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Models for Pavement Deterioration Using LTPP

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16. Abstract

As pavement condition grows to be one of the crucial problems facing our national highway system, a new challenge emerges in developing pavement deterioration prediction models that are reliable yet easily applicable by Highway Pavement Management System (HPMS) in State DOTs and other agencies. This reports presents the research done in this area in Rutgers University. The significant contribution of this research lies in the fact that it utilizes the most comprehensive database of pavement conditions (LTTP) that is readily available and promises to provide the sought data in future years. The Long Term Pavement Project (LTTP) Database developed by the Federal Highway Administration was chosen to provide the required data of related parameters for the model development. The first part of this report reviews the existing literature covering related topics including pavement roughness, the Long Term Pavement Project LTPP background, artificial neural networks, regression analysis and the existing pavement deterioration models developed by Federal Highway Agency or reported by Transportation Research Record as well as the default model that is utilized by the Pavement Management System. The second part discusses the work done in data analysis and data manipulation in addition to the development of the training of the neural network model. The third part deals with various aspects of the model development using neural networks and regression analysis. The next part concludes the research with summarizing the results of model development and then by presenting a comparison between the models developed in this research and some existing models by applying these models to similar data sets and performing statistical analysis of the results. Lastly, the report presents some recommendations for future research in this area.

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INTRODUCTION

There are thousands of miles of paved roads in the United States that are traveled daily by millions of cars and trucks transporting people and goods. For this reason, the condition of the Nation's roadways plays a very important role in everyday life. The importance of the quality of roadways is also clear to the federal government. Billions of dollars are spent to build, maintain, and improve roadways. The cost of building a new roadway or rehabilitating an existing pavement can be considerable. If these roads are not repaired, poor pavement conditions can be just as costly to the driving public. Rough pavements can decrease speeds of traffic flow, cause damage to vehicles, and increase the number of traffic accidents. These costs, defined as social costs, are difficult to quantify and unfortunately, are born by the public at large.

To address these concerns, the Federal Highway Administration has developed guidelines for developing a Pavement System.(1) Many State Departments of Transportation (DOT) have developed to manage their highways. Being able to know when a pavement needs to be repaired before the pavement actually fails is an important element of management.

Development of reliable pavement deterioration prediction models is a challenge to developers. Accurate pavement deterioration prediction models can be a valuable tool to the DOTs to achieve a more efficient highway management. Due to the challenges of modeling the behavior of pavements, current pavement management's strength depends upon the measurement of existing pavement conditions rather than predicting future conditions of pavements. Projected roughness trends are a big factor used for evaluation, since pavement roughness is a good indicator of its future performance.

There is also the need for modeling different types of pavements. Portland cement concrete pavements are solid structures (i.e. rigid pavements). Most deterioration models for these structures are fairly accurate because their failure follows a more typical structural pattern. On the other hand, the deterioration of asphalt pavements is more difficult to predict due to the visco-elastic characteristic of the asphalt. Even though modeling the behavior of asphalt material can be easily done in a pavement laboratory, there are various external conditions that can be impossible to mimic. By including the many variables a roadway pavement endures, such as construction techniques, weathering or aging, the modeling effort becomes even more difficult.

OBJECTIVE AND SCOPE

The objective of this report is to explain the research done at Rutgers University in the area of developing models that can predict pavement deterioration more accurately. Neural networks and linear regression are the tools selected for developing these models. Neural networks are capable of distinguishing trends in data that are not easily recognized by standard statistical techniques. Careful consideration was given to the data used in developing the models, since the information needed to be accurate. The Long Term Pavement Project Database developed by the Federal Highway Administration had the potentials of representing the type of data sought. This program has been collecting data since 1989 at hundreds of sites across North America. The LTTP database gathers data covering a wide-range of variables and employs precise techniques for the collection of the information. These factors make this database an excellent choice for use in developing pavement models.

The scope of research focuses on modeling one particular type of pavement from this database, specifically an asphalt pavement that consists only of its original structure (i.e. the pavement was never rehabilitated). The reason for choosing this type of pavement is that it represents the most basic type of asphalt pavement. All other types of asphalt pavement use this pavement as a foundation. Thus, any model developed in this research could be used as the basis for developing other pavement models.

METHODOLOGY

Figure 1 represents the flow chart of the research methodology followed in this project. Multiple processes, shown in this Figure, are at times accomplished simultaneously. The first area of investigation is surveying the existing information on pavement deterioration models, pavement theory, regression analysis, and neural networks.

In addition to the information on pavements, the LTPP database is investigated thoroughly. As a first step, a search of the database is performed for the sites that should be included for developing the models. After acquiring the requested data for these sites, further inspection of the available data is done. Statistical analysis of the data played an important role in the selection of the variables for the development of models. Once the variables are chosen for developing the models, they are compiled into a database. The neural network and linear regression models are then developed using the compiled database. A comparison of these models with some of the existing models is carried out afterwards.

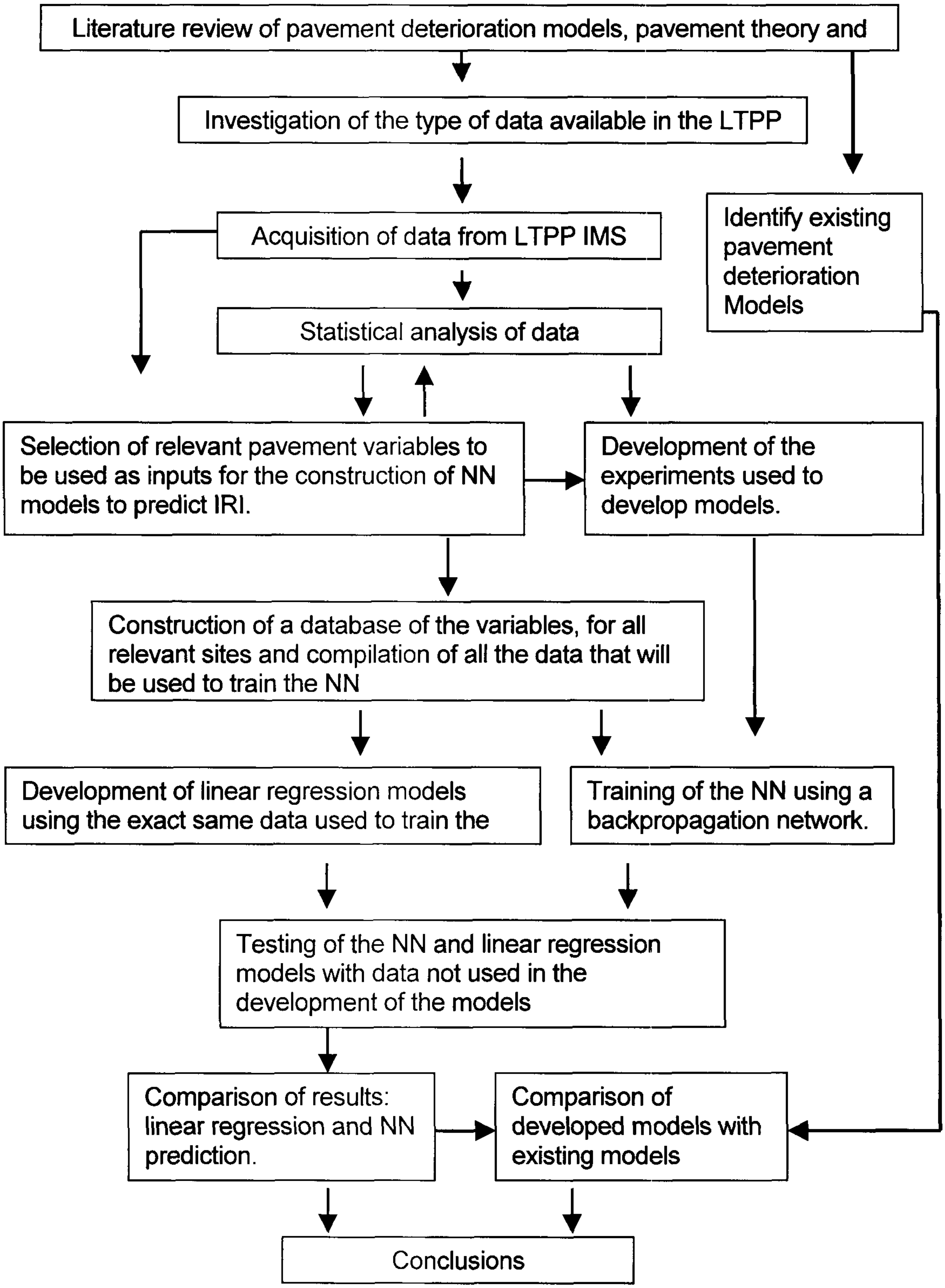

Figure 1. Research Methodology

LITERATURE REVIEW

This section presents a summary of the literature review that was done for the purpose of pavement model development. Pavement theory in general was studied, specifically pavement properties and mechanics. Emphasis was placed on pavement roughness, its measurement, existing indices and their correlation. Prospect tools for model development were also reviewed, mainly Neural Networks and Linear Regression. Their application, precision indicators and their statistical significance were studied thoroughly. LTTP background, data collection, database structure and its accessibility was also examined. Finally, extensive research for existing pavement models was performed by focusing on their input variables, validity and outcome reliability.

REVIEW OF PAVEMENT ROUGHNESS

One of the main objectives of our transportation system is to provide a comfortable ride for users. Roadway roughness is a good indicator of whether this criteria will be fulfilled. A brief look at the historical development of this indicator can be useful. In the 1940's the roadway longitudinal profiles were measured using an in/mile scale, which was the popular basic unit of measurement.[(8)] The in/mile scale represents the change in elevation over a given interval. In the 40's, the devices used were simple and not as sophisticated and efficient as those used in recent years.

There are many reasons why these devices did not measure the true profile of the roadway. One main reason was that the technology was not available to give a continuous reading of the roadway profiles. Another reason is that a vertical drop caused by a crack or a joint in the pavement gave an infinite change in the slope and made calculations difficult, if not impossible. To overcome this problem, data was collected in intervals of a fixed length. The early devices were one foot long sticks that were moved end over end. The difference in height of the ends of the sticks was recorded and converted into the in/mile units. Later devices that could measure the response of springs in a vehicle's suspension were used to measure the roadway roughness by recording the response of those springs as it traveled along a road.

There are many different devices that have been developed to measure roughness or ride quality. The main problem with these devices is that they do not employ a common standard. The different devices did not give results that could be compared to one another even for the same pavement. In the 1970's, the NCHRP studied these different systems to better understand these problems by developing and testing mathematical models to demonstrate the response of vehicles to the roadway.

The most famous model that came out of that NCHRP study was the quarter car model. In this algorithm, the behavior of one wheel of a car is modeled, including the effects of the suspension spring and damper. Including these effects was important because most road roughness was measured based on a response-type measuring system. This model demonstrates how a vehicle or a passenger is affected by the roughness of the road. One major factor in why roughness measurements were not compatible or comparable was that the suspension of vehicles was not calibrated or standardized. Using accelerometers, computers, and the quarter car algorithms, a "virtual response-type system" can be developed.[8] This system can then be used to model the response of a vehicle to a pavement, or use a vehicle to measure the roughness of a pavement.

Inaccurate and incompatible road roughness measurements were not experienced just in the United States. The findings of many World Bank sponsored research programs concluded that poor roads are costly to many developing countries. The cost of repair or reconstruction of pavements is high but the user costs as a result of rough roadways is even higher when calculated over the service life of the pavement. Road roughness indices were a primary factor for investigating the trade-off between the costs. This problem was the same as the one faced earlier in the United States because many countries used different roughness indices and standards. The roughness indices in reports submitted to the World Bank were suspect because they were measured by different standards and methods.[8]

To provide a common quantitative basis on which the different measurement of roughness can be compared, the International Roughness Index (IRI) was developed at the International Road Roughness Experiment held in Brazil in 1982 under the sponsorship of the World Bank. The IRI summarizes the longitudinal surface profile in the wheelpath and is computed from the surface elevation data collected by either a topographic survey or a mechanical profilometer. It is defined by the average rectified slope (ARS), which is the ratio of the accumulated suspension motion to the distance traveled obtained from the mathematical model of a standard quarter car transversing a measured profile at a speed of 50 mph (80 km/h). It is expressed in units of inches per mile (m/km).

One drawback to the IRI is that there exist an infinite number of profiles for a given roadway. A profile is a line along the path of a pavement with no width. Thus, theoretically, an infinite number of profiles exist for each roadway width. The vehicle used in the recording of the IRI will not travel in a perfectly straight line, and could produce a variance in the roughness measured. Procedures exist to compensate for this variability. Each time a profile was recorded, five profile runs were performed so that during each run, the profiles were within a given deviation of the normal (2% deviation) for all the runs. In the next section on building a neural network database, table 6-7 shows a minimum of five runs for each profile date. If one of these runs is not within the 2% deviation then additional runs are preformed. Those that are not within the 2% deviation are removed, and are not included in the database. In the LTPP database each profile run is recorded in the table MON_PROFILE_MASTER. The runs are in numerical sequence and so a profile run is not to be included if a break in the numerical sequence (i.e. 1, 2, 3, 5, 6) would occur.

Several models in the reports reviewed used different types of measurements for roughness and deterioration. Although there is a considerable push for all State agencies to use the same indicators, this has not yet happened, thus reports that study the correlation between different pavement performance indices were investigated. IRI is the roughness indicator used in the LTPP database. For this reason, papers regarding the relationship of IRI and other roughness indicators were closely reviewed. A Transportation Road Research paper showing the relationship between PSR and IRI was used extensively for this project.[18] The document from ITX Stanley was more involved[19] as it includes relationships between several different types of roughness indices. Many of these relationships also involved IRI and RQI.

LONG TERM PAVEMENT PROJECT (LTPP)

In the 1987 Highway Act, congress authorized the Strategic Highway Research Program (SHRP) which was a 5-year, $150 million research program. SHRP concentrated on asphalt, concrete, highway operations and structures, and pavement performance research results. The Long Term Pavement Project (LTPP) was originally designed as a twenty-year project to monitor and gather data on various types of pavements. After the first 5 years of data collection, SHRP had concluded its requirements as set by Congress. The remaining 15 years of the LTPP program was to be managed by the Federal Highway Administration (FHWA). The FHWA is the current coordinator of the LTPP project and database.

The objectives of the LTPP program were the following :[20]

- Evaluate existing design methods.
- Develop improved design methodologies and strategies for rehabilitation of existing pavements
- Develop improved design equations for new and reconstructed pavements.
- Determine the effects of (a) loading, (b) environment, (c) material properties and variability, (d) construction quality, and (e) maintenance level on pavement distress and performance.
- Establish a national long-term pavement database to support SHRP objectives and future needs.

The LTPP program was originally designed to include three types of studies: General Pavement Studies (GPS), Specific Pavement Studies (SPS), and Accelerated Pavement Testing (APT). The largest of these studies is the GPS, and includes 742 in-service sections throughout the United States and Canada. The SPS have specific goals, and are performed by experimental approaches to achieve these goals. The APT has not yet been incorporated into the LTPP database. The GPS experiments within the LTPP program include the types described in table 1. It also includes the number of sites used in each GPS study.

The LTPP project has been in existence for ten years with 7 to 8 years of the data processed and available for use. With more data from future years, any model developed with the first half of the data can be tested, refined and calibrated with the second half of the data.

Table 1. Description of the General Pavement Studies

General Pavement Studies (GPS) Descriptions		Number of GPS Study Sites
GPS 1	Asphalt Concrete (AC) on Granular Base	191
GPS 2	AC on Bound Base	115
GPS 3	Jointed Plain Concrete	128
GPS 4	Jointed Reinforced Concrete	52
GPS 5	Continuously Reinforced Concrete	75
GPS 6A	Existing AC Overlay on AC Pavement	51
GPS 6B	New AC Overlay on AC Pavement	57
GPS 7A	Existing AC Overlay on Portland Cement Concrete (PCC) Pavements	22
GPS 7B	New AC overlay on PCC Pavements	24
GPS 9	Unbonded PCC Overlays on PCC Pavements	27

The data collected for the LTPP project is stored in the LTPP Information Management System (IMS). There are two components that control the data entry in the IMS database, the four regional offices and the central IMS office. The four regional offices focus on the data collection and the submitting of that data to the central office. Another requirement is to exercise quality control of regional personnel and control data collected and submitted by State Highway Agencies (SHA's). The central office is responsible for the climatic data, quality assurance (QA) of all LTPP data, and providing data to the public. The LTPP IMS has seven data modules, which contain the data collected from each GPS site. The modules as shown in table 2 categorize the data. The background information for each site is the most important information contained within these modules.

The *Inventory Module* contains the historical information for each site in the database. The state departments of transportation generally provide this information. This data includes the location of the section, pavement type, layer thickness, layer type, material properties, composition, construction improvements, and other background information.[20] These records might not be always complete.

Table 2. Summary of IMS Database Modules

Module	Sub-module	Number of Tables within Module
Inventory	None	26
Material Testing	None	76
Climate	None	5
Maintenance	None	9
Rehabilitation	None	49
Traffic	None	6
Monitoring		
	Automated and manual distress	8
	Friction	1
	Longitudinal Profile	2
	Cross Profile	4
	Deflection (FWD)	8

Even though some material properties are given in the inventory record, material testing was also separately performed for this study. The information gathered from field sampling and laboratory material testing is contained in the *Material Testing Module.* This data verifies and documents the existing pavement structure for each site in the LTPP study. It also gives an evaluation of existing layers of the pavement. The laboratory testing involves over 40 different types of procedures, many of them are employed currently in designing pavement.[20]

The climate data for a site is available in the *Climate Module.* This module shows the conditions recorded from at least one nearby weather station. Statistical estimates based on as many as five weather stations are also included. A summary of daily measurements, monthly statistics, and yearly average can be found for some of the sites. [20]

Maintenance and rehabilitation is contained in their respective modules: *Maintenance Module* and *Rehabilitation Module.* The primary purpose of the *Maintenance Module* is to record all the activities relating to maintenance that was performed at the GPS site. This could include seal coating, patching, joint resealing, milling, or grooving. The *Rehabilitation Module* on the other hand includes any major improvement at a GPS site. Rehabilitation includes resurfacing, reconstruction, or addition of lanes. Anything that would have altered the structure of a pavement is considered rehabilitation and its data is recorded in this module. [20]

The *Traffic Module* contains data regarding the annual traffic statistics for all the GPS sites. Counts by vehicle classification, and distributions of axle weights are some of the traffic factors in this module. The annual average daily traffic (AADT) statistic in the database applies only to one lane at each site. Traffic statistics in this section are based on monitored data, for approximately two-thirds of the sites. The remaining is based on historical records or is not included at all. [20]

The last module contains information on all the data gathered on the current conditions of the pavement at a site. The *Monitoring Module* contains several sub-modules; automated and manual distress, longitudinal profile, cross profile, and falling weight deflectometer. The *Automated and Manual Distress* section contains information regarding the pavement conditions. This concentrates primarily on the severity of surface defects. The *Friction* section of monitoring stores the friction number, surface type, test methods and other fields relating to the surface friction of the GPS sites. The *Longitudinal Profile* section contains the information on the longitudinal profile which is predominately measured in IRI. The *Cross Profile* section contains information regarding the transverse profile, commonly referred to as rut data. The last section of the *Monitoring Module* is called *Falling-Weight Deflectometer.* A falling-weight deflectometer measures the response of dynamic loads applied to a pavement structure. This loading and the data recorded from this test can determine the strength of the pavement along with the structure of the pavement. [20]

This is an overview of the data contained in the LTPP database. There are many tables of varying length and width. It is difficult to image the full size of the overall database. Table 2 includes the number of table that are within each module. Chapter 3 of this report includes some examples of the table included in the LTPP database, which will give a better understanding of its large size.

Background on Neural Networks

Man has been interested in the workings of the human brain since the beginning of civilization. Many have tried to model its functions. Ancient Greek philosophers tried to conceptualize the thought process into mathematical formulae. This type of thinking has evolved with the aid of more powerful tools, like computers, which can now model the simple learning patterns of the brain.

In the past few decades better understanding of the human process of intelligence has lead to its modeling on a computer. This is how neural networks, or rather artificial neural networks (ANN) come into play. An ANN attempts to model how the brain transmits information to the body.

Major projects, which involved ANN, were performed in the 1960's. One such project was called *The Perception,* which was a mixture of neural networks and pre-processing algorithms. *The Perception* was based on the first stages of primitive vision based on pattern recognition. This program could determine the gender of a person by 'seeing' his/her face. Research continued in the 70's but it was not until the mid-80's that wide spread interest in ANN grew with the proliferation of the computer itself. Now ANNs are used in a wide variety of research fields.

An ANN acts as a biological neural network, that is, it acts as a network of neurons processing information. A single neuron is a single nerve cell and a chain of neurons transfers information to or from the brain. Neurons upon receiving information must interpret the information and determine what to do with it. A neuron could either pass information on to the next cell or it could cause a muscle to contract. The type of information passed on to other cells is dependent on past experiences. That is an infant does not know what pain feels like until it experiences it for the first time. An ANN works in the same way.

Information put into an ANN is just like a signal from the brain or nerve ending in a biological neural network. The individual signals in an ANN are called vectors, pin figure 2 or X in figure 3. What happens is that a set of inputs are applied to a network, which are labeled X_1, X_2,.... , X_n in figure 3 . Each signal is then multiplied by an associated weight, W_{11}, W_{21}...W_{nn}, and then they are passed to the summation block in which they are summed. Each neuron outputs a weighted sum of the inputs. In this case it is a simple matrix multiplication. The example shown in figure 3 is used as an educational tool to understand the basic network structure. One example of this is called an activation function. Example:

$$\text{OUT} = 1 \quad \text{if } Yn > Z$$

$$\text{OUT} = 0 \quad \text{if } Yn \leq Z$$

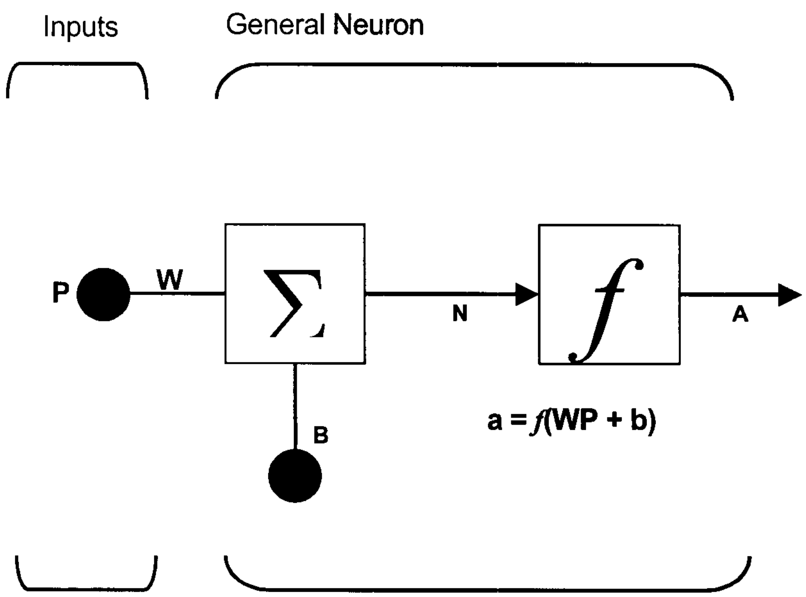

Figure 2. Representation of a single neuron in a neural network

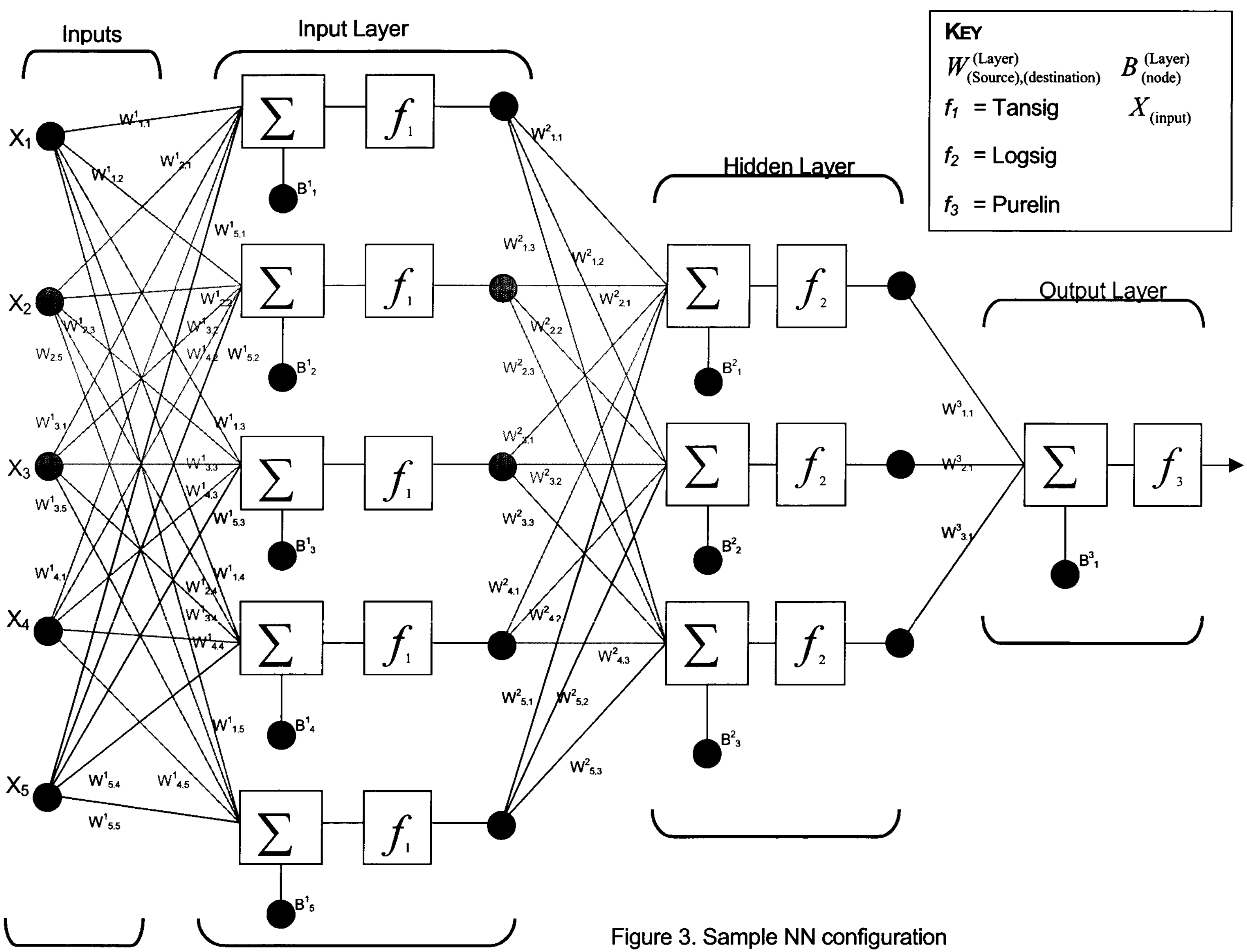

Figure 3. Sample NN configuration

This is commonly used in visual recognition, in which the network will tell you if it is or is not the target sought. This is a linear activation function, but there can be non-linear activation functions too.

Figure 2 represents a single neuron within a network. The variables in the diagram are as follows:

P = all inputs vectors

W= weight applied to the inputs

b = bias applied to the inputs

n = net input vector

a = the final values once all the weights and biases are applied.

A neural network consists of many neurons combined together. The diagram in Figure 3 represents a multiple layer network consisting of nine neurons in three different layers. This network has architecture similar to the one in the program shown in Figure 4. Multilayer networks are more complex than single layer networks, and offer a greater ability for the computational capabilities than a single layer network. This layering mimics portions of the brain by using different algorithms. In the past decade algorithms were perfected and refined in order to train ANN with multiple layers.

Figure 4 is a simple example of a NN training program written in Matlab. This program trains the NN to predict the simple equation:

$$Y = 2X + 5 \qquad [1]$$

```
P = {1 2 3 4 5 6 7 8 9 10};
T = {7 9 11 13 15 17 19 21 23 25};
net = newff([0 10],[4 1 1],{'logsig' 'tansig' 'purelin'});
net.trainParam.goal = 1e-100;
net.trainParam.epochs = 500;
net.trainParam.mu = .01;
net.trainParam.mu_inc = 10;
net.trainParam.mu_dec = .5;
net.trainParam.mu_max = 1e90;
net = train(net,P,T);
```

Figure 4. Example of NN Training Program Written in Matlab Using Matlab NN Toolbox (3)

```
D = {1.5 2.5 3.5 4.5 5.5 6.5 7.5 8.5 9.5};
[R] = sim(net,D);
V = (R)
```

Figure 5. Example of NN Program To Test The Trained Neural Networks

In figure 4, P represents the training input vectors for the NN, to predict equation [1]. Values within the brackets represents one set of input vectors. These values would correspond to the *{X}* values in equation [1].

The T represents the target vectors that the trained NN produces. In this case these values represent the *{2X + 5}* portion of equation [1]. NEWFF is a function that performs a backpropagation NN training algorithm as part of the Matlab program. The brackets following it represent the input ranges and the NN architecture. A value representing the input range must be given in the training program. Since this is only a test this value will range from zero to ten, {P = 1,2...10}. The [4 1 1] is the architecture of the NN program in figure 4. According to this NN architecture first layer has four nodes, the second layer has one nodes and the last (output layer) has one node.

TANSIG represents the transfer function between the layers. This means that the output between the first layer and the second is transformed by a hyperbolic tangent sigmoid function. This function maps a neuron input from an interval of $(-\infty, +\infty)$ into an interval of (-1, +1). There are three different types of transfer functions in the Matlab NN toolbox: TANSIG, LOGSIG, and PURELIN. LOGSIG is a Log-Sigmoid transfer function, which fits the inputs into an interval of (0, +1). The PURLIN is the simplest of the transfer functions because it is simply a linear transformation of the input.

The rest of the lines of the program are different training parameters. These parameters can be changed and adjusted. For example ...GOAL = 1E-100 means that the NN will train until the mean square error (MSE) is under 1E –100. This is only one criteria that the program uses to terminate training. The MSE was chosen to be this low so that other limitations like the numbers of training epochs (net.trainParam.epochs = 500) could be reached. 500 epochs mean that the NN will use the input data 500 times before terminating the training, unless another criteria for ending the training has been met. (3)

To test how well the NN predicts equation [1], the program in figure 5 is run. This program contains nine test points. These test points are, {1.5, 2.5, 3.5, 4.5, 5.5, 6.5, 7.5, 8.5, 9.5}, and are shown as the **D** values. These are nine different points that were not used to train the NN. Table 3 shows the results of using these test points compared to the actual data.

Table 3. Results of example NN training

Y	2X + 5	NN prediction	% Difference
1.5	8	7.65	-4.38
2.5	10	10.16	1.64
3.5	12	11.89	-0.88
4.5	14	14.05	0.36
5.5	16	15.99	-0.06
6.5	18	17.98	-0.12
7.5	20	20.00	<-0.01
8.5	22	22.02	0.09
9.5	24	24.01	0.04

A multilayer network has a matrix (figure 2) of neurons (figure 3). There could be different transfer functions for each layer, thus the variable $\mathbf{s}^n$ is used to distinguish between the different types of layers. The functions shown in figures 2 and 3 represent transfer functions. A transfer function is used to calculate the output from separate layers given the weights, biases and inputs. If the desired output is not achieved the weights and biases would then be adjusted and again fed to the transfer function. This is repeated until the desired output is achieved. Figure 6 represents the algorithms for this process.

The object of training is to make the weights converge to some values that will produce target output values. There are two types of training for ANNs: *supervised* and *unsupervised*. Supervised training requires an input and output vector, and these two vectors are called a training pair. The weights are adjusted until the desired output vector is obtained within a certain percentage of error. Unsupervised training requires no output vector. The network modifies weight until subsequent output vectors are consistent.

Another factor of NN is the type of training algorithm used to train it. There are several types of training algorithms. The training algorithm acts on a principle similar to that used by the brain, the more you use your knowledge the better it becomes. Synaptic strength will increase if both the source and destination neurons are activated. In the NN the specific weights will increase if both the input and output to each NN neuron is used often.

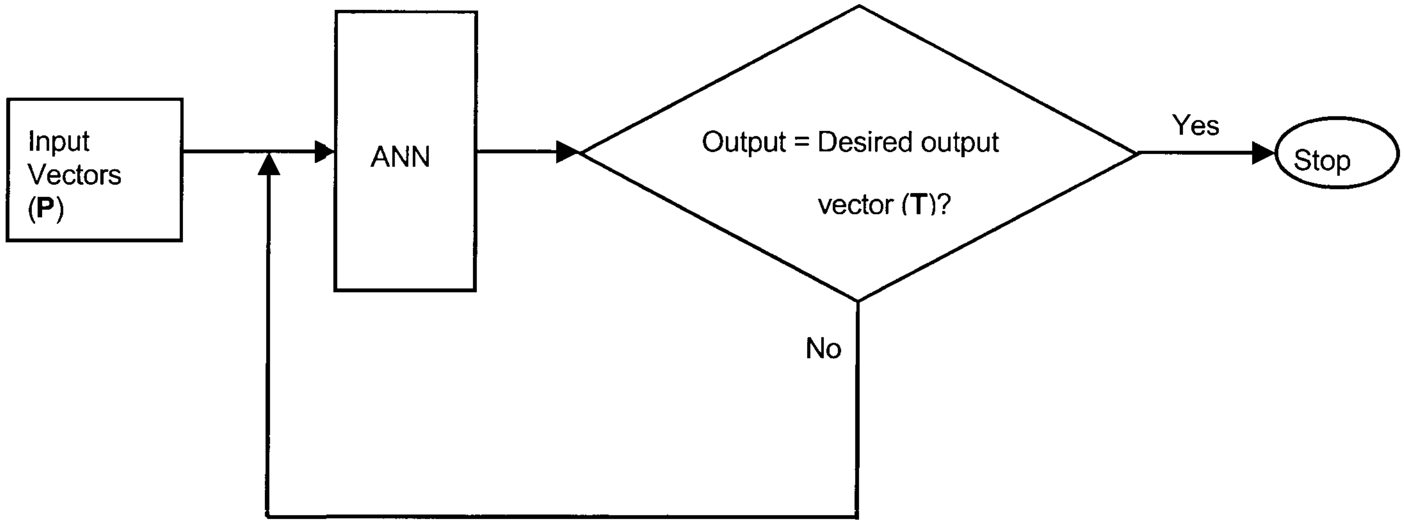

Figure 6. Basic Flowchart for Backpropagation Neural Network Algorithm

REVIEW OF REGRESSION ANALYSIS

Regression analysis is a statistical technique used to express the relationship of a set of variables by an equation. Linear regression is the simplest form of regression analysis. Linear regression consists of two types of variables, a dependant variable (***y***) and an independent variable ***(x).***

The linear regression model is called simple linear regression model when it involves only one independent variable.

A more complicated from of regression is called "multiple linear regression". This model consists of multiple independent variables and corresponding coefficients. It takes the following form:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \qquad [2]$$

There are more advanced forms of regression but multiple linear regression is the most advanced form used for this type of research.

In simple linear regression the parameters β_0 and β_1 must be estimated. For the purpose of explanation, assume that there are ***n*** pairs of (***x***, ***y***) pairs. Were $\bar{x}$ is the average *x* value and $\bar{y}$ is the average *y* value:

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \qquad [3]$$

and

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n} y_i x_i - \frac{\left(\sum_{i=1}^{n} y_i\right)\left(\sum_{i=1}^{n} x_i\right)}{n}}{\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}} \qquad [4]$$

The fitted simple linear regression model then takes the form of a line:

$$y = \hat{\beta}_0 + \hat{\beta}_1 x \qquad [5]$$

There are ways to test how well the regression model estimates the dependant variable.

The coefficient of determination, R^2, estimates how well the data points (x, y) fit the line representing the model. R^2 is calculated as follows:

$$R^2 = \frac{\hat{\beta}_1 \left(\sum_{i=1}^{n} y_i x_i - \frac{\left(\sum_{i=1}^{n} y_i\right)\left(\sum_{i=1}^{n} x_i\right)}{n} \right)}{\sum_{i=1}^{n} y_i - n\bar{y}^2} \qquad [6]$$

The range of R^2 is between zero and one. A coefficient of determination of 1.0 corresponds to a perfect model, while values close to zero indicates little correlation between the model and the data.

The test for significance of regression may also be performed using the t-test and null hypothesis. To test the hypothesis that the slope is equal to zero, the hypotheses are then stated as:

$$H_0 : \beta_1 = 0 \qquad [7]$$

$$H_1 : \beta_1 \neq 0 \qquad [8]$$

This implies that if the hypothesis is proven correct, then the linear regression model is a horizontal line. This means the slope cannot be statistically distinguished from zero, and that *y* may not have a relationship with *x*. (21)

The t-test is used to test the null hypothesis. The t-test equation is:

$$t_0 = \frac{\hat{\beta}_1 - \hat{\beta}_{1_0}}{\sqrt{MS_E / S_{xx}}} \qquad [9]$$

Where,

β_{1_0} = 0

MS_E = $\dfrac{\sum (y_i - \hat{y}_i)^2}{n-2}$

$$S_{xx} = \sum x_i^2 - \frac{\left(\sum x_i\right)^2}{n}$$

By comparing the calculated value of t_o to the $\alpha/2$ percentage point of the t_{n-2} distribution ($t_{\alpha/2,n-2}$). The null hypothesis can be rejected if:

$$|t_0| \geq t_{\alpha/2,n-2} \quad [10]$$

The values of t distributions are usually found in table format in most statistical texts.

