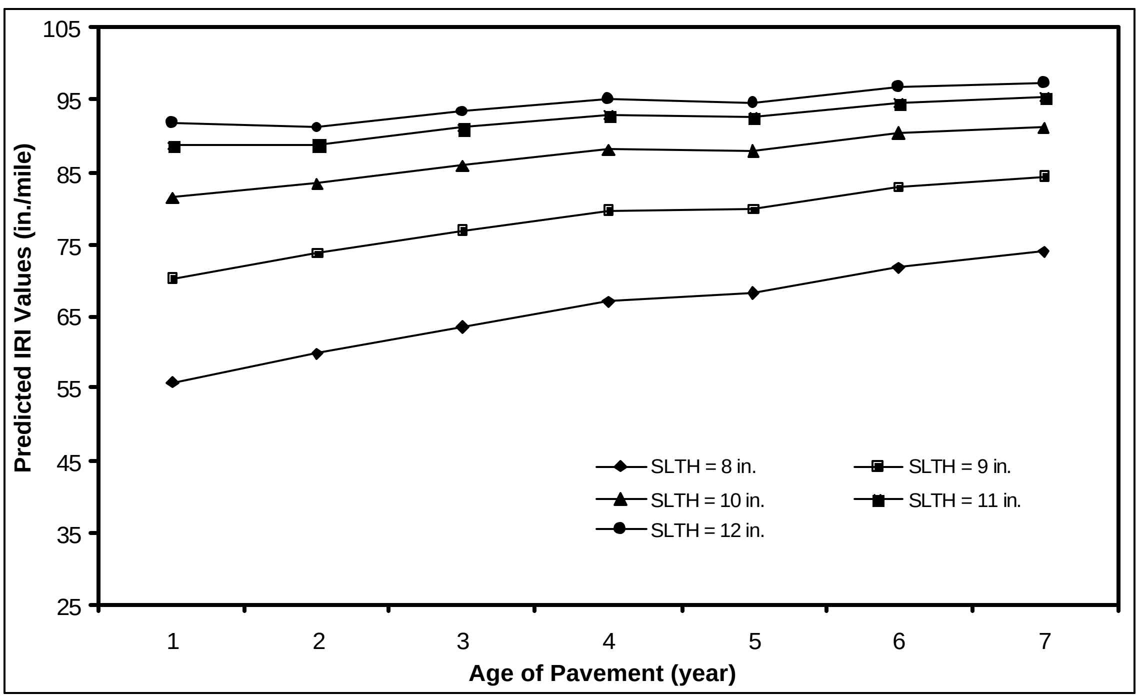

FIGURE 3.7: Predicted IRI for Different Values of PCC Slab Thickness (in.)

Figure 3.8 identifies three different subgrade treatment types as a significant variable affecting the roughness. As noted in Figure 3.8, pavements placed on lime treated subgrades are substantially smoother than those placed on non-treated subgrades. Use of 6 in. lime treated subgrade will tend to decrease the roughness by about 63 in./mile after 7 years. This indicates that subgrade treatment would be the most beneficial to sustain smoothness since a large percentage of subgrade material consists of silt and clay particles. This seems logical, knowing that subgrades with the high presence of clay are commonly treated with lime to reduce swelling potential. This swelling will eventually lead to significant increase in roughness due to changes in the vertical profile of the PCC pavement. Subgrade soils with a high amount of materials passing the 0.075 mm (US No. 200) sieve will generally have the high presence of clay. In these situations, KDOT usually requires some form of subgrade treatment/stabilization. As a result, subgrade treatment reduces the soil volume change potential under varying moisture conditions. Lime-treated subgrade uses the mixture of soil, lime, and water. The lime is placed on the prepared subgrade, mixed and compacted. After the mixture is compacted, the lime-treated subgrade is cured for 7 days by keeping the subgrade moist with water. Water is added as necessary to the mixture during the mixing operation to provide a moisture content above the optimum moisture content of the raw soil being treated (Hancock, 2000; Akhter, 2001).

