Midwest Transportation Consortium

Fall Student Conference, November 19, 2004
Ames, Iowa

USE OF ARTIFICIAL NEURAL NETWORKS FOR PREDICTING RIGID PAVEMENT ROUGHNESS

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Word Count: Abstract: 228
Text: 3,188
Figures: 4 x 250 = 1,000
Tables: 4 x 250 = 1,000
Total: 5,416 < 7,500

Use of Artificial Neural Networks for Predicting Rigid Pavement Roughness

Abstract: This paper focuses on analyzing the Long Term Pavement Performance (LTPP) database to predict the international roughness index (IRI) in rigid pavements using artificial neural networks (ANNs). Large number of input parameters such as pavement layer data including the initial IRI value, age, faulting, traffic data, and transverse cracking data for 3 different severity levels (low, medium, and high) were used to predict the IRI values for jointed Portland cement concrete (JPCC) pavements. Substantial amount of pavement performance data queried from 83 pavement sections that belongs to 9 states were used in developing the ANN pavement roughness prediction models. The developed ANN models were able to successfully predict the measured IRI values with coefficient of multiple determination (R^2) values of 0.84 for the training data set and 0.81 for the testing data set. Results showed that the selection criteria for the testing sets are very important when evaluating the performance of the ANN models. It was demonstrated that ANNs are capable of mapping the complex, nonlinear relationship between the large number of pavement input parameters and the pavement roughness index of IRI value. Such models can be used to predict and forecast the pavement roughness index for pavement management system applications.

Key words: Long term pavement performance, neural networks, international roughness index, rigid pavements, pavement management systems.

1. Introduction

Long Term Pavement Performance (LTPP) program is primarily designed to provide state of the art information to the State Highway Agencies to build and maintain longer lasting pavements (FHWA, 1995). LTPP database is a nationwide effort to collect the pavement information over a long period of time. It contains a wide variety of information on pavement materials, climate, traffic, maintenance, field tests, etc. frequently collected for a particular pavement section. Thus, it provides a unique opportunity for pavement researchers to develop modeling tools which can be used to predict pavement performance (e.g., amount of cracking, faulting, pavement smoothness, etc.) to improve quality and sustainability of transportation infrastructure in a cost effective manner.

2. Background on the LTPP Database

LTPP program started in 1987 with a comprehensive 20-year study of in-service pavements and a series of rigorous long-term field experiments monitoring more than 2,400 flexible and rigid pavement test sections across the United States and Canada. LTPP database is mainly divided into major categories of General Pavement Studies (GPS) and Specific Pavement Studies (SPS). GPS consist of nearly 800 in-service pavement test sections throughout the U.S. and Canada. SPS are intensive studies of specific variables involving new construction, maintenance treatments, and rehabilitation activities (LTPP User Guide, 2004). The organization of LTPP database is shown in Figure 1. Even though it contains a vast amount of information related to pavements, it is organized in a user-friendly format. The data is organized in Relational Database Management System (RDBMS) which provides facility of querying specific data using any type of database softwares e.g. MySQL, Oracle, MS Access, etc. in Graphical User Interface (GUI).

3. Artificial Neural Networks (ANNs) as LTPP Data Modeling Tools

Artificial neural networks (ANNs) are valuable computational tools that are increasingly being used to solve resource-intensive complex problems as an alternative to using more traditional techniques. In recent successful applications at the Iowa State University and University of Illinois, Ceylan et al. (2004) employed ANNs as pavement structural analysis tools for the rapid and accurate prediction of critical responses and deflection profiles of flexible pavements subjected to typical highway loadings. In another successful application, Meier et al. (1997) trained backpropagation type ANNs as surrogates for ELP analysis in a computer program for backcalculating pavement layer moduli and realized a 42 times increase in processing speed. Similar ANN applications were also reported by Meier and Rix (1995), Gucunski and Krstic (1996), Khazanovich and Roesler (1997), and Kim and Kim (1998). The research project team working on the development of the new mechanistic based AASHTO Pavement Design (NCHRP 1-37A) have also recognized ANNs as nontraditional, yet very powerful computing techniques and took advantage of ANN models in preparing the 2002 Design Guide concrete pavement analysis package. In addition, artificial neural networks (Attoh-Okine 1994, 2000, 2001, 2002; Gunaratne and Lu, 2004; Choi, Adams, and