This procedure can be used to test the significance of each independent variable in multiple linear regression. If the null hypothesis tests for β_k = 0 and is proven correct, then the x_k may not be statistically viable. The **x** variable may not have a relationship with the dependant variable, ***y***. These are the basic basis techniques used to statistically validate linear regression models.

EXISTING PAVEMENT MODELS

This section summarizes the most important available pavement models.

FHWA Model

FHWA publication No. FHWA-RD-97-147, employs the first four data entries in the LTPP database to develop a model for each GPS type.(12) The only reason for using so few data points is due to the fact that at the time of the publication they were the only data points available in the LTPP database. There are also no statistics in this report on how well these models perform. This along with the few data points can be considered a drawback to these models and the report.

The GPS 2 sites are broken down, in the FHWA report, into four groups for modeling the pavement based on the type of base used in the construction of GPS-2 pavement namely, AC treated, Hot Mix Asphalt Concrete (HMAC), cement-agg., and soil cement. Below is the HMAC model. This model is the model used primarily in this report.

Asphalt, Hot Mix AC Base Model [12]

$$IRI(t) = IRI_0 e^{r_o \frac{t^S}{T}} \qquad [11]$$

$$\text{(a) } IRI_o = A(ACThick)^B + C(BaseThick)^D + E(P\#4)^F + G(SN)^H \qquad [12]$$

$$\text{(b) } r_o = \left[\frac{I(KESAL/yr)^J}{K(SN)^L} + M(ACThick)^N + O(days32-)^P + Q(AnnPercip)^R \right] \times \frac{1}{1000} \qquad [13]$$

Where,

t	= Age (years)
ACthick	= Thickness of the AC surface course (inches)
BaseThick	= Thickness of the HMAC base (inches)
P#4	= Percentage passing the number 4 sieve
SN	= Structural Number
KESAL/yr	= Thousands of ESALs/yr
Days32-	= Days that were below freezing
AnnPercip	= Annual precipitation (inches of rain)

Table 4. Summary of FHWA Model Parameter for GPS-2 Pavements with HMAC Bases [12]

A=5.375	F=-0.8682	K=20.7016	P=2.3060
B=-0.5110	G=40.0891	L=12.00	Q=9.70E-05
C=1953.287	H=-0.75037	M=2.00E-04	R=0.1813
D=-2.95004	I=101.57589	N=-0.2060	S=1.2379
E=349.64172	J=0.6117952	O=3.12E-09	T=0.0226

Lee Model

A recent Transportation Research Record, TRR, by Ying-Haur Lee describes the need for simplified models that can predict future trends of the pavements with a minimal amount of data. (14) Unlike the other model that predicts IRI, the Lee model calculates present serviceability rating, PSR. There are models in this report for five basic types of pavements namely, flexible, composite, jointed plain cement pavements (JPCP), jointed reinforced concrete pavements (JRCP), and continuous reinforced concrete pavement (CRCP). Since flexible pavements are the focus of this report that model is shown below: (14)

$$PSR = PSR_I - a * STR^b * AGE^c * CESAL^d \qquad [14]$$

PSR_I = Initial value of PSR at construction (4.5 used in analysis)

STR = Existing pavement: structural number for flexible pavements

AGE = Age of pavement since construction (years)

CESAL = Cumulative 18-kip equivalent single-axle load (ESALs) applied to pavement in the heaviest traffic lane. (Millions)

a, b, c, & d are coefficients

This is the original model developed in the TRB report, but there is also a later modification of this model. The modified model uses an adjustment factor that is based on the climate in which the pavement is located. Since both of the test sites are in a wet thaw-freeze zone the adjustment factor that is used is, AF = 0.40. The original model :

$$PSR = PSR_I - AF * (a * STR^{b} * AGE^{c} * CESAL^{d}) \qquad [15]$$

This model was accompanied by two other equations that were used to estimate the original age and the CESAL for pavements. The reason that was used is that many sites in their database did not include the age and traffic data that was required for their original model. Thus, these values had to be predicted.

$$AGE = \left[\frac{PSR_I - PSR_1}{AF * (a * STR^{b} * ESPALYR^{d})}\right] \qquad [16]$$

$$CESAL = AGE * ESPALYR \qquad [17]$$

Since Lee used only roughness indicators in the form of PSR, it has to be converted to IRI using equation [18], which correlates IRI and PSR. The correlation between IRI and PSR is given by: (16)

$$PSR = 5 * e^{(-0.0026*IRI)} \qquad [18]$$

This above formula gives an IRI value in terms of m/km.

The performance of the Lee models for asphalt is given in the report. In the paper, Lee et. al. shows the R^2 value to be 0.52, only explaining about half the variation in the data. This model used all AC pavements and did not separate them into categories, GPS-1, GPS-2, GPS-6.

Default Pavement Management System Models

The New Jersey Department of Transportation (NJDOT) uses a ride quality index (RQI) model for determining life expectancy of its roadways. The performance prediction model used in their HPMS is as follows:

$$P = P_0 - e^{\left(a - bc^t\right)} \qquad [19]$$

Where, P = performance index

P_0 = P at age 0 ($t = 0$)

t = Log_e (1/age)

a,b,c = model coefficients

a = 33.26

b = 34.65

c = 1.02

Above are the values of the coefficients for the default model. This model also assumes that the P_0 is at the value of 4.5 (RQI).

The trigger value for determining the useful life of a pavement is an RQI value of 2.5. [(17)] This would mean that the default model would give all pavements a useful life of about 20 years. Figure 7 shows the trend of the default pavement model. Note that this is the same for all pavements and pavement types.

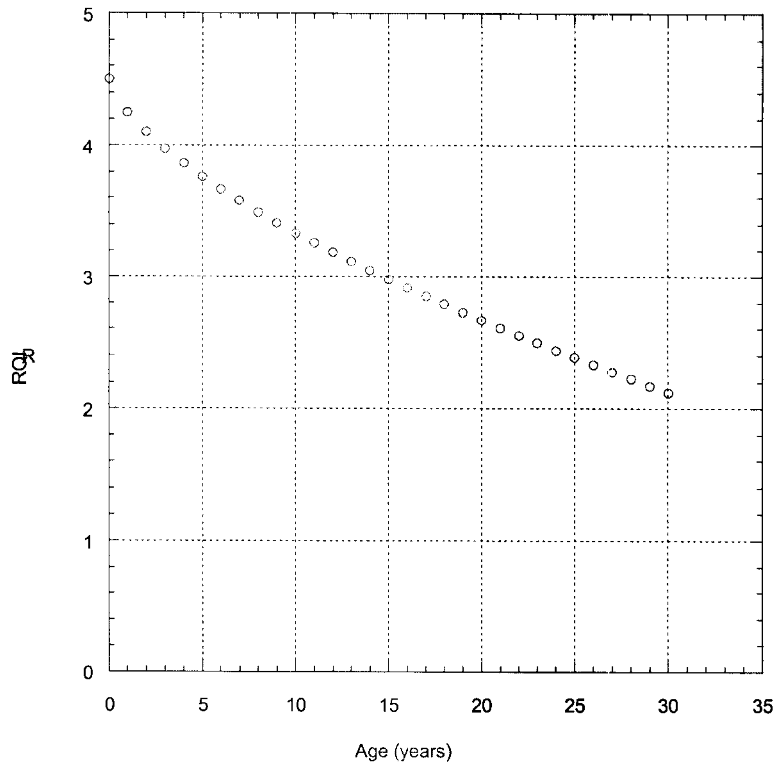

Figure 7. Plot of the Default Pavement Deterioration Model in the NJDOT Pavement Management System

Since this model uses RQI and the others use IRI, RQI had to be converted so that a comparison could be made. A correlation study preformed by ITX Stanley for the NJDOT was used to make this conversion.[19] Equation [20] is the conversion of IRI RT3000 to RQI. (RTIRI refers to IRI recorded by the RT3000 device).

$$RQI = 5.0\, e^{(-0.00511 * RTIRI^{0.872})} \qquad [20]$$

Even though RT3000 measures IRI it is a different type of sensor so a correlation between the two was used to convert RT3000 IRI to K.J. Law T6600 (device used in the LTPP) IRI given by the following equation:

$$RTIRI = 0.9512\ IRI(LTPP) + 23.884 \qquad [21]$$

These two equations, [20] & [21], give the IRI value in the units of inches/mile and would have to be converted to the units of m/km for comparison to the other models.

BUILDING A NEURAL NETWORK TRAINING DATABASE

This section explains the preliminary work done before the actual development of the models. Preparing the data and presenting it in the proper form required extensive efforts. Exploring the LTTP, selecting the candidate sites, choosing the input independent variables, testing their statistical significance, were all tasks that involved thorough inspection in order to avoid any kind of unreliable or biased outcome.

Selecting Sites from LTTP Database

DataPave 97 is the software that FHWA distributes for the purpose of browsing and studying LTPP sitesDataPave97 provide the option of selecting sites according to a certain perceived criteria. In this project, sites in a "wet-freeze" climate are chosen. Our screening process returned only sites from the GPS category.

After receiving the requested data of GPS 2 sites, two concerns became apparent. The first concern was the flaws in the initial assignment. The second was the reclassification of sites.

ITX Stanley is the regional contractor collecting the data for the New Jersey LTPP sites. They revealed at a meeting in Trenton, that the New Jersey GPS 1 sites can also be considered GPS 2 sites. The reasoning behind this is that the original classifications are not assigned properly. The original criteria the State Highway Agencies or SHA used for classifying sites for the LTPP program was not concise enough, the matter that led to the classification problem. Moreover, when data was investigated closely, it was discovered that some of these sites have been reclassified. Most reclassifications are due to rehabilitation done to a section of highway (i.e. a new surface coarse layer). This changes the classification from a GPS 2 to a GPS 6B.

Figure 8 shows both the GPS 1 and the GPS 2 sites in New Jersey. Table 5 shows all the sites requested from the LTPP IMS database.

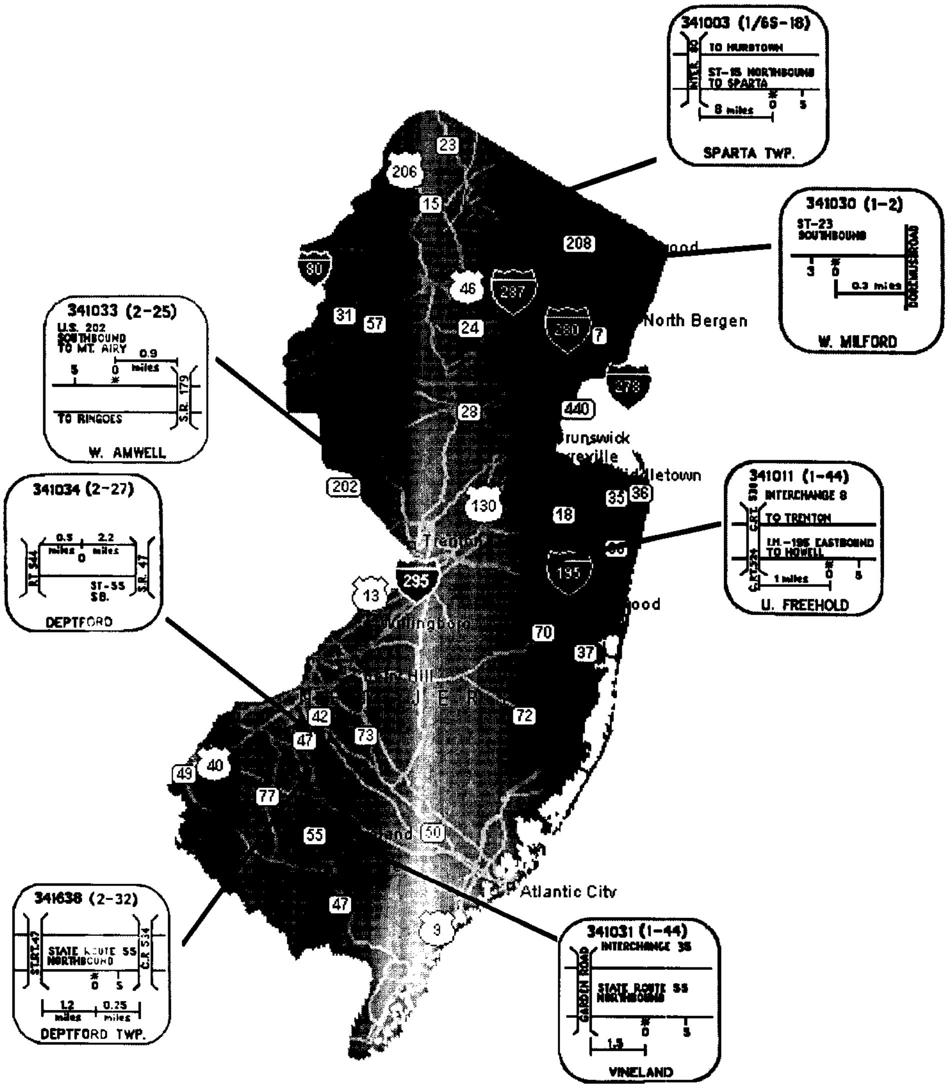

Figure 8. Location of New Jersey GPS 1&2 sites

Table 5. GPS sites in wet freeze zones requested

GPS 2 SITES				GPS 1 SITES		
State	State_ID	SHRP_ID		State	State_ID	SHRP_ID
Arkansas	5	3071		Connecticut	9	1001
Delaware	10	1450		Illinois	17	1004
Indiana	18	2008			17	9035
	18	2009		Indiana	18	7780
Iowa	19	6150			18	1803
Maryland	24	1632		Kansas	20	1400
	24	1634			20	1001
	24	2401			20	9032
	24	2805		Kentucky	21	9034
Minnesota	27	2023			21	1002
Missouri	29	5403			21	1003
	29	5413		Maine	23	1028
New Jersey	34	1033			23	1037
	34	1034			23	1005
	34	1638			23	1009
New York	36	1008			23	1010
	36	1643		Massachusetts	25	1010
	36	1644			25	1014
Oklahoma	40	4165			25	1034
	40	4164		Michigan	26	1001
	40	4164			26	1009
	40	4163			26	1012
	40	4154		Minnesota	27	1026
	40	4088			27	1028
	40	4087			27	1002
	40	4086			27	1003
	40	4086			27	1004
	40	1017			27	1001
	40	1015			27	1004
Tennessee	47	1023			27	1010
	47	1028			27	1016
	47	1029		Missouri	29	1018
	47	2001			29	1019
	47	2008		Nebraska	31	1023
	47	3101			31	1028
	47	3108		New Hampshire	33	1029
	47	3109		New Jersey	34	1085
	47	3110			34	1087
	47	9024			34	6251
	47	9025			34	1002
Vermont	50	1681		New York	36	1011
	50	1683		Pennsylvania	42	1597
West Virginia	54	1640			42	1599
New Brunswick	84	1802			42	1605
Ontario	87	1680			42	1618
Prince Edward Island	88	1642		South Dakota	46	9197
	88	1647		Tennessee	47	3075
Quebec	89	2011			47	3104

DATA MANIPULATION

All data received from the LTPP IMS database is in the Microsoft's (MS) Access 97 format. The data needed from each table is copied and inserted into an excel spreadsheet, for an easier manipulation. The description of the fields in each table is given in an accompanying text file. This text file presents a brief description of each data field and its units of measurement. Appendix A gives the description of the data fields that are used in the tables in this section. The first step investigated the appropriateness of the pavement classification. . The classifications of the sites can change after the data is entered in the DataPave software. Classification information is found in the table, EXPERIMENT_SECTION. An example of this LTTP table is shown in table 6. The column labeled EXPERIMENT_NO gives the current GPS site classification and the column labeled STATUS gives the current status of each site. For instance, if a GPS 2 site is resurfaced with an asphalt layer, then the section should become a GPS 6B site, or it is deassigned. Another column in this table gives the date at which a reclassification took place. Any data before the change can be used for this project. Only in a few cases, the sites requested did change classification.

The next table investigated gives the construction date of the pavement at each site. The table that provides this data is INV_AGE. An example of this is shown in table 7. Since aging of asphalt starts immediately after it is laid, the construction date is used to determine the age of a pavement during which a roughness measurement or other variables are recorded. The factor that measures the roadway roughness in the LTPP database is the International Roughness Index (IRI). IRI measures the height variation of the pavement over a given length in meters/ kilometer.

IRI is entered for both wheel paths and an average IRI value is calculated. This average IRI value is the value used for analysis in this project. The table where the IRI data is located in is MON_PROFILE_MASTER. Table 8 shows an example of this data. The columns where the values are located are in IRI_LEFT_WHEEL_PATH, IRI_RIGHT_WHEEL_PATH, and IRI_AVERAGE. There are multiple profile runs for each date and a corresponding IRI value is entered in the database for each run. Due to the quality control guidelines for IRI profiling, some of these runs are omitted. . The guidelines request providing the IRI profile for each run that is within a maximum preset deviation from the other runs on the same date. Accordingly, the averaging of the IRI runs can be disputed if it was not for the profiler's specification to use only data within a 2% deviation.

Table 8 shows a minimum of five runs for each profile date. If one of these runs is not within the 2% deviation then additional runs are preformed. Those that are not within the 2% deviation are removed, and not included in the database. In the LTPP database each profile run is recorded in the table MON_PROFILE_MASTER. The runs are in numerical sequence and so a profile run is not to be included if a break in the numerical sequence (i.e. 1, 2, 3, 5, 6) would occur.

Table 6. Example of the LTPP table EXPERIMENT_SECTION

SHRP_ID	STATE_CODE	CONSTRUCTION_NO	CN_ASSIGN_DATE	GPS	EXPERIMENT_NO	STATUS	ASSIGN_DATE	DEASSIGN_DATE	SEAS_ID	RECORD_STATUS
2011	89	1	31-May-78	G	2		31-May-78			E
1647	88	1	31-Jul-86	G	2		31-Jul-86			E
1646	88	1	31-May-80	G	2		31-May-80			E
1680	87	1	31-May-84	G	2		31-May-84			E
1802	84	1	30-Sep-80	G	2		30-Sep-80			E
1640	54	1	31-May-83	G	2	O	31-May-83	10-Aug-91		E
1683	50	1	31-Aug-63	G	2	6B	31-Aug-63	24-Sep-91		E
1683	50	2	24-Sep-91	G	6B		24-Sep-91			E
1681	50	1	31-Aug-63	G	2	6B	31-Aug-63	9-Sep-91		E
9025	47	1	31-Dec-79	G	2		31-Dec-79	1-Sep-95		E
9025	47	2	1-Sep-95	G	6B		1-Sep-95			E
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Note: This table is an abbreviated version. The actual table used has 48 rows.

Table 7. Example of the LTPP table INV_AGE

SHRP_ID	STATE_CODE	CONSTRUCTION NO	CONSTRUCTION DATE	TRAFFIC_OPEN DATE	
2011	89	1	1-Jun-78	1-Oct-79	• • •
1647	88	1	1-Aug-86	1-Oct-86	• • •
1646	88	1	1-Jun-80	1-Jun-80	• • •
1680	87	1	1-Jun-84	1-Jun-85	• • •
1802	84	1	1-Oct-80	1-Oct-80	• • •
1640	54	1	1-Jun-83	1-Jun-83	• • •
1683	50	1	1-Sep-63	1-Sep-63	• • •
⋮	⋮	⋮	⋮	⋮	

Note: This table is an abbreviated version. The actual table used has 36 rows and 11 columns

Table 8. Example of LTPP the table MON_PROFILE_MASTER

STATE CODE	SHRP ID	CONSTRUCTION NO	PROFILE DATE	PROFILE TIME	RUN NUMBER		IRI_LEFT WHEEL_PATH		IRI AVERAGE	
47	2008	1	24-May-90	7:39:35	1	...	1.16	1.19	1.18	...
47	[illegible]	1	25-May-90	7:39:35	2	...	1.16	1.21	1.19	...
47	2008	1	26-May-90	7:39:35	3	...	1.18	1.19	1.19	...
47	2008	1	27-May-90	7:39:35	4	...	1.17	1.18	1.18	...
47	2008	1	28-May-90	7:39:35	5	...	1.16	1.19	1.17	...
47	2008	1	29-May-90	7:39:35	6	...	1.17	1.19	1.18	...
47	2008	1	30-May-90	7:39:35	7	...	1.17	1.21	1.19	...
47	2008	1	31-May-90	7:39:35	8	...	1.18	1.2	1.19	...
47	2008	1	31-May-90	7:39:35	9	...	1.17	1.2	1.18	...
47	2008	1	16-Apr-92	16:02:38	1	...	1.14	1.3	1.22	...
47	2008	1	17-Apr-92	16:02:38	2	...	1.11	1.31	1.21	...
47	2008	1	18-Apr-92	16:02:38	3	...	1.13	1.3	1.22	...
47	2008	1	19-Apr-92	16:02:38	4	...	1.12	1.34	1.21	...
47	2008	1	20-Apr-92	16:02:38	5	...	1.1	1.33	1.13	...
47	2008	1	23-Feb-94	8:52:13	1	...	1.11	1.15	1.13	...
47	2008	1	24-Feb-94	8:52:13	2	...	1.1	1.15	1.12	...
47	2008	1	25-Feb-94	8:52:13	3	...	1.12	1.19	1.15	...
47	2008	1	26-Feb-94	8:52:13	4	...	1.12	1.12	1.12	...
47	2008	1	27-Feb-94	8:52:13	5	...	1.13	1.13	1.13	...
47	2008	1	26-Apr-96	9:23:46	1	...	1.12	1.27	1.19	...
47	2008	1	27-Apr-96	9:23:46	2	...	1.11	1.26	1.18	...
47	2008	1	28-Apr-96	9:23:46	3	...	1.1	1.27	1.18	...
47	2008	1	29-Apr-96	9:23:46	4	...	1.13	1.25	1.19	...
47	2008	1	30-Apr-96	9:23:46	5	...	1.11	1.28	1.19	...
⋮	⋮	⋮	⋮	⋮	⋮		⋮	⋮	⋮	

Note: This table is an abbreviated version. The actual table used has 1211 rows and 49 columns.

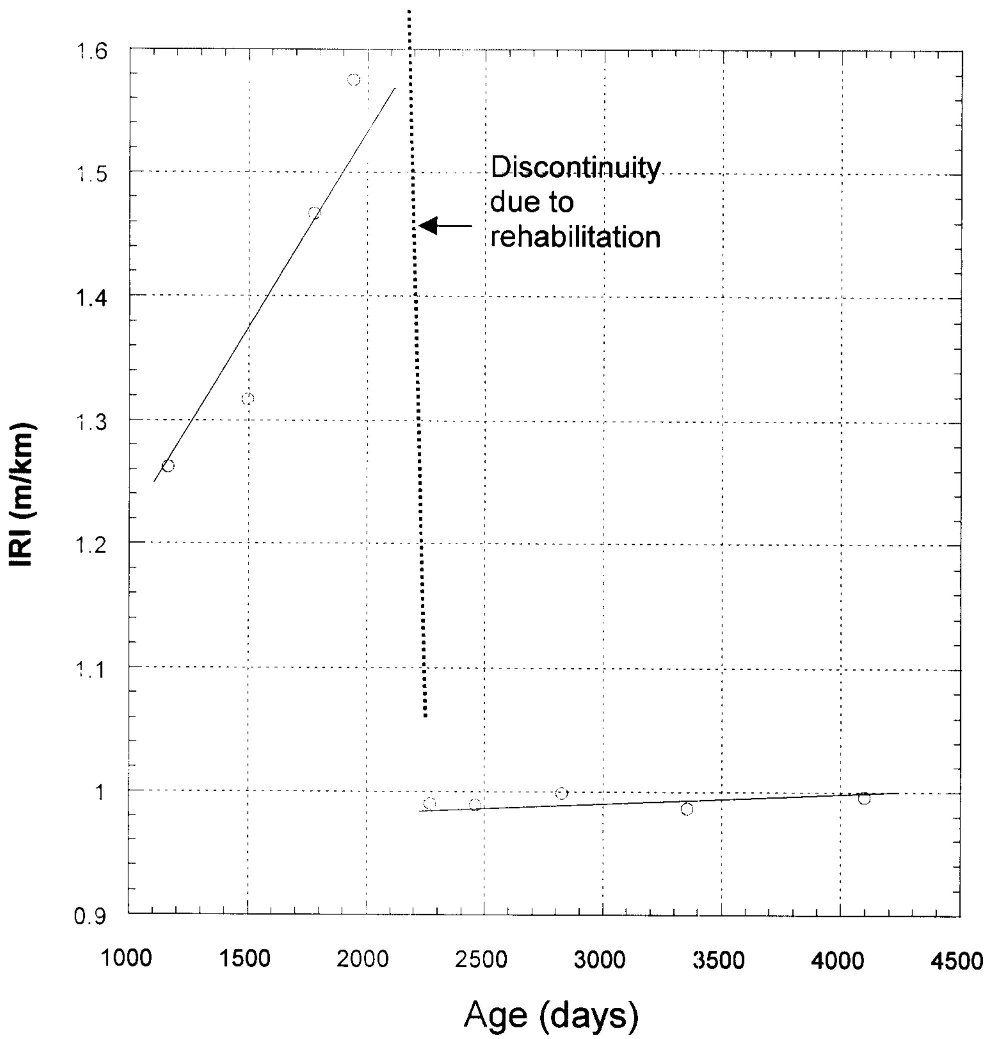

Figure 9. GPS 2 site with irregular trend

IRI should steadily increase with time unless there were some external interferences. This rationale was used to check any abnormal breaks in the time-sequence of the IRI data at each site.

After anomalies similar to that shown in figure 9 are found, the IRI trends are further investigated to ensure the reliability of the data at other sites and to explain such anomalies.

Since rehabilitation or maintenance activities can affect pavement roughness they are assumed to be the major reason for these anomalies. This could be easily checked from the records in the rehabilitation and maintenance module. The following tables were investigated: [20]

MNT_ASPHALT_CRACK_SEAL: Contains information about any crack sealing that took place at a GPS site.

MNT_ASPHALT_PATCH: Contains information about any potholes repaired or any other patchwork that was performed at a GPS site.

MNT_ASPHALT_SEAL: Contains information about any seal coats that were performed at a GPS site.

MNT_HIST: Contains the information on all the maintenacne activities for each site.

RHB_LAYER: Contains information on the layers that were added to a rehabilitated GPS site.

RHB_RESTORE_AC_SHOLDER: Contains information for any data if the site received sholder rehabilitation.

Rehabiliation and maintenance activities justifies, as expected, many of the anomalies in the age vs. IRI relationship. For example, the odd trend in figure 9 was the result of rehabilitation.

The IRI of individual wheel paths versus time is compared for each site and some of the exterior wheel paths can be seen to be more erratic than the interior wheel paths. This could be due to the effects of crack close to the edge of the pavement[12] figure 10 shows a spike in the trend. Upon investigation, it is found that the profile run on that date is in the incorrect lane, thus creating the spike. Another important observation regarding the available IRI values that it is not always recorded during the same time each year. This variation can lead to seasonal and environmental effects, which influence the IRI values. Moisture can cause the subgrade to swell or shrink and during the winter the frost can cause the subgrade to heave. [12]

After all sites are thoroughly investigated to determine the variation of IRI with the age of the pavement, the sites that received maintenance or rehabilitation are eliminated due to the drop in IRI values. Those sites that have erratic IRI values are not included in the NN training database. The criteria used to determine if a site has erratic data is the R^2 value for the linear relationship between IRI and age. Sites with an R^2 value less than 0.5 or negative slopes are not included for future use because it is clear that IRI cannot improve with time without roadway maintenance or rehabilitation. The summary of the R^2 values for individual sites are as follows: over 75% the sites were above R^2 = 0.8, and over 80% above R^2 = 0.7. Approximately 10% of the sites were not above this threshold of R^2 = 0.5.

It is important to note at this stage, that when including all data points, the R^2 value of the relation between age and IRI is calculate 0.11. Data for individual sites seem to contrast this by having a high correlation between age and IRI. This results shows that the deterioration behavior of different sites, within a geographical region, is less considerable than that of one site. Additional research should be conducted to explain this variation.

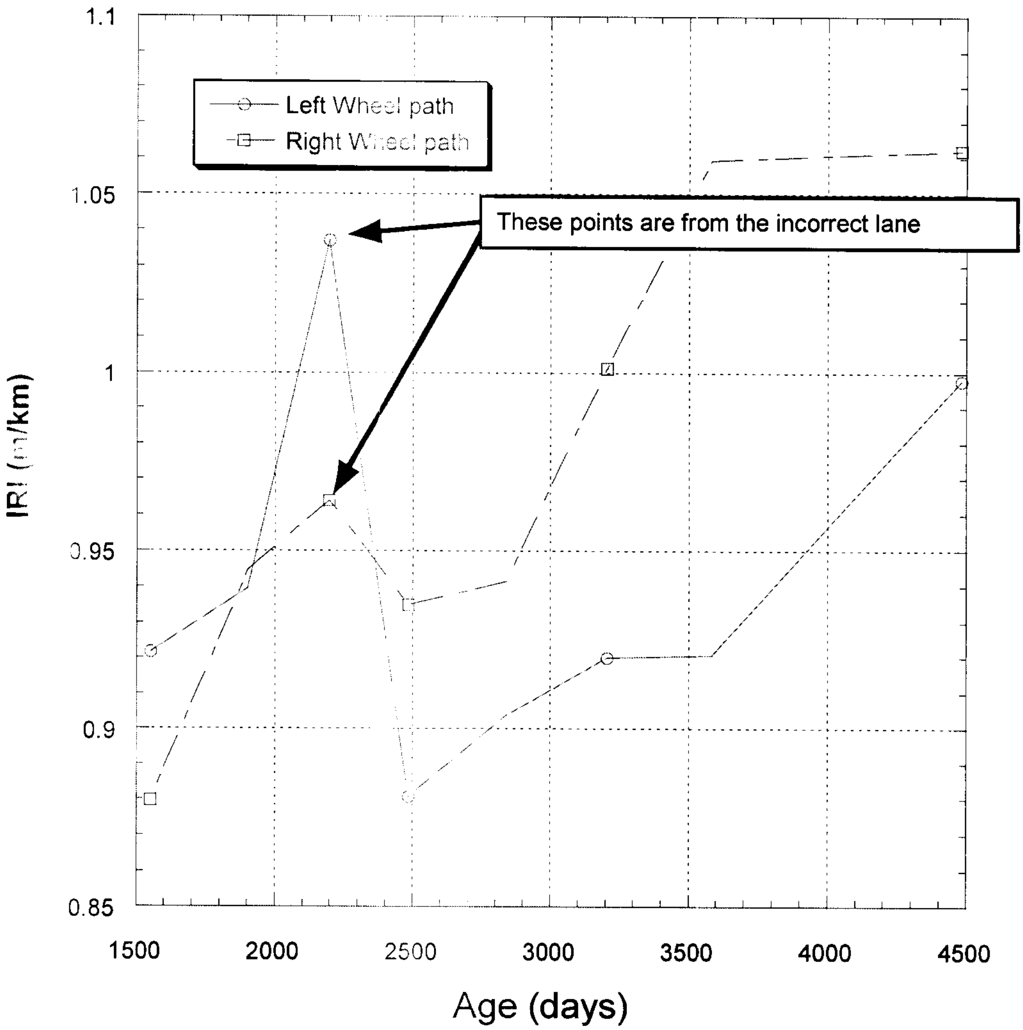

Figure 10. Plot of left and right wheel paths

It is a well-known fact that roads with high levels of traffic, especially truck traffic, need to be repaired more often than roads with lower levels of traffic. Heavy vehicles will do far more damage to pavements than lighter vehicles. The relationship between the weight of the vehicle and the damage it causes to the road is exponential. [22] An equivalent standard axle load (ESAL) equates the weight of a vehicle's axle to a standard load, or 18 kip axle. The concept of vehicles causing damage to the pavement, lead us to the investigation of the relationship between IRI and ESALs. The LTPP database keeps track of the ESAL in table TRF_EST_ANL_TOT_LTPP_LN. Table 9 shows an example of this data. In this table the column labeled KESAL_18K_TOTAL has the total ESALs for each year, and is entered as units of thousands of ESALs, or KESALs (Kilo ESALs). The IMS records that were received first contained only the traffic data before 1993. The remaining data used is also received along with the IMS data, but is from a contractor. This data is unprocessed and is contained in ASCII file format. Macros are written in Microsoft Excel to process these large data files so that the required data can be extracted.

Using the processed data, the ESALs can be determined to the exact day that the IRI was recorded, while the IMS data is only on a yearly basis. The KESALs in the original database are entered on a yearly basis and cannot be used to find the correct relationship with IRI. For example, if the IRI is measured in the spring, the corresponding ESAL entry in the LTPP database is for the whole year, thus these ESALs include those which caused damage to the pavement after the IRI is recorded. Traffic data before 1993 is located in the LTPP database and entered as KESALs/yr. It is unlike the processed data, which can provide ESAL values for each day. A weighted value is used to correct this problem, and is shown in equation [22]. For example the data from site 47-2008, shown in both tables 8 and 9, has no roughness profile for the year 1991. All the ESALs from the previous profile run should be taken into account so as to form an appropriate NN database. Refer to both tables 8 and 9 to validate some of the following numbers:

<u>1st IRI Recorded</u>			<u>KESALs (1990)</u>	
24-may-90	=	221 days remaining in the year	= 171 KESAL/yr (221/365) = 103.5 KESALs	[22]
			<u>KESALs (1991)</u>	
1991	=	365 days in the year	= 182 KESAL/yr (365/365) = 182 KESALs	
<u>2nd IRI Recorded</u>			<u>KESALs(1992)</u>	
16-Apr-92	=	106 days into the year	= 193 KESAL/yr (106/365) = 56.1 KESALs	

103.5 KESALs + 182 KESALs + 56.1 KESALs = 341.6 KESALs

The total ESALs incurred between the 1990 and 1992 profile recording is calculated as 341.6 KESALs. There are other problems associated with the traffic data. There are sites with 'holes' in the data. Some sites have no KESAL data available for a particular year. In these few cases, the KESALs were estimated using Federal guidelines as shown in Chapter 4 of *Investigation of Development of Pavement Roughness.* [12]

Traffic and age are external variables that affect the deterioration of a pavement, but there are characteristics of the pavement itself that affect the rate of deterioration.

Layer thickness and the material properties of those layers have a known effect on pavement life. The structural number (SN) is an appropriate indicator of these characteristics because it combines the layer thickness and materials into one number for each pavement. The SN is supposed to exist in the LTPP database within the table TRF_ESAL_ANL_TOT_LTPP_LN, column ESAL_FACTOR_SN, but there is no data in this column for the sites requested. The SN is instead found in the traffic database files that are sent along with the IMS data. This SN is recently calculated so it has not yet been placed in the IMS database. From a phone conversation with the contractor, it is determined that a backcalculation process using falling weight deflectometer readings is used to calculate the SN. This is a common procedure and there are Federal guidelines for this process.[23, 24]

Table 9. Example of table TRF_EST_ANL_TOT_LTPP_LN

SHRP_ID	STATE CODE	CONSTRUCTION _NO	MODIFICATION NO	BEGIN_DATE	END_DATE	...	KESAL 18 k TOTAL	...
2008	47	1	1	1-Jan-88	31-Dec-88	...	148	...
2008	47	1	1	1-Jan-89	31-Dec-89	...	163	...
2008	47	1	1	1-Jan-90	31-Dec-90	...	171	...
2008	47	1	1	1-Jan-91	31-Dec-91	...	182	...
2008	47	1	1	1-Jan-92	31-Dec-92	...	193	...
2001	47	1	1	1-Jan-93	31-Dec-93	...	203	...
2001	47	1	1	1-Jan-94	31-Dec-94	...	214	...
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Note: This table is an abbreviated version. The actual table used has 538 rows and 27 columns.

Choosing the Variables

The development of the models in this project employed the LTTP data either in its original form or in a manipulated form.Example of data manipulation is that of a time variable, which is calculated by taking the difference in time between one IRI profile and another. This section explains these concepts along with the process of choosing which variables to use in this project.

Determination of Statistical Significance

Roughness is an appropriate way to determine the conditions of a pavement. The roughness measurement in the LTPP database is IRI and it is the variable to be predicted in this research project. Figure 11 shows a good relationship between IRI and age for a site in New Jersey. The R in that figure is the R^2 value. Noticeably, it shows a high correlation between age and IRI for that site. Multiple linear regression and the coefficient of determination, R^2, is used for determining the significance of the variables that are used for the models.

The measure of the improvement in the coefficient of determination, R^2, is used as an indicator of the ability of the variable to predict IRI. As mentioned in the previous section the R^2 for the age vs. IRI is equal to 0.11 when all the sites are combined. With the addition of ESALs to Age and IRI, the multiple regression model for all the sites combined, has an R^2 value of 0.35. This does not explain the variance in the IRI data, but does improve the R^2 value.