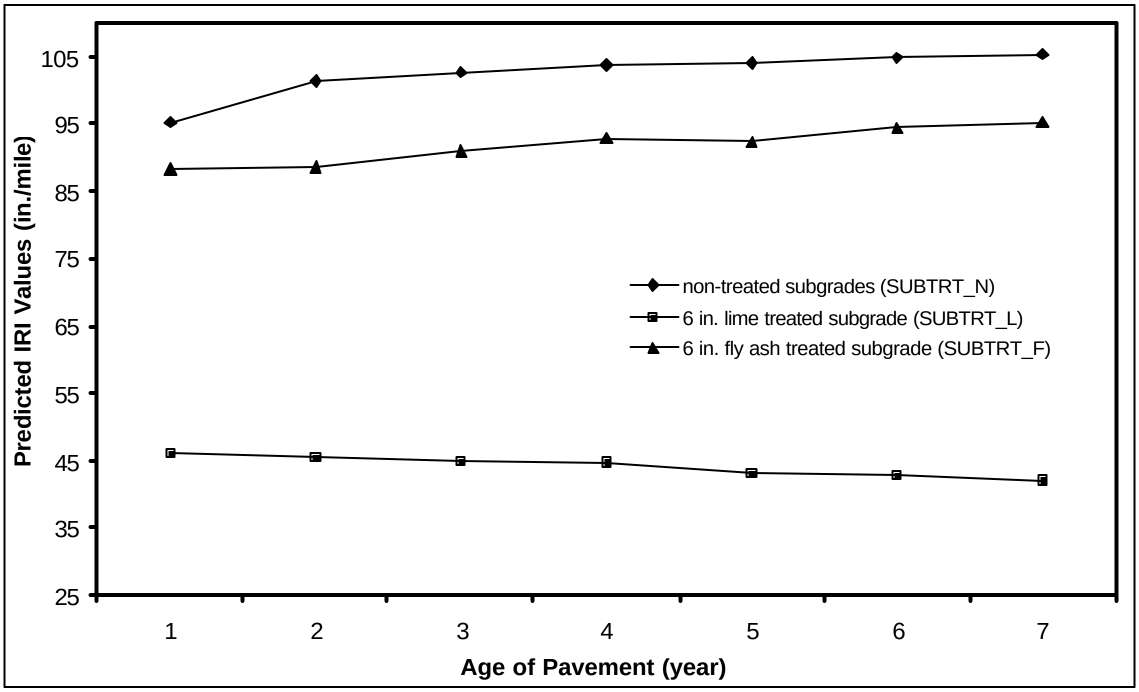

FIGURE 3.8: Predicted IRI Values for Various Subgrade Treatment Cases

3.1.5 Utilization

The resulting 19-10-1 ANN-based IRI prediction model is encoded into an Excel-based software program. Usage of the model will allow KDOT's geotechnical/pavement unit to obtain reliable and accurate predictions of the future roughness conditions of PCC pavements based on given input variables. The user is asked to enter all of the relevant input parameters in order to project the IRI profile for the selected number of years.

3.2 SAS-Based Prediction Equation

3.2.1 Methodology (SAS)

Statistical Analysis System (SAS 1979) is one of the most widely used computer programs to perform regression analysis. In this study, it was used to conduct the statistical analysis for the available database. Among several different selection methods in SAS, the backward selection procedure was used to determine which independent variables most influence the dependent variable in order to select the optimum model in this study (Helwig et al., 1979). This method starts with a full model (all independent variables entered) and then eliminates one variable at a time until a reasonable good regression model is selected in order to identify and distinguish those most significant independent variables which impact the dependent variable. In order to develop a pavement performance predictive equation known as a regression model, multiple regression analysis was used as a statistical tool to find a correlation or relationship between one or more independent variables and a dependent variable (Neter and Wasserman, 1974). The general expression (Boyer, 1999) of the regression model, which is linear in form:

$$\text{Dependent variable} = a + bX_1 + cX_2 + dX_3 + \ldots\ldots \qquad (4)$$

Where roughness (IRI) is the dependent variable; X_1, X_2, and X_3 are independent variables; and a, b, c, and d are the linear correlation coefficients.

The model in this study was selected on the basis of the following criteria:

1. Coefficient of Determination (R^2): R^2 is a statistical quantity that measures how well a model predicts a dependent variable and thereby, represents a measure of the adequacy of the overall model. The selected model in this study usually is the model with the largest R^2 but with a minimum number of independent variables (Felker, 2000; Ott and Longnecker, 1993).
2. Mean Square Error (MSE): The goodness of fit was also examined by the Mean Square Error or Variance (σ^2). The model with the smallest MSE that involves the least number of independent variables can be considered as the best model (Ott and Longnecker, 1993; Felker, 2000).
3. Model Utility Test (F Test): In order to test the overall effectiveness of a model, the F Test evaluated whether at least one of the linear coefficients is non-zero. If at least one of the linear coefficients is non-zero then the developed model will generally predict a dependent variable accurately.

4. t Statistic: The "t" statistic represents the relative assurance that a given independent variable has an effect on the dependent variable. In order to determine whether the independent variables are significant or not, the p-value should be less than 0.05.
5. Correlation Coefficient: The correlation coefficient reflects the magnitude and sign of the effect an independent variable has on the dependent variable.
6. Practicality: From the multiple regression analysis, it may be found that some of the models developed may not be practical, explainable or logical. Engineering judgment was used to interpret which models are practical and which are not.

3.2.2 Model Development (SAS)

In order to develop a roughness prediction equation for the PCC pavements in Kansas, linear regression analysis using SAS program was used to find the best relationship between the independent variables and the dependent variable. The selected model contains the most significant independent variables.

