A Pavement Management System for County Roads

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16. Abstract

In recent years asset management has become important because the public wants to see the Federal, State, and Local governments run more like a private business. A pavement management system (PMS) is one aspect of asset management that deals entirely with roadways. A PMS is essentially a decision support tool that stores various types of information about roads and supports future forecasts of condition. This report covers a PMS that was designed for county roads in the state of Alabama. A PMS computer program was designed with county engineers in mind, for expedient management of their roads. To incorporate future forecasts of condition, road data was collected and analyzed with linear regression to build a pavement deterioration equation.

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Executive Summary

A Pavement Management System is an asset management system that assists decision makers in finding optimum strategies for providing and maintaining pavements in a serviceable condition over a given period of time (Hass et al 1994). A PMS is essentially a decision support tool that stores various types of information about roads and supports future forecasts of condition.

This project examined the development of a PMS for county engineers in Alabama to output pavement information in a clear and understandable format, to help them make better decisions on how to manage their roads. This report includes a description of the PMS system developed for the county engineers and a discussion of a pavement forecasting model that would allow engineers to predict when maintenance activities are necessary. The PMS computer program was developed to provide a tool for county engineers, so that they will no longer have to use guesswork or get by using spreadsheets. The new program provides summaries, future predictions, and pavement condition ratings in digital or paper format, simplifying the process of maintaining, upgrading, analyzing, and accessing the asset data.

Section 1.0
Introduction

Asset management is a systematic process that maintains, upgrades, and operates physical assets cost effectively, and it provides an approach for making organized and logical decisions (FHWA 1999). In recent years asset management has become important because the public wants to see the Federal, State, and Local governments operate more like private businesses. They want to see better management of the resources that were paid for with their tax dollars (FHWA 1999).

1.1 Background Information

One area of asset management that is lacking in Alabama is a pavement management system (PMS) for county roads. A PMS is an asset management system that assists decision makers in finding optimum strategies for providing and maintaining pavements in a serviceable condition over a given period of time (Hass et al 1994). A PMS is essentially a decision support tool that stores various types of information about roads and supports future forecasts of condition. The advantage of a PMS allows users to output the information in a clear and understandable format, which helps them make a better decision on how to manage their roads. There is an established PMS for the Alabama Department of Transportation (ALDOT) that covers the Federal Interstates and State Highways. There is, however, no statewide PMS set in place for county roads. The complexity and data requirements of the ALDOT model make it unsuitable for county engineers. Each county and city in the state is responsible for the upkeep and management of all roads in their jurisdiction except for interstates and highways.

Alabama county engineers have been trying different ways to manage their roads. Some engineers have bought PMS software packages sold by various companies, others have attempted pseudo systems in Microsoft Excel, and others manage by how many complaints they receive from the public on each road. To combat this problem a PMS was developed specifically for Alabama counties. It was designed with county engineers in mind for quick and easy management of their roads.

1.2 Objective of Study

The intent of this report is to present the development of a PMS for use with county roads in the state of Alabama. It details the methods and logic behind the design. It also explains how to use the program and interpret the output data.

1.3 Research Tasks

To complete this research, work was divided into four tasks. Each task is explained in the following paragraphs.

1.3.1 Literary Review

Research for this project began by reviewing transportation journals and online sources. Engineers from two different Alabama counties were interviewed for information and their desires for program output information. Two existing PMS programs were reviewed to get an idea of what a program should look like and reference material for these programs was reviewed.

1.3.2 Pavement Management System Design

After reviewing the material a design for the PMS was established. Obtaining the road information was designed to be quick, easy, and inexpensive, which is what the county engineers wanted. This information would then be input to a computer program developed in this report.

1.3.3 Building Pavement Management System Software

Once the design for the program was in place, the PMS software was developed. Every version of the program was tested for bugs and other errors so that a good working version could be sent to a small number of people for additional testing.

1.3.4 Finding a Deterioration Equation

A deterioration equation that could predict the rating loss of a road over its life was one of the goals in this report. Road data were collected from various counties to build this model. Statistical analysis of the data was used to build a regression equation.

1.4 Document Organization

This report includes five chapters. The first chapter provides a brief overview of asset and pavement management and introduces the reader to the direction of the report. The second chapter covers the literature and the resources studied to find out what other researchers in the PMS field have done and the best direction to proceed. The third chapter is an in-depth look into the methods and reasoning behind a pavement management system. It also describes how to operate the PMS program and interpret the output information. The fourth chapter covers the formulation and statistical analysis of the aforementioned deterioration equation. The final chapter concludes the report and provides brief recommendations on the PMS program and regression analysis used to create the deterioration equation.

Section 2
Literature Review

This chapter begins with a brief overview of asset management. It also reviews what others across the country are, and have been, doing with respect to Management Systems. The chapter concludes with a section on deterioration equations used to predict the rate at which an individual road deteriorates based on several variables.