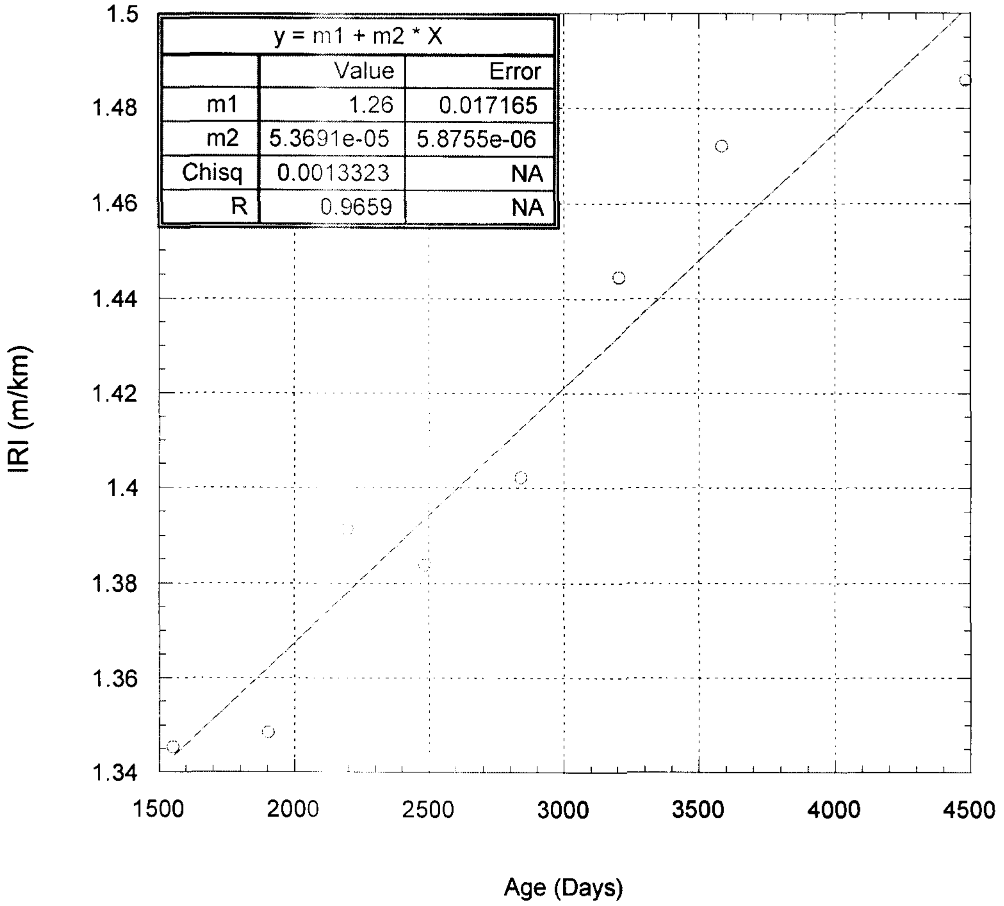

Figure 11. Typical IRI Vs. age plot for a typical GPS 2 site

As for the pavement structural characteristic, SN is chosen as the independent variable. In the determination of the IRI of an individual site there is no correlation between SN and IRI because SN is constant. It does not vary over time, however, when all the sites are pulled together it becomes a distinguishing variable among different sites. The R^2 value for the multiple linear regression involving IRI, age, ESALs and SN improved greatly. The new R^2 becomes 0.49 when SN was added to IRI, age and ESALs in a multiple linear regression model. This means the new regression model can determine about half the variance in the data. A large portion of the remaining variations is thought to be due to the inconsistencies introduced during the initial construction of each pavement. The section on initial IRI and delta variables attempts to explain the use of an initial IRI to incorporate this variance.

A statistical measure is used to compare different models. In the following sections statistical notations of sum squared errors (SSE) or root mean squared error (RMSE) are used for comparison of different models. SSE and RMSE are computed as the following:

$$\text{SSE} = \sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \qquad \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{n}} \qquad [23]$$

Where,

x_i = observation "i"

$\hat{x}_i$ = estimated value of "x_i"

n = sample size

Initial IRIs and Delta Variables

The construction of an asphalt pavement has several variables that can introduce inconsistencies in the initial pavement's roughness. Even though, there already exists many models for estimating the initial IRI of pavements at the time that the pavement is constructed *(12)*, the predicted values are theoretical and could predict quite different values from the actual initial IRI values. Moreover, these models involve the use of numerous variables to predict the initial IRI value (equation [12]), which could be quite in practice due to the availability limitations of data and costly sometimes. Using these calculated IRI values in the development of pavement performance models might question their reliability. Moreover, these models also involve the use of numerous variables to predict the initial IRI value (equation [12]).

Using an initial measured IRI values to alleviate the difficulties of estimating an initial IRI could represent a more practical and yet dependable approach. There are two forms of logic that are used in attempting to adopt an initial IRI value in conjunction with neural networks and multiple regression.

The first approach is to let the neural network take the initial IRI into account by giving it known IRIs as an input vector and the age at which the IRI is measured. The Δ values are the change in time $(t_2 - t_1)$ and change in ESALs $(ESAL_2 - ESAL_1)$ from the date of the known IRI to that of the IRI that is to be predicted.

During training of NN, each data point is considered separately and not associated with any group of points for an individual site, so in the first case of training, each set of data uses the previous IRI value as a basis of predicting the future IRI. To clarify this logic, a small example is shown. The table 10 gives the date at which the IRI is measured. As observed, there is no data recorded before 1990. The pavement is built in 1974, and there is no data on which to base an initial IRI value. Because of this the IRI value (2.787) measured on September 6, 1991 is used as the target value and the IRI (2.743) from Nov. 30, 1990 is employed as an initial IRI indicator. This is for the first data set developed from this site. The next data set uses the IRI (2.787) from Sept. 6, 1991, as its initial IRI indicator. Below are the first three values developed from the site in table 10.

	Input Values			Target Value
	Initial IRI indicator	Δt	$\Delta ESAL$	*IRI*
1.	2.743	280	33068.5	2.787
2.	2.787	286	28627	2.918
3.	2.918	356	46658	2.874

The second logic that could be used in the model is similar to the first, but all data points use Nov. 30, 1990 as a reference point for the initial IRI indicator (2.743). Below is the same three data points developed from table 10, using the second model development logic.

	Input Values			Target Value
	Initial IRI indicator	Δt	$\Delta ESAL$	*IRI*
1.	2.743	280	33068.5	2.787
2.	2.743	566	61695.9	2.918
3.	2.743	922	108354.2	2.874

Notice that the same value is being predicted, and the only difference between the two type of models is the way time between IRI values is measured. Notice also that if the actual initial IRI is known it can be used as the initial IRI variable value, Δt = Age, and ΔESALs = Lifetime ESALs. This, naturally, is correct because a deterioration model should take into account all the damage that has occurred during the pavement's lifetime.

Table 10. Compiled data for a typical GPS-2 site [25]

STATE CODE	SHRP ID	IRI_RUN DATE	CONSTRUCTION	AGE (days)	IRI (Measured)	ESALS	SUM ESALS	SN
34	1033						707000	
34	1033	30-Nov-90	5-Jan-74	6173	2.743	47583.5	754583.6	4.9
34	1033	6-Sep-91	5-Jan-74	6453	2.7874	33068.4	787652.1	4.9
34	1033	18-Jun-92	5-Jan-74	6739	2.9176	28627.4	816279.5	4.9
34	1033	9-Jun-93	5-Jan-74	7095	2.8738	46658.4	862937.8	4.9
34	1033	8-Jun-94	5-Jan-74	7459	2.9016	39753.9	902691.8	4.9
34	1033	22-Jun-95	5-Jan-74	7838	3.1426	26645.6	929337.5	4.9

DEVELOPMENT OF TRAINING DATABASE FOR THE NEURAL NETWORK MODEL

There are 16 GPS-2 sites used for the development of this database. Three GPS-1 sites are also incorporated into a portion of the database for the later experiments. Each site had from three to eight IRI values available. Consequently, there are 101 data points in the database and 118 with the additional GPS-1 sites. There is one target IRI vector for each data point and three different input vectors for each data point. Thus, there are 118 target vectors and 354 input vectors. These are the dimensions for the models developed at the first stage. Later models use more input vectors. These additional input vectors are the Δ's and initial IRI values discussed in the previous section and are the only variants of the original 354-vector database (i.e. change in time, change in ESAL, etc.). This database is located in Appendix B .

MODEL DEVELOPMENT AND RESULTS

MODEL DEVELOPMENT

We employ two types of approaches for developing pavement deterioration models, namely neural networks and multiple linear regression. This project developed four different basic models and these models differ by the type of variables used in developing them. A portion of the available data is not included in developing the models so that it can be used later to test the developed models. The portion of data that is removed for testing purposes is described under each experiment's description.

Our main goal is to develop a model of the following form:

$$Y = f(X_1, X_2, \ldots\ldots X_n)$$

Where, Y = The dependant variable to be estimated

X_n = The independent variables employed for estimating Y

Table 11 describes all the dependant and independent variables used in the development of the models. The following section illustrates each of these four models.

Table 11. Description of variables

VARIABLE	DESCRIPTION	RANGE
AGE	Measured in thousands of days from the date of construction to the day of the IRI reading.	1.2 ~ 16.5
Cumulative ESALs	The number of ESALs the pavement experienced from construction to the day of the IRI reading. (Millions of ESALs)	0.2 ~ 20
Structural Number	The structural number recorded closest to the day of the IRI reading. Most values are from back-calculations of falling weight deflection readings.	2.85 ~ 6.6
Delta Time	The difference in time between the initial IRI reading and the target IRI. Measured in years.	0.4 ~ 3.0
Delta ESALs	The ESALs experienced by the pavement between the initial IRI and the target IRI. (Measured in hundreds of thousands ESALs)	0.1 ~ 8.0
Initial IRI(1)	Uses the IRI of the previous reading and the next IRI.	0.7 ~ 2.9
Initial IRI(2)	Uses only the first recorded IRI as the initial IRI.	0.7 ~ 2.7

BASIC MODEL #1 This model's dependant variable is IRI, in units of m/km. The independent variables used in this model are as follows:

IRI = ***f*** **[age, cumulative ESALs** and **Structural Numbers]**

BASIC MODEL #2 This model's dependant variable is IRI, in units of m/km. This model uses an initial IRI value to estimate the target IRI value. The independent variables used in this model are as follows:

IRI = ***f*** **[initial IRI, age, delta time, structural number** and **delta ESALs]**

BASIC MODEL #3 This model is a simplified version of basic model #2. It is the same model in all ways except ESALs that is not considered. The independent variables used in this model are as follows:

IRI = ***f*** **[initial IRI, age, delta time,** and **structural number]**

BASIC MODEL #4 This model is the same as Basic Model #2 but with a different initial IRI value and different delta values. The input vectors used in this model are as follows:

IRI = ***f*** **[initial IRI, age, delta time, structural number** and **delta ESALs]**

Sub-Model 1a Basic model #1 is used for this sub-model. Six individual data points are randomly removed from the data set for the purpose of testing. These test points are consisted of only GPS 2 sites data.

Sub-Model 2a Basic model #2 is used for this sub-model. Six individual data points are randomly removed from the data set for the purpose of testing. These test points are consisted of only GPS 2 sites data.

Sub-Model 3a Basic model #3 is used for this sub-model. Six individual data points are randomly removed from the data set for the purpose of testing. These test points are consisted of only GPS 2 sites data.

Sub-Model 4a This is exactly the same as Sub-Model 2a except that basic model #4 is used instead of basic model #2.

Sub-Model 1b This is exactly the same as Sub-Model 1a but instead of six points being removed for the creation of an evaluation data set, all the points from two sites are removed. Eleven points in all are removed for testing.

Sub-Model 2b This is exactly the same as sub-model 2a but instead of six points being removed for the creation of an evaluation data set, all the points from two sites are removed. Eleven points in all are removed for testing.

Sub-Model 3b This is exactly the same as sub-model 3a but instead of six points being removed for the creation of an evaluation data set, all the points from two sites are removed. Eleven points in all are removed for testing.

Sub-Model 4b This is exactly the same as sub-model 4a but instead of six points being removed for the creation of an evaluation data set, all the points from two sites are removed. Eleven points in all are removed for testing.

It should be mentioned that the points removed from the data set are not used in planning the NN or developing the linear regression equations. They are used only to test the models after they are trained. Table 12 gives a brief summary of the models developed in terms of variables employed.

Table 12. Summary of Sub-Models variables

BASIC MODEL	MODELS	AGE	SN	CUM. ESAL	DELTA TIME	DELTA ESAL	IRI(1)	IRI(2)
1	1 a&b	YES	YES	YES				
2	2 a&b	YES	YES		YES	YES	YES	
3	3 a&b	YES	YES		YES		YES	
4	4 a&b	YES	YES		YES	YES		YES

LINEAR REGRESSION MODELS

Linear regression models are developed to test the efficiency of the NN models and to use as a guide for developing them. After using the same variables for both types of models, the results are compared. Testing of the linear regression models is performed by using the same points employed to test the NN models. Tables 13 and 14 show the results of regression models. Developed multiple linear regression models are in the following form:

$$Y = B_o + B_1 X_1 + B_2 X_2 + \cdots + B_n X_n \qquad [24]$$

Where, Y = Dependant variable
X_n = Independent variables
B_n = Estimated Parameters

We employed two different techniques for developing multiple linear regression models; Step-wise regression and Standard linear regression.

Table 13 shows the results of a stepwise regression procedure.

Table 14 shows the same results as that of table 13 but this time standard linear regression is used. As indicated by the coefficient of correlation, R^2, the difference between the two types of regression models shows very similar results based on the modeler's understanding of the process that's being modeled.

The significance of the variables and coefficients of the model is not apparent by looking at table 13. In table 14, sub-models 2, 3 and 4 have negative intercepts for both "*a*" and "*b*" series. A negative intercept at first seems to be impossible because this means that at time zero the IRI is negative. This is due to the use of the initial IRI variables. Thus, the IRI intercept at time zero should be either (B_0 + B_1X_1) for Sub-models 2 and 3 or (B_0 + B_2X_2) for sub-model 4.

Table 13. Stepwise Regression

	B_0	B_1	B_2	B_3	B_4	B_5	B_6	B_7	R^2
Sub-Model 1a	0.9956	*	*	0.0638	.0516	**	*	*	0.3192
Sub-Model 2a	-0.1782	1.0642	*	0.0113	*	**	0.0833	.0117	0.9639
Sub-Model 3a	-0.1543	1.0662	*	0.0083	*	**	0.0967	*	0.9608
Sub-Model 4a	-0.1574	*	1.0339	0.0304	*	**	**	0.2131	0.9124
Sub-Model 1b	0.9605	*	*	0.0690	0.0558	**	*	*	0.3465
Sub-Model 2b	-0.1887	1.0594	*	0.0109	*	**	0.0941	0.0131	0.9685
Sub-Model 3b	-0.1695	1.0702	*	0.0071	*	**	0.1101	*	.9632
Sub-Model 4b	-0.0228	*	1.0515	0.0266	*	-0.0298	**	0.2265	0.9223

* Variable is not used in the model

** Negligible

Table 14. Standard Linear Regression

	B_0	B_1	B_2	B_3	B_4	B_5	B_6	B_7	R^2
Sub-Model 1a	0.7289	*	*	0.0687	0.0488	0.0513	*	*	0.3277
Sub-Model 2a	-0.1877	1.0638	*	0.0115	*	0.0049	0.0838	0.0115	0.9639
Sub-Model 3a	-0.1845	1.0636	*	0.0089	*	0.0060	0.0978	*	0.9609
Sub-Model 4a	-0.0779	*	1.0504	0.0267	*	-0.0210	0.0066	0.2110	0.9142
Sub-Model 1b	0.6773	*	*	0.0745	0.0533	0.0530	*	*	0.3553
Sub-Model 2b	-0.1648	1.0611	*	0.0104	*	-0.0047	0.0931	0.0134	0.9685
Sub-Model 3b	-0.1886	1.0687	*	0.0076	*	0.0037	0.1106	*	.9632
Sub-Model 4b	-0.0698	*	1.0653	0.0239	*	-0.0289	0.0138	0.2152	0.9237

* Variable is not used in the model

Table 15. T values for the Standard Linear Regression presented in table 13

	B_0	B_1	B_2	B_3	B_4	B_5	B_6	B_7	t-Table (0.90)
Sub-Model 1a	2.7282	*	*	4.0097	4.8267	1.0696	*	*	1.658
Sub-Model 2a	-2.2534	39.6824	*	2.3417	*	0.1440	2.9551	2.9428	1.671
Sub-Model 3a	-2.1929	39.1095	*	1.7533	*	0.4592	3.3465	*	1. 671
Sub-Model 4a	-0.6490	*	21.6151	3.3973	*	-1.0584	0.5475	8.8786	1. 671
Sub-Model 1b	2.1695	*	*	3.7090	4.6999	0.9808	*	*	1. 658
Sub-Model 2b	-2.0371	41.3676	*	2.0978	*	-0.3812	3.0858	3.3848	1. 671
Sub-Model 3b	-2.1807	38.9688	*	1.4386	*	0.2846	3.4682	*	1. 671
Sub-Model 4b	-0.5887	*	22.1653	1.1281	*	-1.5057	9.1880	3.0148	1. 671

* Variable is not used in the model

LINEAR MODELS

Model 1	Y(IRI) =	$B_0 + B_3X_3 + B_4X_4 + B_5X_5$	**Sub-Models 1a & 1b**	[1]
Model 2	Y(IRI) =	$B_0 + B_1X_1 + B_3X_3 + B_5X_5 + B_6X_6 + B_7X_7$	**Sub-Models 2a & 2b**	[2]
Model 3	Y(IRI) =	$B_0 + B_1X_1 + B_3X_3 + B_5X_5 + B_6X_6$	**Sub-Models 3a & 3b**	[3]
Modal 4	Y(IRI) =	$B_0 + B_2X_2 + B_3X_3 + B_5X_5 + B_6X_6 + B_7X_7$	**Sub-Models 4a & 4b**	[4]

Where,

B_0 = Intercept
X_1 = IRI(1) (m/km)
X_2 = IRI(2) (m/km)
X_3 = Age (Thousands of days)
X_4 = Millions of ESALs
X_5 = Structural number
X_6 = Delta time (years)
X_7 = Delta ESALs (100,000)

The coefficients (B_n) are displayed in tables 13 and 14. The t-values for each parameter are shown in table 15.

In table 16 testing results are shown for sub-models 1b-4b. Table 17 shows the SSE and RMSE of the results for each model. Tables 16 and 17 only include the results for the "b" series. The main reason for this elimination, to prevent any biased outcome from the series "a" in the neural network, since the test data points originated from the same set that used to train the neural network, whereas the "b" series test data points come from the two sets. Another reason is to simplify the already exorbitant amount of data and results. The ***D*** values in table 16 and subsequent tables represent which data point is tested. For example ***D1*** through ***D11*** represent the eleven test data points in the 'b' series. This is just the nomenclature used to distinguish among the individual test data points. This same system is applied later in the paper to other test data points, in which case the numbering is just increased sequentially (***D12, D13***, etc.).

Table 16. Linear Regression Sub-Model Testing Results

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
Sub-Model 1b	1.0959	1.1266	1.1573	1.2027	1.2562	1.3043	1.4163	1.2434	1.278	1.3292	1.3568
Sub-Model 2b	1.3745	1.3649	1.4129	1.4503	1.4943	1.5309	1.7652	1.0932	1.1956	1.2018	1.245
Sub-Model 3b	1.387	1.3751	1.4209	1.4364	1.4612	1.514	1.7079	1.1159	1.22	1.2326	1.2537
Sub-Model 4b	1.6667	1.6642	1.7045	2.1143	2.4365	2.2004	3.268	1.1404	1.1613	1.2277	1.336
Actual	1.3486	1.3914	1.3838	1.4022	1.4446	1.4722	1.486	1.1462	1.0924	1.2086	1.268

Table 17. Sum Squared Errors and standard error for the test results of table 4-6

Test Data	*D1*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*D10*	*D11*	Overall S.S.E.	RMSE
Sub-Model 1b	0.0639	0.0701	0.0513	0.0398	0.0355	0.0282	0.0049	0.0094	0.0344	0.0145	0.0079	0.3599	0.1900
Sub-Model 2b	0.0007	0.0007	0.0008	0.0023	0.0025	0.0034	0.0780	0.0028	0.0107	0.0000	0.0005	0.1024	0.1010
Sub-Model 3b	0.0015	0.0003	0.0014	0.0012	0.0003	0.0017	0.0492	0.0009	0.0163	0.0006	0.0002	0.0735	0.0860
Sub-Model 4b	0.1012	0.0744	0.1028	0.5071	0.9839	0.5303	3.1755	0.0000	0.0047	0.0004	0.0046	5.4850	0.7410

NEURAL NETWORK (NN)

The NN used in the experiments employs feed-forward backpropagation training. Each experiment used at least a three-layered network with the first layer having a number of nodes equal to the number of input variables used in each individual experiment. The second or hidden layer consists of a varying number of nodes and the last layer has one output node. The first two transfer functions vary between tan-sigmoid functions and log-sigmoid functions. The output, unlike the other two layers, is determined by a linear transfer function. Matlab NN Toolbox is used to train and to test the NN developed in this project [3].

Determination Of The Optimal Number Of Layers And Nodes In The NN

A NN should have both an optimal number of layers and an optimal number of nodes in each layer. This section discusses the determination of the optimal number of hidden layers and number of nodes in each layer. First, the optimal number of nodes is investigated and then the optimal number of layers. The optimization of the number of nodes starts with using only one hidden layer.

The optimal number of nodes is determined by simply running the Matlab NN training program with varied number of nodes in the hidden layer. This means that a single hidden layer is used and the number of nodes starts at one. It is then increased by one node for each consecutive run until the NN is trained for **'n'** nodes. **'n'** is the number of nodes in the hidden layer. The NN reaches a point where the number of nodes becomes too high. This phenomena is called diverging of the NN. Divergence is apparent when all the test points return the same value. To test the results of this section the same eleven test data points are used from sub-models 1b, 2b, 3b and 4b. The optimal number of nodes is determined by comparing the sum-squared error (SSE) for the eleven test points.

```
net = newff([0 5;0 18;2 7;0 3;0.1 20],[5 n 1],{'tansig' 'tansig' 'purelin'});
```

The line above represents the Matlab command that creates the desired NN architecture. The vector `[5 n 1]` describes the architecture of the NN. The first variable, 5, represents the number of nodes in the input layer. **'n'** represents the number of nodes in the hidden layer that will be determined in this section. It is the number of nodes in the first hidden layer. The last number represents the nodes in the output layer, namely one.

Figure 12 is a flowchart demonstrating the process used to find the optimal number of nodes and hidden layers for the NNs used in this section. This process is preformed for all the sub-models in the *b* series only (see previous for explanation). On an average, seventeen different NN programs are created for determining the optimal number of nodes and layers for each sub-model. Sub-model 2b results are used in this section for the purpose of demonstrating this research process. Figure 13 shows the SSE for sub-model 2b as the number of nodes in the hidden layer increase. Thus, for this sub-model, three nodes in the hidden layer are found to be the optimal number.

Table 18 shows the actual values of the S.S.E. for the number of nodes in the first hidden layer. Figure 14 shows the plot of the measured IRI versus the IRI predicted by the NN. Series 1 on the chart shows the linear interpretation of the data, if the NN were to predict the data perfectly (45-degree line). Equation [29] shows the equation of the fit

$$y = 1.2417x - 0.3261 \quad R^2 = 0.8559 \tag{29}$$

for the predicted IRI vs. measured IRI of figure 14. The correlation coefficient (R^2) is shown for equation [29], this illustrates how well sub-model 2b estimates IRI. The predicted IRI has a fairly good correlation value and is close to the 45-degree line. The equation would have an intercept of zero along with a slope of one, if it were to predict the data perfectly.

After the optimal number of nodes is determined for one hidden layer, the next thing that must be optimized is the number of layers. The number of nodes first remains constant at the optimal number of three for each hidden layer. Then the number of nodes will vary for each additional hidden layer. Table 19 shows the results of introducing additional hidden layers. After three hidden layers, the NN started diverging. In other words, it is not training properly at this point.

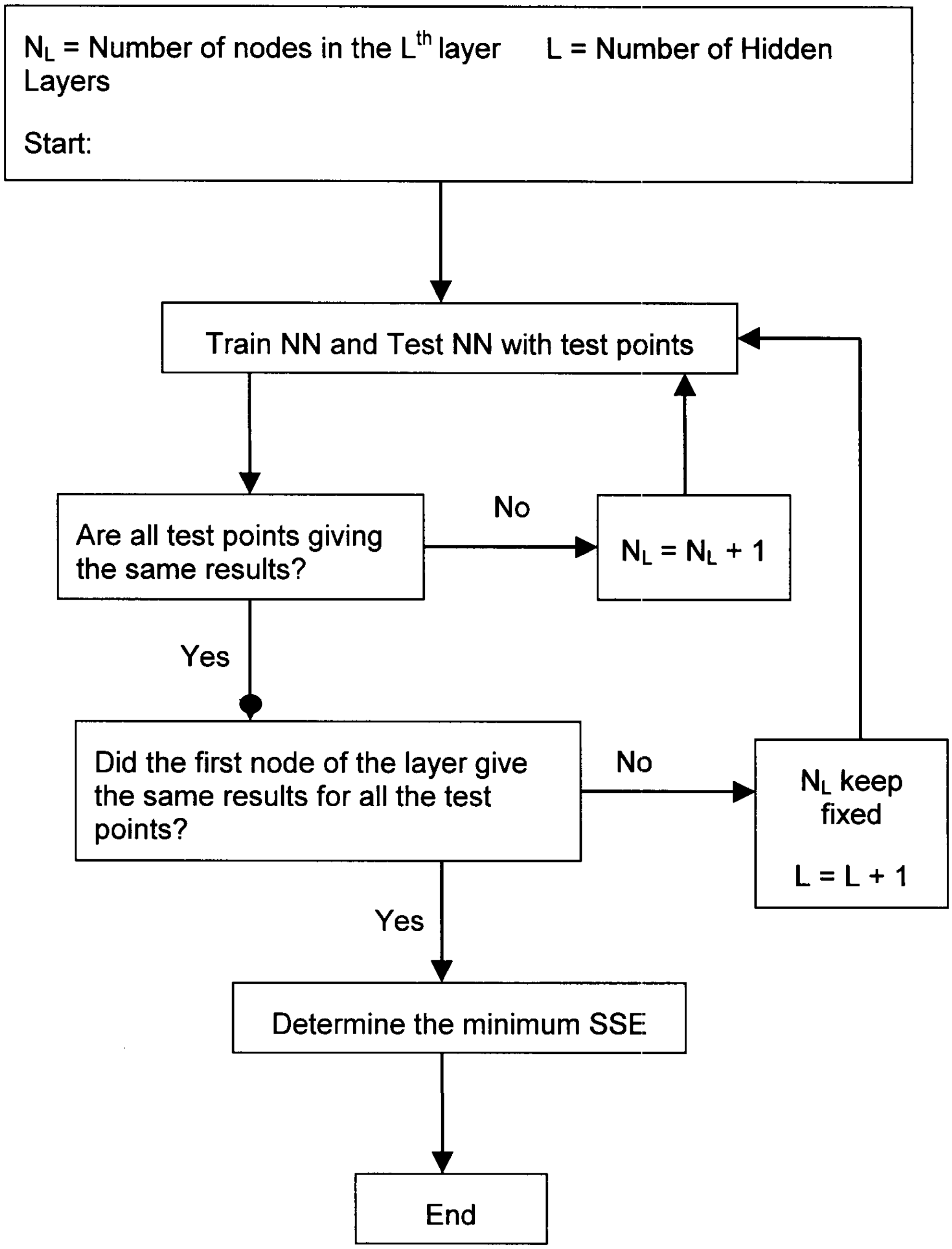

Figure 12. Flowchart for determining the optimal NN architecture

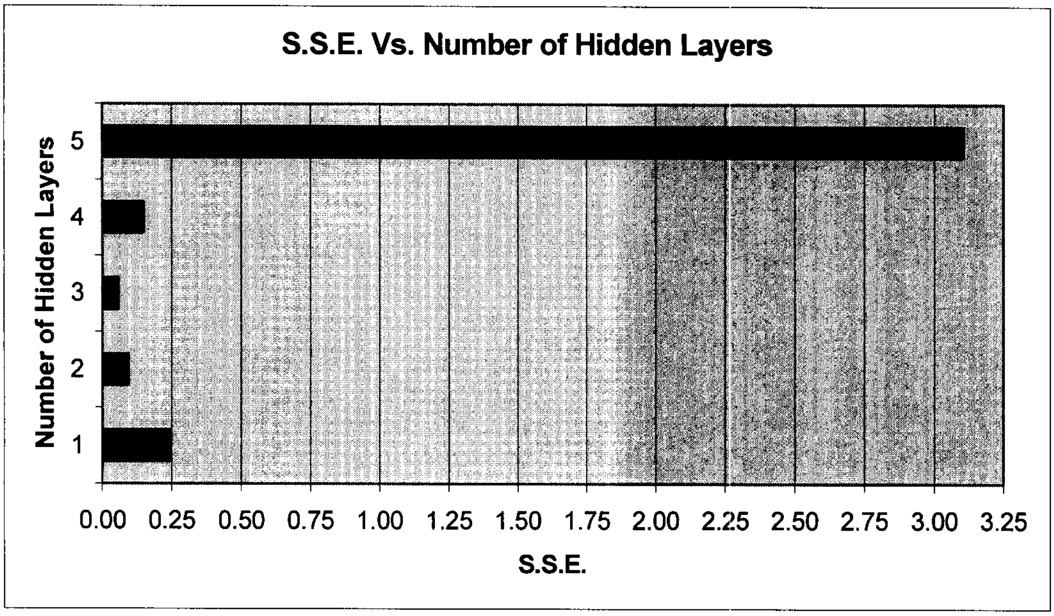

Figure 13. Sum squared error of NN with respect to the number of nodes in the hidden layer in sub-model 2b.

Table 18. Sum Squared Error for different number of nodes in sub-model 2b

Number of nodes	1	2	3	4	5
S.S.E.	0.2435	0.0916	0.0570	0.1495	3.1046

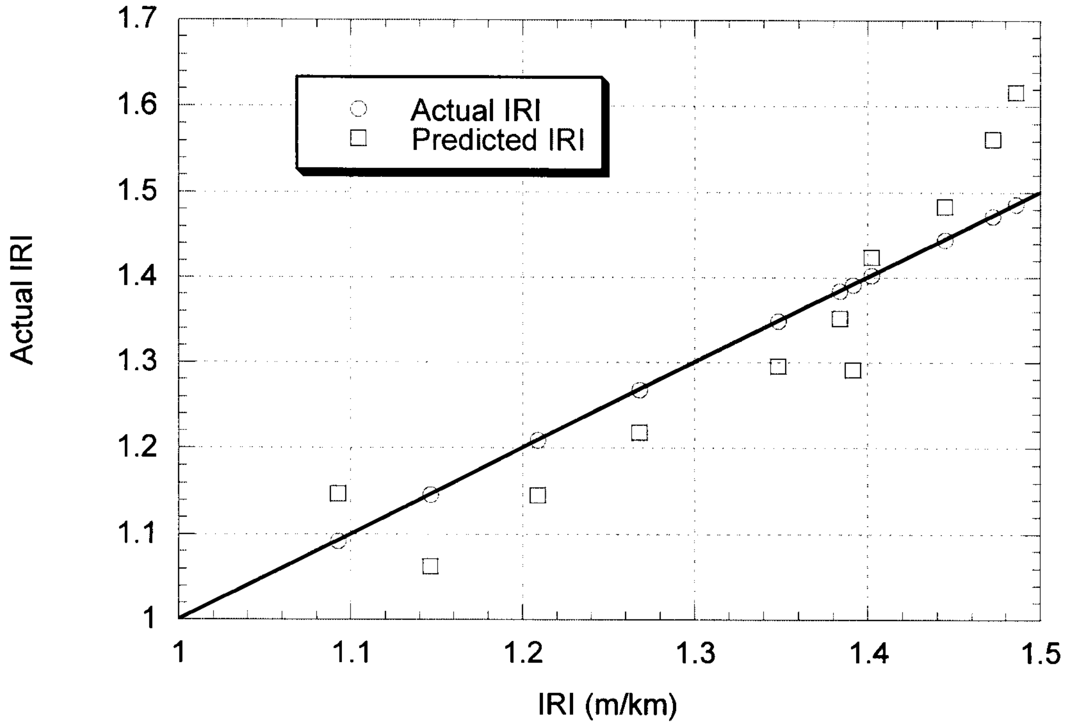

Figure 14. Correlation of the Predicted IRI Vs. the Actual IRI

Different NN architectures are identified as a result of the optimization process described in Figure 12. The NN architecture in this report is represented as follows; **'H'** followed by a number represents the number of hidden layers and the numbers that follow after that (**_3_**) is the number of nodes in each layer. Example **H4_3_3_3_3** has four hidden layers (**H4**) and each layer contains 3 nodes (**_3_3_3_3**). The Matlab command would be changed in to the following:

```
net = newff([0 5;0 18;2 7;0 3;0.1 20],[5 3 3 3 3 1],
     {'tansig''logsig''logsig''logsig''logsig''purelin'});
```

The "**3**'s" represent hidden layers which can be seen between the "**5**" node input layer and the "**1**" node output layer, `[5 3 3 3 3 1]`. Figures 15 and 16 show the graphic representation of the summed squared error as the number of layers increases.

Next, the number of nodes is varied within each of the layers to determine the optimal configuration of nodes and layers. Table 20 shows the results for the optimal configuration for each hidden layer that is determined by trial and error. The way to read the architecture is the same as in table 19 and it shows that the number of nodes in the hidden layers is different for each trial.

The conclusion is that one hidden layer with three nodes is the optimal configuration for sub-model 2b. This process is used to determine the optimal configuration for each model. Table 21 shows the optimal configuration determined by this procedure for each NN sub-model in the *b* series.

Table 19. Sum Squared Error as Number of Hidden Layers Increase for Sub-model 2b

Architecture	H1_3	H2_3_3	H3_3_3_3	H4_3_3_3_3
S.S.E.	0.057	1.7477	14.462	0.4243

Figure 15. S.S.E. of NN with respect to the number of nodes in the first hidden layers for Sub-model 2b

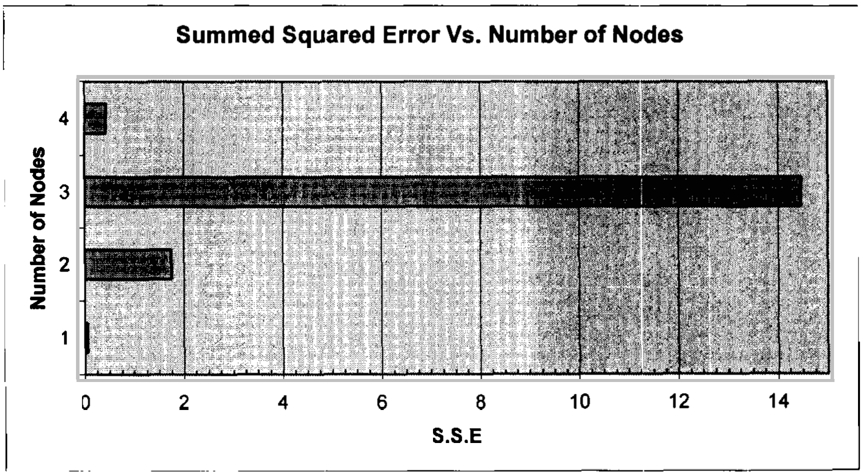

Figure 16. Figure 15 magnified

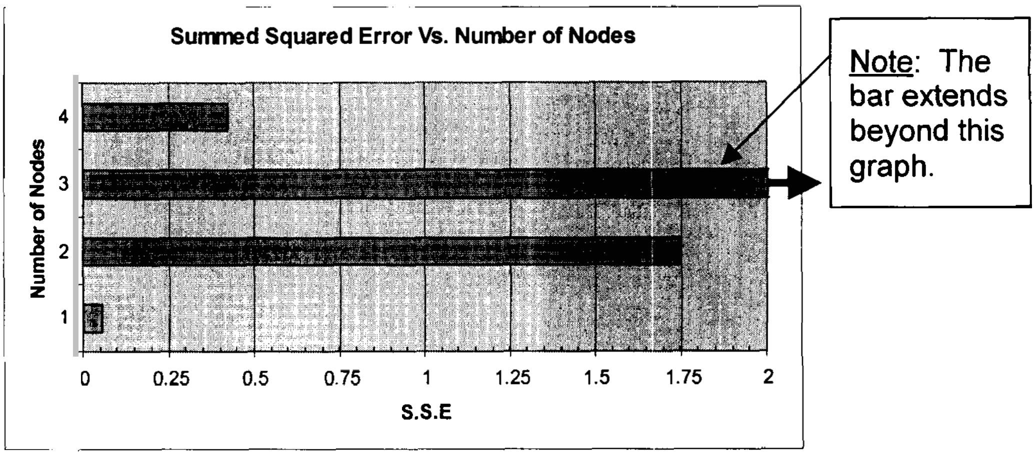

Table 20. Optimized Sum Squared Error as Hidden Layers Increase for Sub-model 2b

Architecture	H1_3	H2_3_1	H3_3_2_2	H4_4_3_2_1
S.S.E.	0.057	0.0641	0.1678	0.1311

Table 21 Optimal configurations of the NN sub-models shown in chapter 4

	Numbers of layers	Numbers of nodes in hidden layer
Sub-model 1b	3	1
Sub-model 2b	3	3
Sub-model 3b	3	1
Sub-model 4b	3	1

SUMMARY OF NN TESTING RESULTS

The optimal NN architecture, determined in the previous section, is used for each sub-model as described earlier in this chapter . Tables 22 and 23 summarize the testing results of the NN models. All the models in *a* series use the same six test data points and those in the *b* series all use the same eleven data points to test each sub-model. Table 23 gives the SSE and RMSE for each sub-model's output compared to actual IRI. Note that ***D1*** through ***D11*** each represents a test data point as indicated by the sub-model's description in the first section of this chapter.