The following model for predicting future IRI of the PCC pavements consisting of a dependent variable and ten independent variables was obtained:

$$\begin{aligned} IRI\ (R^2 = 0.73) = {} & 218.38 - 0.61*FSI - 0.07*TSI + 7.88*MIAT \\ & + 9.10*SLTH + 8.45*BTY + 1.64*AP + 0.78*IIRI \\ & - 0.01*WET - 1.673e\text{-}7*ESAL + 11.97*SUBTRT \end{aligned} \tag{5}$$

where:

IRI	=	yearly right wheel path roughness IRI value;
FSI	=	% subgrade materials passing No.4 sieve;
TSI	=	% subgrade materials passing No. 200 sieve;
MIAT	=	minimum annual temperature (°F);
SLTH	=	PCC slab thickness (inch);
BTY	=	drainable base or non-drainable base;

AP = age of pavement (year);

IIRI = initial right wheel path IRI (in./mile);

WET = cumulative number of wet days per year (more than 0.4 in. precipitation);

ESAL = cumulative yearly ESAL values; and

SUBTRT = subgrade treatment: no treatment, 6” lime-treated subgrade, or 6” fly ash treated subgrade

The IRI prediction model yielded a coefficient of determination, R^2 of 0.73 as shown in Figure 3.9.

Table 3.1 represents each project by its identifying project K-number, the PCC slab thickness in inches, the type of subgrade treatment and whether the base is drainable. Using the developed IRI prediction model, the 20-year and 30-year IRI values were projected. Table 3.2 shows the predicted IRI values.

The IRI values for 5 of the 23 constructed projects are shown in Figures 3.10 through 3.14. The graphs show that although the measured IRI data is highly variable, the developed SAS-based prediction equation tends to adequately model the data in several projects (e.g. Figure 3.11 and 3.13). Figures 3.10, 3.12, and 3.14 show a variety of accuracies between the model and the actual data.

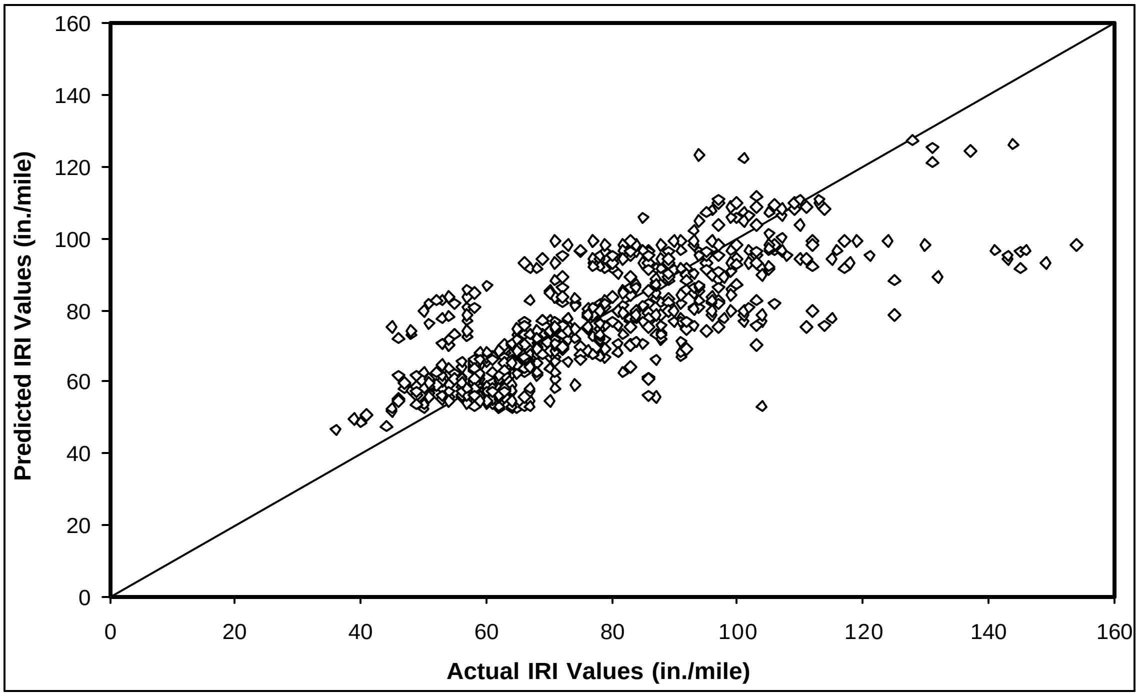

FIGURE 3.9: Comparison between Actual and Predicted IRI Values for the SAS-based Prediction Equation (R^2=0.73)

In Figures 3.10 through 3.14, the x axis is the time in years that the IRI roughness values have been measured. The y axis represents the IRI values according to each section (i.e. from county milepost 11.41 to 12.05 as shown in Figure 3.10). The legend gives the county mileposts of each section boundary, and the average and the predicted IRI values for each project. These figures show that the model consistently underestimated the actual IRI values, but followed the general trend of the actual IRI data. The scatter of the actual IRI data will determine the general overall look of the graph. In some figures, for example, Figure 3.10, there seems to be little correlation between the model and the actual data, but an examination of Figure 3.11 shows a good relationship between the model and the actual data.