2.1 Asset Management System Overview

Asset management systems (AMS) have become an important tool in the management and maintenance of roads throughout the United States. The Federal Highway Administration states that AMS is "a systematic process of maintaining, upgrading and operating physical assets cost-effectively" (FHWA 1999). AMSs are designed from the outset to be used in the communication for planning and decision making steps (FHWA 1999). AMS can include the use of geographical information systems, database information, statistical analysis, practical experience, policies, goals, and other tools to provide an easily accessible system to analyze and process the database into a structure that is usable to the viewers (see Figure 2-1) (FHWA 1999).

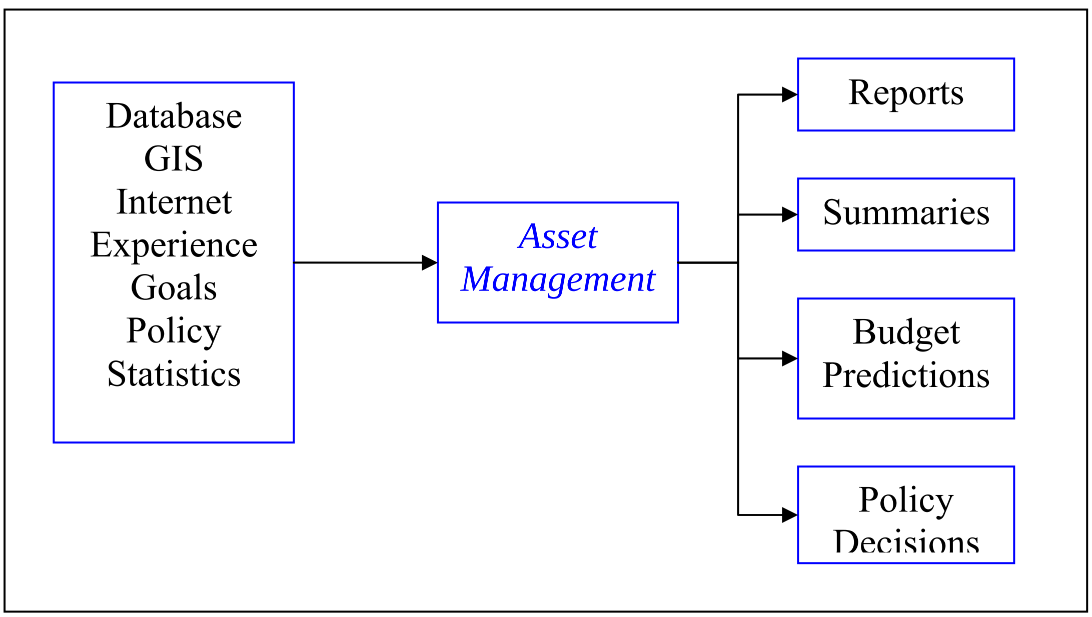

Figure 2-1. Asset management structure flowchart

The New York State Department of Transportation states that AMS is a procedure to "maximize the benefits of a transportation system to its customers and users, based on well-defined goals and with available resources" (FHWA 1999). As seen in figure 2-2, an AMS uses on-hand data and resources to provide a knowledgeable foundation for making decisions.

The federal government supported the development AMS through legislation in all parts of governmental operations. The application of Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) and the 1997 update, the Transportation Efficiency Act of the 21^{st} Century (TEA-21) by the United States Department of Transportation set up strict rules on the management of resources that were under its authority. This set of laws brought about a need to improve or create management systems throughout state DOT's across the country.

2.2 Asset Management System Structure

The fundamental structure of any AMS requires an underlying information database, a condition rating and a goal for the field the system covers (see Figure 2-2) (FHWA 1999).