Table 22. NN model predictions for their respective test points

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
Sub-model 1a	1.6253	1.5393	1.118	1.0051	1.491	0.9124					
Sub-model 2a	1.5454	1.6201	0.8658	1.0478	1.4813	0.8972					
Sub-model 3a	1.6165	1.664	1.151	1.0872	1.4318	0.7973					
Sub-model 4a	1.5782	1.5143	1.0814	1.0403	1.4025	1.0444					
Actual	1.5484	1.5944	1.0782	1.0178	1.4446	0.9058					
Sub-model 1b	1.0234	1.0512	1.0826	1.1504	1.2586	1.3526	1.5966	1.0656	1.0745	1.0884	1.104
Sub-model 2b	1.2956	1.2913	1.3515	1.4235	1.4829	1.5615	1.6161	1.0629	1.1469	1.1459	1.2179
Sub-model 3b	1.4326	1.4305	1.4686	1.4704	1.4894	1.5325	1.4613	1.1092	1.2147	1.1644	1.2746
Sub-model 4b	1.3972	1.4765	1.5353	1.5301	1.4264	1.4785	1.9294	1.0195	1.0705	1.1506	1.2028
Actual	1.3486	1.3914	1.3838	1.4022	1.4446	1.4722	1.486	1.1462	1.0924	1.2086	1.268

Table 23. Sum Squared Errors for results presented in table 22

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	S.S.E.	RMSE
Sub-model 1a	0.0059	0.003	0.0016	0.0002	0.0022	0.0000						0.0129	0.051
Sub-model 2a	0.0000	0.0007	0.0451	0.0009	0.0013	0.0001						0.0481	0.098
Sub-model 3a	0.0046	0.0048	0.0053	0.0048	0.0002	0.0118						0.0315	0.079
Sub-model 4a	0.0009	0.0064	0.0000	0.0005	0.0018	0.0192						0.0288	0.076
Sub-model 1b	0.1058	0.1157	0.0907	0.0634	0.0346	0.0143	0.0122	0.0065	0.0003	0.0144	0.0269	0.4849	0.22
Sub-model 2b	0.0028	0.0100	0.0010	0.0005	0.0015	0.008	0.0169	0.0069	0.003	0.0039	0.0025	0.057	0.075
Sub-model 3b	0.0071	0.0015	0.0072	0.0047	0.002	0.0036	0.0006	0.0014	0.015	0.002	0.0000	0.045	0.067
Sub-model 4b	0.0024	0.0072	0.023	0.0164	0.0003	0.0000	0.1966	0.0161	0.0005	0.0034	0.0043	0.27	0.164

RESULTS OF SUB-MODELS

Sub-Models in the 'a' series show that NN trained with data from any site can produce excellent results for the same site. Unfortunately this is not applicable to a real situation, because a model should be able to be used without having three or four years worth of data available. For that reason the rest of this report will focus on the later sub-models which contain less bias (i.e. the 'b' series). This bias is explained earlier in this chapter.

In sub-models 2b, 3b and 4b, a lower SSE is produced by the NN models compared to the linear regression models (compare results in table 23 to those in 16), while in sub-model 1b, the linear regression produced lower SSE than the NN model. Both the linear regression and the NN models have SSE's that are relatively close in value, except for sub-model 4b, which produced poor results when linear regression is used. This may be possible because in sub-model 4b the initial IRI used is not a linear function, but is constant for the whole site over a length of time. The NN experiment, which has more input vectors, performed better than sub-model 1b, which only has three input vectors. NN models should improve in accuracy if trained with additional data.

ADDITIONAL DATA

With more data, it is expected that the NN models can perform better than they do in the previous sub-models. Thus, three more sub-models are created using the same parameters as the previous models but include additional data. The new series is called the 'c' series. The data included was from three new GPS 1 sites.

To test how these models performed with additional data three new sub-models are developed. These sub-models used the additional data from three GPS 1 sites.

Sub-Model 1c This is the same as Sub-Model 1b with the exception of the three GPS 1 sites added to the training set.

Sub-Model 2c This is the same as Sub-Model 2b with the exception of the three GPS 1 sites added to the training set.

Sub-Model 3c This is the same as Sub-Model 3b with the exception of the three GPS 1 sites added to the training set.

Table 24 shows the test results of the NN models and table 25 gives the sum-squared errors of estimated values in table 24 compared to the actual values.

Table 24. Neural Network Models Predicted Results Using Additional Data

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
Sub-Model 1c	0.9006	0.9307	0.9816	1.1	1.2949	1.4815	1.6281	1.1014	1.1798	1.2787	1.3985
Sub-model 2c	1.3888	1.3912	1.4254	1.4339	1.4564	1.4775	1.6587	1.0832	1.1631	1.109	1.24
Sub-Model 3c	1.3737	1.3931	1.427	1.45	1.4846	1.4862	1.4743	1.23	1.385	1.213	1.2563
Actual	1.3486	1.3914	1.3838	1.4022	1.4446	1.4722	1.486	1.1462	1.0924	1.2086	1.268

Table 25. Sum Squared Error (SSE) for test results shown in table 24

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	SEE	RMSE
Sub-Model 1c	0.2007	0.2122	0.1618	0.0913	0.0224	0.0001	0.0202	0.0020	0.0076	0.0049	0.0170	0.7403	0.2720
Sub-model 2c	0.0016	0.0000	0.0017	0.0010	0.0001	0.0000	0.0298	0.0040	0.0050	0.0099	0.0008	0.0540	0.0730
Sub-Model 3c	0.0006	0.0000	0.0019	0.0023	0.0016	0.0002	0.0001	0.0070	0.0856	0.0000	0.0001	0.0995	0.1000

The linear regression models are also developed using the same additional data that is used to train the NNs sub-models in the 'c' series. Because the stepwise and standard multiple linear regression are very similar, only the standard multiple linear regression is used in this section with the additional data. Table 24 shows the test results of the regression models and table 25 gives the sum-squared error of table 24.

Table 26. Linear Regression Sub-model Results with Additional Data

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11
Sub-Model 1c	1.1040	1.1340	1.1650	1.2100	1.2630	1.3110	1.4230	1.2560	1.2910	1.3430	1.3700
Sub-model 2c	1.3810	1.3760	1.4250	1.4570	1.5010	1.5360	1.7270	1.0980	1.1970	1.1850	1.2580
Sub-Model 3c	1.5320	1.5270	1.5730	1.5830	1.6070	1.6590	1.8020	1.2610	1.3620	1.3540	1.4100
Actual	1.3486	1.3914	1.3838	1.4022	1.4446	1.4722	1.4860	1.1462	1.0924	1.2086	1.2680

Table 27. Sum Squared Error for Results of table 26

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	SSE	RMSE
Sub-Model 1c	0.0599	0.066	0.0478	0.0368	0.0328	0.0259	0.004	0.0121	0.0394	0.018	0.0105	0.3533	0.188
Sub-model 2c	0.001	0.0002	0.0017	0.003	0.0031	0.004	0.058	0.0023	0.0109	0.0005	0.0001	0.085	0.092
Sub-Model 3c	0.0337	0.0183	0.036	0.0326	0.0265	0.0349	0.0999	0.0133	0.0726	0.0212	0.0202	0.4092	0.202

Sub-Model 1c, which has only three types of input vectors, performed worse for the NN, and gives relatively unchanged results for linear regression when compared to sub-model 1b. Sub-Model 2c gives the best results for both NN and linear regression. The sum-squared errors for both are lower than those for the sub-models in the 'b' series. This improvement in the model is due to having more input vectors than sub-model 1c. Generally the more input vectors, the more data is needed to train a NN. With this additional data, better results were obtained.

On the other hand, sub-model 3c produced larger errors for both linear regression and NN than the 'b' series. An explanation of this could be that Model #3 does not use ESAL data. Therefore it may not be able to explain the variations the ESALs component in the IRI data.

GENERAL REGRESSION NEURAL NETWORKS

In some of the models, linear regression performed as well as the backpropagation NN models; so, general regression neural networks (GRNN) are also tested to see if GRNN produced better results than backpropagation NN. Specht states that GRNN could be a better alternative to backpropagation for certain cases.[4] GRNN trains faster because it uses a one-pass training algorithm while backpropagation uses many passes or training epochs. Regression uses a dependant variable, Y, and independent variables, X_i. There are also unknown parameters, a_i. The GRNN training algorithm uses a probabilistic density function to determine the a_i values from the input vectors. This form of training can be used to determine linear and non-linear functions.

The 'b' series and the 'c' series are both tested using a GRNN. The results of training are given in table 28. The results indicate that GRNN did not perform as well as the standard linear regression or the backpropagation NN. There are a few drawbacks to GRNN networks, which help to explain these results. The estimate is controlled by the bounds of the minimum and maximum observations. An accurate estimate cannot be produced for cases that has not been seen.

Unfortunately, the test data is all within the bounds of what is being used for training. This does not account for the difference in error. Since this is a function approximation, it tends to smooth functions and thus will not converge to local max and minimum. This is probably not the case for pavements because they do not behave erratic enough to cause these local peaks. Another reason for the GRNN's poor performance compared to the backpropagation NN may be due to the type of training adopted by GRNN. The small data sets and multiple epoch training adopted by backpropagation algorithm may be more suitable for our database which has a limited number of data points.

Table 28. Testing Results of GRNN estimation using the test data

	SSE	RMSE
Sub-Model 1b	0.807969	0.284248
Sub-Model 2b	0.581686	0.241182
Sub-Model 3b	0.896429	0.299404
Sub-Model 1c	0.838612	0.289588
Sub-Model 2c	0.534082	0.231102
Sub-Model 3c	0.691628	0.262988

RUTGERS' PAVEMENT DETERIORATION ESTIMATION MODELS

RUTGERS' MODELS

This section selects the best pavement deterioration prediction models from all the models developed and presents them in detail. The goal of this section is to allow the reader to observe and understand more closely the best models developed using both multiple linear regression and backpropagation NN's.

For the purpose of comparing models and identifying the best NN and linear regression models, each was given a name. The best NN model is selected to be Basic Model 2. It exhibits the second best results in sub-model b, as well as the best results with the additional data in Sub-model 2c. The NN Basic Model 2 tested in the 'b' and 'c' series is called the RITS NN Model.

In order to be able to reproduce this model and to understand the NN model better, a longhand calculation is performed. You can refer figure 3 for the visual representation of the NN architecture. Tables 29 through 30 contain the weights and biases for the RITS NN model.

Table 29. WEIGHTS FOR THE INPUT LAYER OF THE RITS NN MODEL

Weight's Target Node	***WEIGHT'S ORIGIN***				
	1	**2**	**3**	**4**	**5**
1	1.2111	0.02	-0.0161	0.0822	0.0282
2	-5.9494	0.099	1.7012	-0.0747	0.1173
3	2.8307	0.0522	-0.7862	-0.2387	-0.1166
4	1.1258	-2.3302	1.0154	-5.3858	-2.1901
5	4.8948	-0.5412	1.2339	-2.4529	-0.9398

Note: In the notation in figure 1-1 the origin comes before the target.

Example: $W^1_{1,1}$ = 1.2111, $W^1_{3,4}$= -0.2387

Table 30. BIASES FOR ALL THE LAYERS OF THE RITS NN MODEL

Layer	*Node 1*	*Node 2*	*Node 3*	*Node 4*	*Node5*
1	2.262	1.472	-1.33	-2.26	-0.521
2	5.9256	0.7037	3.5716	-	-
3	1.5698	-	-	-	-

Table 31. WEIGHTS FOR THE HIDDEN LAYER OF THE RITS NN MODEL

Weight's Target Node	***WEIGHT'S ORIGIN***				
	1	**2**	**3**	**4**	**5**
1	-3.1957	2.3895	7.7277	5.6957	0.9123
2	-3.6448	-0.5572	2.5455	0.9412	-0.0447
3	5.1541	-4.3272	0.2448	0.307	0.8164

Table 32. WEIGHTS FOR THE OUTPUT LAYER OF THE RITS NN MODEL

Weight's Target Node	***WEIGHT'S ORIGIN***		
	1	**2**	**3**
1	1.2285	-2.2312	1.0732

Below is the matrix form of the NN model using the above weights and biases and the first data point that is used to test all the models. Table 33 has the actual values of the matrix products and sums.

$$
\begin{array}{cccc}
\text{Weights in input layer} & \text{Input} & \text{Biases in first layer} & \\
\begin{pmatrix}
1.2111 & 0.0200 & -0.0161 & 0.0822 & 0.0282 \\
-5.9494 & 0.0990 & 1.7012 & -0.0747 & 0.1173 \\
2.8307 & 0.0522 & -0.7862 & -0.2387 & -0.1166 \\
1.1258 & -2.3302 & 1.0154 & -5.3858 & -2.1901 \\
4.8948 & -0.5412 & 1.2339 & -2.4529 & -0.9398
\end{pmatrix} *
&
\begin{pmatrix} 1.345 \\ 1.903 \\ 4.5 \\ 0.964 \\ 1.704 \end{pmatrix}
+ &
\begin{pmatrix} -2.262 \\ 1.472 \\ -1.330 \\ -2.260 \\ -0.521 \end{pmatrix}
= &
\begin{pmatrix} -0.539 \\ 1.444 \\ -1.394 \\ -9.616 \\ 6.585 \end{pmatrix}
\end{array}
$$

Layer output

$$
\text{Tansig} \begin{pmatrix} -0.539 \\ 1.444 \\ -1.394 \\ -9.616 \\ 6.585 \end{pmatrix} = \begin{pmatrix} -0.492 \\ 0.895 \\ -0.895 \\ -1.000 \\ 1.000 \end{pmatrix}
$$

<u>Transfer Function:</u>

$$
\text{Tansig(n)} = \left(2 / 1 + \exp(-2 * n) \right) - 1
$$

n = a numeric output of a node

$$
\begin{array}{cccc}
\text{Weights in first hidden layer} & \text{Input from input layer} & & \\
\begin{pmatrix}
-3.1957 & 2.3895 & 7.7277 & 5.6957 & 0.9123 \\
-3.6448 & -0.5572 & 2.5455 & 0.9412 & -0.0447 \\
5.1541 & -4.3272 & 0.2448 & 0.3070 & 0.8164
\end{pmatrix} *
&
\begin{pmatrix} - \\ 0.492 \\ 0.895 \\ -0.895 \\ -1.000 \end{pmatrix}
+ &
\begin{pmatrix} 5.9256 \\ 0.7037 \\ 3.5716 \end{pmatrix}
= &
\begin{pmatrix} -1.980 \\ -1.238 \\ -2.542 \end{pmatrix}
\end{array}
$$

$$\text{Logsig}*\begin{pmatrix}-1.980\\-1.238\\-2.542\end{pmatrix}=\begin{pmatrix}0.1213\\0.2248\\0.0729\end{pmatrix}$$

<u>*Transfer Function:*</u>

$$\text{Logsig}(n) = \left(\frac{1}{1+\exp(-n)}\right)$$

n = a numeric output of a node

Weights in output layer; Input from hidden layer; Bias in the output layer

$$\begin{bmatrix}+1.2285 & -2.2312 & 0.0732\end{bmatrix}*\begin{pmatrix}0.1213\\0.2248\\0.0729\end{pmatrix}+\begin{pmatrix}1.5698\end{pmatrix}=\begin{pmatrix}1.2955\end{pmatrix}$$

The output of the NN model using the same architecture gives the IRI value of 1.2956. The hand calculations give a value of 1.2955. The 0.0001 difference is the result of the rounding error by the Matlab Code. The above hand calculations show the procedure using the NN weight and biases that can be used to calculate the IRI of a site without using the Matlab NN training program. The best linear regression model is also determined by the results of the additional data experiments. Even though Model 3 gives better results than Model 2 in the 'a' and 'b' series, Model 2 is chosen as the basis of RITS model. This is because of better performance of Sub-model 2c with the additional data. The linear regression model 2 used in sub-model 2b and 2c is called the RITS LR Model.

RITS LR MODEL

$$Y(IRI) = B_0 + B_1X_1 + B_3X_3 + B_5X_5 + B_6X_6 + B_7X_7 \quad [26]$$

$$Y(IRI) = -0.056 + 1.066\,X_1 + 0.0018\,X_3 - 0.006\,X_5 + 0.027\,X_6 + 0.014\,X_7 \quad [30]$$

Table 33. EXCEL IMPLEMENTATION OF NN CALCULATIONS

Input Layer

Input	Weights	Product	Sum	Bias	Sum	Tran. Func.
NODE 1						
1.0154	1.211	1.2297				
0.8	0.02	0.016				
7.85	-0.016	-0.1264				
2.1918	0.082	0.1802				
1.1232	0.028	0.0317	1.331	-2.26	-0.93	-0.731
NODE 2						
1.0154	-5.949	-6.041				
0.8	0.099	0.0792				
7.85	1.701	13.354				
2.1918	-0.075	-0.1637				
1.1232	0.117	0.1317	7.361	1.473	8.834	1
NODE 3						
1.0154	2.831	2.8743				
0.8	0.052	0.0418				
7.85	-0.786	-6.1717				
2.1918	-0.239	-0.5232				
1.1232	-0.117	-0.131	-3.91	-1.33	-5.24	-0.999
NODE 4						
1.0154	1.126	1.1431				
0.8	-2.33	-1.8642				
7.85	1.015	7.9709				
2.1918	-5.386	-11.804				
1.1232	-2.19	-2.4599	-7.01	-2.26	-9.28	-1.00
NODE 5						
1.0154	4.895	4.9701				
0.8	-0.541	-0.433				
7.85	1.234	9.6861				
2.1918	-2.453	-5.3762				
1.1232	-0.94	-1.0556	7.791	-0.52	7.27	1.000

Hidden Layer

Input	Weights	Product	Sum	Bias	Sum	Tran. Func.
NODE 1						
-0.731	-3.196	2.33611				
1	2.3895	2.3895				
-0.9999	7.7277	-7.72727				
-1	5.6957	-5.6957				
1	0.9123	0.9123	-7.785	5.9256	-1.859	0.1348
NODE 2						
-0.731	-3.645	2.66441				
1	-0.557	-0.5572				
-0.9999	2.5455	-2.54536				
-1	0.9412	-0.9412				
1	-0.045	-0.0447	-1.424	0.7037	-0.72	0.3273
NODE 3						
-0.731	5.1541	-3.76773				
1	-4.327	-4.3272				
-0.9999	0.2448	-0.24479				
-1	0.307	-0.307				
1	0.8164	0.8164	-7.83	3.5716	-4.259	0.0139

Output Layer

Input	Weigts	Product	Sum	Bias	Sum
NODE 1					
0.1348	1.2285	0.16556			
0.3273	-2.231	-0.73031			
0.0139	1.0732	0.01496	-0.55	1.5698	1.02

NN CALCULATED IRI 1.0200

PAVEMENT DETERIORATION MODELS

There are a few existing models as discussed in the literature review that can be used for comparison with the RITS Models selected in the previous section. To conduct a fair comparison, these existing models are tested using the same eleven test points that are used in testing the models developed in this project. In some cases the feasibility of the models for use in a Highway Pavement Management Systems, HPMS, is further discussed.

FHWA MODEL [12]

The FWHA model is investigated using the data received from the LTPP IMS database, more specifically using the eleven test points previously used to test the RITS models. The data obtained from the FHWA database had to be complimented with additional data of the model's input variables to be able to apply this model. The first drawback is that only one of the eleven test points could be estimated due the unavailability of data in the original FHWA database. A large amount of environmental data is not currently available for the most recent years. Only data up to 1990 is currently recorded in their relative environmental fields of the database. Since the test data entries start in the year 1990 the data points available for the test are immediately reduced to two points. The second site's data entries in the database are missing the gradations for its layers, thus only one point remains for comparing the results. Table 35 shows this missing information.

The second drawback is that this model requires many variables that are difficult to obtain for many sites. Because of the amount of data required, this model is complicated and costly to implement into a Pavement Management System. The environmental data in this model takes time to obtain and process. For this reason, the model could not be fully tested in this case. Even after approximately eight years of data collection the data has not been completely processed and entered into the LTPP database. Because of the length of time to enter data into a federal database, it is assumed that it will also take an equal amount of time for a state agency to process the same data. More practical models should be derived without using environmental data.

Another problem is that a few of these variables are difficult to predict. This makes this model only applicable for present validation of values. For example, trying to predict the annual precipitation in the next five to ten years and the days below 32 degrees in each year is quite difficult. Weather forecasters have a difficult time predicting what will happen in the next week. The next several years would be even more difficult to forecast. Traffic is another factor that is difficult to prefigure, however, it can be predicted easier and more accurate than the weather.

Conversations with the developers of the Federal models, addressed the concerns about the missing climatic data. The annual precipitation and the days under 32 degrees could be taken as an average of the historical data. [25] These values are taken from the DataPave97 data that has already calculated those values. The traffic data, KESALs/yr, which is used in the model, are estimated using an exponential growth type model. [(12)] Table 35 gives the total variables used to validate the FHWA report's model and the missing gradation values.

Table 36 shows the data obtained from the developers. This data is used to develop the FHWA model for these two sites. This data is directly taken from the developers of that model, and is not directly obtained from the LTPP database. The reason for using data obtained from the developers is the unavailability of data when the model was originally developed. It would be unfair to compare this model to other models without first knowing the differences in the data.

There are two factors that can cause differences between the two sets of data. First, there is only four years of data available for the FHWA model when it was first developed, so any data after that time might have been collected using a different data collection procedure. This is the case where the allowable standard deviation of profile runs is changed from 3% to 2% at the beginning of the LTPP program. This can definitely affect the models. Second, much of the data has not yet undergone the statistical processing. Therefore, some values could have been changed or deleted from the database after further statistical processing. Information in the database can be different or missing from the data that the developers have used to develop those models.

Finally the results of the FHWA model are compared to the RITS Models. Tables 37 and 38 compare the results of those models. The results shown in this table indicate the FHWA model that produces higher Squared Error. The FHWA model has more input parameters, and is more complicated. The simpler models (RITS Model), in terms of input variables, provide better results and would be easier to implement into a pavement management system.

Table 34. Data retrieved from the ITPP database for validation of FHWA model [26]

SHRP ID	STATE CODE	RUN DATE	NO_4 PASSING	Annual Percip.	Day -32	AC Thick	Base Thick	KESAL 18K TOTAL	SN	AGE
1034	34	17-Nov-90	97	169	57.78	2	10	187	4.5	5.2137
1034	34	07-Sep-91	99	N/A	N/A	2	10	215	4.5	6.0192
1034	34	20-Jun-92		N/A	N/A	2	10	243	4.5	6.8055
1034	34	11-Jun-93		N/A	N/A	2	10	N/A	4.5	7.7808
1034	34	10-Jun-94		N/A	N/A	2	10	N/A	4.5	8.7781
1034	34	24-Jun-95		N/A	N/A	2	10	N/A	4.5	9.8164
1034	34	09-Dec-97		N/A	N/A	2	10	N/A	4.5	12.279
3101	47	17-Jun-91	N/A	N/A	N/A	3.8	4.8	39	4.36	11.466
3101	47	27-Aug-92	N/A	N/A	N/A	3.8	4.8	38	4.36	12.663
3101	47	10-Jun-94		N/A	N/A	3.8	4.8	N/A	4.36	14.449
3101	47	10-Apr-95		N/A	N/A	3.8	4.8	N/A	4.36	15.282

Note: This data is what was available at the time the data was requested, summer 1998

Table 35. Partial data used for validation of FHWA model [26, 27]

SHRP ID	STATE CODE	RUN DATE	NO_4 PASSING	Annual Percip.	Day -32	AC Thick	Base Thick	KESAL 18K TOTAL	SN	AGE
1034	34	17-Nov-90	97	169	57.78	2	10	187	4.5	5.2137
1034	34	07-Sep-91	99	44.23	86.17	2	10	215	4.5	6.0192
1034	34	20-Jun-92		44.23	86.17	2	10	243	4.5	6.8055
1034	34	11-Jun-93		44.23	86.17	2	10	279.372	4.5	7.7808
1034	34	10-Jun-94		44.23	86.17	2	10	317.0872	4.5	8.7781
1034	34	24-Jun-95		44.23	86.17	2	10	359.894	4.5	9.8164
1034	34	09-Dec-97		44.23	86.17	2	10	463.6244	4.5	12.279
3101	47	17-Jun-91	N/A	52.52	86.27	3.8	4.8	39	4.36	11.466
3101	47	27-Aug-92	N/A	52.52	86.27	3.8	4.8	38	4.36	12.663
3101	47	10-Jun-94		52.52	86.27	3.8	4.8	48	4.36	14.449
3101	47	10-Apr-95		52.52	86.27	3.8	4.8	52	4.36	15.282

Table 36. Data used for validation of FHWA model [25]

SHRP ID	STATE CODE	RUN DATE	NO_4 PASSING	Annual Percip.	Day -32	AC Thick	Base Thick	KESAL 18K TOTAL	SN	AGE
1034	34	17-Nov-90	98	44	86	2	10	187	4.5	5.2137
1034	34	07-Sep-91		44	86	2	10	215	4.5	6.0192
1034	34	20-Jun-92		44	86	2	10	243	4.5	6.8055
1034	34	11-Jun-93		44	86	2	10	279.372	4.5	7.7808
1034	34	10-Jun-94		44	86	2	10	317.0872	4.5	8.7781
1034	34	24-Jun-95		44	86	2	10	359.894	4.5	9.8164
1034	34	09-Dec-97		44	86	2	10	463.6244	4.5	12.279
3101	47	17-Jun-91	96	53	86	9.5	5.5	39	4.36	11.466
3101	47	27-Aug-92		53	86	9.5	5.5	38	4.36	12.663
3101	47	10-Jun-94		53	86	9.5	5.5	48	4.36	14.449
3101	47	10-Apr-95		53	86	9.5	5.5	52	4.36	15.282

Table 37. Testing results of the FHWA model using data from table 36

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	
RITS LR Model	1.381	1.376	1.425	1.457	1.501	1.536	1.727	1.098	1.197	1.185	1.258
FWHA model	0.9308	0.9597	0.9897	1.0294	1.0731	1.1219	1.2523	1.0518	1.105	1.1921	1.236
Actual	1.3486	1.3914	1.3838	1.4022	1.4446	1.4722	1.486	1.1462	1.0924	1.2086	1.268

Table 38. Comparison on sum squared errors of both models

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	Overall S.S.E.
RITS LR Model	0.001	0.0002	0.0017	0.003	0.0031	0.004	0.058	0.0023	0.0109	0.0005	0.0001	0.085
FWHA model	0.1745	0.1864	0.1553	0.139	0.138	0.1227	0.0546	0.0089	0.0002	0.0003	0.001	0.9808

PAVEMENT DETERIORATION MODEL BY LEE [14]

A recent Transportation Research Record (TRR) by Lee describes the need for simplified models that can predict future trends of the pavements with a minimal amount of data.[14] Unlike the other model that predicted IRI, the model by Lee is developed to calculate Present Serviceability Rating, PSR. In this report there are models using five basic types of pavements namely, flexible, composite, jointed plain cement pavements (JPCP), jointed reinforced concrete pavements (JRCP), and continuous reinforced concrete pavement (CRCP). The data used to develop these models come from the Highway Performance Monitoring System (HPMS) and is supplemented with data from the Illinois Department of Transportation [14]. The flexible model is used to predict the PSR for the types of pavements that the RITS models developed to predict.

These models by Lee are also tested with the eleven test data points used to test the RITS models. The model [15] with the adjustment factors also used the equations [15 & 16] to predict the age and the CESALs. Those equations are only used to predict age and CESALS for the first data point and then adjusted by the known change in time and ESALs for later data points. This procedure was adopted from the explanation of how the data was prepared in Lee et. al.[14]. Since Lee used only the roughness indicators of PSR, the output in table 39 has to be converted into IRI using equation 13 that correlates IRI and PSR. [18] The correlation between IRI and PSR is given by:

$$PSR = 5 * e^{(-0.0026*IRI)} \qquad [13]$$

This above formula gives an IRI value in terms of cm/km. The results of the conversion are shown in table 41. Table 42 gives the standard error for the results of this model using the actual data from the LTPP database.

The error is higher than all the other models investigated so far. This fact is also pointed out in Lee et. al.[14] The R^2 value of 0.52 from the report, means that it can only explain about half the variation in the data. In addition this model used all AC pavements and did not separate them into categories, GPS-1, GPS-2, GPS-6 (table 1). Figure 17 shows the Lee model compared to the perfect fit (45 degree line).

Table 39. PSR Predicted for the eleven test points using the Lee Model [14]

STATE CODE	SHRP ID	PSR (predicted)	
		Original	With Adjustment Factor
34	1034	3.136669	3.015301
34	1034	2.962869	2.789777
34	1034	2.794196	2.743146
34	1034	2.528377	2.379117
34	1034	2.223608	2.139788
34	1034	1.984971	2.372318
34	1034	1.474213	2.087751
47	3101	2.892111	3.425283
47	3101	2.786978	3.421431
47	3101	2.643436	3.438719
47	3101	2.500016	2.887399

Table 40. IRI converted from the PSR values in table 39

STATE CODE	SHRP ID	IRI (predicted m/km)	
		Original	With Adjustment Factor
34	1034	1.793226	1.9450
34	1034	2.012469	2.1619
34	1034	2.237906	2.2753
34	1034	2.622393	2.5211
34	1034	3.116419	2.7999
34	1034	3.553061	3.0008
34	1034	4.697214	3.7624
47	3101	2.105435	1.4547
47	3101	2.247854	1.5974
47	3101	2.451233	1.7190
47	3101	2.665781	1.7831

Table 41. Sum squared errors for the lee model [14]

Test Data	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	
Model output	1.7932	2.0125	2.2379	2.6224	3.1164	3.5531	4.6972	2.1054	2.2479	2.451	2.665	
AF Model output	1.945	2.1619	2.2753	2.5211	2.7999	3.0008	3.7624	1.4547	1.5974	1.719	1.783	
Actual	1.3486	1.3914	1.3838	1.4022	1.4446	1.4722	1.486	1.1462	1.0924	1.208	1.268	
Sum Squared Errors												Overall
S.S.E.												
Original model	0.1977	0.3858	0.7295	1.4889	2.7949	4.3301	10.312	0.9201	1.3352	1.544	1.953	25.9918
AF model	0.3557	0.5937	0.7948	1.2519	1.8368	2.3366	5.182	0.0952	0.255	0.260	0.265	13.2276

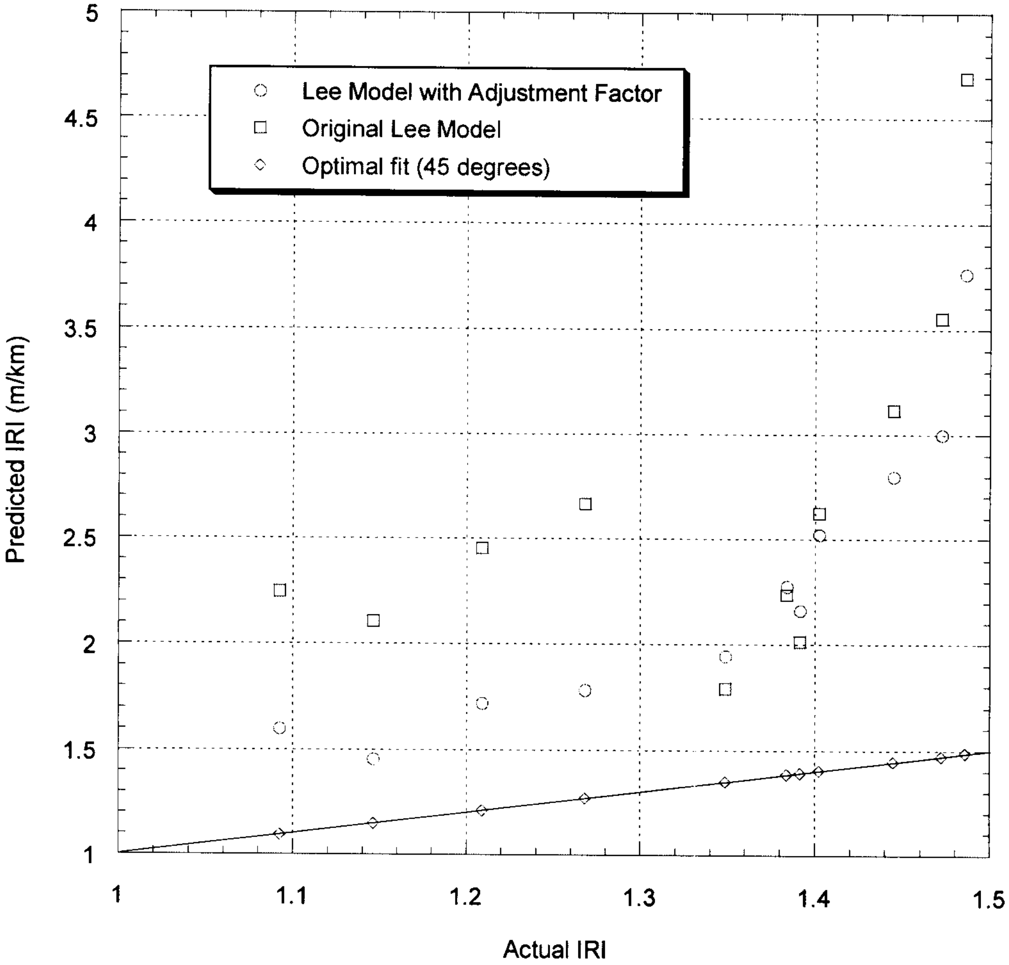

Figure 17. Results of the Lee model [14]

DEFAULT PAVEMENT MANAGEMENT SYSTEM MODELS [17]

Using eleven test points the default model is also tested. The results are given in both table 42 and figure 18. The default model is only intended for use as a benchmark for deterioration.

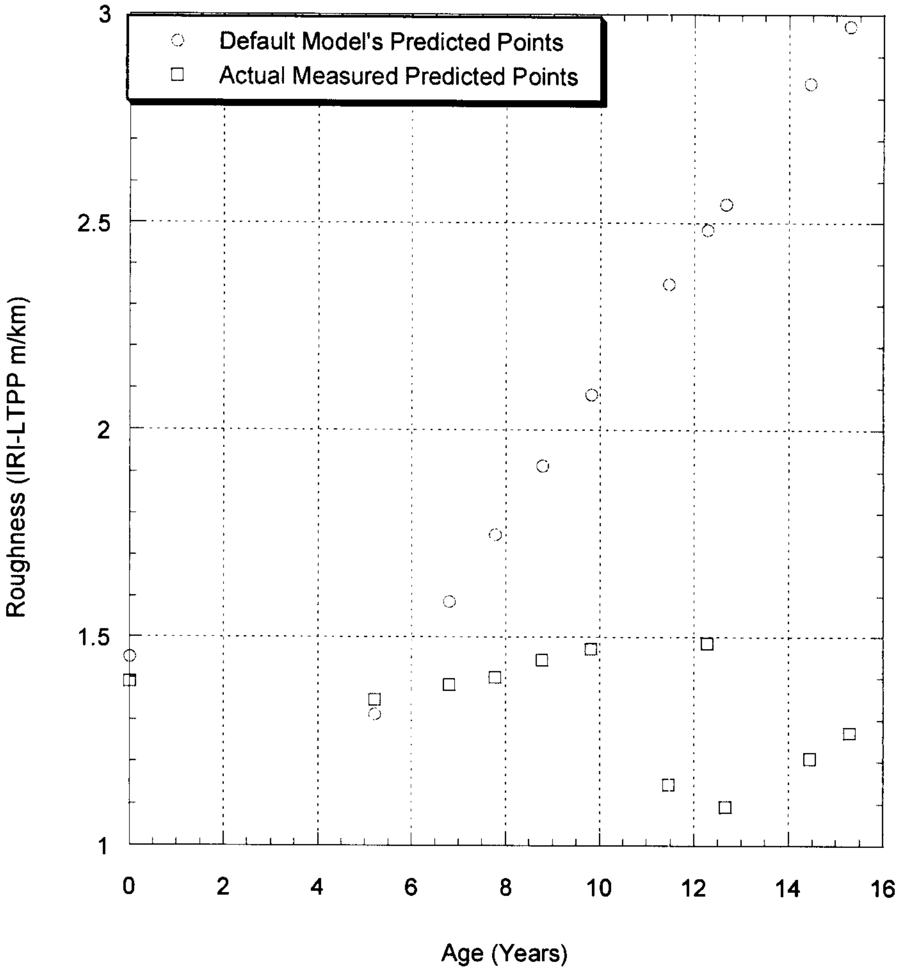

Figure 18. Predicted vs. actual roughness for the eleven random test data points using the default Pavement Management Model

Table 42. Testing results of the default HPMS model

Test Data	*D1*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*D10*	*D11*	*S.S.E*
Predicted IRI	1.3137	1.453	1.5865	1.7497	1.9144	2.0844	2.4844	2.3525	2.5466	2.8364	2.972	
Actual IRI	1.3486	1.3914	1.3838	1.4022	1.4446	1.4722	1.486	1.1462	1.0924	1.2086	1.268	
Squared Error	0.0012	0.0038	0.0411	0.1208	0.2207	0.3748	0.9968	1.4552	2.1147	2.6497	2.9036	10.882

CONCLUSIONS

There is potential for using the RITS models in a pavement management system as default models for predicting future roadway roughness.The need for a further validation of these models using actual data, is apparent. There is a prospect that models of rehabilitated pavements can be improved and incorporated into the models developed here.

Tables 43 & 44 and figure 19 summarize all the models from this section along with the RITS models. Those tables show that the RITS models outperform the other models by at least a factor of 10. Figure 19 shows the actual measured IRI values as to compare visually the accuracy of each model.