TABLE 3.1: Portland Cement Concrete (PCC) Projects Major Input Variables

No.	Project K number	PCC slab thickness (in.)	Subgrade treatment	Avg. no. of freeze-thaw cycles per year	Drainable base or non-drainable base
1	K-2633-01	10	1	87	1
2	K-2633-01	10	1	87	1
3	K-3596-01	11	1	80	1
4	K-3596-02	12	1	80	0
5	K-4088-02	11	1	72	1
6	K-4088-02	11	1	72	1
7	K-2446-01	11	1	84	0
8	K-3344-01	10.5	1	84	0
9	K-2447-01	11	2	75	0
10	K-2447-01	11	2	75	0
11	K-3637-01	11	1	72	1
12	K-4058-03	9	1	84	1
13	K-3216-02	10	1	88	0
14	K-3217-02	10	1	88	0
15	K-4422-02	9	0	93	1
16	K-3251-01	9	1	88	1
17	K-3251-01	9	1	88	1
18	K-3251-01	9	1	88	1
19	K-3251-01	9	1	88	1
20	K-4341-01	9	1	84	1
21	K-4341-01	9	1	84	1
22	K-3684-01	9	1	81	0
23	K-4460-01	10	0	81	0

Subgrade Treatment: no treatment (N/A) (=0),
6” lime treated subgrade (=1), and
6” fly ash treated subgrade (=2)
Drainable Base (=1) or Non-drainable Base (=0)

TABLE 3.2: Future 20-Year and 30-Year IRI Using SAS-based Prediction Equation

No.	Project K Number	Route	Lane	Initial IRI (in./mile)	20-yr IRI (in./mile)	30-yr IRI (in./mile)
1	K-2633-01*	I-35	East	84	111	121
2	K-2633-01*	I-35	West	99	111	121
3	K-3596-01*	I-35	East	52	96	106
4	K-3596-02**	I-35	East	90	100	110
5	K-4088-02*	I-35	East	97	92	101
6	K-4088-02*	I-35	West	100	123	132
7	K-2446-01**	I-70	North	46	76	86
8	K-3344-01**	I-70	South	36	66	76
9	K-2447-01**	I-70	North	110	120	129
10	K-2447-01**	I-70	South	97	120	129
11	K-3637-01*	I-435	West	80	92	101
12	K-4058-03*	US-50	Undivided	93	108	119
13	K-3216-02**	US-50	Undivided	57	82	91
14	K-3217-02**	US-50	Undivided	71	93	102
15	K-4422-02*	US-56	Undivided	97	113	125
16	K-3251-01*	US-75	East	71	87	95
17	K-3251-01*	US-75	East	67	87	95
18	K-3251-01*	US-75	West	71	87	96
19	K-3251-01*	US-75	West	68	83	92
20	K-4341-01*	US-75	East	68	90	100
21	K-4341-01*	US-75	West	85	92	103
22	K-3684-01**	K-15	West	50	74	84
23	K-4460-01**	K-96	North	67	73	83

* Drainable Base: Edge Drain, Cement Treated Drainable Base (CTDB), Bound Drainable Base (BDB)
** Non-drainable Base: No Edge Drain, Portland Cement Treated Base (PCTB)