Bahia, 2004; Sundin and Braban-Ledoux, 2001; Roberts and Attoh-Okine, 1998; Owusu-Ababia, 1998; Alsugair and Al-Qudrah, 1998; Huang and Moore, 1997; Eldin and Senouci, 1995; Eldin and Senouci, 1995; Fwa and Chan, 1993) have recently been used in pavement deterioration, pavement-performance prediction, flexible pavement cracking prediction, and condition ratings of jointed concrete pavements. As listed above, several neural network studies have been conducted to estimate current pavement condition, to predict pavement deterioration, and finally to assist engineers in selecting optimal maintenance and rehabilitation activities. Such applications help the pavement management engineers to choose the best available resource allocation strategies.

Recent research studies at Iowa State University focused on using the pavement performance data obtained from the Pavement Management Information System (PMIS) of the Iowa Department of Transportation (DOT). The objective of this research was to predict pavement roughness (IRI) values using ANN models, but the authors were not able to obtain adequate amount of data from the PMIS. Thus, it was decided to use the LTPP database having all desired information for a wide range of pavement sections throughout the United States including different climatic zones, pavement materials, pavement types, construction and maintenance practices, etc.

4. Methodology

In this study, ANN models were developed to predict the value of International Roughness Index (IRI) for rigid pavement sections and several ANN architectures were studied to obtain the best results. ANN models were developed for *the jointed Portland cement concrete (JPCC) pavement.* For the neural network trainings, the back propagation algorithm, which is the most commonly used type of artificial neural networks, was employed. Identification of input parameters used for the trainings and the generation of the ANN training databases are discussed below.

4.1. Identification of Needed Parameters

Past studies (Attoh-Okine, 2000; Attoh-Okine and Appea, 1998; Choi et al., 2004; and Najjar, 2003) on pavement performance indicated that the initial IRI value (iniIRI), time of overlay, faulting, average daily truck traffic (ADTT), equivalent single axle load (ESAL), pavement distress type and severity are the parameters that affect the IRI values. Thus, it was decided to use the data on traffic, pavement distresses, time of overlay information, and pavement initial smoothness queried from the LTPP database to train the ANN models for predicting the IRI values. Table 1 shows the category of data and variables used to generate the training data sets for the ANN models.

4.2. Training Set Generation

This study focuses on the rigid pavement sections from the LTPP database; jointed Portland cement concrete (JPCC) pavements. A common methodology was adopted to extract the desired data from the LTPP database for JPCC pavement type. Firstly, the research team prepared a consolidated table from all available distress data (see Table 2) for different pavement sections obtained by manual field observations. Then, the consolidated table was summarized over three fields (State_code, Shrp_id, Construction_no) to identify pavement sections having distress data. This summary table was used to extract the information on traffic, faulting, pavement distress, time of overlay information, and IRI measurements using appropriate condition statements in MS Access for JPCC pavement database. LTPP tables used for these data are shown in Table 2. Thus, separate tables were prepared having traffic, IRI, and pavement layer data in MS Access for JPCC pavement sections. Then, these tables were integrated to obtain a single dataset having all desired data from these tables. Once a single table was generated, an important factor "pavement age" was computed by taking the difference of date of distress survey and year of date of traffic open date or if there has been an overlay, the date of the 1st IRI measurement after the overlay (which is the section's new initial IRI).

5. ANN Models for Predicting the International Roughness index (IRI)

In this research study, the backpropagation type neural network (BPNN) algorithm was used to estimate the international roughness index. The backpropagation neural network is similar to other types of ANNs in its analogy to the human brain. Like the human brain, ANNs are composed of numerous small neurons (termed nodes in ANN literature) that receive input (signals) from certain nodes and in turn stimulate other nodes. A process of learning takes place in the nodes as they are presented with stimuli over a period of time. Artificial neural networks act in much the same way by receiving input (data values) and processing them through a series of nodes that organize themselves so as to best predict a certain output. Receiving stimuli (inputs) numerous times and arriving at the best association between the stimuli and an output is termed learning. The exact method in which the human brain learns is not known, and thus cannot be replicated in a computer, but the idea of interconnected nodes that perform relatively simple tasks, and organize themselves so as to best predict an output can be replicated.