Table 43. Summarized test results of all the models

Test Data	*D1*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*		*D9*	*D10*	*D11*
RITS NN Model	1.3888	1.3912	1.4254	1.4339	1.4564	1.4775	1.6587	1.0832	1.1631	1.109	1.24
RITS LR Model	1.381	1.376	1.425	1.457	1.501	1.536	1.727	1.098	1.197	1.185	1.258
FHWA Model	0.9308	0.9597	0.9897	1.0294	1.0731	1.1219	1.2523	1.0518	1.105	1.1921	1.236
Lee Model	1.945	2.1619	2.2753	2.5211	2.7999	3.0008	3.7624	1.4547	1.5974	1.719	1.7831
NJDOT HPMS Model	1.3137	1.453	1.5865	1.7497	1.9144	2.0844	2.4844	2.3525	2.5466	2.8364	2.972
Actual	1.3486	1.3914	1.3838	1.4022	1.4446	1.4722	1.486	1.1462	1.0924	1.2086	1.268

Table 44. Squared error for all the models for the test data

Test Data	*D1*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*		*D11*	Overall S.S.E.
RITS NN Model	0.0016	0.0000	0.0017	0.0010	0.0001	0.0000	0.0298	0.0040	0.0050	0.0099	0.0008	0.054
RITS LR Model	0.0010	0.0002	0.0017	0.0030	0.0032	0.0041	0.0581	0.0023	0.0109	0.0006	0.0001	0.085
FHWA Model	0.1746	0.1864	0.1553	0.1390	0.1380	0.1227	0.0546	0.0089	0.0002	0.0003	0.0010	0.981
Lee Model	0.3557	0.5937	0.7948	1.2519	1.8368	2.3366	5.1820	0.0952	0.2550	0.2605	0.2653	13.228
NJDOT HPMS Model	0.0012	0.0038	0.0411	0.1208	0.2207	0.3748	0.9968	1.4552	2.1147	2.6497	2.9036	10.882

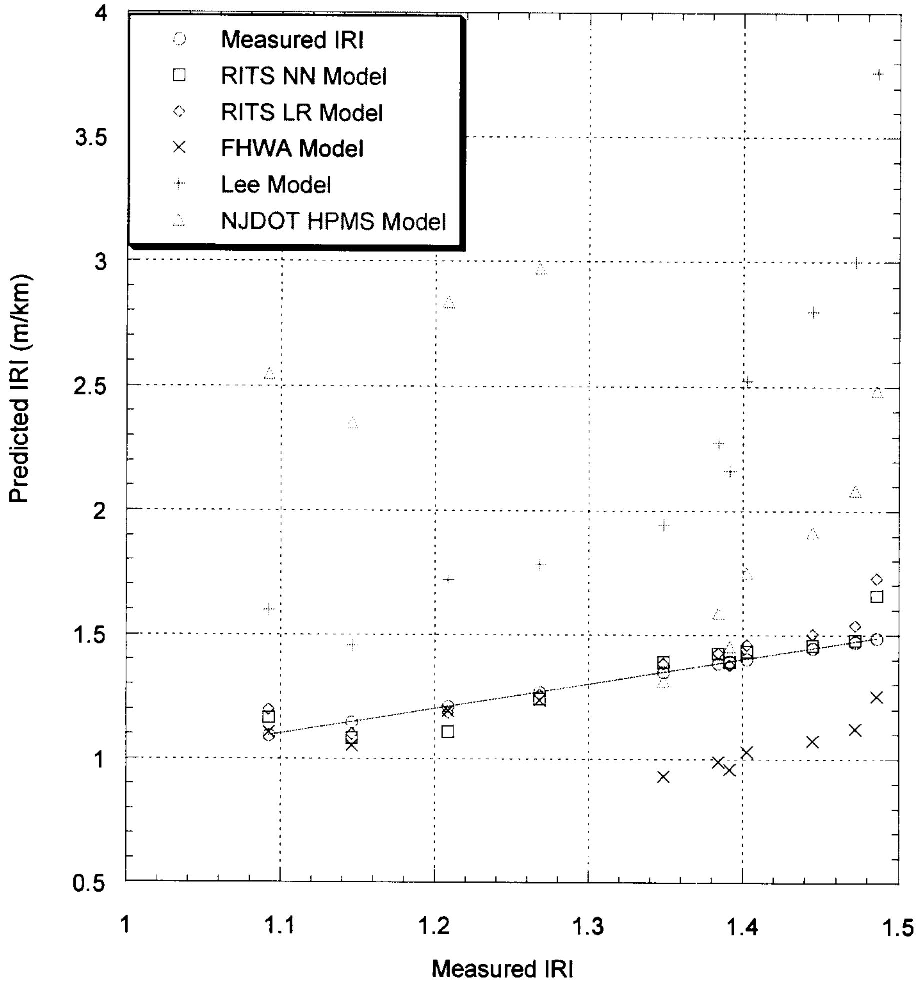

Figure 19. Plot of all pavement models' result

COMPARING RUTGER'S MODELS WITH EXISTING PAVEMENT DETERIORATION MODELS

NEW JERSEY PAVEMENT MANAGEMENT SYSTEM DATA

More data is needed for further validation of the RITS models. The New Jersey Department of Transportation's Pavement Management System provided this data. The acquired data enables us to test those models that were developed. We can also confirm the feasibility of using the RITS models in this Pavement Management System. Roughness measurements for seventeen different roadway sections in New Jersey were requested and received.

After reviewing the initial data from these sections, the SN and the traffic data is then requested. The NJDOT permitted researchers from Rutgers, under their supervision, access to the pavement Management System. The as-built portion of the Pavement Management Database contains the existing layer structures of the pavements. It shows the thickness, the material type, and the date the pavement is constructed. Unfortunately, there are several holes in the database. Large sections of roadway are missing. Many of the existing roads have unknown structures (i.e. historical data is missing) and many rehabilitation of pavements have not yet been entered into the database.

The interstate highways have better potentials of providing the information for the RITS models, but even the data for those roadways were not completely entered in the database. Some of the required traffic data is taken from the pavement design parameters also in the as-built database. The remaining traffic data is taken from traffic count data on the NJDOT webpage. [28] After reviewing the seventeen initial sites, three of the sites had sufficient data for the RITS models.

The three sites, for which appropriate data can be obtained, are considered relatively new construction. Still two sites are classified as being rehabilitated, while the third is a new construction. The RITS models are applied using pavements with original pavement structures. None of the sites used for development of the RITS Models contained rehabilitated structures. It is uncertain that how the RITS model will behave with rehabilitated sites. The following sections present the performance of RITS Models with data from those sites.

INITIAL IRI OR IRI INDICES

This section discusses the viability of employing a measured initial IRI input variable instead of the estimated or calculated IRI values..

This reasoning is explained by the fact that initial pavement conditions, such as temperature of the pavement during compaction, construction techniques and practices control the initial roughness of a pavement and play a role in the overall life of a pavement

Employing RITS models validates using a measured IRI over an estimated one. A Calculated IRI usually gives one IRI value for one site, whereas the measured IRI can give a different IRI values for 0.2 mile segment of a site. Table 45 shows the results of the deviation in new pavement roughness for sites where IRI is measured every 0.2 miles. The 0.2 miles section is used since the NJPMS contains roughness data at this interval. It is shown that for the same pavement, constructed at the same time, using the same material, the initial roughness has a large variation. This comparison proves that the IRI indices used in the RITS models are needed to account for this initial variation.

Table 45. Deviation of initial IRI in new pavements in New Jersey

Route	Mile Post		Directions	Average IRI	Standard deviation	% Variation
	Begin	End		(m/km)		
3	5	8	E & W	1.226933	0.291989	23.79831
17	23.4	26.4	N & S	1.385406	0.265091	19.13457
31	34	39	N	0.992396	0.13827	13.93293
	3.8	4.8	N & S	0.954082	0.316446	33.16758
46	58	60.2	E & W	1.002411	0.361303	36.04335
78	6	9.6	E & W	0.964188	0.12017	12.46339
80	7.6	12.8	E & W	0.872591	0.125294	14.35888
295	62.4	68	N & S	0.918638	0.249926	27.20615

RESULTS USING NJDOT PAVEMENT MANAGEMENT DATA

The pavement management data was used to test the RITS LR and the RITS NN models. As stated earlier there are some data limitations on the sites used for testing these models. Fortunately three stretches of highway could be tested. The first section of highway is on Interstate 78 (I-78). The pavement at this site is a new asphalt pavement (GPS 2 classification). The other two sections are rehabilitated sections on Interstate 80 (I-80). One of these rehabilitated sections is a new asphalt concrete layer on an existing concrete pavement (GPS 7 classification) and the other is a new asphalt concrete layer on an existing asphalt concrete pavement (GPS 6 classification).

The three stretches of highway have multiple sections that are tested by each model. The I-78 site has 92 sections that are tested, the I-80 asphalt on asphalt has 41 sections that are tested and the I-80 asphalt on concrete has 26 sections to use for testing the models. Each stretch of highway is a true test for each model because it tests multiple sections and not just a few points. This give reasons for significant deviations in table 46.

Figure 20 shows the results from I-78. Figure 21 shows the results of the models' prediction versus the actual roughness for the asphalt on asphalt pavement sections of I-80. Figure 22 shows the asphalt on concrete pavement's results. The results of these figures are shown as a ratio of IRI actual to that predicted by the individual models. The 45° slope of the Actual IRI on these figures represent the measured IRI. This line is the target for all the models. In figures 20, 21 and 22, the closer the other model's points to that line, the better the model predicts the IRI. Table 46 summarizes the results of these three sites and it shows the standard error of each model.

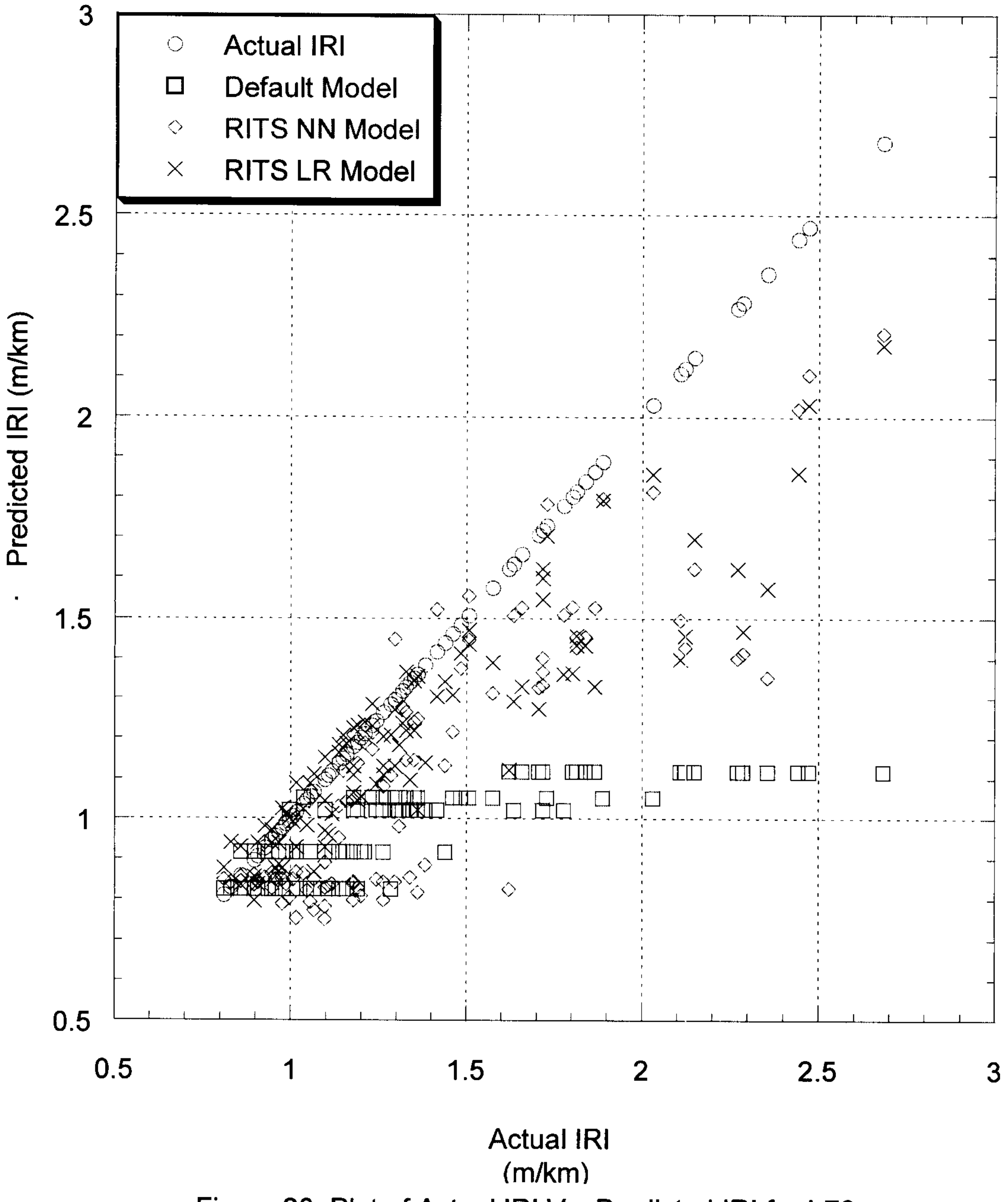

Figure 20. Plot of Actual IRI Vs. Predicted IRI for I-78

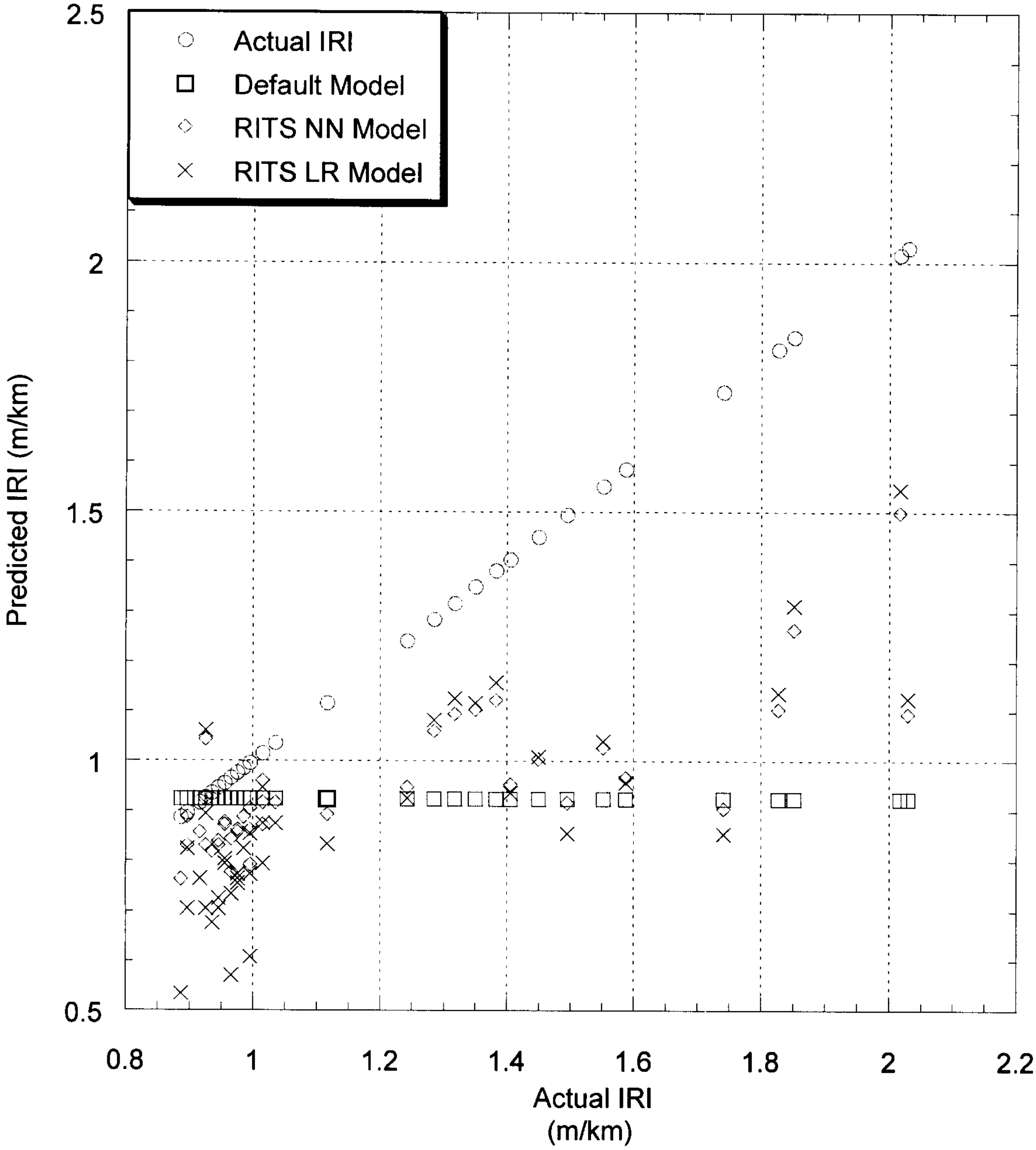

Figure 21. Plot of Actual IRI Vs. Predicted IRI for I-80 (Asphalt on Asphalt)

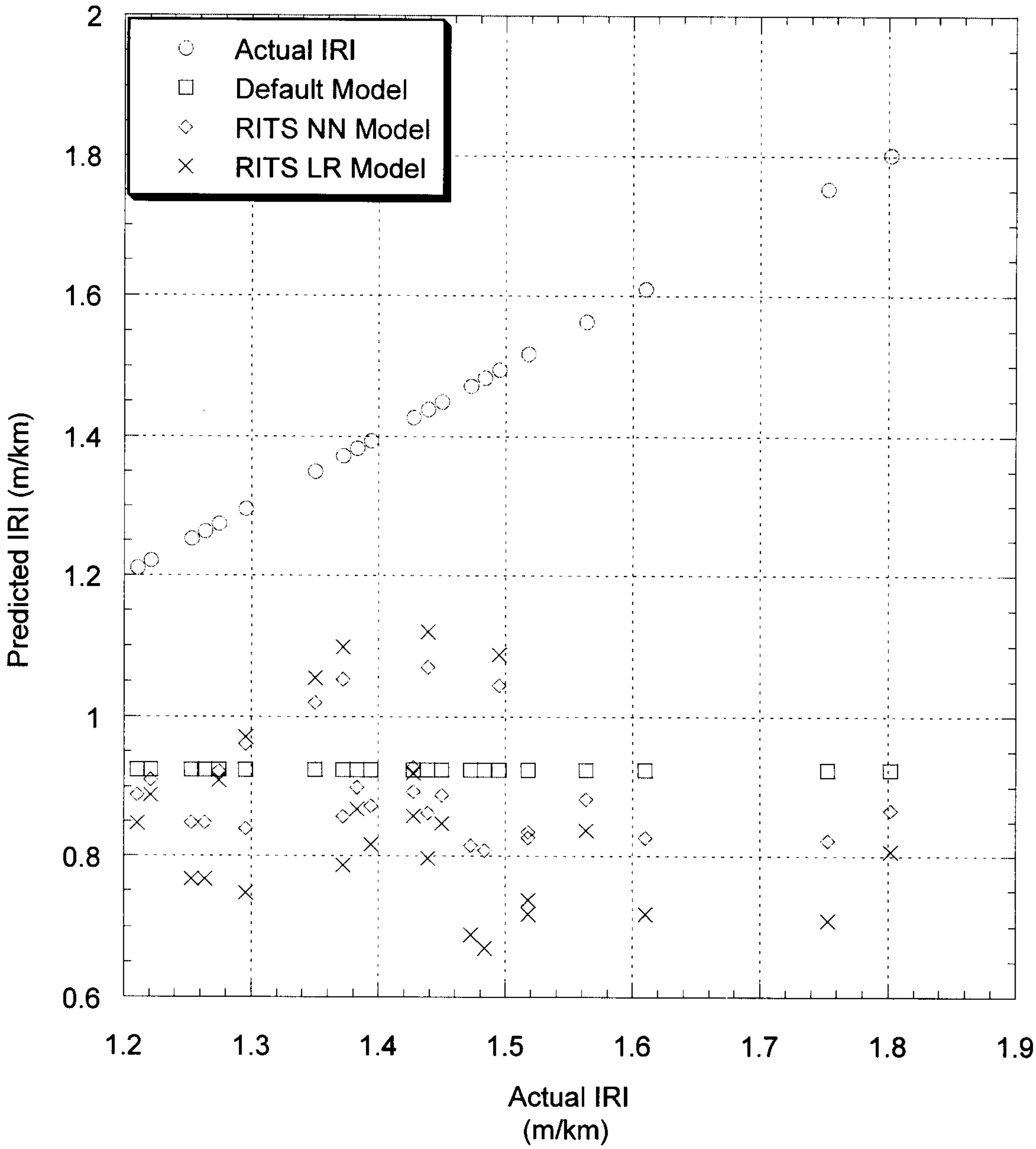

Figure 22. Plot of Actual IRI Vs. Predicted IRI for I-80 (Asphalt on Concrete)

Table 46. Summary of RMSE (iri m/km) for actual IRI vs. predicted IRI

	Interstate 80 (Asphalt on Concrete)	Interstate 80 (Asphalt on Asphalt)	Interstate 78 (New Pavement)
Default Model	0.5705	0.4273	0.5199
RITS LR Model	0.6300	0.3732	0.2582
RITS NN Model	0.5325	0.3460	0.3265

SUMMARY OF RESULTS

The results of the tests in this section show that the RITS models can be valuable tool for estimating pavement roughness. Table 46 gives the summary of the resulting standard errors. The predicted results for I-78 are the best overall for all the sections tested. The RITS LR model preformed the best for this section. The default model produced over 100% more standard error for this section then the RITS LR Model, while the RITS NN model produced only 26% more standard error. The two RITS models are specifically developed for the type of pavement that makes up this section of I-78. Thus the accuracy of these models are expected to be superior.

The other two sections are not the same type of pavements that were used to develop the RITS models. The rehabilitated pavement section on I-80 with asphalt pavement overlay on an existing asphalt pavement still produced acceptable results using the RITS Models when compared to the default model. Both the RITS models give better standard error than the default model produced. The RITS NN model produced the overall best results for this section and the RITS LR model produced only 8% more error than the RITS NN Model. The default model produced about 37% more error than the RITS NN model.

The section of I-80 with asphalt pavement overlay on a Portland cement concrete pavement is the worst case scenario. Not only was concrete pavements not used to develop the RITS models but also concrete has different failure mechanisms than asphalt. Also this type of rehabilitation is known to deteriorate faster than other types of rehabilitation. The RITS models produce mixed results for this section. The RITS NN model gives the best results. The RITS LR model produced 18% more error than the RITS NN model, while the default model only produced 7% more. Even though the percentage difference between the models is low, the standard error for the RITS NN is 54% higher than for the other section of I-80. This means all the models are predicting this type of pavement less accurately.

Figure 23 shows a graphical representation of the RMSE. The RITS LR model predicted the roughness of pavement type that it is trained to predict. The further the pavement type deviates from the original type of pavement, the worse the results become. The RITS NN on the other hand does not predict the original pavement as well as the linear regression model does, but is the best model for the other two sections. The NN results are referred to as surfaces and is not at all linear. This non-linear surface of results could be the reason it is able to predict the other sections better than the other models.

As seen in figures 20 through 22, all the models under-estimate the pavement roughness. Some of the points predicted for the section of I-78 are slightly over-estimated but overall they are under-estimated. A trend is also noted regarding this under-estimation; the further the pavement deviates from the new pavement, the more the models under-estimate the roughness. This shows that rehabilitated pavements deteriorate faster than new pavements and asphalt paved over concrete pavements deteriorates faster than asphalt paved over asphalt pavements.

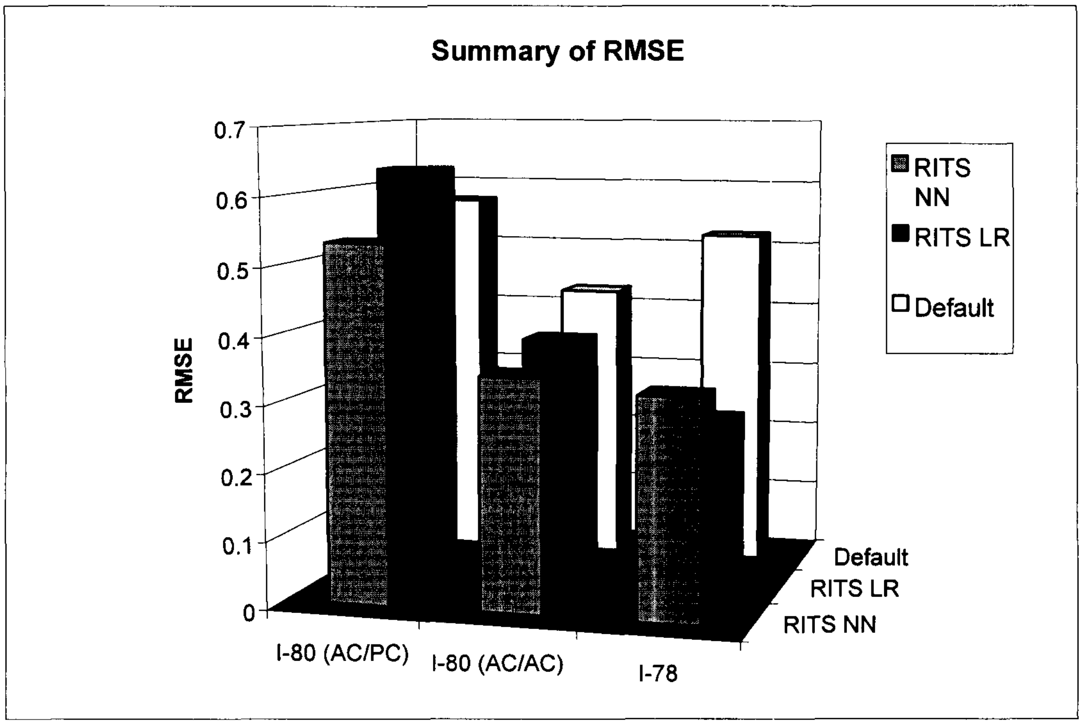

Figure 23. Summary of Model RMSE

CONCLUSIONS AND FUTURE RESEARCH

The RITS Models performed better than any other pavement deterioration model studied in this report. The following shows the root mean square errors of model estimations:

♦ RITS NN Model RMSE	0.0701
♦ RITS LR Model RMSE	0.0879
♦ FHWA Model RMSE	0.2986
♦ Lee Model RMSE	1.0966
♦ Pavement Management Default model RMSE	0.9946

In brief, this project has generated promising results in developing pavement deterioration prediction models using NN and linear regression. The models developed in this research are specifically developed for new pavements. The NN models have shown potential for predicting deterioration in other types of pavements as demonstrated by the results of earlier presented section. Further research with NN could possibly lead to the development of better models that could predict the deterioration of all types of pavements.

Another possible area for future research would be to test how well the ESALs are estimated in New Jersey. This is one possible reason for the models underestimating the roughness. Because if the trucks using the roadways are heavier than estimated for the ESAL data the roughness would have been underestimated. If weigh-station data is used, or even weigh in motion equipment installed then ESALs can be estimated more accurately. A weigh-station is located near the site on I-78 that is discussed in the previous section. A better understanding of the traffic that uses the pavement at a site can lead to a better model.

Summary of the future research needs are:

- More data for more training
- More test data
- Evaluation using IRI form newly constructed pavement sites
- Testing and developing other pavement types

APPENDIX A

The following are excepts from the IMS database field descriptions file. Only those fields that were used primary in this report are given below due to the large size of the original file. The original field descriptions is over 5000 pages when opened in MS Word.

SHRP_ID Table: ALL

SHRP SECTION IDENTIFICATION.

Data Type:VARCHAR2(4) Protocol:

Units: Validation:

QC Required:No QC Range:

Source: Item Number:

STATE_CODE Table: ALL

CODE IDENTIFYING THE STATE OR PROVINCE.

Data Type:NUMBER(2,0) Protocol:

Units: Validation: STATE_PROVINCE

QC Required:No QC Range:

Source:INVENTORY Sheet Item Number:

1

CONSTRUCTION_NO Table: INV_LAYER

EVENT NUMBER INDICATING PAVEMENT LAYER CHANGES IN A SECTION. SET TO 1 WHEN A SECTION IS CHOSEN FOR INCLUSION IN THE LTPP STUDY AND INCREMENTED AFTER EACH PAVEMENT LAYER CHANGE. IT IS ALL TABLES THAT RELATE TO A SECTION AT A SPECIFIC TIME.

Data Type:NUMBER(2,0) Protocol:

Units: Validation:

QC Required:No QC Range:

Source:INVENTORY Sheet Item Number:

3

CN_ASSIGN_DATE Table: EXPERIMENT_SECTION

A VALID DATE THAT INDICATES THE DATE THE CONSTRUCTION EVENT WAS ASSIGNED. FOR INVENTORY, IT WILL BE THE DATE THE SECTION IS CHOSEN FOR THE LTPP STUDIES. FOR ALL OTHER CONSTRUCTION EVENTS, IT WILL BE THE DATE THE LAYER STRUCTURE CHANGED.

Data Type:DATE Protocol:

Units: Validation:

QC Required:No QC Range:

Source:NIMS/L05B Item Number:

GPS_SPS Table: EXPERIMENT_SECTION

A code indicating if the section is a GPS (G) or SPS (S) section.

Data Type:CHAR(1) Protocol:

Units: Validation:

QC Required:No QC Range:

Source:NIMS/L05B Item Number:

EXPERIMENT_NO Table: EXPERIMENT_SECTION

The GPS or SPS experiment designation to which the section is assigned.

Data Type:CHAR(3) Protocol:

Units: Validation:

QC Required:No QC Range:

Source:NIMS/L05B Item Number:

STATUS Table: EXPERIMENT_SECTION

A code indicating the status (null is approved, O is out of study, and R is released) of a section for a given construction event. An experiment number (i.e., 6B, 7B, etc.), indicates the section is planned for the specified experiment.

Data Type:CHAR(2) Protocol:

Units: Validation:

QC Required:No QC Range:

Source:NIMS/L05B Item Number:

ASSIGN_DATE Table: EXPERIMENT_SECTION

Date representing when the section was chosen for the LTPP study or when the pavement was modified so that the section was assigned to the given experiment.

Data Type:DATE Protocol:

Units: Validation:

QC Required:No QC Range:

Source:NIMS/L05B Item Number:

DEASSIGN_DATE Table: EXPERIMENT_SECTION

Date representing when the section was removed from the LTPP study or when the pavement was modified so that the section was no longer assigned to the given experiment.

Data Type:DATE Protocol:

Units: Validation:

QC Required:No QC Range:

Source:NIMS/L05B Item Number:

SEAS_ID Table: EXPERIMENT_SECTION

State specific seasonal identification code

Data Type:CHAR(1) Protocol:

Units: Validation:

QC Required:No QC Range:

Source:NIMS/L05B Item Number:

RECORD_STATUS Table: EXPERIMENT_SECTION

A code indicating the general quality of the data as outlined based on the level of QC checks described in the Data User's Guide.

Data Type:VARCHAR2(1) Protocol:

Units: Validation:

QC Required:No QC Range:

Source:NIMS/L05B Item Number:

CONSTRUCTION_DATE Table: INV_AGE

Date of latest (re)construction. The date is entered as month and year only. QC applies to GPS, see QC Manual for SPS.

Data Type:DATE Protocol:

Units: Validation:

QC Required:Yes QC Range:

Source:INVENTORY Sheet Item Number:

TRAFFIC_OPEN_DATE Table: INV_AGE

Date when pavement was originally opened to traffic. The date is entered as a month and year only. QC applies to GPS, see QC Manual for SPS.

Data Type:DATE Protocol:

Units: Validation:

QC Required:Yes QC Range:

Source:INVENTORY Sheet Item Number:

4

PROFILE_DATE Table: MON_PROFILE_DATA

The date of the profilometer run.

Data Type:DATE Protocol:

Units: Validation:

QC Required:No QC Range:

Source:Profilometer Item Number:

Data File

PROFILE_TIME Table: MON_PROFILE_DATA

The time of the profilometer run.

Data Type:CHAR(8) Protocol:

Units: Validation:

QC Required:No QC Range:

Source:Profilometer Item Number:

Data File

RUN_NUMBER Table: MON_PROFILE_DATA

A number indicating the position of the run in the series.

Data Type:CHAR(1) Protocol:

Units: Validation:

QC Required:No QC Range:

Source:Profilometer Item Number:

IRI_LEFT_WHEEL_PATH Table: MON_PROFILE_MASTER

IRI value for left wheel path.

Data Type:NUMBER(5,3) Protocol:

Units:m/km Validation:

QC Required:Yes QC Range: 0.4 - 4.8

Source:Profilometer Item Number:

Data File

IRI_RIGHT_WHEEL_PATH Table: MON_PROFILE_MASTER

IRI value for right wheel path.

Data Type:NUMBER(5,3) Protocol:

Units:m/km Validation:

QC Required:Yes QC Range: 0.4 - 4.8

Source:Profilometer Item Number:

Data File

IRI_AVERAGE Table: MON_PROFILE_MASTER

Average IRI value.

Data Type:NUMBER(5,3) Protocol:

Units:m/km Validation:

QC Required:Yes QC Range: 0.4 - 4.8

Source:Profilometer Item Number:

Data File

MODIFICATION_NO Table: TRF_EST_ANL_TOT_LTPP_

A sequential number indicating the number of modifications made to the estimates.

Data Type:NUMBER(2,0) Protocol:

Units: Validation:

QC Required:No QC Range:

Source: Item Number:

BEGIN_DATE Table: TRF_EST_ANL_TOT_LTPP_

First day of the year to which estimate applies.

Data Type:DATE Protocol:

Units: Validation:

QC Required:No QC Range:

Source: Item Number:

END_DATE Table: TRF_EST_ANL_TOT_LTPP_

Last day of year to which estimate applies

Data Type:DATE Protocol:

Units: Validation:

QC Required:No QC Range:

Source: Item Number:

KESAL_18K_SAMPLE_SIZE Table: TRF_EST_ANL_TOT_LTPP_

The weighted sample size used for computing the average annual traffic load.

Data Type:NUMBER(5,0) Protocol:

Units: Validation:

QC Required:No QC Range:

APPENDIX B

This is the first data base developed from the GPS 2 sites in the LTPP.