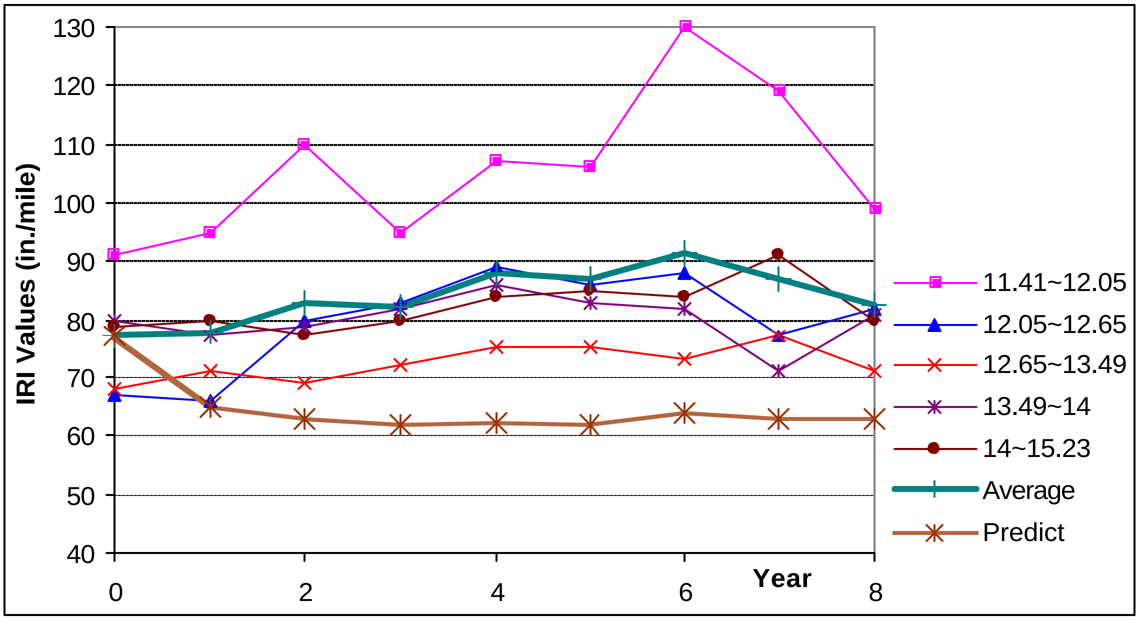

Figure 3.10: IRI Values: I-35, Lyon County, Miles 11.41~15.23 (K-2633-01, East)

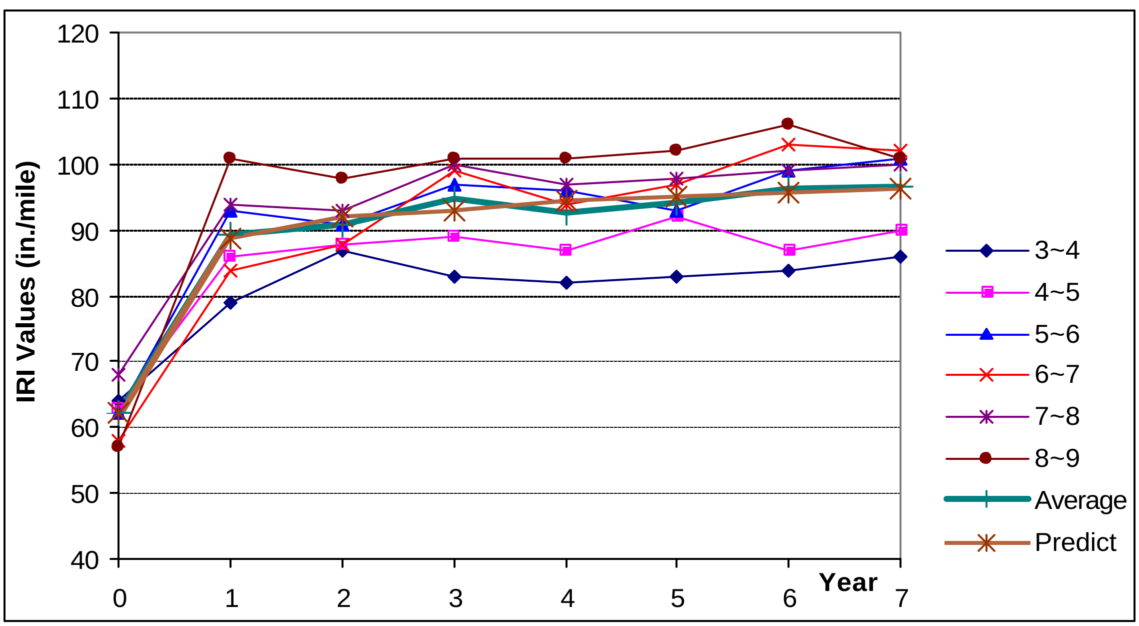

FIGURE 3.11: IRI Values: I-35, Franklin County, Miles 3~9 (K-3596-02, East)