Backpropagation ANNs are very powerful and versatile networks that can be taught a mapping from one data space to another using a representative set of patterns/examples to be learned. The term "backpropagation network" actually refers to a multi-layered, feed-forward neural network trained using an error backpropagation algorithm. (Haykin, 1999; Hecht-Nielsen, 1990; Parker,1985; Rumelhart, 1986; and Werbos, 1974). As with many ANNs, the connection weights in the backpropagation ANNs are initially selected at random. Inputs from the mapping examples are propagated forward through each layer of the network to emerge as outputs. The errors between those outputs and the correct answers are then propagated backwards through the network and the connection weights are individually adjusted to reduce the error. After many examples (training patterns) have been propagated through the network many times, the mapping function is learned with some specified error tolerance. This is called supervised learning because the network has to be shown the correct answers for it to learn. Backpropagation ANNs excel at data modeling with their superior function approximation capabilities (Haykin, S., 1999; and Meier and Tutumluer, 1998).

The ANN models developed in this study are very comprehensive because of the large number of records used to train them. A total of 5309 records were used to train and test the ANN models for JPCC pavement types. Pavement performance data queried from 83 LTPP test sections from 9 states were used to generate the databases for training and testing the ANN models.

5.1. Model for Jointed Plain Concrete Pavements (JPCC)

JPCC data set was queried for 9 states and 83 sections. The JPCC training data comprised of 7 input parameters of the initial IRI value, age, faulting, traffic data, and transverse cracking data for 3 different severity levels (low, medium, and high). The only output parameter was the average IRI value for the studied pavement test sections. Training and testing data sets were first randomly partitioned from the JPCC database. The ANN models gave higher R^2 values when the testing data set was randomly selected from the JPCC database. On the other hand, models produced lower R^2 values depending on the number of input parameters and the network architectures, when completely independent testing data sets were used. The term "completely independent testing data set" means the pavement performance data belonging to the same pavement test sections were not included in both the training and the testing sets. In this study, completely independent testing data set results are given. The pavement input parameters used for developing the ANN JPCC model are given in Table 3. The summary of the training and testing results of the JPCC model is tabulated in Table 4.

6. Performance of ANN Based Models for Predicting the IRI

6.1. Performance of JPCC Model

The 77-10-10-10-1 architecture (7 inputs, 10 hidden nodes in 1st, 2nd, and 3rd hidden layers, and 1 output node) was chosen as the best architecture for JPCC model based on its lowest training and testing MSEs. In the JPCC model, a total of 5,045 selected records out of 5,309 were reserved for testing and the remaining 264 records were used for training. The predictions for the JPCC model had an R^2 value of 0.84 for the training set and an R^2 value of 0.81 for the testing set. Figures 3 and 4 depict the actual versus predicted IRI values for both training and testing sets.

7. Summary and Conclusions

Neural Networks (NN) have recently received lots of attention and contributed in a wide variety of applications in civil engineering as well as in other fields. They have been found to be useful for modeling the complex relationships involved in physical phenomena and used in place of equation-based models. This paper demonstrated the successful use of the artificial neural networks (ANNs) to model the complex relationship between the large number of pavement parameters and the international roughness index (IRI).

It was shown in the this study that ANN models were able to successfully predict the measured IRI values with coefficient of multiple determination (R^2) values of 0.84 for training data set and 0.81 for testing data set for JPCC model when the testing set was selected completely independent from the training data set. It is very difficult to develop an ANN model that will generalize the pavement performance data for all the states and LTPP test sections. Better and more general pavement performance models can be developed when more data are made available in the LTPP database. In addition, the most important parameters affecting the value of international roughness index have been found as age, ADTT, and initial IRI variables based on the parametric sensitivity analysis and these results show good agreement with the literature.

In the field of pavement engineering, pavement management and maintenance issues must be considered very seriously in the selection of an economical treatment for rehabilitation of a deteriorated pavement sections. In order to preserve or improve pavement condition, there are many maintenance and rehabilitation treatments that have to be chosen very carefully due to financial problems. So, the engineering judgment and experience on deciding the maintenance and repair actions have significant importance. The crucial importance of being able to predict the future pavement condition can be understood easily when the financial savings are considered. The value of having an artificial neural network model that can predict the future conditions of the pavements accurately is very high. This proposed ANN model provide very useful information to the pavement engineers regarding with the needs of the deteriorated pavement sections.