STATE _CODE	SHRP _ID	RUN_DATE	Construction	AGE (Days)	IRI (m/Km)	ESALS	SUM_ESALS (Millions of ESALS)	SN
18	2008	04-Oct-89	1/1/80	3564	1.8198	948630.1	11.81063	7.22
18	2008	25-Mar-91	1/1/80	4101	2.259	323967.2	13.73397	7.22
18	2008	11-Sep-91	1/1/80	4271	2.4399	655648	14.38962	7.22
18	2008	02-Oct-92	1/1/80	4658	2.753	369500.7	15.18722	7.22
18	2008	01-Feb-94	1/1/80	5145	2.79325	107547.2	15.3971	7.22
19	6150	17-Jun-90	6/1/52	13895	1.2432	3682.192	0.184682	3.52
19	6150	20-Jun-91	6/1/52	14263	1.3074	8065.753	0.192748	3.52
19	6150	12-May-92	6/1/52	14590	1.3558	7681.524	0.200429	3.52
19	6150	17-Oct-93	6/1/52	15113	1.3928	12901.9	0.213331	3.52
19	6150	17-Sep-94	6/1/52	15448	1.4482	8033.842	0.221365	3.52
19	6150	07-Aug-97	6/1/52	16503	2.2294	26241.98	0.247607	3.52
24	1632	12-Nov-90	10/1/86	1503	0.7772	100446.9	0.978447	5.17
24	1632	08-Apr-91	10/1/86	1650	0.8622	49997.77	1.028445	5.17
24	1632	30-Jun-92	10/1/86	2099	0.8612	164033.8	1.192478	5.17
24	1632	23-Jun-93	10/1/86	2457	0.8592	146040.6	1.338519	5.17
24	1632	18-Jun-94	10/1/86	2817	0.9058	162007.5	1.500527	5.17
24	1632	04-Dec-95	10/1/86	3351	0.9166	269888.7	1.770415	5.17
24	1632	09-Jun-97	10/1/86	3904	1.014	131080.9	2.112707	5.17
24	1632	15-Dec-97	10/1/86	4093	0.9846	120850.2	2.233557	5.17
24	2401	04-Dec-89	7/1/87	887	0.83	50000	0.149	5.68
24	2401	10-Oct-90	7/1/87	1197	0.8714	40092.57	0.189093	5.68
24	2401	10-Aug-91	7/1/87	1501	0.867	43378.44	0.232471	5.68
24	2401	01-Jul-92	7/1/87	1827	0.8602	46753.2	0.279224	5.68
24	2401	23-Jun-93	7/1/87	2184	0.9022	51820.71	0.331045	5.68
24	2401	17-Jun-94	7/1/87	2543	0.9664	52603.86	0.383649	5.68
34	1033	30-Nov-90	5/1/74	6057	2.743	47583.56	0.754584	4.9
34	1033	06-Sep-91	5/1/74	6337	2.7874	33068.49	0.787652	4.9
34	1033	18-Jun-92	5/1/74	6623	2.9176	28627.4	0.816279	4.9
34	1033	09-Jun-93	5/1/74	6979	2.8738	46658.4	0.862938	4.9
34	1033	08-Jun-94	5/1/74	7343	2.9016	39753.98	0.902692	4.9
34	1033	22-Jun-95	5/1/74	7722	3.1426	26645.68	0.929338	4.9
34	1034	30-Nov-89	9/1/85	1551	1.3454	158893.2	0.544893	4.5
34	1034	17-Nov-90	9/1/85	1903	1.3486	174024.7	0.718918	4.5
34	1034	07-Sep-91	9/1/85	2197	1.3914	164424.7	0.883342	4.5
34	1034	20-Jun-92	9/1/85	2484	1.3838	174926	1.058268	4.5
34	1034	11-Jun-93	9/1/85	2840	1.4022	226005.1	1.41343	4.5
34	1034	10-Jun-94	9/1/85	3204	1.4446	494435.1	1.907865	4.5
34	1034	24-Jun-95	9/1/85	3583	1.4722	373861.7	2.281726	4.5
34	1034	09-Dec-97	9/1/85	4482	1.486	435679.9	3.125886	4.5
34	1638	30-Nov-89	9/1/85	1551	0.8798	158893.2	0.544893	5.3
34	1638	16-Nov-90	9/1/85	1902	0.9446	174024.7	0.718918	5.3
34	1638	07-Sep-91	9/1/85	2197	0.9638	164424.7	0.883342	5.3
34	1638	20-Jun-92	9/1/85	2484	0.9348	174926	1.058268	5.3

34	1638	11-Jun-93	9/1/85	2840	0.9414	130000	1.317425	5.3
34	1638	10-Jun-94	9/1/85	3204	1.0178	560003.5	1.877428	5.3
34	1638	24-Jun-95	9/1/85	3583	1.0594	249743.1	2.127171	5.3
34	1638	09-Dec-97	9/1/85	4482	1.0622	397018.5	2.52419	5.3
36	1643	23-Aug-89	5/1/78	4132	1.3246	1484384	15.85708	4.6
36	1643	08-Jun-90	5/1/78	4421	1.475667	985687.7	16.84276	4.6
36	1643	19-Apr-91	5/1/78	4736	1.51	466833.4	18.16182	4.6
36	1643	09-Jul-92	5/1/78	5183	1.8066	291042.5	18.45286	4.6
36	1643	14-Sep-93	5/1/78	5615	2.1176	318310.9	18.77117	4.6
36	1643	28-Jun-94	5/1/78	5902	2.608	420928.4	19.1921	4.6
36	1643	05-Jul-95	5/1/78	6274	2.8008	305878.7	19.49798	4.6
36	1644	23-Aug-89	8/1/80	3309	0.9482	67493.15	0.376849	3.4
36	1644	06-Jun-90	8/1/80	3596	0.9694	51109.59	0.427959	3.4
36	1644	21-Nov-90	8/1/80	3764	0.9466	29917.81	0.457877	3.4
36	1644	07-Jul-92	8/1/80	4358	0.9892	24910.02	0.537047	3.4
36	1644	13-Sep-93	8/1/80	4791	1.0618	16325.45	0.553372	3.4
36	1644	29-Jun-94	8/1/80	5080	1.0782	12717.76	0.56609	3.4
36	1644	06-Jul-95	8/1/80	5452	1.0926	13601.36	0.579692	3.4
36	1644	09-May-96	8/1/80	5760	1.1942	26046.08	0.605738	3.4
47	1029	08-May-90	01-Oct-82	2776	0.706111	64430.14	0.376455	4.79
47	1029	15-Apr-92	01-Oct-82	3484	0.728144	107287.7	0.572068	4.79
47	1029	25-Feb-94	01-Oct-82	4165	0.7502	122631.3	0.947191	4.79
47	1029	07-Dec-95	01-Oct-82	4815	0.9032	1527681	2.474873	4.79
47	1028	09-May-90	9/1/83	2442	1.209	101761.6	0.599055	4.23
47	1028	15-May-92	9/1/83	3179	1.3414	92150.68	0.779329	4.23
47	1028	28-Feb-94	9/1/83	3833	1.3632	126943.9	1.010371	4.23
47	1028	02-May-96	9/1/83	4627	1.452	175545	1.376097	4.23
47	3101	16-May-90	1/1/80	3788	1.0632	37353.42	0.394022	4.36
47	3101	17-Jun-91	1/1/80	4185	1.1462	41158.9	0.435181	4.36
47	3101	27-Aug-92	1/1/80	4622	1.0924	38345.21	0.473526	4.36
47	3101	10-Jun-94	1/1/80	5274	1.2086	10738.25	0.524016	4.36
47	3101	10-Apr-95	1/1/80	5578	1.268	92091.49	0.616107	4.36
47	9025	16-May-90	1/1/80	3788	1.5066	37353.42	0.394022	3.23
47	9025	20-Apr-92	1/1/80	4493	1.5792	38698.63	0.486945	3.23
47	9025	25-Feb-94	1/1/80	5169	1.8448	24657.4	0.531901	3.23
47	9025	10-Apr-95	1/1/80	5578	1.9234	84729.22	0.61663	3.23
84	1802	28-Sep-89	10/1/80	3284	1.4974	268454.8	1.724466	6.78
84	1802	23-Jul-90	10/1/80	3582	1.5622	292356.2	2.016822	6.78
84	1802	20-Aug-91	10/1/80	3975	1.4848	236268.5	2.25309	6.78
84	1802	23-Sep-92	10/1/80	4375	1.352	242827.4	2.495918	6.78
84	1802	23-Aug-93	10/1/80	4709	1.4396	261000	2.756918	6.78
84	1802	07-Aug-94	10/1/80	5058	1.5944	312600	3.069518	6.78
84	1802	02-Aug-95	10/1/80	5418	1.664	290715.1	3.360233	6.78
84	1802	24-Jul-97	10/1/80	6140	2.1566	183107.6	3.992665	6.78
88	1647	29-Sep-89	8/1/86	1155	1.2512	95000.27	0.224	4
88	1647	25-Jul-90	8/1/86	1454	1.3994	1254384	1.478384	4
88	1647	22-Aug-91	8/1/86	1847	1.4988	800983.6	2.279368	4
88	1647	21-Sep-92	8/1/86	2243	1.5456	56721.01	2.336089	4
88	1647	20-Aug-93	8/1/86	2576	1.5818	74306.63	2.410396	4
88	1647	09-Aug-94	8/1/86	2930	1.5484	82900.22	2.493296	4

88	1647	05-Aug-95	8/1/86	3291	1.6106	74492.05	2.567788	4
88	1647	26-Jul-97	8/1/86	4012	1.874	56797.68	2.735532	4
89	2011	21-Sep-89	6/1/78	4130	1.1358	60446.58	0.573654	6.6
89	2011	21-Jun-90	6/1/78	4403	1.132	61942.47	0.635596	6.6
89	2011	13-Jul-91	6/1/78	4790	1.161	65657.53	0.701254	6.6
89	2011	27-Aug-92	6/1/78	5201	1.181	46833.01	0.748087	6.6
89	2011	22-Jul-94	6/1/78	5895	1.1692	43855.98	0.866032	6.6
89	2011	16-Jul-95	6/1/78	6254	1.1658	73107.7	0.93914	6.6

This is the database that contains the IRI indicators and delta values. This is a variation of the above database.

STATE_CODE	SHRP_ID	AGE (Days)	IRI (m/Km)	SUM_ESALS (Millions of ESALS)	SN	IRI(i)	Delta T	Delta ESAL
18	2008	4101.00	2.2590	13.7340	7.22	1.8198	1.4712	19.2334
18	2008	4271.00	2.4399	14.3896	7.22	2.2590	0.4658	6.5565
18	2008	4658.00	2.7530	15.1872	7.22	2.4399	1.0603	7.9760
18	2008	5145.00	2.7933	15.3971	7.22	2.7530	1.3342	2.0989
19	6150	14263.00	1.3074	0.1927	3.52	1.2432	1.0082	0.0807
19	6150	14590.00	1.3558	0.2004	3.52	1.3074	0.8959	0.0768
19	6150	15113.00	1.3928	0.2133	3.52	1.3558	1.4329	0.1290
19	6150	15448.00	1.4482	0.2214	3.52	1.3928	0.9178	0.0803
19	6150	16503.00	2.2294	0.2476	3.52	1.4482	2.8904	0.2624
24	1632	1650.00	0.8622	1.0284	5.17	0.7772	0.4027	0.5000
24	1632	2099.00	0.8612	1.1925	5.17	0.8622	1.2301	1.6403
24	1632	2457.00	0.8592	1.3385	5.17	0.8612	0.9808	1.4604
24	1632	2817.00	0.9058	1.5005	5.17	0.8592	0.9863	1.6201
24	1632	3351.00	0.9166	1.7704	5.17	0.9058	1.4630	2.6989
24	1632	3904.00	1.0140	2.1127	5.17	0.9166	1.5151	3.4229
24	1632	4093.00	0.9846	2.2336	5.17	1.0140	0.5178	1.2085
24	2401	1197.00	0.8714	0.1891	5.68	0.8300	0.8493	0.4009
24	2401	1501.00	0.8670	0.2325	5.68	0.8714	0.8329	0.4338
24	2401	1827.00	0.8602	0.2792	5.68	0.8670	0.8932	0.4675
24	2401	2184.00	0.9022	0.3310	5.68	0.8602	0.9781	0.5182
24	2401	2543.00	0.9664	0.3836	5.68	0.9022	0.9836	0.5260
34	1033	6337.00	2.7874	0.7877	4.90	2.7430	0.7671	0.3307
34	1033	6623.00	2.9176	0.8163	4.90	2.7874	0.7836	0.2863
34	1033	6979.00	2.8738	0.8629	4.90	2.9176	0.9753	0.4666
34	1033	7343.00	2.9016	0.9027	4.90	2.8738	0.9973	0.3975
34	1033	7722.00	3.1426	0.9293	4.90	2.9016	1.0384	0.2665
34	1034	1903.00	1.3486	0.7189	4.50	1.3454	0.9644	1.7402
34	1034	2197.00	1.3914	0.8833	4.50	1.3486	0.8055	1.6442
34	1034	2484.00	1.3838	1.0583	4.50	1.3914	0.7863	1.7493
34	1034	2840.00	1.4022	1.4134	4.50	1.3838	0.9753	3.5516
34	1034	3204.00	1.4446	1.9079	4.50	1.4022	0.9973	4.9444
34	1034	3583.00	1.4722	2.2817	4.50	1.4446	1.0384	3.7386
34	1034	4482.00	1.486	3.1259	4.50	1.4722	2.4630	8.4416
34	1638	1902.00	0.9446	0.7189	5.30	0.8798	0.9616	1.7402
34	1638	2197.00	0.9638	0.8833	5.30	0.9446	0.8082	1.6442
34	1638	2484.00	0.9348	1.0583	5.30	0.9638	0.7863	1.7493
34	1638	2840.00	0.9414	1.3174	5.30	0.9348	0.9753	2.5916
34	1638	3204.00	1.0178	1.8774	5.30	0.9414	0.9973	5.6000
34	1638	3583.00	1.0594	2.1272	5.30	1.0178	1.0384	2.4974
34	1638	4482.00	1.0622	2.5242	5.30	1.0594	2.4630	3.9702
36	1643	4421.00	1.4757	16.8428	4.60	1.3246	0.7918	9.8569
36	1643	4736.00	1.5100	18.1618	4.60	1.4757	0.8630	13.1905
36	1643	5183.00	1.8066	18.4529	4.60	1.5100	1.2247	2.9104
36	1643	5615.00	2.1176	18.7712	4.60	1.8066	1.1836	3.1831

36	1643	5902.00	2.6080	19.1921	4.60	2.1176	0.7863	4.2093
36	1643	6274.00	2.8008	19.4980	4.60	2.6080	1.0192	3.0588
36	1644	3596.00	0.9694	0.4280	3.40	0.9482	0.7863	0.5111
36	1644	3764.00	0.9466	0.4579	3.40	0.9694	0.4603	0.2992
36	1644	4358.00	0.9892	0.5370	3.40	0.9466	1.6274	0.7917
36	1644	4791.00	1.0618	0.5534	3.40	0.9892	1.1863	0.1633
36	1644	5080.00	1.0782	0.5661	3.40	1.0618	0.7918	0.1272
36	1644	5452.00	1.0926	0.5797	3.40	1.0782	1.0192	0.1360
36	1644	5760.00	1.1942	0.6057	3.40	1.0926	0.8438	0.2605
47	1029	3484.00	0.7281	0.5721	4.79	0.7061	1.9397	1.9561
47	1029	4165.00	0.7502	0.9472	4.79	0.7281	1.8658	3.7512
47	1029	4815.00	0.9032	2.4749	4.79	0.7502	1.7808	15.2768
47	1028	3179.00	1.3414	0.7793	4.23	1.2090	2.0192	1.8027
47	1028	3833.00	1.3632	1.0104	4.23	1.3414	1.7918	2.3104
47	1028	4627.00	1.4520	1.3761	4.23	1.3632	2.1753	3.6573
47	3101	4185.00	1.1462	0.4352	4.36	1.0632	1.0877	0.4116
47	3101	4622.00	1.0924	0.4735	4.36	1.1462	1.1973	0.3835
47	3101	5274.00	1.2086	0.5240	4.36	1.0924	1.7863	0.5049
47	3101	5578.00	1.268	0.6161	4.36	1.2086	0.8329	0.9209
47	9025	4493.00	1.5792	0.4869	3.23	1.5066	1.9315	0.9292
47	9025	5169.00	1.8448	0.5319	3.23	1.5792	1.8521	0.4496
47	9025	5578.00	1.9234	0.6166	3.23	1.8448	1.1205	0.8473
84	1802	3582.00	1.5622	2.0168	6.78	1.4974	0.8164	2.9236
84	1802	3975.00	1.4848	2.2531	6.78	1.5622	1.0767	2.3627
84	1802	4375.00	1.3520	2.4959	6.78	1.4848	1.0959	2.4283
84	1802	4709.00	1.4396	2.7569	6.78	1.3520	0.9151	2.6100
84	1802	5058.00	1.5944	3.0695	6.78	1.4396	0.9562	3.1260
84	1802	5418.00	1.6640	3.3602	6.78	1.5944	0.9863	2.9072
84	1802	6140.00	2.1566	3.9927	6.78	1.6640	1.9781	6.3243
88	1647	1454.00	1.3994	1.4784	4.00	1.2512	0.8192	12.5438
88	1647	1847.00	1.4988	2.2794	4.00	1.3994	1.0767	8.0098
88	1647	2243.00	1.5456	2.3361	4.00	1.4988	1.0849	0.5672
88	1647	2576.00	1.5818	2.4104	4.00	1.5456	0.9123	0.7431
88	1647	2930.00	1.5484	2.4933	4.00	1.5818	0.9699	0.8290
88	1647	3291.00	1.6106	2.5678	4.00	1.5484	0.9890	0.7449
88	1647	4012.00	1.8740	2.7355	4.00	1.6106	1.9753	1.6774
89	2011	4403.00	1.1320	0.6356	6.60	1.1358	0.7479	0.6194
89	2011	4790.00	1.1610	0.7013	6.60	1.1320	1.0603	0.6566
89	2011	5201.00	1.1810	0.7481	6.60	1.1610	1.1260	0.4683
89	2011	5895.00	1.1692	0.8660	6.60	1.1810	1.9014	1.1795
89	2011	6254.00	1.1658	0.9391	6.60	1.1692	0.9836	0.7311

These are the additional data points added later to the above database.

STATE_CODE	SHRP_ID	AGE (Days)	IRI (m/Km)	SUM_ESALS (Millions of ESALS)	SN	IRI(i)	Delta T	Delta ESAL
5	3071	1086	0.5940	1.8611	4.54	0.5938	0.3973	1.8221
5	3071	1865	0.6458	2.8400	4.54	0.5940	2.1342	9.7891
5	3071	2431	0.7056	3.5500	4.54	0.6458	1.5507	7.0999
5	3071	3297	0.7968	4.6382	4.54	0.7056	2.3726	10.8823
40	4087	1766	1.1248	0.6736	2.85	1.0596	0.3890	0.5952
40	4087	2544	1.1066	1.0029	2.85	1.1248	2.1315	3.2931
40	4087	3178	1.1176	1.2900	2.85	1.1066	1.7370	2.8708
40	4087	4082	1.1892	1.7375	2.85	1.1176	2.4767	4.4750
51	2021	2057	1.4820	0.7442	3.60	1.4608	0.7452	0.5515
51	2021	2155	1.5098	0.7643	3.60	1.4820	0.2685	0.2010
51	2021	2775	1.4640	0.9048	3.60	1.5098	1.6986	1.4057
51	2021	3116	1.6086	0.9920	3.60	1.4640	0.9342	0.8721
51	2021	3478	1.7622	1.0895	3.60	1.6086	0.9918	0.9748

APPENDIX C

Sub-Model 1b

Figure A-1 Matlab NN Program

```
P = {[4.13;0.5737;6.6] [4.40;0.6356;6.6] [4.79;0.7013;6.6] [5.20;0.7481;6.6] [5.90;0.8660;6.6]
[6.25;0.9391;6.6] [1.16;0.2240;4] [1.45;1.4784;4] [1.85;2.2794;4] [2.24;2.3361;4] [2.58;2.4104;4]
[2.93;2.4933;4] [3.29;2.5678;4] [4.01;2.7355;4] [3.28;1.7245;6.78] [3.58;2.0168;6.78] [3.98;2.2531;6.78]
[4.38;2.4959;6.78] [4.71;2.7569;6.78] [5.06;3.0695;6.78] [5.42;3.3602;6.78] [6.14;3.9927;6.78]
[3.79;0.3940;3.23] [4.49;0.4869;3.23] [5.17;0.5319;3.23] [5.58;0.6166;3.23] [3.79;0.3940;4.36]
[4.19;0.4352;4.36] [4.62;0.4735;4.36] [5.27;0.5240;4.36] [5.58;0.6161;4.36] [2.78;0.3765;4.79]
[3.48;0.5721;4.79] [4.17;0.9472;4.79] [4.82;2.4749;4.79] [2.44;0.5991;4.23] [3.18;0.7793;4.23]
[3.83;1.0104;4.23] [4.63;1.3761;4.23] [3.31;0.3768;3.4] [3.60;0.4280;3.4] [3.76;0.4579;3.4]
[4.36;0.5370;3.4] [4.79;0.5534;3.4] [5.08;0.5661;3.4] [5.45;0.5797;3.4] [5.76;0.6057;3.4]
[1.55;0.5449;5.3] [1.90;0.7189;5.3] [2.20;0.8833;5.3] [2.48;1.0583;5.3] [2.84;1.3174;5.3]
[3.20;1.8774;5.3] [3.58;2.1272;5.3] [4.48;2.5242;5.3] [6.06;0.7546;4.9] [6.34;0.7877;4.9]
[6.62;0.8163;4.9] [6.98;0.8629;4.9] [7.34;0.9027;4.9] [7.72;0.9293;4.9] [0.89;0.1490;5.68]
[1.20;0.1891;5.68] [1.50;0.2325;5.68] [1.83;0.2792;5.68] [2.18;0.3310;5.68] [2.54;0.3836;5.68]
[1.50;0.9784;5.17] [1.65;1.0284;5.17] [2.10;1.1925;5.17] [2.46;1.3385;5.17] [2.82;1.5005;5.17]
[3.35;1.7704;5.17] [3.90;2.1127;5.17] [4.09;2.2336;5.17] [13.90;0.1847;3.52] [14.26;0.1927;3.52]
[14.59;0.2004;3.52] [15.11;0.2133;3.52] [15.45;0.2214;3.52] [16.50;0.2476;3.52] [3.56;11.8106;7.22]
[4.10;13.7340;7.22] [4.27;14.3896;7.22] [4.66;15.1872;7.22] [5.15;15.3971;7.22]};
T = {1.1358 1.1320 1.1610 1.1810 1.1692 1.1658 1.2512 1.3994 1.4988 1.5456 1.5818 1.5484 1.6106 1.8740
1.4974 1.5622 1.4848 1.3520 1.4396 1.5944 1.6640 2.1566 1.5066 1.5792 1.8448 1.9234 1.0632 1.1462 1.0924
1.2086 1.2680 0.7061 0.7281 0.7502 0.9032 1.2090 1.3414 1.3632 1.4520 0.9482 0.9694 0.9466 0.9892 1.0618
1.0782 1.0926 1.1942 0.8798 0.9446 0.9638 0.9348 0.9414 1.0178 1.0594 1.0622 2.7430 2.7874 2.9176 2.8738
2.9016 3.1426 0.8300 0.8714 0.8670 0.8602 0.9022 0.9664 0.7772 0.8622 0.8612 0.8592 0.9058 0.9166 1.0140
0.9846 1.2432 1.3074 1.3558 1.3928 1.4482 2.2294 1.8198 2.2590 2.4399 2.7530 2.7933};
net = newff([0.5 17;0 20;2 7],[3 1 1],{'logsig' 'tansig' 'purelin'});
net.trainParam.goal = 1e-100;
net.trainParam.epochs = 500;
net.trainParam.mu = .01;
net.trainParam.mu_inc = 10;
net.trainParam.mu_dec = .5;
net.trainParam.mu_max = 1e90;
net = train(net,P,T);
```

Table A-1 Weights for the input layer

Weight's Target Node (j)	***Weight's Origin(i)***		
	1	**2**	**3**
1	0.0044	-0.337	0.4178
2	0.164	0.9666	-5.5199
3	0.9303	-1.4499	8.4575

Table A-2 Biases for all the Layers

Layer	***Node 1***	***Node 2***	***Node 3***
1	-0.9570	28.2244	-47.8449
2	-24.2128	-	-
3	1.9188	-	-

Table A-3 Weights for the hidden layer

Weight's Target Node (j)	***Weight's Origin(i)***		
	1	**2**	**3**
1	-3.7680	25.6871	26.4507

Table A-4 Weights for the output layer

Weight's Target Node (j)	***Weight's Origin(i)***
	1
1	1.0257

Sub-Model 2b

Figure A-2 Matlab NN Program

```
P = {[1.1358;4.4030;6.6000;0.7479;0.6194] [1.1320;4.7900;6.6000;1.0603;0.6566]
[1.1610;5.2010;6.6000;1.1260;0.4683] [1.1810;5.8950;6.6000;1.9014;1.1795] [1.1692;6.2540;6.6000;0.9836;0.7311]
[1.2512;1.4540;4.0000;0.8192;12.5438] [1.3994;1.8470;4.0000;1.0767;8.0098]
[1.4988;2.2430;4.0000;1.0849;0.5672] [1.5456;2.5760;4.0000;0.9123;0.7431] [1.5818;2.9300;4.0000;0.9699;0.8290]
[1.5484;3.2910;4.0000;0.9890;0.7449] [1.6106;4.0120;4.0000;1.9753;1.6774] [1.4974;3.5820;6.7800;0.8164;2.9236]
[1.5622;3.9750;6.7800;1.0767;2.3627] [1.4848;4.3750;6.7800;1.0959;2.4283] [1.3520;4.7090;6.7800;0.9151;2.6100]
[1.4396;5.0580;6.7800;0.9562;3.1260] [1.5944;5.4180;6.7800;0.9863;2.9072] [1.6640;6.1400;6.7800;1.9781;6.3243]
[1.5066;4.4930;3.2300;1.9315;0.9292] [1.5792;5.1690;3.2300;1.8521;0.4496] [1.8448;5.5780;3.2300;1.1205;0.8473]
[0.7061;3.4840;4.7900;1.9397;1.9561] [0.7281;4.1650;4.7900;1.8658;3.7512]
[0.7502;4.8150;4.7900;1.7808;15.2768] [1.2090;3.1790;4.2300;2.0192;1.8027]
[1.3414;3.8330;4.2300;1.7918;2.3104] [1.3632;4.6270;4.2300;2.1753;3.6573] [0.9482;3.5960;3.4000;0.7863;0.5111]
[0.9694;3.7640;3.4000;0.4603;0.2992] [0.9466;4.3580;3.4000;1.6274;0.7917] [0.9892;4.7910;3.4000;1.1863;0.1633]
[1.0618;5.0800;3.4000;0.7918;0.1272] [1.0782;5.4520;3.4000;1.0192;0.1360] [1.0926;5.7600;3.4000;0.8438;0.2605]
[1.3246;4.4210;4.6000;0.7918;9.8569] [1.4757;4.7360;4.6000;0.8630;13.1905]
[1.5100;5.1830;4.6000;1.2247;2.9104] [1.8066;5.6150;4.6000;1.1836;3.1831] [2.1176;5.9020;4.6000;0.7863;4.2093]
[2.6080;6.2740;4.6000;1.0192;3.0588] [0.8798;1.9020;5.3000;0.9616;1.7402] [0.9446;2.1970;5.3000;0.8082;1.6442]
[0.9638;2.4840;5.3000;0.7863;1.7493] [0.9348;2.8400;5.3000;0.9753;2.5916] [0.9414;3.2040;5.3000;0.9973;5.6000]
[1.0178;3.5830;5.3000;1.0384;2.4974] [1.0594;4.4820;5.3000;2.4630;3.9702] [2.7430;6.3370;4.9000;0.7671;0.3307]
[2.7874;6.6230;4.9000;0.7836;0.2863] [2.9176;6.9790;4.9000;0.9753;0.4666] [2.8738;7.3430;4.9000;0.9973;0.3975]
[2.9016;7.7220;4.9000;1.0384;0.2665] [0.8300;1.1970;5.6800;0.8493;0.4009] [0.8714;1.5010;5.6800;0.8329;0.4338]
[0.8670;1.8270;5.6800;0.8932;0.4675] [0.8602;2.1840;5.6800;0.9781;0.5182] [0.9022;2.5430;5.6800;0.9836;0.5260]
[0.7772;1.6500;5.1700;0.4027;0.5000] [0.8622;2.0990;5.1700;1.2301;1.6403] [0.8612;2.4570;5.1700;0.9808;1.4604]
[0.8592;2.8170;5.1700;0.9863;1.6201] [0.9058;3.3510;5.1700;1.4630;2.6989] [0.9166;3.9040;5.1700;1.5151;3.4229]
[1.0140;4.0930;5.1700;0.5178;1.2085] [1.2432;14.2630;3.5200;1.0082;0.0807]
[1.3074;14.5900;3.5200;0.8959;0.0768] [1.3558;15.1130;3.5200;1.4329;0.1290]
[1.3928;15.4480;3.5200;0.9178;0.0803] [1.4482;16.5030;3.5200;2.8904;0.2624]
[1.8198;4.1010;7.2200;1.4712;19.2334] [2.2590;4.2710;7.2200;0.4658;6.5565]
[2.4399;4.6580;7.2200;1.0603;7.9760] [2.7530;5.1450;7.2200;1.3342;2.0989]};
T = {1.1320 1.1610 1.1810 1.1692 1.1658 1.3994 1.4988 1.5456 1.5818 1.5484 1.6106 1.8740 1.5622 1.4848 1.3520
1.4396 1.5944 1.6640 2.1566 1.5792 1.8448 1.9234 0.7281 0.7502 0.9032 1.3414 1.3632 1.4520 0.9694 0.9466
0.9892 1.0618 1.0782 1.0926 1.1942 1.4757 1.5100 1.8066 2.1176 2.6080 2.8008 0.9446 0.9638 0.9348 0.9414
1.0178 1.0594 1.0622 2.7874 2.9176 2.8738 2.9016 3.1426 0.8714 0.8670 0.8602 0.9022 0.9664 0.8622 0.8612
0.8592 0.9058 0.9166 1.0140 0.9846 1.3074 1.3558 1.3928 1.4482 2.2294 2.2590 2.4399 2.7530 2.7933};
net = newff([0 5;0 18;2 7;0 3;0.1 20],[5 3 1],{'tansig' 'logsig' 'purelin'});
net.trainParam.goal = 1e-100;
net.trainParam.epochs = 500;
net.trainParam.mu = .01;
net.trainParam.mu_inc = 10;
net.trainParam.mu_dec = .5;
net.trainParam.mu_max = 1e90;
net = train(net,P,T);
```

Table A-5 Weights for the input layer

Weight's Target Node (j)	***Weight's Origin(i)***				
	1	**2**	**3**	**4**	**5**
1	1.2111	0.02	-0.0161	0.0822	0.0282
2	-5.9494	0.099	1.7012	-0.0747	0.1173
3	2.8307	0.0522	-0.7862	-0.2387	-0.1166
4	1.1258	-2.3302	1.0154	-5.3858	-2.1901
5	4.8948	-0.5412	1.2339	-2.4529	-0.9398

Table A-6 Biases for all the Layers

Layer	*Node 1*	*Node 2*	*Node 3*	*Node 4*	*Node5*
1	2.262	1.472	-1.33	-2.26	-0.521
2	5.9256	0.7037	3.5716	-	-
3	1.5698	-	-	-	-

Table A-7 Weights for the hidden layer

Weight's Target Node (j)	***Weight's Origin(i)***				
	1	**2**	**3**	**4**	**5**
1	-3.1957	2.3895	7.7277	5.6957	0.9123
2	-3.6448	-0.5572	2.5455	0.9412	-0.0447
3	5.1541	-4.3272	0.2448	0.307	0.8164

Table A-8 Weights for the output layer

Weight's Target Node (j)	***Weight's Origin(i)***		
	1	**2**	**3**
1	1.2285	-2.2312	1.0732

Sub-Model 3b

Figure A-3 Matlab NN Program

```
P = {[1.1358;4.4030;6.6000;0.7479] [1.1320;4.7900;6.6000;1.0603] [1.1610;5.2010;6.6000;1.1260]
[1.1810;5.8950;6.6000;1.9014] [1.1692;6.2540;6.6000;0.9836] [1.2512;1.4540;4.0000;0.8192]
[1.3994;1.8470;4.0000;1.0767] [1.4988;2.2430;4.0000;1.0849] [1.5456;2.5760;4.0000;0.9123]
[1.5818;2.9300;4.0000;0.9699] [1.5484;3.2910;4.0000;0.9890] [1.6106;4.0120;4.0000;1.9753]
[1.4974;3.5820;6.7800;0.8164] [1.5622;3.9750;6.7800;1.0767] [1.4848;4.3750;6.7800;1.0959]
[1.3520;4.7090;6.7800;0.9151] [1.4396;5.0580;6.7800;0.9562] [1.5944;5.4180;6.7800;0.9863]
[1.6640;6.1400;6.7800;1.9781] [1.5066;4.4930;3.2300;1.9315] [1.5792;5.1690;3.2300;1.8521]
[1.8448;5.5780;3.2300;1.1205] [0.7061;3.4840;4.7900;1.9397] [0.7281;4.1650;4.7900;1.8658]
[0.7502;4.8150;4.7900;1.7808] [1.2090;3.1790;4.2300;2.0192] [1.3414;3.8330;4.2300;1.7918]
[1.3632;4.6270;4.2300;2.1753] [0.9482;3.5960;3.4000;0.7863] [0.9694;3.7640;3.4000;0.4603]
[0.9466;4.3580;3.4000;1.6274] [0.9892;4.7910;3.4000;1.1863] [1.0618;5.0800;3.4000;0.7918]
[1.0782;5.4520;3.4000;1.0192] [1.0926;5.7600;3.4000;0.8438] [1.3246;4.4210;4.6000;0.7918]
[1.4757;4.7360;4.6000;0.8630] [1.5100;5.1830;4.6000;1.2247] [1.8066;5.6150;4.6000;1.1836]
[2.1176;5.9020;4.6000;0.7863] [2.6080;6.2740;4.6000;1.0192] [0.8798;1.9020;5.3000;0.9616]
[0.9446;2.1970;5.3000;0.8082] [0.9638;2.4840;5.3000;0.7863] [0.9348;2.8400;5.3000;0.9753]
[0.9414;3.2040;5.3000;0.9973] [1.0178;3.5830;5.3000;1.0384] [1.0594;4.4820;5.3000;2.4630]
[2.7430;6.3370;4.9000;0.7671] [2.7874;6.6230;4.9000;0.7836] [2.9176;6.9790;4.9000;0.9753]
[2.8738;7.3430;4.9000;0.9973] [2.9016;7.7220;4.9000;1.0384] [0.8300;1.1970;5.6800;0.8493]
[0.8714;1.5010;5.6800;0.8329] [0.8670;1.8270;5.6800;0.8932] [0.8602;2.1840;5.6800;0.9781]
[0.9022;2.5430;5.6800;0.9836] [0.7772;1.6500;5.1700;0.4027] [0.8622;2.0990;5.1700;1.2301]
[0.8612;2.4570;5.1700;0.9808] [0.8592;2.8170;5.1700;0.9863] [0.9058;3.3510;5.1700;1.4630]
[0.9166;3.9040;5.1700;1.5151] [1.0140;4.0930;5.1700;0.5178] [1.2432;14.2630;3.5200;1.0082]
[1.3074;14.5900;3.5200;0.8959] [1.3558;15.1130;3.5200;1.4329] [1.3928;15.4480;3.5200;0.9178]
[1.4482;16.5030;3.5200;2.8904] [1.8198;4.1010;7.2200;1.4712] [2.2590;4.2710;7.2200;0.4658]
[2.4399;4.6580;7.2200;1.0603] [2.7530;5.1450;7.2200;1.3342]};
T = {1.1320 1.1610 1.1810 1.1692 1.1658 1.3994 1.4988 1.5456 1.5818 1.5484 1.6106 1.8740 1.5622 1.4848
1.3520 1.4396 1.5944 1.6640 2.1566 1.5792 1.8448 1.9234 0.7281 0.7502 0.9032 1.3414 1.3632 1.4520 0.9694
0.9466 0.9892 1.0618 1.0782 1.0926 1.1942 1.4757 1.5100 1.8066 2.1176 2.6080 2.8008 0.9446 0.9638 0.9348
0.9414 1.0178 1.0594 1.0622 2.7874 2.9176 2.8738 2.9016 3.1426 0.8714 0.8670  0.8602 0.9022 0.9664 0.8622
0.8612 0.8592 0.9058 0.9166 1.0140 0.9846 1.3074 1.3558  1.3928 1.4482 2.2294 2.2590 2.4399 2.7530
2.7933};
net = newff([0 5;0 18;2 7;0 3],[4 1 1],{'logsig' 'tansig' 'purelin'});
net.trainParam.goal = 1e-100;
net.trainParam.epochs = 500;
net.trainParam.mu = .01;
net.trainParam.mu_inc = 10;
net.trainParam.mu_dec = .5;
net.trainParam.mu_max = 1e90;
net = train(net,P,T);
```

Table A-9 Weights for the input layer

Weight's Target Node (j)	***Weight's Origin(i)***			
	1	**2**	**3**	**4**
1	5.4544	0.1439	0.4710	1.2711
2	-3.9576	0.0159	0.0349	-0.0698
3	-5.2678	-0.1252	-0.4788	-1.3044
4	5.2053	-0.4420	1.6612	3.5388

Table A-10 Biases for all the Layers

Layer	***Node 1***	***Node 2***	***Node 3***	***Node 4***
1	-17.3689	1.6958	16.8817	-22.3594
2	-33.1917	-	-	-
3	64.9048	-	-	-

Table A-11 Weights for the hidden layer

Weight's Target Node (j)	***Weight's Origin(i)***			
	1	**2**	**3**	**4**
1	34.2096	5.6532	35.6650	0.9821

Table A-12 Weights for the output layer

Weight's Target Node (j)	***Weight's Origin (i)***
	1
1	-64.1458

Sub-Model 4b

Figure A-4 Matlab NN Program

```
P = {[1.1358;0.7479;6.6000;0.0619;4.4030] [1.1358;1.8082;6.6000;0.1276;4.7900]
[1.1358;2.9342;6.6000;0.1744;5.2010] [1.1358;4.8356;6.6000;0.2924;5.8950]
[1.1358;5.8192;6.6000;0.3655;6.2540] [1.2512;0.8192;4.0000;1.2544;1.4540]
[1.2512;1.8959;4.0000;2.0554;1.8470] [1.2512;2.9808;4.0000;2.1121;2.2430]
[1.2512;3.8932;4.0000;2.1864;2.5760] [1.2512;4.8630;4.0000;2.2693;2.9300]
[1.2512;5.8521;4.0000;2.3438;3.2910] [1.2512;7.8274;4.0000;2.5115;4.0120]
[1.4974;0.8164;6.7800;0.2924;3.5820] [1.4974;1.8932;6.7800;0.5286;3.9750]
[1.4974;2.9890;6.7800;0.7715;4.3750] [1.4974;3.9041;6.7800;1.0325;4.7090]
[1.4974;4.8603;6.7800;1.3451;5.0580] [1.4974;5.8466;6.7800;1.6358;5.4180]
[1.4974;7.8247;6.7800;2.2682;6.1400] [1.5066;1.9315;3.2300;0.0929;4.4930]
[1.5066;3.7836;3.2300;0.1379;5.1690] [1.5066;4.9041;3.2300;0.2226;5.5780]
[0.7061;1.9397;4.7900;0.1956;3.4840] [0.7061;3.8055;4.7900;0.5707;4.1650]
[0.7061;5.5863;4.7900;2.0984;4.8150] [1.2090;2.0192;4.2300;0.1803;3.1790]
[1.2090;3.8110;4.2300;0.4113;3.8330] [1.2090;5.9863;4.2300;0.7770;4.6270]
[0.9482;0.7863;3.4000;0.0511;3.5960] [0.9482;1.2466;3.4000;0.0810;3.7640]
[0.9482;2.8740;3.4000;0.1602;4.3580] [0.9482;4.0603;3.4000;0.1765;4.7910]
[0.9482;4.8521;3.4000;0.1892;5.0800] [0.9482;5.8712;3.4000;0.2028;5.4520]
[0.9482;6.7151;3.4000;0.2289;5.7600] [1.3246;0.7918;4.6000;0.9857;4.4210]
[1.3246;1.6548;4.6000;2.3047;4.7360] [1.3246;2.8795;4.6000;2.5958;5.1830]
[1.3246;4.0630;4.6000;2.9141;5.6150] [1.3246;4.8493;4.6000;3.3350;5.9020]
[1.3246;5.8685;4.6000;3.6409;6.2740] [0.8798;0.9616;5.3000;0.1740;1.9020]
[0.8798;1.7699;5.3000;0.3384;2.1970] [0.8798;2.5562;5.3000;0.5134;2.4840]
[0.8798;3.5315;5.3000;0.7725;2.8400] [0.8798;4.5288;5.3000;1.3325;3.2040]
[0.8798;5.5671;5.3000;1.5823;3.5830] [0.8798;8.0301;5.3000;1.9793;4.4820]
[2.7430;0.7671;4.9000;0.0331;6.3370] [2.7430;1.5507;4.9000;0.0617;6.6230]
[2.7430;2.5260;4.9000;0.1084;6.9790] [2.7430;3.5233;4.9000;0.1481;7.3430]
[2.7430;4.5616;4.9000;0.1748;7.7220] [0.8300;0.8493;5.6800;0.0401;1.1970]
[0.8300;1.6822;5.6800;0.0835;1.5010] [0.8300;2.5753;5.6800;0.1302;1.8270]
[0.8300;3.5534;5.6800;0.1820;2.1840] [0.8300;4.5370;5.6800;0.2346;2.5430]
[0.7772;0.4027;5.1700;0.0500;1.6500] [0.7772;1.6329;5.1700;0.2140;2.0990]
[0.7772;2.6137;5.1700;0.3601;2.4570] [0.7772;3.6000;5.1700;0.5221;2.8170]
[0.7772;5.0630;5.1700;0.7920;3.3510] [0.7772;6.5781;5.1700;1.1343;3.9040]
[0.7772;7.0959;5.1700;1.2551;4.0930] [1.2432;1.0082;3.5200;0.0081;14.2630]
[1.2432;1.9041;3.5200;0.0157;14.5900] [1.2432;3.3370;3.5200;0.0286;15.1130]
[1.2432;4.2548;3.5200;0.0367;15.4480] [1.8198;1.4712;7.2200;1.9233;4.1010]
[1.8198;1.9370;7.2200;2.5790;4.2710] [1.8198;2.9973;7.2200;3.3766;4.6580]
[1.8198;4.3315;7.2200;3.5865;5.1450]};
T = {1.1320 1.1610 1.1810 1.1692 1.1658 1.3994 1.4988 1.5456 1.5818 1.5484 1.6106 1.8740 1.5622
1.4848 1.3520 1.4396 1.5944 1.6640 2.1566 1.5792 1.8448 1.9234 0.7281 0.7502 0.9032 1.3414 1.3632
1.4520 0.9694 0.9466 0.9892 1.0618 1.0782 1.0926 1.1942 1.4757 1.5100 1.8066 2.1176  2.6080 2.8008
0.9446 0.9638 0.9348 0.9414 1.0178 1.0594 1.0622 2.7874 2.9176 2.8738 2.9016 3.1426 0.8714 0.8670
0.8602 0.9022 0.9664 0.8622 0.8612 0.8592 0.9058 0.9166 1.0140 0.9846 1.3074 1.3558 1.3928 1.4482
2.2590 2.4399 2.7530 2.7933};
net = newff([0 5;0 18;2 7;0 3;0.1 20],[5 1 1],{'tansig' 'tansig' 'purelin'});
net.trainParam.goal = 1e-100;
net.trainParam.epochs = 500;
net.trainParam.mu = .01;
net.trainParam.mu_inc = 10;
net.trainParam.mu_dec = .5;
net.trainParam.mu_max = 1e90;
net = train(net,P,T);
```