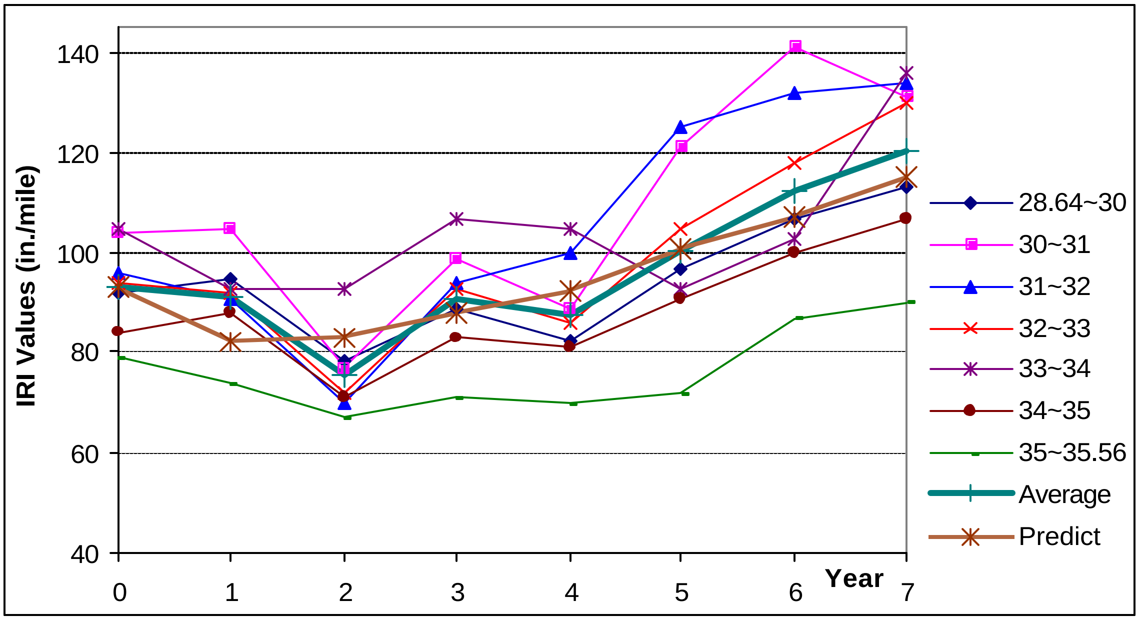

FIGURE 3.12: IRI Values: US-50, Harvey County, Miles 28.64~35.56 (K-4058-03, Undivided)

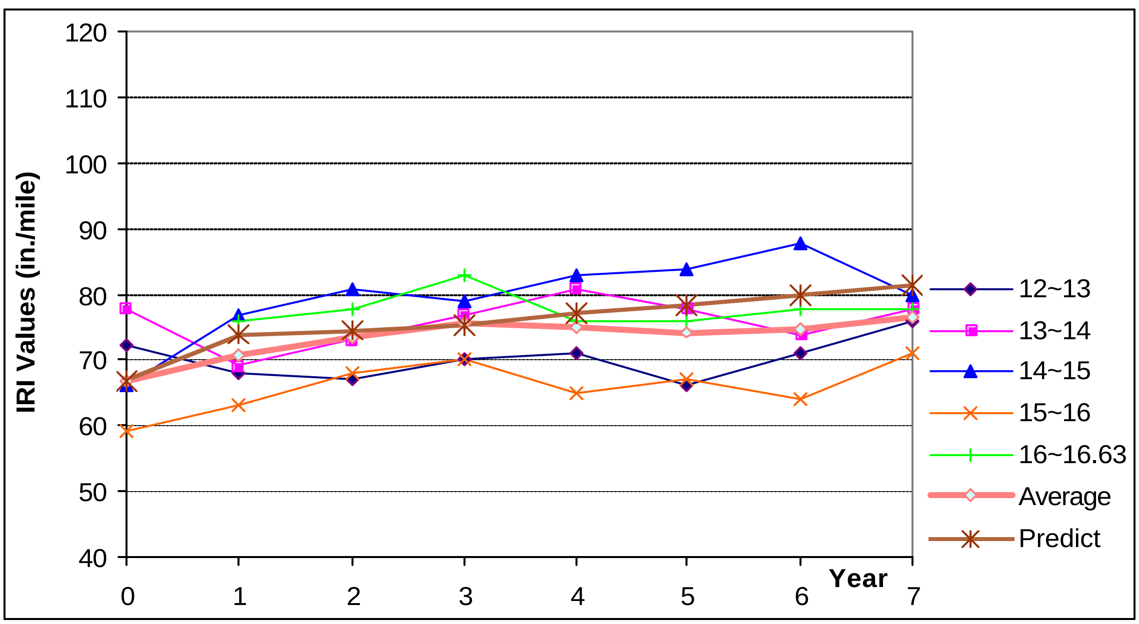

FIGURE 3.13: IRI Values: US-75, Jackson County, Miles 12~16.63 (K-3251-01, East)