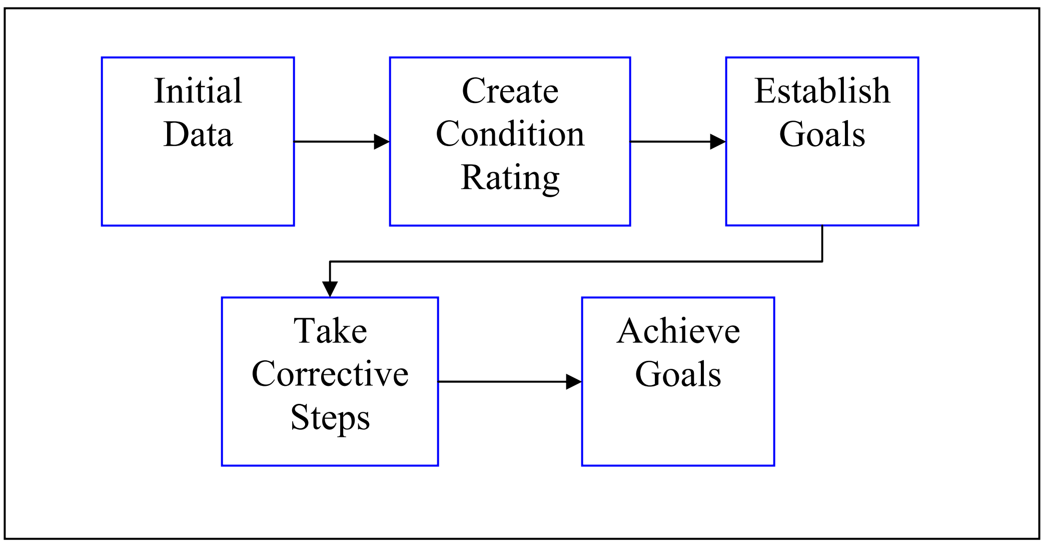

Figure 2-2. Basic asset management process flowchart

The information database consists of individualized data for each asset and its characteristics. The reliability of the data is crucial in determining the quality of the system because the majority of the analysis is based on the initial database. Even minor entry errors into the database or incorrect information can result in flawed output, incorrect data summaries and analysis which will likely lead to wrong decisions. Study of the asset characteristics enables the system to generate a bottom line to determine if the asset is performing above or below acceptable standards. The condition rating system can be used on other data to determine if the assets are meeting the standards of the predicted performance criteria. Goals can then be set to calculate the system's overall performance and if necessary, corrective steps can be taken for improvement (FHWA 1999). The process needed to reach the desired goals can often be taken from the AMS using the variables that determine the condition ratings.

2.3 Pavement Management Systems

A PMS is essentially an AMS designed for the specific use of properly managing roads. All roads constantly deteriorate because of traffic loadings and other factors, such as climatic conditions (Bandara and Gunaratne 2001). A PMS will keep track of all the roads in a network, which will enable a technician to decide what roads need maintenance and at what time the maintenance will be most effective. A PMS with easy-to-understand output is an invaluable tool. It allows an engineer to quickly see the situation and it aids in making a knowledgeable decisions.

The heart of a PMS is an internal database. This is where all the road information is stored. A computer based software package allows easy access to the data. All the recorded data that was tediously gathered can now be easily and efficiently viewed. Query functions are built into the software which examines the database. The user is able to mine the data to quickly and effectively find the answer they are seeking for a question. One good point to mention is that a PMS is only as good as the quality of its input. The better quality the output data, the easier it is to understand, the faster it can be interpreted, and the better the decision.

There are two types of PMS. The types are a network level system and a project level system. They differ in how they collect data and the way the data is used. The first type to be discussed is a network level system. The definition for a network level PMS is an agency wide set of plans for new construction, maintenance, or rehabilitation which will have the greatest benefit for a given time period (Hass et al 1994). This statement means to look at the big picture, to review the entire system of roads under a particular jurisdiction and to decide on the best way to take care of the roads so that they do not drop below a desirable level (see Figure 2-3)

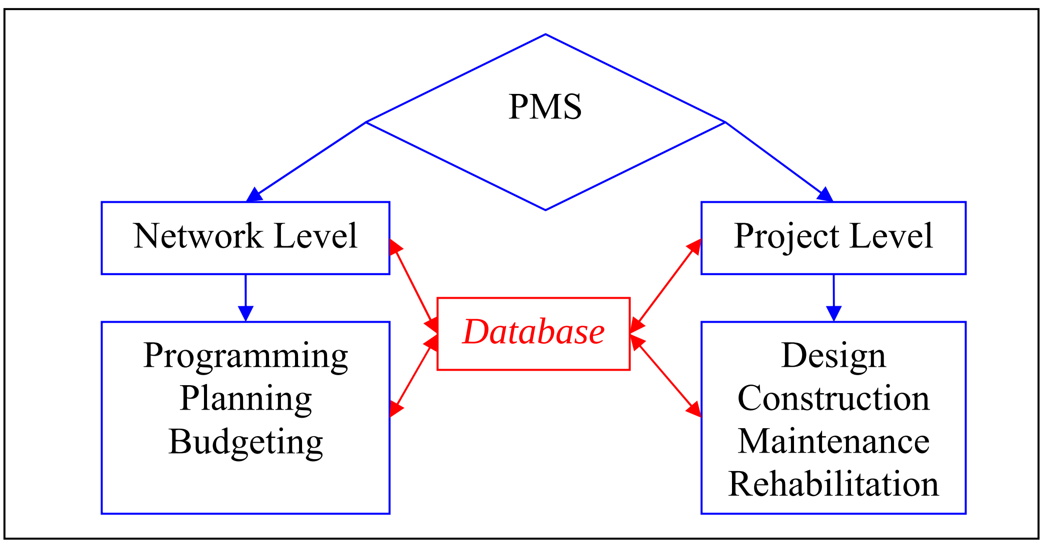

Figure 2-3. Major components of a PMS (Hass et al 1994)