Table A-13 Weights for the input layer

Weight's Target Node (j)	*Weight's Origin(i)*				
	1	**2**	**3**	**4**	**5**
1	2.3099	0.2508	2.0016	-1.8884	-0.1629
2	2.0509	0.1527	0.3554	1.408	0.0384
3	-0.8833	-1.3167	-1.8835	3.0791	-0.5122
4	0.1421	0.0049	0.0019	0.0297	0.0005
5	-1.2195	0.5035	-1.6419	-1.9977	-1.4773

Table A-14 Biases for all the Layers

Layer	*Node 1*	*Node 2*	*Node 3*	*Node 4*	*Node5*
1	-6.6118	-6.5387	-3.1838	-0.3425	2.8079
2	-0.5069	-	-	-	-
3	1.8992	-	-	-	-

Table A-15 Weights for the hidden layer

Weight's Target Node (j)	*Weight's Origin(i)*				
	1	**2**	**3**	**4**	**5**
1	-0.4077	-0.3762	-0.0021	10.733	-1.5516

Table A-16 Weights for the output layer

Weight's Target Node (j)	*Weight's Origin(i)*
	1
1	1.2816

Sub-Model 1c

Figure A-5 Matlab NN Program

```
P = {[4.13;0.5737;6.6] [4.40;0.6356;6.6] [4.79;0.7013;6.6] [5.20;0.7481;6.6] [5.90;0.8660;6.6]
[6.25;0.9391;6.6] [1.16;0.2240;4] [1.45;1.4784;4] [1.85;2.2794;4] [2.24;2.3361;4] [2.58;2.4104;4]
[2.93;2.4933;4] [3.29;2.5678;4] [4.01;2.7355;4] [3.28;1.7245;6.78] [3.58;2.0168;6.78] [3.98;2.2531;6.78]
[4.38;2.4959;6.78] [4.71;2.7569;6.78] [5.06;3.0695;6.78] [5.42;3.3602;6.78] [6.14;3.9927;6.78]
[3.79;0.3940;3.23] [4.49;0.4869;3.23] [5.17;0.5319;3.23] [5.58;0.6166;3.23] [3.79;0.3940;4.36]
[4.19;0.4352;4.36] [4.62;0.4735;4.36] [5.27;0.5240;4.36] [5.58;0.6161;4.36] [2.78;0.3765;4.79]
[3.48;0.5721;4.79] [4.17;0.9472;4.79] [4.82;2.4749;4.79] [2.44;0.5991;4.23] [3.18;0.7793;4.23]
[3.83;1.0104;4.23] [4.63;1.3761;4.23] [3.31;0.3768;3.4] [3.60;0.4280;3.4] [3.76;0.4579;3.4]
[4.36;0.5370;3.4] [4.79;0.5534;3.4] [5.08;0.5661;3.4] [5.45;0.5797;3.4] [5.76;0.6057;3.4]
[1.55;0.5449;5.3] [1.90;0.7189;5.3] [2.20;0.8833;5.3] [2.48;1.0583;5.3] [2.84;1.3174;5.3]
[3.20;1.8774;5.3] [3.58;2.1272;5.3] [4.48;2.5242;5.3] [6.06;0.7546;4.9] [6.34;0.7877;4.9]
[6.62;0.8163;4.9] [6.98;0.8629;4.9] [7.34;0.9027;4.9] [7.72;0.9293;4.9] [0.89;0.1490;5.68]
[1.20;0.1891;5.68] [1.50;0.2325;5.68] [1.83;0.2792;5.68] [2.18;0.3310;5.68] [2.54;0.3836;5.68]
[1.50;0.9784;5.17] [1.65;1.0284;5.17] [2.10;1.1925;5.17] [2.46;1.3385;5.17] [2.82;1.5005;5.17]
[3.35;1.7704;5.17] [3.90;2.1127;5.17] [4.09;2.2336;5.17] [13.90;0.1847;3.52] [14.26;0.1927;3.52]
[14.59;0.2004;3.52] [15.11;0.2133;3.52] [15.45;0.2214;3.52] [16.50;0.2476;3.52] [3.56;11.8106;7.22]
[4.10;13.7340;7.22] [4.27;14.3896;7.22] [4.66;15.1872;7.22] [5.15;15.3971;7.22] [1.785;0.689;3.6]
[2.057;0.7442;3.6] [2.155;0.7643;3.6] [2.775;0.9048;3.6] [3.116;0.992;3.6] [3.478;1.0895;3.6]
[0.941;1.6788;4.54] [1.086;1.8611;4.54] [1.865;2.84;4.54] [2.431;3.55;4.54] [3.297;4.6382;4.54]};
T = {1.1358 1.1320 1.1610 1.1810 1.1692 1.1658 1.2512 1.3994 1.4938 1.5456 1.5818 1.5484 1.6106 1.8740
1.4974 1.5622 1.4848 1.3520 1.4396 1.5944 1.6640 2.1566 1.5066 1.5792 1.8448 1.9234 1.0632 1.1462 1.0924
1.2086 1.2680 0.7061 0.7281 0.7502 0.9032 1.2090 1.3414 1.3632 1.4520 0.9482 0.9694 0.9466 0.9892 1.0618
1.0782 1.0926 1.1942 0.8798 0.9446 0.9638 0.9348 0.9414 1.0178 1.0594 1.0622 2.7430 2.7874 2.9176 2.8738
2.9016 3.1426 0.8300 0.8714 0.8670 0.8602 0.9022 0.9664 0.7772 0.8622 0.8612 0.8592 0.9058 0.9166 1.0140
0.9846 1.2432 1.3074 1.3558 1.3928 1.4482 2.2294 1.8198 2.2590 2.4399 2.7530 2.79331.4608 1.4820 1.5098
1.4640 1.6086 1.7622 0.5938 0.5940 0.6458 0.7056 0.7968};
net = newff([0.5 17;0 20;2 7],[3 1 1],{'logsig' 'tansig' 'purelin'});
net.trainParam.goal = 1e-100;
net.trainParam.epochs = 500;
net.trainParam.mu = .01;
net.trainParam.mu_inc = 10;
net.trainParam.mu_dec = .5;
net.trainParam.mu_max = 1e90;
net = train(net,P,T);
```

Table A-17 Weights for the input layer

Weight's Target Node (j)	***Weight's Origin (i)***		
	1	**2**	**3**
1	6.0435	-3.8313	0.3209
2	1.9036	0.5316	-2.9015
3	4.111	-0.2141	5.0176

Table A-18 Biases for all the Layers

Layer	***Node 1***	***Node 2***	***Node 3***
1	-18.2123	6.0453	-46.144
2	-0.6514	-	-
3	3.0227	-	-

Table A-19 Weights for the hidden layer

Weight's Target Node (j)	*Weight's Origin (i)*		
	1	**2**	**3**
1	-0.1605	0.2997	0.2936

Table A-20 Weights for the output layer

Weight's Target Node (j)	*Weight's Origin (i)*
	1
1	3.7689

Sub-Model 2c

Figure A-6 Matlab NN program

```
P = {[1.1358;4.4030;6.6000;0.7479;0.6194] [1.1320;4.7900;6.6000;1.0603;0.6566]
[1.1610;5.2010;6.6000;1.1260;0.4683] [1.1810;5.8950;6.6000;1.9014;1.1795]
[1.1692;6.2540;6.6000;0.9836;0.7311] [1.2512;1.4540;4.0000;0.8192;12.5438]
[1.3994;1.8470;4.0000;1.0767;8.0098] [1.4988;2.2430;4.0000;1.0849;0.5672]
[1.5456;2.5760;4.0000;0.9123;0.7431] [1.5818;2.9300;4.0000;0.9699;0.8290]
[1.5484;3.2910;4.0000;0.9890;0.7449] [1.6106;4.0120;4.0000;1.9753;1.6774]
[1.4974;3.5820;6.7800;0.8164;2.9236] [1.5622;3.9750;6.7800;1.0767;2.3627]
[1.4848;4.3750;6.7800;1.0959;2.4283] [1.3520;4.7090;6.7800;0.9151;2.6100]
[1.4396;5.0580;6.7800;0.9562;3.1260] [1.5944;5.4180;6.7800;0.9863;2.9072]
[1.6640;6.1400;6.7800;1.9781;6.3243] [1.5066;4.4930;3.2300;1.9315;0.9292]
[1.5792;5.1690;3.2300;1.8521;0.4496] [1.8448;5.5780;3.2300;1.1205;0.8473]
[0.7061;3.4840;4.7900;1.9397;1.9561] [0.7281;4.1650;4.7900;1.8658;3.7512]
[0.7502;4.8150;4.7900;1.7808;15.2768] [1.2090;3.1790;4.2300;2.0192;1.8027]
[1.3414;3.8330;4.2300;1.7918;2.3104] [1.3632;4.6270;4.2300;2.1753;3.6573]
[0.9482;3.5960;3.4000;0.7863;0.5111] [0.9694;3.7640;3.4000;0.4603;0.2992]
[0.9466;4.3580;3.4000;1.6274;0.7917] [0.9892;4.7910;3.4000;1.1863;0.1633]
[1.0618;5.0800;3.4000;0.7918;0.1272] [1.0782;5.4520;3.4000;1.0192;0.1360]
[1.0926;5.7600;3.4000;0.8438;0.2605] [1.3246;4.4210;4.6000;0.7918;9.8569]
[1.4757;4.7360;4.6000;0.8630;13.1905] [1.5100;5.1830;4.6000;1.2247;2.9104]
[1.8066;5.6150;4.6000;1.1836;3.1831] [2.1176;5.9020;4.6000;0.7863;4.2093]
[2.6080;6.2740;4.6000;1.0192;3.0588] [0.8798;1.9020;5.3000;0.9616;1.7402]
[0.9446;2.1970;5.3000;0.8082;1.6442] [0.9638;2.4840;5.3000;0.7863;1.7493]
[0.9348;2.8400;5.3000;0.9753;2.5916] [0.9414;3.2040;5.3000;0.9973;5.6000]
[1.0178;3.5830;5.3000;1.0384;2.4974] [1.0594;4.4820;5.3000;2.4630;3.9702]
[2.7430;6.3370;4.9000;0.7671;0.3307] [2.7874;6.6230;4.9000;0.7836;0.2863]
[2.9176;6.9790;4.9000;0.9753;0.4666] [2.8738;7.3430;4.9000;0.9973;0.3975]
[2.9016;7.7220;4.9000;1.0384;0.2665] [0.8300;1.1970;5.6800;0.8493;0.4009]
[0.8714;1.5010;5.6800;0.8329;0.4338] [0.8670;1.8270;5.6800;0.8932;0.4675]
[0.8602;2.1840;5.6800;0.9781;0.5182] [0.9022;2.5430;5.6800;0.9836;0.5260]
[0.7772;1.6500;5.1700;0.4027;0.5000] [0.8622;2.0990;5.1700;1.2301;1.6403]
[0.8612;2.4570;5.1700;0.9808;1.4604] [0.8592;2.8170;5.1700;0.9863;1.6201]
[0.9058;3.3510;5.1700;1.4630;2.6989] [0.9166;3.9040;5.1700;1.5151;3.4229]
[1.0140;4.0930;5.1700;0.5178;1.2085] [1.2432;14.2630;3.5200;1.0082;0.0807]
[1.3074;14.5900;3.5200;0.8959;0.0768] [1.3558;15.1130;3.5200;1.4329;0.1290]
[1.3928;15.4480;3.5200;0.9178;0.0803] [1.4482;16.5030;3.5200;2.8904;0.2624]
[1.8198;4.1010;7.2200;1.4712;19.2334] [2.2590;4.2710;7.2200;0.4658;6.5565]
[2.4399;4.6580;7.2200;1.0603;7.9760] [2.7530;5.1450;7.2200;1.3342;2.0989]
[1.4608;2.057;3.6;0.745205;0.055145] [1.482;2.155;3.6;0.268493;0.020099]
[1.5098;2.775;3.6;1.69863;0.14057] [1.464;3.116;3.6;0.934247;0.087212]
[1.6086;3.478;3.6;0.991781;0.09748] [1.0596;1.766;2.85;0.389041;0.059523]
[1.1248;2.544;2.85;2.131507;0.329305] [1.1066;3.178;2.85;1.736986;0.287083]
[1.1176;4.082;2.85;2.476712;0.447504] [0.593778;1.086;4.54;0.39726;0.18221]
[0.594;1.865;4.54;2.134247;0.978908] [0.6458;2.431;4.54;1.550685;0.709991]
[0.7056;3.297;4.54;2.372603;1.088235]};
T = {1.1320 1.1610 1.1810 1.1692 1.1658 1.3994 1.4988 1.5456 1.5818 1.5484 1.6106 1.8740 1.5622 1.4848
1.3520 1.4396 1.5944 1.6640 2.1566 1.5792 1.8448 1.9234 0.7281 0.7502 0.9032 1.3414 1.3632 1.4520
0.9694 0.9466 0.9892 1.0618 1.0782 1.0926 1.1942 1.4757 1.5100 1.8066 2.1176 2.6080 2.8008 0.9446
0.9638 0.9348 0.9414 1.0178 1.0594 1.0622 2.7874 2.9176 2.8738 2.9016 3.1426 0.8714 0.8670 0.8602
0.9022 0.9664 0.8622 0.8612 0.8592 0.9058 0.9166 1.0140 0.9846 1.3074 1.3558 1.3928 1.4482 2.2294
2.2590 2.4399 2.7530 2.7933 1.482 1.5098 1.464 1.6086 1.7622 1.1248 1.1066 1.1176 1.1892 0.594 0.6458
0.7056 0.7968};
net = newff([0 5;0 18;2 7;0 3;0.1 20],[5 3 1 1],{'tansig' 'logsig' 'logsig' 'purelin'});
net.trainParam.goal = 1e-100;
net.trainParam.epochs = 500;
net.trainParam.mu = .01;
net.trainParam.mu_inc = 10;
net.trainParam.mu_dec = .5;
net.trainParam.mu_max = 1e90;
net = train(net,P,T);
```

Table A-21 Weights for the input layer

Weight's Target Node (j)	***Weight's Origin (i)***				
	1	**2**	**3**	**4**	**5**
1	-2.9398	-5.5444	-5.0563	-0.8952	-3.9407
2	-1.9047	0.0952	-1.7833	0.7767	-0.769
3	-10.2404	-7.0474	6.4027	3.9701	5.6018
4	-4.9464	-0.0558	-0.3084	-0.983	-0.0411
5	1.0932	0.001	-0.0071	-0.0075	0.0115

Table A-22 Biases for all the Layers

Layer	***Node 1***	***Node 2***	***Node 3***	***Node 4***	***Node5***
1	-3.9338	-1.1644	-2.8237	14.1146	-1.8147
2	3.7965	-2.1073	5.033	-	-
3	0.2705	-	-	-	-
4	-4.2629	-	-	-	-

Table A-23 Weights for the first hidden layer

Weight's Target Node (j)	***Weight's Origin (i)***				
	1	**2**	**3**	**4**	**5**
1	-3.0208	-2.8189	0.8574	-7.6968	2.7748
2	0.8061	-3.1505	0.9124	1.6547	2.5761
3	-1.4026	-1.9401	1.5259	1.4104	0.8474

Table A-24 Weights for the second hidden layer

Weight's Target Node (j)	***Weight's Origin (i)***		
	1	**2**	**3**
1	13.1202	-12.51	0.6376

Table A-25 Weights for the output layer

Weight's Target Node (j)	***Weight's Origin (i)***
	1
1	7.1527

Sub-Model 3c

Figure A-7 Matlab NN program

```
P = {[1.1358;4.4030;6.6000;0.7479] [1.1320;4.7900;6.6000;1.0603] [1.1610;5.2010;6.6000;1.1260]
[1.1810;5.8950;6.6000;1.9014] [1.1692;6.2540;6.6000;0.9836] [1.2512;1.4540;4.0000;0.8192]
[1.3994;1.8470;4.0000;1.0767] [1.4988;2.2430;4.0000;1.0849] [1.5456;2.5760;4.0000;0.9123]
[1.5818;2.9300;4.0000;0.9699] [1.5484;3.2910;4.0000;0.9890] [1.6106;4.0120;4.0000;1.9753]
[1.4974;3.5820;6.7800;0.8164] [1.5622;3.9750;6.7800;1.0767] [1.4848;4.3750;6.7800;1.0959]
[1.3520;4.7090;6.7800;0.9151] [1.4396;5.0580;6.7800;0.9562] [1.5944;5.4180;6.7800;0.9863]
[1.6640;6.1400;6.7800;1.9781] [1.5066;4.4930;3.2300;1.9315] [1.5792;5.1690;3.2300;1.8521]
[1.8448;5.5780;3.2300;1.1205] [0.7061;3.4840;4.7900;1.9397] [0.7281;4.1650;4.7900;1.8658]
[0.7502;4.8150;4.7900;1.7808] [1.2090;3.1790;4.2300;2.0192] [1.3414;3.8330;4.2300;1.7918]
[1.3632;4.6270;4.2300;2.1753] [0.9482;3.5960;3.4000;0.7863] [0.9694;3.7640;3.4000;0.4603]
[0.9466;4.3580;3.4000;1.6274] [0.9892;4.7910;3.4000;1.1863] [1.0618;5.0800;3.4000;0.7918]
[1.0782;5.4520;3.4000;1.0192] [1.0926;5.7600;3.4000;0.8438] [1.3246;4.4210;4.6000;0.7918]
[1.4757;4.7360;4.6000;0.8630] [1.5100;5.1830;4.6000;1.2247] [1.8066;5.6150;4.6000;1.1836]
[2.1176;5.9020;4.6000;0.7863] [2.6080;6.2740;4.6000;1.0192] [0.8798;1.9020;5.3000;0.9616]
[0.9446;2.1970;5.3000;0.8082] [0.9638;2.4840;5.3000;0.7863] [0.9348;2.8400;5.3000;0.9753]
[0.9414;3.2040;5.3000;0.9973] [1.0178;3.5830;5.3000;1.0384] [1.0594;4.4820;5.3000;2.4630]
[2.7430;6.3370;4.9000;0.7671] [2.7874;6.6230;4.9000;0.7836] [2.9176;6.9790;4.9000;0.9753]
[2.8738;7.3430;4.9000;0.9973] [2.9016;7.7220;4.9000;1.0384] [0.8300;1.1970;5.6800;0.8493]
[0.8714;1.5010;5.6800;0.8329] [0.8670;1.8270;5.6800;0.8932] [0.8602;2.1840;5.6800;0.9781]
[0.9022;2.5430;5.6800;0.9836] [0.7772;1.6500;5.1700;0.4027] [0.8622;2.0990;5.1700;1.2301]
[0.8612;2.4570;5.1700;0.9808] [0.8592;2.8170;5.1700;0.9863] [0.9058;3.3510;5.1700;1.4630]
[0.9166;3.9040;5.1700;1.5151] [1.0140;4.0930;5.1700;0.5178] [1.2432;14.2630;3.5200;1.0082]
[1.3074;14.5900;3.5200;0.8959] [1.3558;15.1130;3.5200;1.4329] [1.3928;15.4480;3.5200;0.9178]
[1.4482;16.5030;3.5200;2.8904] [1.8198;4.1010;7.2200;1.4712] [2.2590;4.2710;7.2200;0.4658]
[2.4399;4.6580;7.2200;1.0603] [2.7530;5.1450;7.2200;1.3342][1.4608;2.0570;3.6000;0.7452]
[1.4820;2.1550;3.6000;0.2685] [1.5098;2.7750;3.6000;1.6986] [1.4640;3.1160;3.6000;0.9342]
[1.6086;3.4780;3.6000;0.9918] [1.0596;1.7660;2.8500;0.3890] [1.1248;2.5440;2.8500;2.1315]
[1.1066;3.1780;2.8500;1.7370] [1.1176;4.0820;2.8500;2.4767] [0.5938;1.0860;4.5400;0.3973]
[0.5940;1.8650;4.5400;2.1342] [0.6458;2.4310;4.5400;1.5507] [0.7056;3.2970;4.5400;2.3726]};
T = {1.1320 1.1610 1.1810 1.1692 1.1658 1.3994 1.4988 1.5456 1.5818 1.5484 1.6106 1.8740 1.5622 1.4848
1.3520 1.4396 1.5944 1.6640 2.1566 1.5792 1.8448 1.9234 0.7281 0.7502 0.9032 1.3414 1.3632 1.4520
0.9694 0.9466 0.9892 1.0618 1.0782 1.0926 1.1942 1.4757 1.5100 1.8066 2.1176 2.6080 2.8008 0.9446
0.9638 0.9348 0.9414 1.0178 1.0594 1.0622 2.7874 2.9176 2.8738 2.9016 3.1426 0.8714 0.8670 0.8602
0.9022 0.9664 0.8622 0.8612 0.8592 0.9058 0.9166 1.0140 0.9846 1.3074 1.3558 1.3928 1.4482 2.2294
2.2590 2.4399 2.7530 2.7933 1.482 1.5098 1.464 1.6086 1.7622 1.1248 1.1066 1.1176 1.1892 0.594 0.6458
0.7056 0.7968};
net = newff([0 5;0 18;2 7;0 3],[4 1 1],{'logsig' 'tansig' 'purelin'});
net.trainParam.goal = 1e-100;
net.trainParam.epochs = 500;
net.trainParam.mu = .01;
net.trainParam.mu_inc = 10;
net.trainParam.mu_dec = .5;
net.trainParam.mu_max = 1e90;
net = train(net,P,T);
```

Table A-26 Weights for the input layer

Weight's Target Node (j)	***Weight's Origin (i)***			
	1	**2**	**3**	**4**
1	-0.7775	-0.014	0.0143	0.0068
2	-16.8961	-0.3985	-0.4806	-5.2564
3	22.7923	1.6488	-12.268	-6.8246
4	-1.681	-1.3998	-0.85	-0.8758

Table A-27 Biases for all the Layers

Layer	*Node 1*	*Node 2*	*Node 3*	*Node 4*
1	3.9005	41.6026	-0.5269	-3.594
2	-9.2356	-	-	-
3	-4.9507	-	-	-

Table A-28 Weights for the first hidden layer

Weight's Target Node (j)	***Weight's Origin (i)***			
	1	**2**	**3**	**4**
1	8.4304	0.2078	0.0856	1.0293

Table A-29 Weights for the output layer

Weight's Target Node (j)	***Weight's Origin (i)***
	1
1	-8.1231

APPENDIX D

This is data from NJDOT's Pavement Management System. These are the sites that were used to test the models in chapter 7.

				Undivided			Mile Post				
Route Type	Route Number	Route Aux	Direction	Lane Dir	Test Date	Test Year	From	To	IRI	Rut Depth	RQI
I	78		E		06/20/89	1989	6.4	6.6	60.5	0.3	3.9
I	78		E		05/24/90	1990	6.4	6.6	62.4	0.1	3.87
I	78		E		07/12/91	1991	6.4	6.6	71.4	0.2	3.73
I	78		E		09/01/93	1993	6.4	6.6	81.4	0.2	3.58
I	78		E		06/24/94	1994	6.4	6.6	80.7	0.2	3.59
I	78		E	E	08/23/96	1996	6.4	6.6	0	0.17	3.09
I	78		E		06/20/89	1989	6.6	6.8	59.3	0.2	3.92
I	78		E		05/24/90	1990	6.6	6.8	70.1	0.1	3.75
I	78		E		07/12/91	1991	6.6	6.8	69.4	0.2	3.76
I	78		E		09/01/93	1993	6.6	6.8	82.8	0.2	3.56
I	78		E		06/24/94	1994	6.6	6.8	86.2	0.2	3.51
I	78		E	E	08/23/96	1996	6.6	6.8	0	0.17	2.76
I	78		E		06/20/89	1989	6.8	7	66.9	0.1	3.8
I	78		E		05/24/90	1990	6.8	7	64.3	0.1	3.84
I	78		E		07/12/91	1991	6.8	7	76	0.1	3.66
I	78		E		09/01/93	1993	6.8	7	103.5	0.1	3.27
I	78		E		06/24/94	1994	6.8	7	109.5	0.1	3.19
I	78		E	E	08/23/96	1996	6.8	7	0	0.16	2.65
I	78		E		06/20/89	1989	7	7.2	72.1	0.1	3.72
I	78		E		05/24/90	1990	7	7.2	84.1	0	3.54
I	78		E		07/12/91	1991	7	7.2	87.6	0.1	3.49
I	78		E		09/01/93	1993	7	7.2	101.2	0.1	3.3
I	78		E		06/24/94	1994	7	7.2	103.5	0.1	3.27
I	78		E	E	08/23/96	1996	7	7.2	0	0.13	2.66
I	78		E		06/20/89	1989	7.2	7.4	54.4	0.2	4
I	78		E		05/24/90	1990	7.2	7.4	60.5	0.1	3.9
I	78		E		07/12/91	1991	7.2	7.4	63.7	0.1	3.85
I	78		E		09/01/93	1993	7.2	7.4	78.7	0.1	3.62
I	78		E		06/24/94	1994	7.2	7.4	78	0.1	3.63
I	78		E	E	08/23/96	1996	7.2	7.4	0	0.14	3.08
I	78		E		06/20/89	1989	7.8	8	54.4	0.1	4
I	78		E		05/24/90	1990	7.8	8	51.3	0	4.05
I	78		E		07/12/91	1991	7.8	8	54.4	0.1	4
I	78		E		09/01/93	1993	7.8	8	69.4	0.1	3.76
I	78		E		06/24/94	1994	7.8	8	82.1	0.2	3.57
I	78		E	E	08/23/96	1996	7.8	8	0	0.15	2.89
I	78		E		06/20/89	1989	8	8.2	49.5	0.1	4.08
I	78		E		05/24/90	1990	8	8.2	56.8	0	3.96
I	78		E		07/12/91	1991	8	8.2	64.3	0.1	3.84
I	78		E		09/01/93	1993	8	8.2	84.8	0.1	3.53
I	78		E		06/24/94	1994	8	8.2	99.8	0.1	3.32
I	78		E	E	08/23/96	1996	8	8.2	0	0.16	2.86

I	78		E		06/20/89	1989	8.2	8.4	51.9	0.1	4.04
I	78		E		05/24/90	1990	8.2	8.4	57.4	0	3.95
I	78		E		07/12/91	1991	8.2	8.4	59.9	0.1	3.91
I	78		E		09/01/93	1993	8.2	8.4	86.2	0.1	3.51
I	78		E		06/24/94	1994	8.2	8.4	94	0.1	3.4
I	78		E	E	08/23/96	1996	8.2	8.4	0	0.15	3.2
I	78		E		06/20/89	1989	8.4	8.6	58.1	0.1	3.94
I	78		E		05/24/90	1990	8.4	8.6	52.6	0	4.03
I	78		E		07/12/91	1991	8.4	8.6	56.8	0.1	3.96
I	78		E		09/01/93	1993	8.4	8.6	69.4	0.1	3.76
I	78		E		06/24/94	1994	8.4	8.6	74.7	0.2	3.68
I	78		E	E	08/23/96	1996	8.4	8.6	0	0.14	3.21
I	78		E		06/20/89	1989	8.6	8.8	68.2	0.1	3.78
I	78		E		05/24/90	1990	8.6	8.8	67.5	0.1	3.79
I	78		E		07/12/91	1991	8.6	8.8	74.7	0.1	3.68
I	78		E		09/01/93	1993	8.6	8.8	82.1	0.1	3.57
I	78		E		06/24/94	1994	8.6	8.8	85.5	0.1	3.52
I	78		E	E	08/23/96	1996	8.6	8.8	0	0.13	3.12
I	78		E		06/20/89	1989	9.2	9.4	53.8	0.2	4.01
I	78		E		05/24/90	1990	9.2	9.4	53.2	0.1	4.02
I	78		E		07/12/91	1991	9.2	9.4	63.1	0.1	3.86
I	78		E		09/01/93	1993	9.2	9.4	89.7	0.2	3.46
I	78		E		06/24/94	1994	9.2	9.4	99.8	0.2	3.32
I	78		E	E	08/23/96	1996	9.2	9.4	0	0.15	2.35
I	78		E		06/20/89	1989	9.4	9.6	51.3	0.1	4.05
I	78		E		05/24/90	1990	9.4	9.6	54.4	0	4
I	78		E		07/12/91	1991	9.4	9.6	66.9	0.1	3.8
I	78		E		09/01/93	1993	9.4	9.6	102.7	0.1	3.28
I	78		E		06/24/94	1994	9.4	9.6	110.3	0.2	3.18
I	78		E	E	08/23/96	1996	9.4	9.6	0	0.15	2.22
I	78		E		06/20/89	1989	9.6	9.8	63.7	0.1	3.85
I	78		E		05/24/90	1990	9.6	9.8	51.3	0.1	4.05
I	78		E		07/12/91	1991	9.6	9.8	76.7	0.1	3.65
I	78		E		09/01/93	1993	9.6	9.8	108.7	0.2	3.2
I	78		E		06/24/94	1994	9.6	9.8	113.4	0.2	3.14
I	78		E	E	08/23/96	1996	9.6	9.8	0	0.16	2.31
I	78		W		06/20/89	1989	6	6.2	60.5	0.2	3.9
I	78		W		05/24/90	1990	6	6.2	62.4	0.1	3.87
I	78		W		07/12/91	1991	6	6.2	63.1	0.2	3.86
I	78		W		09/01/93	1993	6	6.2	72.7	0.2	3.71
I	78		W		06/24/94	1994	6	6.2	78.7	0.2	3.62
I	78		W	W	08/23/96	1996	6	6.2	0	0.19	3.11
I	78		W		06/20/89	1989	6.2	6.4	61.2	0.2	3.89
I	78		W		05/24/90	1990	6.2	6.4	65	0.1	3.83
I	78		W		07/12/91	1991	6.2	6.4	64.3	0.2	3.84
I	78		W		09/01/93	1993	6.2	6.4	72.1	0.2	3.72
I	78		W		06/24/94	1994	6.2	6.4	70.1	0.2	3.75
I	78		W	W	08/23/96	1996	6.2	6.4	0	0.18	3.26
I	78		W		06/20/89	1989	6.4	6.6	53.8	0.1	4.01
I	78		W		05/24/90	1990	6.4	6.6	55	0	3.99

I	78		W		07/12/91	1991	6.4	6.6	65.6	0.2	3.82
I	78		W		09/01/93	1993	6.4	6.6	76	0.2	3.66
I	78		W		06/24/94	1994	6.4	6.6	78.7	0.2	3.62
I	78		W	W	08/23/96	1996	6.4	6.6	0	0.17	3
I	78		W		06/20/89	1989	6.6	6.8	58.1	0.2	3.94
I	78		W		05/24/90	1990	6.6	6.8	57.4	0.1	3.95
I	78		W		07/12/91	1991	6.6	6.8	61.2	0.2	3.89
I	78		W		09/01/93	1993	6.6	6.8	75.4	0.2	3.67
I	78		W		06/24/94	1994	6.6	6.8	78	0.2	3.63
I	78		W	W	08/23/96	1996	6.6	6.8	0	0.16	3.25
I	78		W		06/20/89	1989	6.8	7	63.1	0.2	3.86
I	78		W		05/24/90	1990	6.8	7	61.8	0.2	3.88
I	78		W		07/12/91	1991	6.8	7	70.7	0.3	3.74
I	78		W		09/01/93	1993	6.8	7	80	0.3	3.6
I	78		W		06/24/94	1994	6.8	7	92.5	0.4	3.42
I	78		W	W	08/23/96	1996	6.8	7	0	0.2	2.71
I	78		W		06/20/89	1989	7	7.2	75.4	0.2	3.67
I	78		W		05/24/90	1990	7	7.2	75.4	0.1	3.67
I	78		W		07/12/91	1991	7	7.2	76.7	0.2	3.65
I	78		W		09/01/93	1993	7	7.2	89.7	0.2	3.46
I	78		W		06/24/94	1994	7	7.2	95.4	0.2	3.38
I	78		W	W	08/23/96	1996	7	7.2	0	0.18	3.2
I	78		W		06/20/89	1989	7.2	7.4	57.4	0.2	3.95
I	78		W		05/24/90	1990	7.2	7.4	54.4	0.1	4
I	78		W		07/12/91	1991	7.2	7.4	61.2	0.2	3.89
I	78		W		09/01/93	1993	7.2	7.4	69.4	0.2	3.76
I	78		W		06/24/94	1994	7.2	7.4	80	0.3	3.6
I	78		W	W	08/23/96	1996	7.2	7.4	0	0.17	3.13
I	78		W		06/20/89	1989	7.4	7.6	74.7	0.2	3.68
I	78		W		05/24/90	1990	7.4	7.6	77.4	0.1	3.64
I	78		W		07/12/91	1991	7.4	7.6	82.1	0.2	3.57
I	78		W		09/01/93	1993	7.4	7.6	96.1	0.1	3.37
I	78		W		06/24/94	1994	7.4	7.6	104.2	0.2	3.26
I	78		W	W	08/23/96	1996	7.4	7.6	0	0.15	2.68
I	78		W		06/20/89	1989	7.6	7.8	74	0.1	3.69
I	78		W		05/24/90	1990	7.6	7.8	81.4	0.1	3.58
I	78		W		07/12/91	1991	7.6	7.8	91.1	0.1	3.44
I	78		W		09/01/93	1993	7.6	7.8	108.7	0.1	3.2
I	78		W		06/24/94	1994	7.6	7.8	119.6	0.2	3.06
I	78		W	W	08/23/96	1996	7.6	7.8	0	0.13	2.63
I	78		W		06/20/89	1989	7.8	8	53.8	0.1	4.01
I	78		W		05/24/90	1990	7.8	8	67.5	0	3.79
I	78		W		07/12/91	1991	7.8	8	80	0.1	3.6
I	78		W		09/01/93	1993	7.8	8	112.6	0.1	3.15
I	78		W		06/24/94	1994	7.8	8	128.6	0.2	2.95
I	78		W	W	08/23/96	1996	7.8	8	0	0.15	2.49
I	78		W		06/20/89	1989	8	8.2	60.5	0.1	3.9
I	78		W		05/24/90	1990	8	8.2	66.2	0	3.81
I	78		W		07/12/91	1991	8	8.2	66.9	0.1	3.8
I	78		W		09/01/93	1993	8	8.2	87.6	0.1	3.49