In addition to the network configurations and architectures performed in this study, different network architectures can be used in the training of the network by changing the network's internal parameters and network performance for these models can be investigated. Alternative to the backpropagation (BP) used in this study, other neural network types such as general regression neural network algorithm (GRNN), probabilistic neural network (PNN), and polynomial neural network (GDMH), whose learning algorithms are different from the backpropagation can be used.

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Table 1. General category of data needs and parameters.

Category	**Variables**
Layer data	Location of pavements, time of overlay.
Traffic data	Location of pavements, AADTT (Annual Average Daily Truck Traffic), ESALs (Equivalent Single Axle Loading), year of survey, date of opening for traffic, etc.
Distress data	Location of pavements, date and year of survey, different type of distress along the pavements, IRI values.

Table 2. LTPP tables used for generating the ANN training sets.

Category	Modules in LTPP Database	Tables	Description	Parameters no from Table 3
Layer Data	RHB	RHB_IMP	Improvement data	1
	INV	INV_AGE	Date when pavement was opened to traffic	1
	SPS	SPS_ID	Date when pavement was opened to traffic	1
Traffic Data	TRF	TRF_MON_EST_ESAL	Estimated annual traffic volumes, ESAL values	3,4
Distress and IRI Data	MON	MON_DIS_JPCC_REV	Distress survey ratings from manual field inspections of pavements with JPCC surface	6,7
		MON_DIS_JPCC_FAULT	Joint faulting for JPCC pavement surfaces	5
		MON_PROFILE_MASTER	Monitoring profilometer master record	2, Output

Table 3. Variables used in ANN training data sets for the JPCC pavement sections.

No	Parameters
1	AGE
2	INITIAL IRI
3	ANL_KESAL_LTPP_LN_YR
4	AADT_TRUCK_COMBO
5	WHEELPATH_AVG_MM
6	TRANS_CRACK_NO_L
	TRANS_CRACK_NO_M
	TRANS_CRACK_NO_H
7	TRANS_CRACK_L_L
	TRANS_CRACK_L_M
	TRANS_CRACK_L_H
Output	AVERAGE IRI

Table 4. Training and testing summary of the JPCC model.

	JPCC Model
ANN Layer Configuration	7-10-10-10-1
Number of Inputs	7
Number of Outputs	1
Number of Training Patterns	5,045
Number of Testing Patterns	264
R^2 (Training Set)	0.84
R^2 (Testing Set)	0.81