On the other hand a project level PMS is more focused. It gives detailed consideration to alternative designs, construction, maintenance, or rehabilitation activities for a pinpointed section within the overall program to provide the desired benefits or service levels at the lowest total cost for a given time period (Hass et al 1994). The project level PMS deals with only one specific area inside the network. It may be a maintenance project where the goal is to increase the present condition of the road. It will look at more than one way to get to the desired goal, and base its recommendation on the benefit versus the cost for the project.

Two PMS computer software packages were investigated. The first was RoadSoft GIS which was developed by Michigan Technological University (RoadSoft 2005). This program stores many road aspects in its database, including present condition rating of each road, locations of car accidents, traffic counts, and various geographic data just to name a few. The program has standard query functions to search the information in the database but the main feature is that it can search and display maps and other data by using geographical information systems (GIS). GIS allows the user to visually examine the mined data on a map, which helps with the perception and understanding of the data.

The other program reviewed was Road Manager 2000 which was developed by Vanasse Hangen Brustlin, Inc. (Road Manager 2005). It is built more to meet individual customer's needs rather than just as a stock package. The program that was reviewed was used by David Palmer, the county engineer for Franklin County, Alabama (Palmer 2005). It was custom tailored to meet his needs. One item he had customized was subdivision of the county into a pattern of grids to make it easier to do queries. The program stores information, including the road condition index and drainage quality among other things. The software uses standard queries to find the desired information. It displays its output in spreadsheet form.

Both of these computer programs are designed at the network level. They store information on all the roads and allow the user to view how individual roads compare to each other, to assist with deciding which roads need maintenance and when they will reach a point where they will need maintenance.

2.4 Data Collection

The first step to building a PMS is to obtain the information that will be put into the database. This largely depends on whether a project level or network level PMS is being deployed. At the project level a detailed analysis of the road and its surroundings needs to take place, especially with new construction projects. A team of people must be deployed to walk the road for the entire length of the designated construction or maintenance zone to obtain the necessary data. On the surface of the road the cracks must be hand measured for length and width. Core samples may be needed and the drainage of the road needs to be taken into account. A project level PMS requires a lot of work and manpower to be successful.

A network level survey needs to be easier, faster, and cheaper to accomplish because there are many more miles of road to be covered in a network than on a project. Data collection must use the optimum means within available funds and labor (Bandara and Gunaratne 2001). The number one item to collect is the present condition of the road. It is possible to find the present condition of the road by sending a team of people to measure the length and width of every crack and the depth and width of ruts but this method is not feasible for most agencies due to the monumental cost associated with this type of data collection.

There are two common ways to collect present condition of the road. The first is by calculating the international roughness index (IRI). IRI is “a scale for roughness based on the response of a generic motor vehicle to roughness of the road surface” (Gillespie 2005). To obtain the IRI a measuring device is usually installed in the tire well of a car and the car is driven at 50 miles per hour. The device is mounted to the suspension and it vibrates as the car is driven down the road. An algorithm converts the vibration into a numeric value which is in terms of inches/mile. The Federal Highway Administration found that if the IRI is 170 inches/mile or less, 85 percent of the public considers the road acceptable (Zineddin et al 2005). Interestingly, the Swedish National Road Administration uses a device that has 17 lasers on a beam in front of a vehicle along with an accelerometer to calculate IRI along with maximal rut depth (see Figure 2-4) (Thomas 2003).