I	78		W		06/24/94	1994	8	8.2	95.4	0.2	3.38
I	78		W	W	08/23/96	1996	8	8.2	0	0.19	2.77
I	78		W		06/20/89	1989	8.2	8.4	54.4	0.1	4
I	78		W		05/24/90	1990	8.2	8.4	61.8	0	3.88
I	78		W		07/12/91	1991	8.2	8.4	62.4	0.1	3.87
I	78		W		09/01/93	1993	8.2	8.4	74.7	0.1	3.68
I	78		W		06/24/94	1994	8.2	8.4	85.5	0.2	3.52
I	78		W	W	08/23/96	1996	8.2	8.4	0	0.15	2.88
I	78		W		06/20/89	1989	8.4	8.6	61.2	0.1	3.89
I	78		W		05/24/90	1990	8.4	8.6	63.7	0	3.85
I	78		W		07/12/91	1991	8.4	8.6	65	0.1	3.83
I	78		W		09/01/93	1993	8.4	8.6	76.7	0.1	3.65
I	78		W		06/24/94	1994	8.4	8.6	78	0.1	3.63
I	78		W	W	08/23/96	1996	8.4	8.6	0	0.16	2.81
I	78		W		06/20/89	1989	8.6	8.8	71.4	0.1	3.73
I	78		W		05/24/90	1990	8.6	8.8	72.1	0.1	3.72
I	78		W		07/12/91	1991	8.6	8.8	72.1	0.2	3.72
I	78		W		09/01/93	1993	8.6	8.8	74.7	0.1	3.68
I	78		W		06/24/94	1994	8.6	8.8	84.1	0.1	3.54
I	78		W	W	08/23/96	1996	8.6	8.8	0	0.16	3.12
I	78		W		06/20/89	1989	8.8	9	72.7	0.1	3.71
I	78		W		05/24/90	1990	8.8	9	73.4	0.1	3.7
I	78		W		07/12/91	1991	8.8	9	72.7	0.2	3.71
I	78		W		09/01/93	1993	8.8	9	83.5	0.2	3.55
I	78		W		06/24/94	1994	8.8	9	84.1	0.2	3.54
I	78		W	W	08/23/96	1996	8.8	9	0	0.17	3.1
I	78		W		06/20/89	1989	9	9.2	59.9	0.2	3.91
I	78		W		05/24/90	1990	9	9.2	59.9	0.2	3.91
I	78		W		07/12/91	1991	9	9.2	58.7	0.3	3.93
I	78		W		09/01/93	1993	9	9.2	63.1	0.3	3.86
I	78		W		06/24/94	1994	9	9.2	65.6	0.3	3.82
I	78		W	W	08/23/96	1996	9	9.2	0	0.17	3.28
I	78		W		06/20/89	1989	9.2	9.4	56.2	0.2	3.97
I	78		W		05/24/90	1990	9.2	9.4	56.8	0.2	3.96
I	78		W		07/12/91	1991	9.2	9.4	63.1	0.3	3.80
I	78		W		09/01/93	1993	9.2	9.4	72.7	0.3	3.71
I	78		W		06/24/94	1994	9.2	9.4	70.1	0.3	3.75
I	78		W	W	08/23/96	1996	9.2	9.4	0	0.14	2.98
I	78		W		06/20/89	1989	9.4	9.6	61.2	0.2	3.89
I	78		W		05/24/90	1990	9.4	9.6	66.9	0.1	3.8
I	78		W		07/12/91	1991	9.4	9.6	66.9	0.2	3.8
I	78		W		09/01/93	1993	9.4	9.6	86.9	0.3	3.5
I	78		W		06/24/94	1994	9.4	9.6	93.3	0.4	3.41
I	78		W	W	08/23/96	1996	9.4	9.6	0	0.15	2.62

				Undivided			Mile Post				
Route Type	Route Number	Route Aux	Direction	Lane Dir	Test Date	Test Year	From	To	IRI	Rut Depth	RQI
I	80		E		6/20/94	1994	7.60	7.80	64.30	0.20	3.84
I	80		E	E	8/28/96	1996	7.60	7.80	0.00	0.09	3.52
I	80		E		6/20/94	1994	7.80	8.00	51.90	0.10	4.04
I	80		E	E	8/28/96	1996	7.80	8.00	0.00	0.06	3.43
I	80		E		6/20/94	1994	8.00	8.20	52.60	0.10	4.03
I	80		E	E	8/28/96	1996	8.00	8.20	0.00	0.04	3.45
I	80		E		6/20/94	1994	8.20	8.40	56.20	0.10	3.97
I	80		E	E	8/28/96	1996	8.20	8.40	0.00	0.04	3.45
I	80		E		6/20/94	1994	8.40	8.60	50.10	0.20	4.07
I	80		E	E	8/28/96	1996	8.40	8.60	0.00	0.06	3.48
I	80		E		6/20/94	1994	8.60	8.80	46.00	0.20	4.14
I	80		E	E	8/28/96	1996	8.60	8.80	0.00	0.06	3.57
I	80		E		6/20/94	1994	8.80	9.00	48.40	0.10	4.10
I	80		E	E	8/28/96	1996	8.80	9.00	0.00	0.06	3.50
I	80		E		6/20/94	1994	9.00	9.20	51.90	0.10	4.04
I	80		E	E	8/28/96	1996	9.00	9.20	0.00	0.07	3.65
I	80		E		6/20/94	1994	9.20	9.40	55.60	0.20	3.98
I	80		E	E	8/28/96	1996	9.20	9.40	0.00	0.05	3.59
I	80		E		6/20/94	1994	9.40	9.60	47.20	0.10	4.12
I	80		E	E	8/28/96	1996	9.40	9.60	0.00	0.06	3.60
I	80		E		6/20/94	1994	9.60	9.80	47.20	0.20	4.12
I	80		E	E	8/28/96	1996	9.60	9.80	0.00	0.07	3.61
I	80		E		6/20/94	1994	9.80	10.00	54.40	0.10	4.00
I	80		E	E	8/28/96	1996	9.80	10.00	0.00	0.05	3.64
I	80		E		6/20/94	1994	10.00	10.20	53.20	0.20	4.02
I	80		E	E	8/28/96	1996	10.00	10.20	0.00	0.06	3.49
I	80		E		6/20/94	1994	10.20	10.40	49.50	0.10	4.08
I	80		E	E	8/28/96	1996	10.20	10.40	0.00	0.08	3.13
I	80		E		6/20/94	1994	10.40	10.60	49.00	0.10	4.09
I	80		E	E	8/28/96	1996	10.40	10.60	0.00	0.08	3.44
I	80		E		6/20/94	1994	10.60	10.80	51.30	0.10	4.05
I	80		E	E	8/28/96	1996	10.60	10.80	0.00	0.08	3.33
I	80		E		6/20/94	1994	10.80	11.00	42.50	0.10	4.20
I	80		E	E	8/28/96	1996	10.80	11.00	0.00	0.07	3.41
I	80		E		6/20/94	1994	11.00	11.20	44.20	0.20	4.17
I	80		E	E	8/28/96	1996	11.00	11.20	0.00	0.08	3.37
I	80		E		6/20/94	1994	11.20	11.40	41.30	0.10	4.22
I	80		E	E	8/28/96	1996	11.20	11.40	0.00	0.09	3.40
I	80		E		6/20/94	1994	11.40	11.60	44.20	0.10	4.17
I	80		E	E	8/28/96	1996	11.40	11.60	0.00	0.09	3.29
I	80		E		6/20/94	1994	11.60	11.80	45.40	0.20	4.15
I	80		E	E	8/28/96	1996	11.60	11.80	0.00	0.06	3.37
I	80		E		6/20/94	1994	11.80	12.00	43.60	0.20	4.18
I	80		E	E	8/28/96	1996	11.80	12.00	0.00	0.10	3.17
I	80		E		6/20/94	1994	12.00	12.20	68.20	0.20	3.78
I	80		E	E	8/28/96	1996	12.00	12.20	0.00	0.17	3.44
I	80		E		6/20/94	1994	12.20	12.40	66.20	0.20	3.81

I	80		E	E	8/28/96	1996	12.20	12.40	0.00	0.17	3.39
I	80		E		6/20/94	1994	12.40	12.60	59.30	0.20	3.92
I	80		E	E	8/28/96	1996	12.40	12.60	0.00	0.15	3.57
I	80		E		6/20/94	1994	12.60	12.80	66.90	0.20	3.80
I	80		E	E	8/28/96	1996	12.60	12.80	0.00	0.14	3.50
I	80		W		6/20/94	1994	7.60	7.80	61.20	0.20	3.89
I	80		W	W	8/28/96	1996	7.60	7.80	0.00	0.12	3.47
I	80		W		6/20/94	1994	7.80	8.00	59.30	0.10	3.92
I	80		W	W	8/28/96	1996	7.80	8.00	0.00	0.10	3.39
I	80		W		6/20/94	1994	8.00	8.20	65.00	0.20	3.83
I	80		W	W	8/28/96	1996	8.00	8.20	0.00	0.09	3.55
I	80		W		6/20/94	1994	8.20	8.40	62.40	0.10	3.87
I	80		W	W	8/28/96	1996	8.20	8.40	0.00	0.09	3.45
I	80		W		6/20/94	1994	8.40	8.60	63.70	0.10	3.85
I	80		W	W	8/28/96	1996	8.40	8.60	0.00	0.08	3.46
I	80		W		6/20/94	1994	8.60	8.80	57.40	0.10	3.95
I	80		W	W	8/28/96	1996	8.60	8.80	0.00	0.10	3.40
I	80		W		6/20/94	1994	8.80	9.00	53.20	0.10	4.02
I	80		W	W	8/28/96	1996	8.80	9.00	0.00	0.08	3.68
I	80		W		6/20/94	1994	9.00	9.20	54.40	0.10	4.00
I	80		W	W	8/28/96	1996	9.00	9.20	0.00	0.11	3.32
I	80		W		6/20/94	1994	9.20	9.40	48.40	0.10	4.10
I	80		W	W	8/28/96	1996	9.20	9.40	0.00	0.11	3.32
I	80		W		6/20/94	1994	9.40	9.60	46.60	0.10	4.13
I	80		W	W	8/28/96	1996	9.40	9.60	0.00	0.12	3.19
I	80		W		6/20/94	1994	9.60	9.80	53.80	0.10	4.01
I	80		W	W	8/28/96	1996	9.60	9.80	0.00	0.12	3.24
I	80		W		6/20/94	1994	9.80	10.00	53.80	0.10	4.01
I	80		W	W	8/28/96	1996	9.80	10.00	0.00	0.12	3.25
I	80		W		6/20/94	1994	10.00	10.20	57.40	0.20	3.95
I	80		W	W	8/28/96	1996	10.00	10.20	0.00	0.06	3.74
I	80		W		6/20/94	1994	10.20	10.40	49.00	0.10	4.09
I	80		W	W	8/28/96	1996	10.20	10.40	0.00	0.09	3.71
I	80		W		6/20/94	1994	10.40	10.60	59.90	0.10	3.91
I	80		W	W	8/28/96	1996	10.40	10.60	0.00	0.10	3.66
I	80		W		6/20/94	1994	10.60	10.80	59.90	0.10	3.91
I	80		W	W	8/28/96	1996	10.60	10.80	0.00	0.09	3.35
I	80		W		6/20/94	1994	10.80	11.00	51.30	0.20	4.05
I	80		W	W	8/28/96	1996	10.80	11.00	0.00	0.13	3.50
I	80		W		6/20/94	1994	11.00	11.20	55.00	0.20	3.99
I	80		W	W	8/28/96	1996	11.00	11.20	0.00	0.10	3.54
I	80		W		6/20/94	1994	11.20	11.40	62.40	0.10	3.87
I	80		W	W	8/28/96	1996	11.20	11.40	0.00	0.08	3.58
I	80		W		6/20/94	1994	11.40	11.60	57.40	0.10	3.95
I	80		W	W	8/28/96	1996	11.40	11.60	0.00	0.08	3.40
I	80		W		6/20/94	1994	11.60	11.80	53.20	0.10	4.02
I	80		W	W	8/28/96	1996	11.60	11.80	0.00	0.10	3.47
I	80		W		6/20/94	1994	11.80	12.00	66.20	0.20	3.81
I	80		W	W	8/28/96	1996	11.80	12.00	0.00	0.09	3.49
I	80		W		6/20/94	1994	12.00	12.20	74.00	0.20	3.69

I	80		W	W	8/28/96	1996	12.00	12.20	0.00	0.10	3.52
I	80		W		6/20/94	1994	12.20	12.40	70.10	0.20	3.75
I	80		W	W	8/28/96	1996	12.20	12.40	0.00	0.10	3.55
I	80		W		6/20/94	1994	12.40	12.60	67.50	0.20	3.79
I	80		W	W	8/28/96	1996	12.40	12.60	0.00	0.09	3.48
I	80		W		6/20/94	1994	12.60	12.80	61.20	0.20	3.89
I	80		W	W	8/28/96	1996	12.60	12.80	0.00	0.09	3.57

				Undivided			Mile Post				
Route Type	Route Number	Route Aux	Direction	Lane Dir	Test Date	Test Year	From	To	IRI	Rut Depth	RQI
I	80		E		6/20/94	1994	20.00	20.20	54.40	0.20	4.00
I	80		E	E	8/28/96	1996	20.00	20.20	0.00	0.17	3.74
I	80		E		6/20/94	1994	20.20	20.40	51.30	0.10	4.05
I	80		E	E	8/28/96	1996	20.20	20.40	0.00	0.18	3.86
I	80		E		6/20/94	1994	20.40	20.60	41.30	0.10	4.22
I	80		E	E	8/28/96	1996	20.40	20.60	0.00	0.17	3.87
I	80		E		6/20/94	1994	20.60	20.80	41.90	0.10	4.21
I	80		E	E	8/28/96	1996	20.60	20.80	0.00	0.17	3.85
I	80		E		6/20/94	1994	20.80	21.00	45.40	0.20	4.15
I	80		E	E	8/28/96	1996	20.80	21.00	0.00	0.18	3.88
I	80		E		6/20/94	1994	21.00	21.20	44.20	0.10	4.17
I	80		E	E	8/28/96	1996	21.00	21.20	0.00	0.15	3.85
I	80		E		6/20/94	1994	21.20	21.40	43.60	0.10	4.18
I	80		E	E	8/28/96	1996	21.20	21.40	0.00	0.17	3.87
I	80		E		6/20/94	1994	21.40	21.60	44.80	0.10	4.16
I	80		E	E	8/28/96	1996	21.40	21.60	0.00	0.17	3.84
I	80		E		6/20/94	1994	21.60	21.80	49.50	0.20	4.08
I	80		E	E	8/28/96	1996	21.60	21.80	0.00	0.16	3.69
I	80		E		6/20/94	1994	21.80	22.00	45.40	0.10	4.15
I	80		E	E	8/28/96	1996	21.80	22.00	0.00	0.17	3.66
I	80		E		6/20/94	1994	22.00	22.20	45.40	0.10	4.15
I	80		E	E	8/28/96	1996	22.00	22.20	0.00	0.17	3.88
I	80		E		6/20/94	1994	22.20	22.40	46.60	0.10	4.13
I	80		E	E	8/28/96	1996	22.20	22.40	0.00	0.17	3.95
I	80		E		6/20/94	1994	22.40	22.60	45.40	0.10	4.15
I	80		E	E	8/28/96	1996	22.40	22.60	0.00	0.17	3.92
I	80		E		6/20/94	1994	22.60	22.80	50.70	0.10	4.06
I	80		E	E	8/28/96	1996	22.60	22.80	0.00	0.18	3.87
I	80		E		6/20/94	1994	22.80	23.00	55.60	0.20	3.98
I	80		E	E	8/28/96	1996	22.80	23.00	0.00	0.18	3.52
I	80		E		6/20/94	1994	23.00	23.20	44.80	0.10	4.16
I	80		E	E	8/28/96	1996	23.00	23.20	0.00	0.17	3.93
I	80		E		6/20/94	1994	23.20	23.40	69.40	0.10	3.76
I	80		E	E	8/28/96	1996	23.20	23.40	0.00	0.16	3.28
I	80		E		6/20/94	1994	23.40	23.60	42.50	0.10	4.20
I	80		E	E	8/28/96	1996	23.40	23.60	0.00	0.16	3.94
I	80		E		6/20/94	1994	23.60	23.80	45.40	0.10	4.15

I	80		E	E	8/28/96	1996	23.60	23.80	0.00	0.18	3.96
I	80		E		6/20/94	1994	23.80	24.00	46.60	0.20	4.13
I	80		E	E	8/28/96	1996	23.80	24.00	0.00	0.19	3.93
I	80		E		6/20/94	1994	24.00	24.20	43.10	0.20	4.19
I	80		E	E	8/28/96	1996	24.00	24.20	0.00	0.17	3.86
I	80		E		6/20/94	1994	24.20	24.40	43.10	0.20	4.19
I	80		E	E	8/28/96	1996	24.20	24.40	0.00	0.15	3.99
I	80		E		6/20/94	1994	24.40	24.60	43.10	0.10	4.19
I	80		E	E	8/28/96	1996	24.40	24.60	0.00	0.16	3.96
I	80		E		6/20/94	1994	24.60	24.80	41.90	0.20	4.21
I	80		E	E	8/28/96	1996	24.60	24.80	0.00	0.16	3.92
I	80		E		6/20/94	1994	24.80	25.00	43.10	0.10	4.19
I	80		E	E	8/28/96	1996	24.80	25.00	0.00	0.16	3.87
I	80		E		6/20/94	1994	25.00	25.20	46.60	0.20	4.13
I	80		E	E	8/28/96	1996	25.00	25.20	0.00	0.15	3.90
I	80		E		6/20/94	1994	25.20	25.40	65.00	0.20	3.83
I	80		E	E	8/28/96	1996	25.20	25.40	0.00	0.15	3.16
I	80		E		6/20/94	1994	25.40	25.48	51.90	0.30	4.04
I	80		E	E	8/28/96	1996	25.40	25.48	0.00	0.14	3.68
I	80		E		6/20/94	1994	25.48	25.60	51.90	0.30	4.04
I	80		E	E	8/28/96	1996	25.48	25.60	0.00	0.14	3.68
I	80		E		6/20/94	1994	25.60	25.80	55.60	0.30	3.98
I	80		E	E	8/28/96	1996	25.60	25.80	0.00	0.15	3.54
I	80		E		6/20/94	1994	25.80	26.00	65.60	0.20	3.82
I	80		E	E	8/28/96	1996	25.80	26.00	0.00	0.18	3.14
I	80		E		6/20/94	1994	26.00	26.20	64.30	0.10	3.84
I	80		E	E	8/28/96	1996	26.00	26.20	0.00	0.17	3.58
I	80		E		6/20/94	1994	26.20	26.40	91.80	0.20	3.43
I	80		E	E	8/28/96	1996	26.20	26.40	0.00	0.16	2.96
I	80		E		6/20/94	1994	26.40	26.60	56.20	0.20	3.97
I	80		E	E	8/28/96	1996	26.40	26.60	0.00	0.16	3.84
I	80		E		6/20/94	1994	26.60	26.80	51.90	0.20	4.04
I	80		E	E	8/28/96	1996	26.60	26.80	0.00	0.14	3.82
I	80		E		6/20/94	1994	26.80	26.88	46.00	0.20	4.14
I	80		E	E	8/28/96	1996	26.80	26.88	0.00	0.14	3.88
I	80		E		6/20/94	1994	26.88	27.00	46.00	0.20	4.14
I	80		E	E	8/28/96	1996	26.88	27.00	0.00	0.14	3.88
I	80		E		6/20/94	1994	27.00	27.20	51.90	0.20	4.04
I	80		E	E	8/28/96	1996	27.00	27.20	0.00	0.15	3.39
I	80		E		6/20/94	1994	27.20	27.40	67.50	0.10	3.79
I	80		E	E	8/28/96	1996	27.20	27.40	0.00	0.14	3.52
I	80		E		6/20/94	1994	27.40	27.60	55.00	0.20	3.99
I	80		E	E	8/28/96	1996	27.40	27.60	0.00	0.13	3.62
I	80		E		6/20/94	1994	27.60	27.80	51.90	0.20	4.04
I	80		E	E	8/28/96	1996	27.60	27.80	0.00	0.14	3.84
I	80		E		6/20/94	1994	27.80	28.00	47.20	0.20	4.12
I	80		E	E	8/28/96	1996	27.80	28.00	0.00	0.13	3.84
I	80		E		6/20/94	1994	28.00	28.20	67.50	0.30	3.79
I	80		E	E	8/28/96	1996	28.00	28.20	0.00	0.14	3.11
I	80		E		6/20/94	1994	28.20	28.40	36.20	0.20	4.31

I	80		E	E	8/28/96	1996	28.20	28.40	0.00	0.13	3.86
I	80		E		6/20/94	1994	28.40	28.60	31.70	0.20	4.39
I	80		E	E	8/28/96	1996	28.40	28.60	0.00	0.13	3.97
I	80		E		6/20/94	1994	28.60	28.80	33.90	0.20	4.35
I	80		E	E	8/28/96	1996	28.60	28.80	0.00	0.16	3.89
I	80		E		6/20/94	1994	28.80	29.00	78.00	0.20	3.63
I	80		E	E	8/28/96	1996	28.80	29.00	0.00	0.16	3.09
I	80		E		6/20/94	1994	29.00	29.20	56.80	0.10	3.96
I	80		E	E	8/28/96	1996	29.00	29.20	0.00	0.17	3.31
I	80		E		6/20/94	1994	29.20	29.40	68.80	0.20	3.77
I	80		E	E	8/28/96	1996	29.20	29.40	0.00	0.13	3.49
I	80		E		6/20/94	1994	29.40	29.60	41.90	0.20	4.21
I	80		E	E	8/28/96	1996	29.40	29.60	0.00	0.13	3.96
I	80		E		6/20/94	1994	29.60	29.80	47.20	0.10	4.12
I	80		E	E	8/28/96	1996	29.60	29.80	0.00	0.12	3.90
I	80		E		6/20/94	1994	29.80	30.00	63.10	0.10	3.86
I	80		E	E	8/28/96	1996	29.80	30.00	0.00	0.13	3.93
I	80		E		6/20/94	1994	30.00	30.20	49.50	0.20	4.08
I	80		E	E	8/28/96	1996	30.00	30.20	0.00	0.12	3.74
I	80		E		6/20/94	1994	30.20	30.40	43.60	0.20	4.18
I	80		E	E	8/28/96	1996	30.20	30.40	0.00	0.13	3.89
I	80		E		6/20/94	1994	30.40	30.60	41.90	0.10	4.21
I	80		E	E	8/28/96	1996	30.40	30.60	0.00	0.13	3.93
I	80		E		6/20/94	1994	30.60	30.80	55.60	0.20	3.98
I	80		E	E	8/28/96	1996	30.60	30.80	0.00	0.11	3.47
I	80		E		6/20/94	1994	30.80	31.00	47.80	0.20	4.11
I	80		E	E	8/28/96	1996	30.80	31.00	0.00	0.12	3.90
I	80		E		6/20/94	1994	31.00	31.20	49.00	0.20	4.09
I	80		E	E	8/28/96	1996	31.00	31.20	0.00	0.14	3.87
I	80		E		6/20/94	1994	31.20	31.40	45.40	0.20	4.15
I	80		E	E	8/28/96	1996	31.20	31.40	0.00	0.14	3.94
I	80		E		6/20/94	1994	31.40	31.60	40.20	0.20	4.24
I	80		E	E	8/28/96	1996	31.40	31.60	0.00	0.13	3.92
I	80		E		6/20/94	1994	31.60	31.80	45.40	0.20	4.15
I	80		E	E	8/28/96	1996	31.60	31.80	0.00	0.14	3.88
I	80		E		6/20/94	1994	31.80	32.00	50.70	0.20	4.06
I	80		E	E	8/28/96	1996	31.80	32.00	0.00	0.16	3.18
I	80		E		6/20/94	1994	32.00	32.20	66.90	0.20	3.80
I	80		E	E	8/28/96	1996	32.00	32.20	0.00	0.13	3.55
I	80		E		6/20/94	1994	32.20	32.40	50.70	0.20	4.06
I	80		E	E	8/28/96	1996	32.20	32.40	0.00	0.13	3.86
I	80		E		6/20/94	1994	32.40	32.60	66.90	0.20	3.80
I	80		E	E	8/28/96	1996	32.40	32.60	0.00	0.17	2.95
I	80		E		6/20/94	1994	32.60	32.80	49.00	0.20	4.09
I	80		E	E	8/28/96	1996	32.60	32.80	0.00	0.14	3.96
I	80		E		6/20/94	1994	32.80	33.00	43.10	0.20	4.19
I	80		E	E	8/28/96	1996	32.80	33.00	0.00	0.13	3.91
I	80		E		6/20/94	1994	33.00	33.20	41.90	0.20	4.21
I	80		E	E	8/28/96	1996	33.00	33.20	0.00	0.12	3.91
I	80		E		6/20/94	1994	33.20	33.40	46.00	0.20	4.14

I	80		E	E	8/28/96	1996	33.20	33.40	0.00	0.13	3.86
I	80		E		6/20/94	1994	33.40	33.60	61.80	0.20	3.88
I	80		E	E	8/28/96	1996	33.40	33.60	0.00	0.13	3.34
I	80		E		6/20/94	1994	33.60	33.80	53.20	0.20	4.02
I	80		E	E	8/28/96	1996	33.60	33.80	0.00	0.13	3.93
I	80		E		6/20/94	1994	33.80	34.00	59.90	0.20	3.91
I	80		E	E	8/28/96	1996	33.80	34.00	0.00	0.15	3.43
I	80		W		6/20/94	1994	20.00	20.20	49.50	0.20	4.08
I	80		W	W	8/28/96	1996	20.00	20.20	0.00	0.08	3.89
I	80		W		6/20/94	1994	20.20	20.40	57.40	0.20	3.95
I	80		W	W	8/28/96	1996	20.20	20.40	0.00	0.08	3.87
I	80		W		6/20/94	1994	20.40	20.60	53.80	0.10	4.01
I	80		W	W	8/28/96	1996	20.40	20.60	0.00	0.07	3.82
I	80		W		6/20/94	1994	20.60	20.80	42.50	0.20	4.20
I	80		W	W	8/28/96	1996	20.60	20.80	0.00	0.05	3.88
I	80		W		6/20/94	1994	20.80	21.00	56.20	0.20	3.97
I	80		W	W	8/28/96	1996	20.80	21.00	0.00	0.05	3.75
I	80		W		6/20/94	1994	21.00	21.20	54.40	0.20	4.00
I	80		W	W	8/28/96	1996	21.00	21.20	0.00	0.09	2.63
I	80		W		6/20/94	1994	21.20	21.40	48.40	0.20	4.10
I	80		W	W	8/28/96	1996	21.20	21.40	0.00	0.11	3.82
I	80		W		6/20/94	1994	21.40	21.60	49.50	0.20	4.08
I	80		W	W	8/28/96	1996	21.40	21.60	0.00	0.14	3.80
I	80		W		6/20/94	1994	21.60	21.80	43.10	0.20	4.19
I	80		W	W	8/28/96	1996	21.60	21.80	0.00	0.09	3.84
I	80		W		6/20/94	1994	21.80	22.00	53.80	0.20	4.01
I	80		W	W	8/28/96	1996	21.80	22.00	0.00	0.08	3.86
I	80		W		6/20/94	1994	22.00	22.20	46.00	0.30	4.14
I	80		W	W	8/28/96	1996	22.00	22.20	0.00	0.12	3.89
I	80		W		6/20/94	1994	22.20	22.40	47.80	0.30	4.11
I	80		W	W	8/28/96	1996	22.20	22.40	0.00	0.09	3.85
I	80		W		6/20/94	1994	22.40	22.60	44.80	0.20	4.16
I	80		W	W	8/28/96	1996	22.40	22.60	0.00	0.12	3.79
I	80		W		6/20/94	1994	22.60	22.80	45.40	0.30	4.15
I	80		W	W	8/28/96	1996	22.60	22.80	0.00	0.10	3.86
I	80		W		6/20/94	1994	22.80	23.00	62.40	0.20	3.87
I	80		W	W	8/28/96	1996	22.80	23.00	0.00	0.07	3.47
I	80		W		6/20/94	1994	23.00	23.20	37.90	0.20	4.28
I	80		W	W	8/28/96	1996	23.00	23.20	0.00	0.06	3.81
I	80		W		6/20/94	1994	23.20	23.40	54.40	0.20	4.00
I	80		W	W	8/28/96	1996	23.20	23.40	0.00	0.09	3.74
I	80		W		6/20/94	1994	23.40	23.60	43.10	0.20	4.19
I	80		W	W	8/28/96	1996	23.40	23.60	0.00	0.08	3.94
I	80		W		6/20/94	1994	23.60	23.80	39.00	0.20	4.26
I	80		W	W	8/28/96	1996	23.60	23.80	0.00	0.08	3.94
I	80		W		6/20/94	1994	23.80	24.00	40.70	0.10	4.23
I	80		W	W	8/28/96	1996	23.80	24.00	0.00	0.07	3.92
I	80		W		6/20/94	1994	24.00	24.20	41.90	0.10	4.21
I	80		W	W	8/28/96	1996	24.00	24.20	0.00	0.06	3.91
I	80		W		6/20/94	1994	24.20	24.40	47.80	0.20	4.11

I	80		W	W	8/28/96	1996	24.20	24.40	0.00	0.07	3.80
I	80		W		6/20/94	1994	24.40	24.60	48.40	0.20	4.10
I	80		W	W	8/28/96	1996	24.40	24.60	0.00	0.07	3.86
I	80		W		6/20/94	1994	24.60	24.80	46.60	0.20	4.13
I	80		W	W	8/28/96	1996	24.60	24.80	0.00	0.08	3.93
I	80		W		6/20/94	1994	24.80	25.00	46.60	0.10	4.13
I	80		W	W	8/28/96	1996	24.80	25.00	0.00	0.09	3.83
I	80		W		6/20/94	1994	25.00	25.20	50.10	0.20	4.07
I	80		W	W	8/28/96	1996	25.00	25.20	0.00	0.09	3.79
I	80		W		6/20/94	1994	25.20	25.40	73.40	0.20	3.70
I	80		W	W	8/28/96	1996	25.20	25.40	0.00	0.11	3.29
I	80		W		6/20/94	1994	25.40	25.48	46.60	0.30	4.13
I	80		W	W	8/28/96	1996	25.40	25.48	0.00	0.13	3.77
I	80		W		6/20/94	1994	25.48	25.60	46.60	0.30	4.13
I	80		W	W	8/28/96	1996	25.48	25.60	0.00	0.13	3.77
I	80		W		6/20/94	1994	25.60	25.80	54.40	0.10	4.00
I	80		W	W	8/28/96	1996	25.60	25.80	0.00	0.13	3.76
I	80		W		6/20/94	1994	25.80	26.00	66.20	0.20	3.81
I	80		W	W	8/28/96	1996	25.80	26.00	0.00	0.13	3.71
I	80		W		6/20/94	1994	26.00	26.20	76.70	0.30	3.65
I	80		W	W	8/28/96	1996	26.00	26.20	0.00	0.16	3.13
I	80		W		6/20/94	1994	26.20	26.40	121.20	0.20	3.04
I	80		W	W	8/28/96	1996	26.20	26.40	0.00	0.14	2.87
I	80		W		6/20/94	1994	26.40	26.60	62.40	0.30	3.87
I	80		W	W	8/28/96	1996	26.40	26.60	0.00	0.16	3.45
I	80		W		6/20/94	1994	26.60	26.80	57.40	0.20	3.95
I	80		W	W	8/28/96	1996	26.60	26.80	0.00	0.18	3.54
I	80		W		6/20/94	1994	26.80	26.88	50.10	0.30	4.07
I	80		W	W	8/28/96	1996	26.80	26.88	0.00	0.17	3.62
I	80		W		6/20/94	1994	26.88	27.00	50.10	0.30	4.07
I	80		W	W	8/28/96	1996	26.88	27.00	0.00	0.17	3.62
I	80		W		6/20/94	1994	27.00	27.20	62.40	0.30	3.87
I	80		W	W	8/28/96	1996	27.00	27.20	0.00	0.18	3.29
I	80		W		6/20/94	1994	27.20	27.40	73.40	0.30	3.70
I	80		W	W	8/28/96	1996	27.20	27.40	0.00	0.16	3.17
I	80		W		6/20/94	1994	27.40	27.60	56.20	0.30	3.97
I	80		W	W	8/28/96	1996	27.40	27.60	0.00	0.11	3.74
I	80		W		6/20/94	1994	27.60	27.80	43.60	0.30	4.18
I	80		W	W	8/28/96	1996	27.60	27.80	0.00	0.09	3.84
I	80		W		6/20/94	1994	27.80	28.00	46.60	0.20	4.13
I	80		W	W	8/28/96	1996	27.80	28.00	0.00	0.11	3.58
I	80		W		6/20/94	1994	28.00	28.20	70.70	0.30	3.74
I	80		W	W	8/28/96	1996	28.00	28.20	0.00	0.13	2.96
I	80		W		6/20/94	1994	28.20	28.40	42.50	0.20	4.20
I	80		W	W	8/28/96	1996	28.20	28.40	0.00	0.06	3.80
I	80		W		6/20/94	1994	28.40	28.60	46.00	0.20	4.14
I	80		W	W	8/28/96	1996	28.40	28.60	0.00	0.08	3.84
I	80		W		6/20/94	1994	28.60	28.80	47.80	0.30	4.11
I	80		W	W	8/28/96	1996	28.60	28.80	0.00	0.09	3.65
I	80		W		6/20/94	1994	28.80	29.00	82.80	0.30	3.56

I	80		W	W	8/28/96	1996	28.80	29.00	0.00	0.11	3.33
I	80		W		6/20/94	1994	29.00	29.20	76.70	0.20	3.65
I	80		W	W	8/28/96	1996	29.00	29.20	0.00	0.11	3.44
I	80		W		6/20/94	1994	29.20	29.40	55.00	0.20	3.99
I	80		W	W	8/28/96	1996	29.20	29.40	0.00	0.08	3.78
I	80		W		6/20/94	1994	29.40	29.60	51.30	0.20	4.05
I	80		W	W	8/28/96	1996	29.40	29.60	0.00	0.11	3.66
I	80		W		6/20/94	1994	29.60	29.80	43.60	0.20	4.18
I	80		W	W	8/28/96	1996	29.60	29.80	0.00	0.11	3.92
I	80		W		6/20/94	1994	29.80	30.00	50.10	0.30	4.07
I	80		W	W	8/28/96	1996	29.80	30.00	0.00	0.12	3.86
I	80		W		6/20/94	1994	30.00	30.20	55.60	0.30	3.98
I	80		W	W	8/28/96	1996	30.00	30.20	0.00	0.13	3.67
I	80		W		6/20/94	1994	30.20	30.40	53.80	0.20	4.01
I	80		W	W	8/28/96	1996	30.20	30.40	0.00	0.11	3.64
I	80		W		6/20/94	1994	30.40	30.60	61.80	0.30	3.88
I	80		W	W	8/28/96	1996	30.40	30.60	0.00	0.09	3.41
I	80		W		6/20/94	1994	30.60	30.80	49.50	0.30	4.08
I	80		W	W	8/28/96	1996	30.60	30.80	0.00	0.10	3.62
I	80		W		6/20/94	1994	30.80	31.00	49.00	0.20	4.09
I	80		W	W	8/28/96	1996	30.80	31.00	0.00	0.11	3.86
I	80		W		6/20/94	1994	31.00	31.20	48.40	0.20	4.10
I	80		W	W	8/28/96	1996	31.00	31.20	0.00	0.11	3.80
I	80		W		6/20/94	1994	31.20	31.40	46.00	0.20	4.14
I	80		W	W	8/28/96	1996	31.20	31.40	0.00	0.11	3.86
I	80		W		6/20/94	1994	31.40	31.60	46.00	0.20	4.14
I	80		W	W	8/28/96	1996	31.40	31.60	0.00	0.12	3.76
I	80		W		6/20/94	1994	31.80	32.00	75.40	0.30	3.67
I	80		W	W	8/28/96	1996	31.80	32.00	0.00	0.14	2.91
I	80		W		6/20/94	1994	32.00	32.20	47.20	0.20	4.12
I	80		W	W	8/28/96	1996	32.00	32.20	0.00	0.11	3.93
I	80		W		6/20/94	1994	32.20	32.40	46.60	0.20	4.13
I	80		W	W	8/28/96	1996	32.20	32.40	0.00	0.13	3.63
I	80		W		6/20/94	1994	32.40	32.60	82.80	0.20	3.56
I	80		W	W	8/28/96	1996	32.40	32.60	0.00	0.16	3.13
I	80		W		6/20/94	1994	32.60	32.80	43.60	0.20	4.18
I	80		W	W	8/28/96	1996	32.60	32.80	0.00	0.13	3.96
I	80		W		6/20/94	1994	32.80	33.00	43.60	0.20	4.18
I	80		W	W	8/28/96	1996	32.80	33.00	0.00	0.09	3.91
I	80		W		6/20/94	1994	33.00	33.20	46.60	0.20	4.13
I	80		W	W	8/28/96	1996	33.00	33.20	0.00	0.09	3.88
I	80		W		6/20/94	1994	33.20	33.40	53.80	0.20	4.01
I	80		W	W	8/28/96	1996	33.20	33.40	0.00	0.13	3.88
I	80		W		6/20/94	1994	33.40	33.60	66.20	0.20	3.81
I	80		W	W	8/28/96	1996	33.40	33.60	0.00	0.10	3.25
I	80		W		6/20/94	1994	33.60	33.80	52.60	0.30	4.03
I	80		W	W	8/28/96	1996	33.60	33.80	0.00	0.11	3.35
I	80		W		6/20/94	1994	33.80	34.00	85.50	0.20	3.52
I	80		W	W	8/28/96	1996	33.80	34.00	0.00	0.13	3.34
I	80		W		6/20/94	1994	34.00	34.20	91.80	0.20	3.43

I	80		W	W	8/28/96	1996	34.00	34.20	0.00	0.14	3.35
I	80		W		6/20/94	1994	34.20	34.40	60.50	0.30	3.90
I	80		W	W	8/28/96	1996	34.20	34.40	0.00	0.15	3.34
I	80		W		6/20/94	1994	34.40	34.60	39.60	0.20	4.25
I	80		W	W	8/28/96	1996	34.40	34.60	0.00	0.12	3.89
I	80		W		6/20/94	1994	34.60	34.80	50.70	0.20	4.06
I	80		W	W	8/28/96	1996	34.60	34.80	0.00	0.11	3.73
I	80		W		6/20/94	1994	34.80	35.00	56.80	0.20	3.96
I	80		W	W	8/28/96	1996	34.80	35.00	0.00	0.11	3.80
I	80		W		6/20/94	1994	35.00	35.20	54.40	0.20	4.00
I	80		W	W	8/28/96	1996	35.00	35.20	0.00	0.08	3.61

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