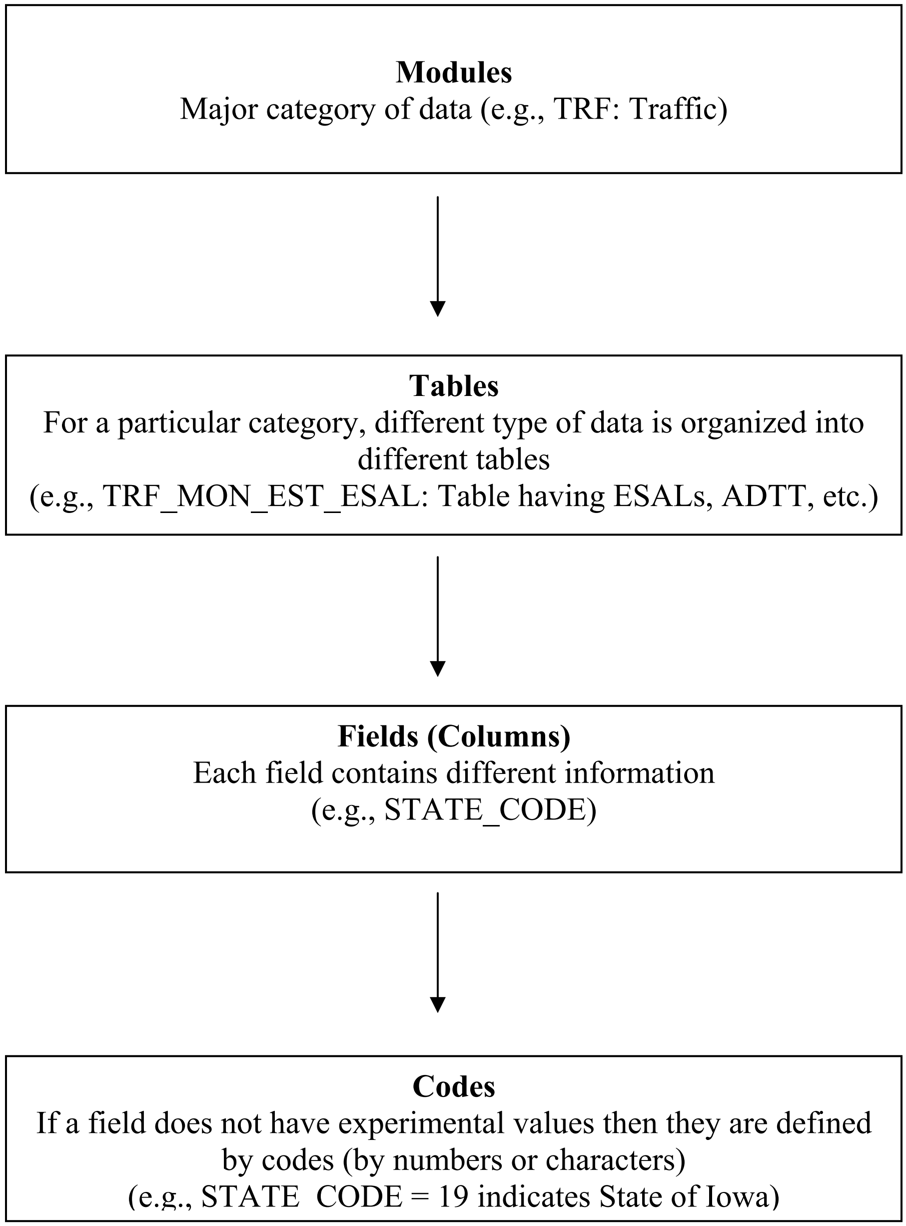

Figure 1. Organization of the LTPP database.