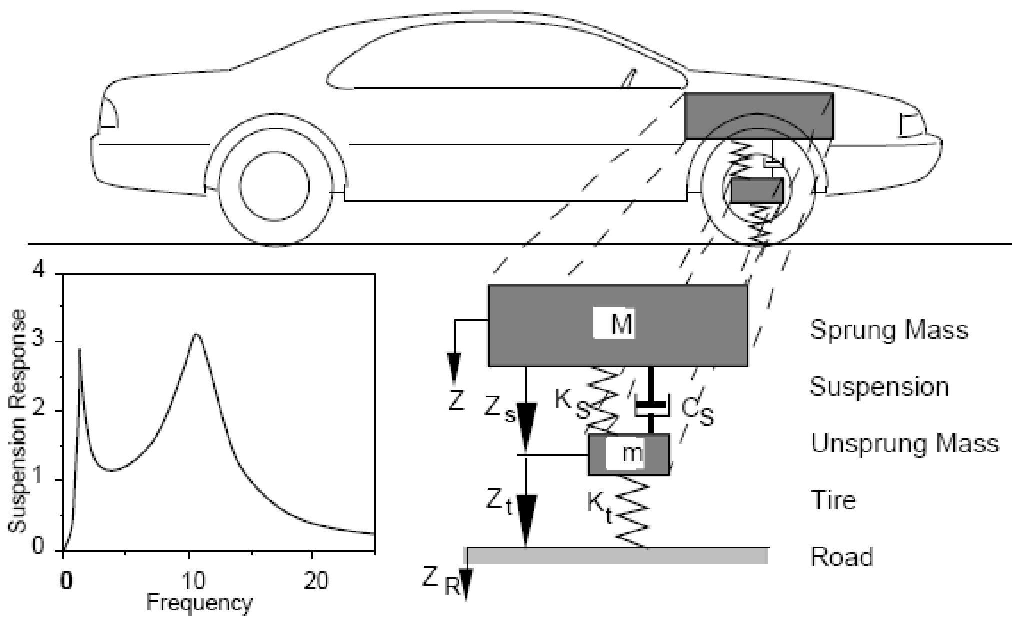

Figure 2-4. Demonstration of IRI Measuring Device (Gillespie 2005)

An equation that is used to convert IRI to pavement serviceability index (PSI) (Equation 2.1) (Zineddin et al 2005).

$$PSI \approx 5.0 - IRI/100 \qquad \text{for } 0 < IRI < 300 \text{ (in/mile)} \tag{2.1}$$

PSI is calculated on a scale of zero to five, based on equation 2.1, with zero being an extremely rough road that is almost impassible and five being excellent road with no roughness at all. Many agencies use IRI for calculating the present condition of a road. It is fairly quick and simple to accomplish. The main drawback is installing the expensive device to measure IRI.

The second most common way to find the present condition of a road is by using pavement condition index (PCI) based on a visual inspection rating (VSR). The PCI is simply a user defined scale such as one to ten, where one is a road that is completely deteriorated and must be reconstructed and ten is road that has just been paved. A VSR, also known as a windshield survey, is a rating that is based purely on how the surface of the pavement looks. The most common way to perform the VSR is to drive a vehicle at 20 mph and evaluate how the road looks from the cab of the truck.

The University of Wisconsin-Madison developed a visual inspection manual known as the Pavement Surface Evaluation and Rating Manual (PASER) (PASSER 2002). PASER is very simple to use. It has a ranking of one to ten that is illustrated through a process of pictures and explanations of what is being seen. All the person rating the road has to do is find the picture that most closely matches the road that is being viewed. They have a manual for most types of road surfaces. The manual that was reviewed in this project was the Asphalt PASER. The Wisconsin Department of Transportation and the Michigan Department of Transportation both use PASER to evaluate their local roads. Using VSR to evaluate the roads is the cheapest and easiest way to obtain PCI. Engineers for rural counties and small cities will greatly benefit from this rating technique because it does not require any startup cost and all the training required to use PASER is to simply read the manual (see Figure 2-5)