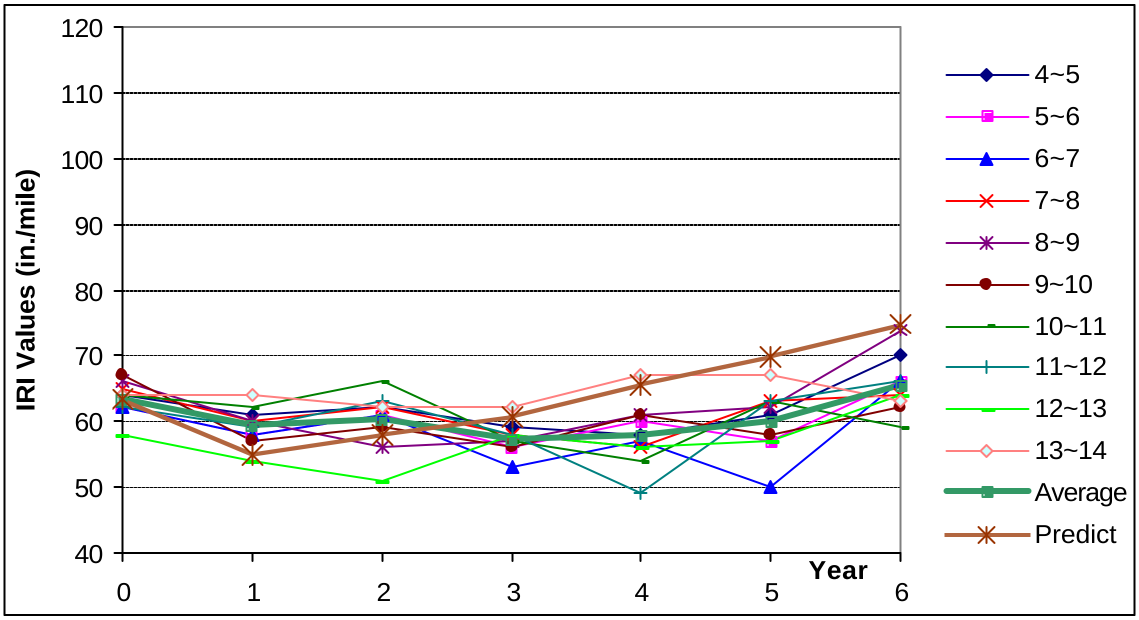

FIGURE 3.14: IRI Values: K-96, Sedgwick County, Miles 4~14 (K-4460-01, North)

3.2.3 SAS Sensitivity Analysis

In order to assess the impact of each independent input variable on the time-dependent IRI profile, a sensitivity analysis was performed (Figure 3.15). The sensitivity analysis determined the effects of three levels, minimum, median, and maximum, of each independent variable while keeping all other input variables stationary. Also, the age of the pavement was constant at seven years. As shown in Figure 3.15, the PCC slab thickness and the initial roughness have greater impact on the roughness profile than the percent subgrade materials passing the US No. 200 sieve and cumulative yearly ESAL values. Thinner PCC pavements tend to be smoother than thicker ones. This may be attributed to the fact that thicker PCC slabs are generally associated with higher initial IRI values. Similar observations have also been made by Siddique et al. (2003) for some other Kansas PCC pavements and by Perera and Kohn (2001) for the PCC pavements in the LTPP program. Also, PCC pavements built with lower IRI values tend to sustain smoothness longer. Subgrade soils with a high amount of materials passing the US No. 200 sieve tend to remain smoother. This may appear to defy common experience. However, it is to be noted that those soils will generally have higher plasticity. In that situation, KDOT usually would require some form of subgrade treatment/stabilization using lime to reduce volume change potential under varying moisture conditions. Thus, a treated subgrade would be beneficial for sustaining smooth PCC pavements. Also, the developed model is not highly sensitive to the traffic loading parameter (ESAL).