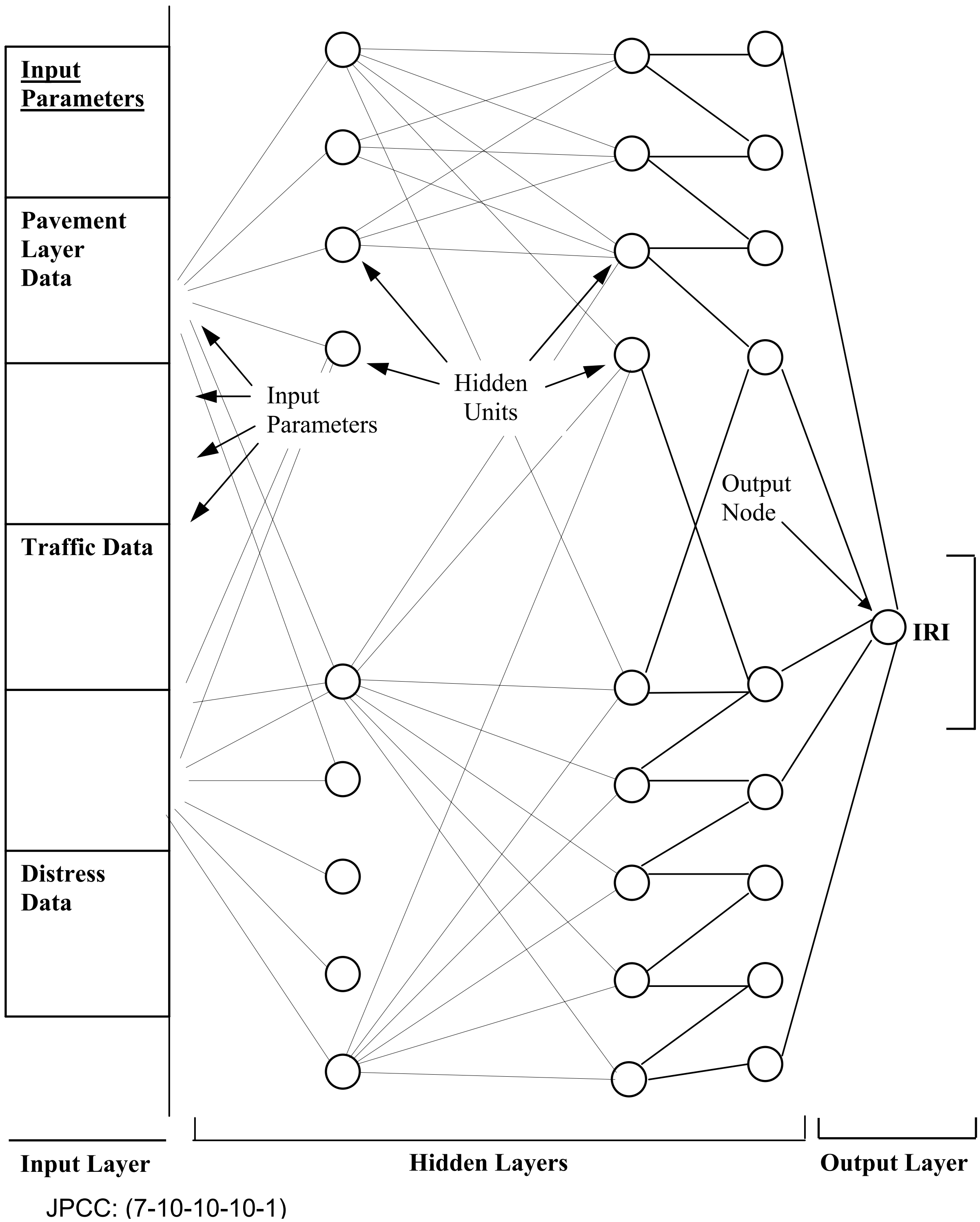

FIG. 2. ANN architecture with input parameters and the output

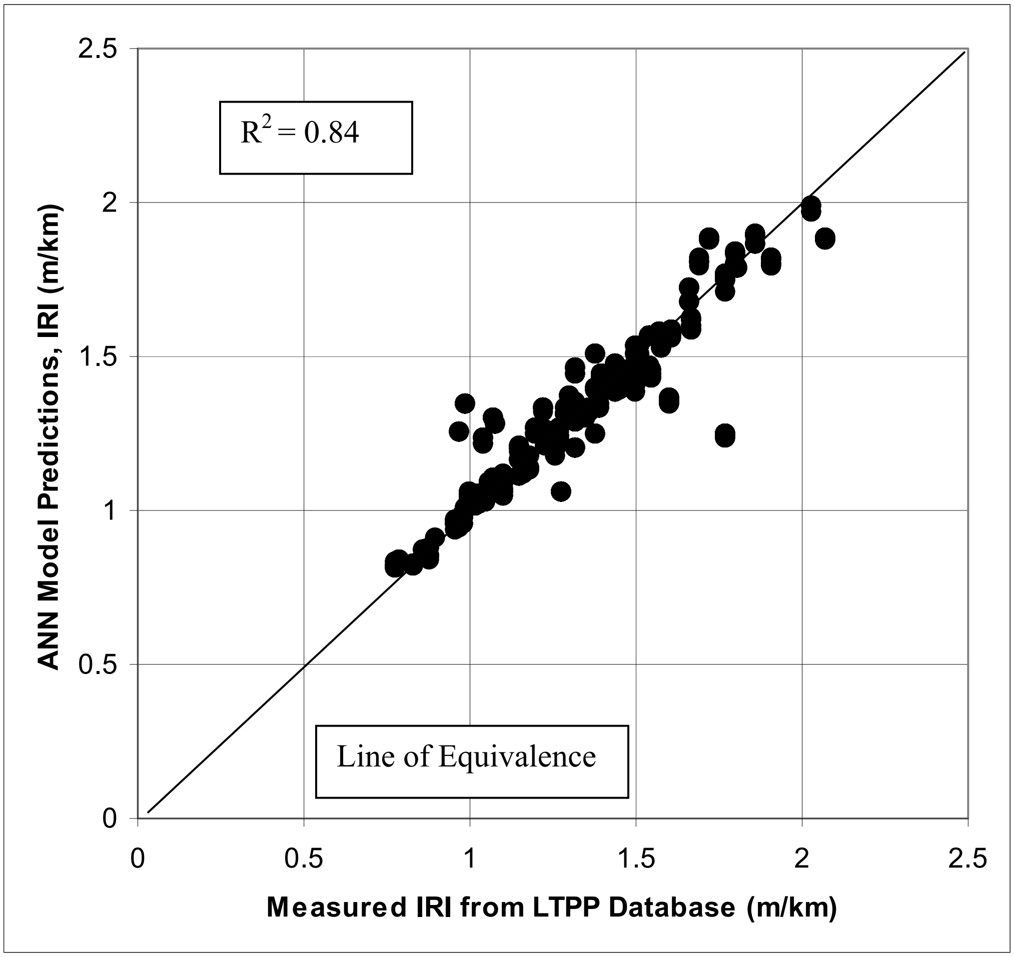

Figure 3. Performance of the 7-10-10-10-1 network for predicting the IRI