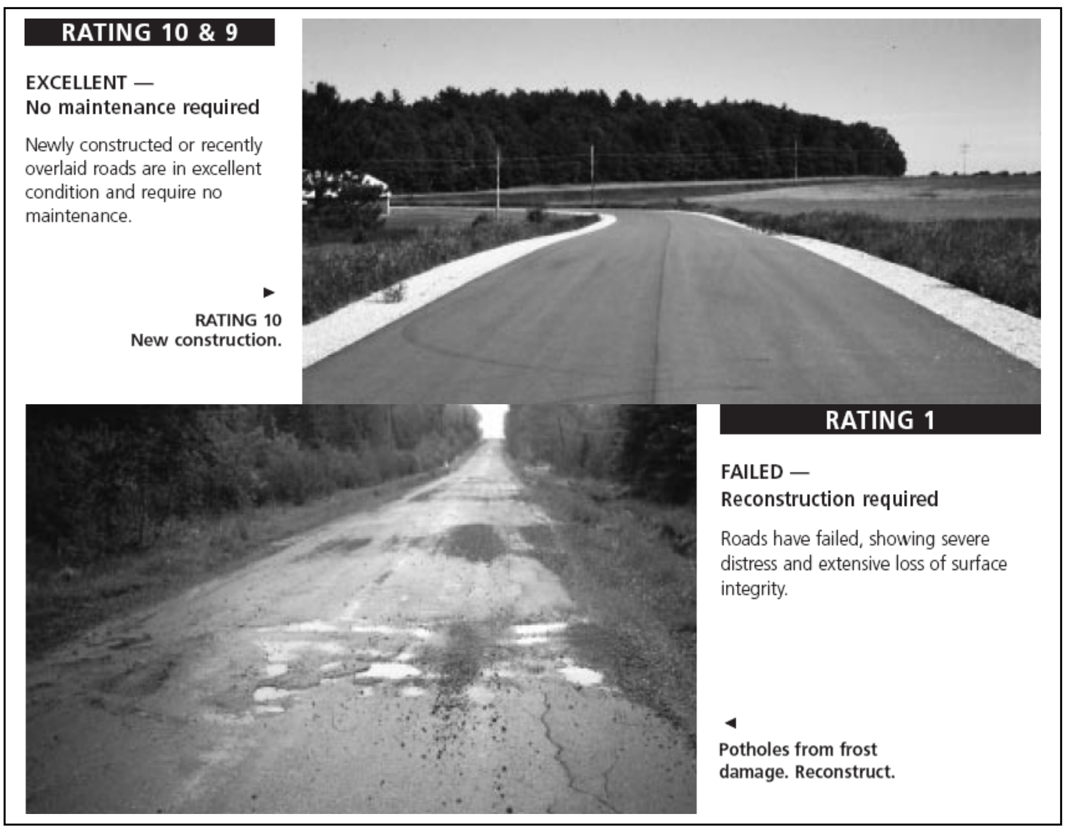

Figure 2-5. Photographs from Asphalt PASER (PASSER 2002)

A study was performed by a panel of trained raters followed a well documented visual inspection manual and rated a set number of roads (Bandara and Gunaratne 2001). It found that the accuracy of their judgments fell within 10 percent of each other (Bandara and Gunaratne 2001). This study showed that a visual inspection rating will have some human error and a little differentiation between each person, but the results are reasonably close for a quick and easy survey of the roads.

2.5 Prediction Models

Everybody in charge of a network of roads wants to know when the roads will deteriorate to a certain point that is considered to be the lowest desirable level. It is also nice to know that when the road reaches the minimum desirable level, what the condition of the road would be like if no maintenance is done for another one or two years. Unfortunately, there is no crystal ball to ask how fast a road will deteriorate. A combination of statistical analysis and engineering judgment has to be used to solve this problem. The statistical analysis that is used to attempt to predict the way a road deteriorates is linear regression.

2.5.1 Fundamentals of Linear Regression

Regression analysis relates one population, designated Y, to another population or populations, designated x, based on observations in one of the populations (Equation 2.2) (Montgomery 2001).

$$Y = (f(x)) \tag{2.2}$$

In simple linear regression, Y is expressed as a function of two regression coefficients β_0 and $\beta_{1,}$ and the independent or response variable, X (Equation 2.3).

$$Y = \beta_0 + \beta_1 X + \varepsilon \tag{2.3}$$

The coefficient β_0 is known as the intercept and specifies the point at which the model crosses the Y axis. The β_1 coefficient, known as the slope, defines the rise and fall of the prediction line. The size of the predictor determines the position of the point along the slope and thus the value of the response, Y. The statistical error, ε, inborn in all models, is usually shown in the general model. Montgomery, Peck and Vining define the statistical error as "a random variable that accounts for the failure of a model to fit the data exactly" (Montgomery 2001). The size of the statistical error plays an important role in determining the how well the model explains the data.

Three assumptions are made when performing linear regression analysis on the data. These assumptions must be correct for the regression to be considered satisfactory. The first is that the statistical errors are assumed to be normally distributed. The second assumption is the variance of the error is constant. The third is that the errors are not dependant (Montgomery 2001). These assumptions are checked for a model by evaluating a series of residual plots.

In multiple linear regression analysis the response is a function of multiple predictors which allows the model to take into account multiple factors that would be left out of a simpler model. As with simple linear regression, the three assumptions must be checked. The structure of the equation follows the basic format of the simple linear regression adding to the slope, β_1 through β_n. Where n is the total number of regressors, and the regressor variables, X_1 through X_n. As with the previous model, the statistical error is represented by ε. (equation 2.4)

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \ldots + \beta_n X_n + \varepsilon \tag{2.4}$$

The use of multiple regressors introduces a new concern during the model creation process known as multicolinearity. Multicolinearity occurs when two regressors are linearly related, making it hard to distinguish the effects of each variable on the model (Montgomery 2001). The way to check for multicolinearity is a Pearson Correlation Table. It calculates the linearity between each regressor and supplies a value to the degree of linear relation. It is also possible to plot regressors against each other and look for linear trends in the data.

2.5.2 Predicting the Deterioration of Asphalt Roads

Several studies have been done to predict the deterioration rate of asphalt roads. Possibly, the two main reasons for roads deteriorating are traffic loadings and weather conditions. Over time traffic will strain the asphalt and cracks will begin to form. When water is able to get into those cracks and freeze, the cracks expand and continually get larger. Water and heavily loaded tractor-trailers are a road's worst enemies.