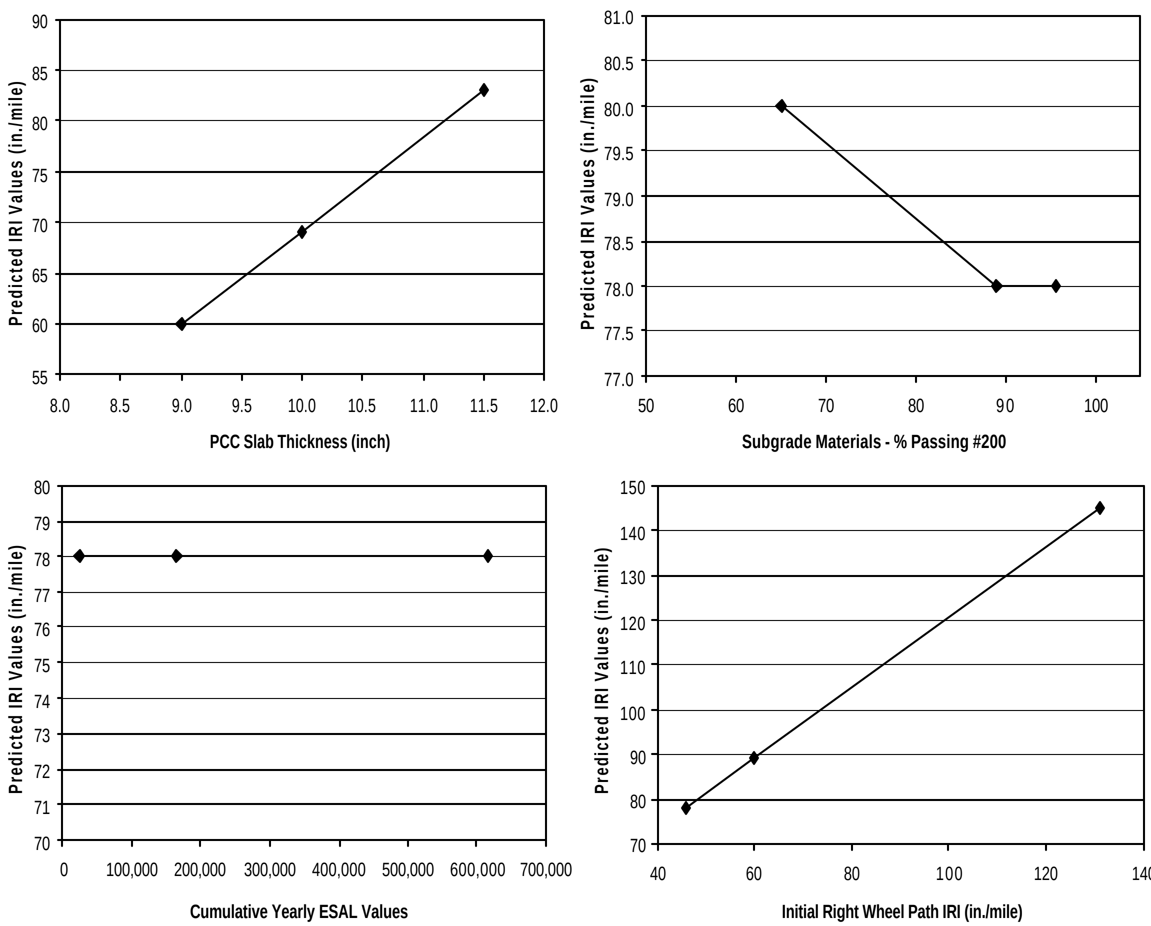

FIGURE 3.15: SAS Sensitivity Analysis

Chapter 4

Summary, Conclusions and Recommendations

4.1 Summary

The dynamic ANN modeling strategy and linear regression analysis using the SAS program were used in this study to develop efficient time-dependent PCC pavement roughness prediction models. Inputs for the developed models take into consideration various parameters related to the following seven categories:

1. Pavement design factors; represented by slab thickness and the use of drainable or non-drainable bases.
2. Concrete material parameters; characterized by the use of unit weight and cement factor.
3. Subgrade treatment; accounted for by the use of non-treated subgrades, 6 in. lime treated subgrade, and 6 in. fly ash treated subgrade.
4. Foundation soil properties; represented in the model by the parameters such as % of natural subgrade soil material passing No. 4 sieve, % passing No. 200 sieve, and plasticity index.
5. Prevailing traffic loadings; accounted for by the use of the cumulative yearly ESAL values.
6. Prevailing climatic conditions; reflected in the model via the use of average number of freeze-thaw cycles per year, cumulative total number of days below 32 $^{\circ}$F/yr, cumulative total number of days above 90 $^{\circ}$F/yr, cumulative number of wet days/yr (i.e., having more than 0.4 in. precipitation) and minimum annual temperature ($^{\circ}$F) .
7. Construction quality; characterized by the initial IRI value.

4.2 CONCLUSIONS

4.2.1 Conclusions Regarding ANN-based Model

Notable conclusions derived from this study are listed below:

1. The developed model produced output values that are very close to the actual (measured) IRI values. The developed model could project the time-dependant roughness behavior with a reasonably high coefficient of determination, $R^2 = 0.90$.
2. Overall, roughness is more sensitive to PCC slab thickness, base drainability, initial IRI values, and subgrade treatment than the remaining factors.
3. A higher initial roughness value (built-in construction irregularities) results in an overall higher roughness profile throughout the project service life. As traffic passes over the pavement, a sudden drop from the higher initial IRI value may be expected due to some degree of pavement "smoothing" and stabilization of subgrade soil moisture.
4. Of all the factors considered, drainable bases (or proper drainage of the sub-bases) influence the roughness the most for the JPCP pavements. Non-drainable bases will result in PCC pavements having a higher roughness profile, and drainable bases tend to decrease the roughness. Drainable bases help eliminate trapped water, which is the chief factor behind any soil swelling problems for subgrades or bases. Therefore, drainable bases tend to help retain the smoothness for longer durations than non-drainable bases.
5. Subgrade treatment type was identified as a significant variable affecting the roughness. PCC pavements built on 6 in. lime treated subgrade (LTSG) are generally smoother than those built on non-treated subgrades or 6 in. fly ash treated subgrade.

4.2.2 Conclusions Regarding SAS-based Model

Roughness prediction models were developed in this study for Jointed Plain Concrete Pavements (JPCP) in Kansas using historical roughness, traffic and climatic data. Thicker PCC slabs would generally lead to higher future roughness values. This may be attributed to the fact that thicker PCC slabs are generally associated with higher initial IRI values. The same would happen for higher initial (as constructed) roughness. The future predicted roughness did not appear to be very sensitive to the traffic loading.

The actual measured IRI roughness values for many of these projects have not stabilized and have a relatively large fluctuation. Due to these large variations, the predicted IRI values do not necessarily closely match the raw actual data. This discrepancy between the actual and the predicted IRI values do not arbitrarily mean the developed model is faulty. The more important concept in the study is that the trend of the actual roughness over time and the predicted IRI roughness values have a great deal of similarity, and both of these measures are similar to the actual measured IRI data. For this inquiry based on a SAS model, R-squared values are not reliable measure to determine the validity of these predictions.

4.3 Recommendations

Since IRI values for many projects were still fluctuating, future updates of the developed models (as the age is increased and the trend of IRI profiles is stabilized) are expected to produce more accurate ANN-based and SAS-based models. Moreover, model prediction accuracy decreases as extrapolation time is increased. For this reason, it is imperative that such models should be annually updated on newly acquired data. This update will allow the modified ANN-based model and SAS-based model to better project and predict IRI values for future years.

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