values from the JPCC sections – Training set results.

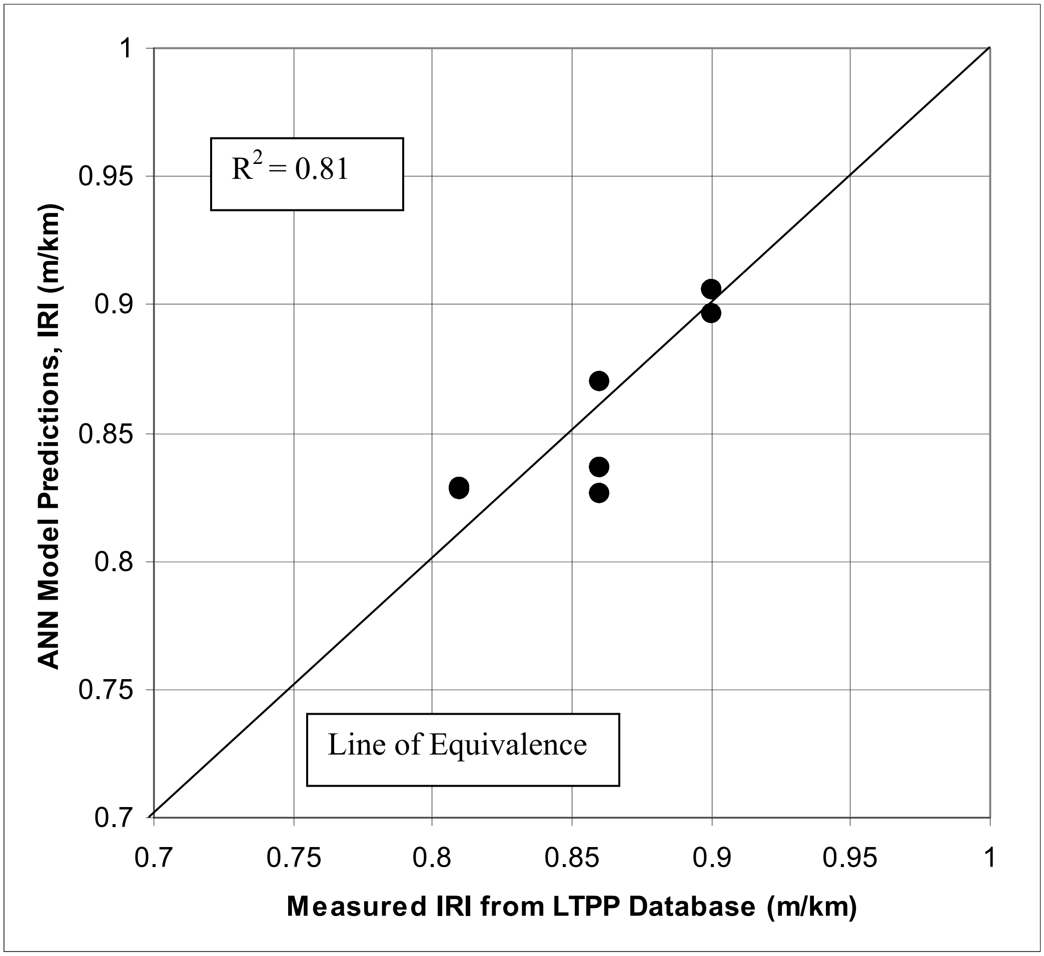

Figure 4. Performance of the 7-10-10-10-1 network for predicting the IRI values from the JPCC sections – Testing set results.