It is possible to predict the way a road will deteriorate due to traffic loadings but it is nearly impossible to predict what the weather is going to be like from year to year to include it in a model. The traffic loadings to collect are Average Daily Traffic (ADT) and the percent of ADT that are tractor-trailers. The last time the road had any major maintenance done to it should be recorded as well. Building an extremely accurate model is not possible because there are many different variables that could affect the way a road deteriorates. Differences in the soil structure from one area to another will play a role in how a road reacts to traffic loads. The difference in the rock used for the base may be slightly different from quarry to quarry. The drainage quality along the road could be an important factor on road deterioration. There are other small factors that have not yet been identified that could play a role in road deterioration. A study by the Indiana Department of Transportation found that when the correlation of determination, R^2, is greater than or equal to 0.50 the regression model is acceptable (Flora et al 2001). The correlation of determination is the percent of the information that is obtainable from the regression model by the dependant variables (Flora et al 2001).

The University of Texas experimented with building a dynamic model (Li and Zhang 2005). This is where data is continually added to the system. By doing this they tried to avoid one of the fallbacks to linear regression which is the error term (Li and Zhang 2005). Continually refining the model to make it work better and minimizing the error term is an interesting step. They built a probability equation to predict what the PSI of the road would be in at a given period. The variables collected to build the model surface thickness, base thickness, equivalent single axle load, and a spring seasonal factor. The spring seasonal factor takes into account the severity of the climate over a certain period and to takes weather-related deterioration into account. This model is very in-depth and it is not easy for someone to obtain all of these factors. It would also be time consuming and costly to continually collect new data to refine the model.

A study by the Kentucky Transportation Center built a survival model to predict pavement deterioration (Allen and Wang 2005). It was developed to make the contractor give a warranty period on an asphalt overlay. With standard linear regression the data is assumed to be normally distributed, but with a survival model it is possible to choose a different probability distribution. It can also be used to estimate a probability distribution for each combination of factors (Allen and Wang 2005). The variables that were selected to build the model were resurfacing thickness, existing thickness of dense graded aggregate base, pavement condition points before resurfacing, annual average daily traffic, interstate or parkway, and thickness of existing asphalt. The model yields its answers in two stages. The first stage is how long the asphalt overlay will be above a minimum desirable level. The second stage is how long the road can go before it deteriorates too rapidly to apply an overlay. The contractor should give a warranty period for the length of stage one on the asphalt overlay. This style of predicting pavement performance does not fit with the focus of this report because it is only interested in a warranty period, not how a road deteriorates from beginning to end or how long it will take to reach each consecutive stage of its deterioration.

2.6 Summary of Chapter

It has been shown that the heart of a PMS is its database and a PMS is only as good as the quality of its input. The simplest and cheapest way to obtain the present condition of a road is through a visual inspection rating. Linear regression is the easiest way to predict the length of time it takes for a road to deteriorate.

Section 3
Pavement Management Methods and Display

This chapter explains the methods and reasoning behind the pavement management system that was designed for use with county roads in Alabama. It also gives an overview of the PMS computer software package that was created for this report. Proper pavement management is important for spending the taxpayer's money as wisely as possible and to increase the useful life of the roadways.

The chapter begins with network segmentation. It discusses how and where to make both area and roadway segments. It then explains the methods used to collect required roadway data. It describes the development and usage of the PMS computer software program discussed in this report. It ends with a section on the computer program's database and how to extract the data.

3.1 Network Segmentation

The first step to proper pavement management is to define boundaries. The first boundary is the largest and it is the county in which the road network lies. The county is then further divided county commission seats and districts. Dividing by county commission seats will enable the engineer to show the commissioners where the worst county roads are, so that money can be spent in areas that need it the most regardless of which commissioner resides there. It can also be used at public meetings to show the citizens how the roads for their zone compare to those of the rest of the county. Going a step further and dividing the commission seats into districts will help with database queries. The districts can be any number of zone configurations. They could be school districts, police and fire districts, imaginary lines drawn on the map, or a pattern of roads drawn of the map (see Figure 3-1).

It is important to properly segment the roadways. The segments should start and stop at definite geographical points, such as intersections and bridges. This will help contractors and maintenance crews to know exactly where to do their work. If the points are vague, like from the city limits to the corner of the road, then there may be some confusion as to where to begin and end the project.

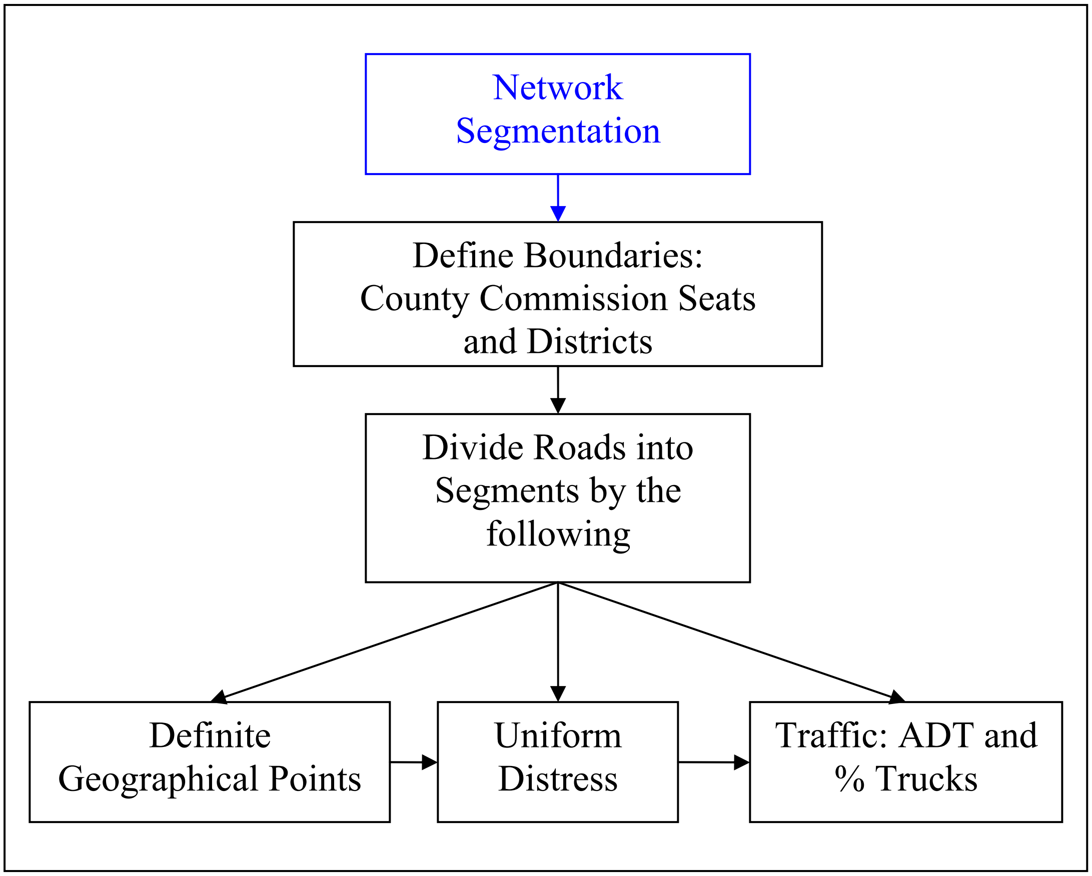

Figure 3-1. Network segmentation flow chart

The length of a segment should always be less than five miles. The majority of segments should only be about one mile long. The reason is to keep continuity in the segment. It is important to divide roads into segments that have uniform distresses. The two main reasons for doing this are to correctly rate the condition of the pavement and to keep deterioration the same throughout the segment. This will make it easier to administer the proper maintenance to the segment. Suppose a segment is six miles long, it may start with freshly overlaid asphalt in excellent condition and end with pavement that is in poor condition with ruts and extensive alligator cracking. It would not be possible to correctly rate the condition of this segment. If a maintenance plan was prescribed, it would have to tell the crew to do work on the worst part of the segment. This is vague and the crews may begin and end in the wrong part of the section. The best way to segment a road like this would be to have one segment cover the freshly paved asphalt and then have a second segment cover the pavement in poor condition.

It is also necessary to divide segments by the amount and type of traffic on the road. The number of vehicles driving on a road is presumed to be directly proportional to the amount of deterioration so the higher the average daily traffic (ADT) the faster the road deteriorates. The amount of tractor-trailer traffic also contributes greatly to the deterioration of a road. If the starting point of a road that is uniformly distressed across its entire length has an ADT of 500 vehicles and two miles down the line there is a point where the ADT jumps to 1000 vehicles then the segment should be divided at the point where the traffic increases. An increase in ADT like this usually happens at an intersection, so that would be point where the segment should be divided. For the second scenario, assume there is a point along a road where the amount of tractor-trailer traffic increases, such as the entrance of a rock quarry. Then it would be best to make the entrance to the quarry the beginning of a new segment.

Network segmentation is not a hard process. An engineer could do the majority of segmentation by simply using a county road map and making segments based on intersections. Further revisions could then be made based on ADT and amount of tractor-trailers.

3.2 Data Collection

Collecting data is an important process that takes time, but is necessary for operating a PMS. There are several kinds of data that must be collected to begin a PMS. The three most important pieces of information to collect are the PCI, ADT, and amount of tractor-trailer traffic. The length, beginning point, and ending point of the road segment, along with the dates that all the information was taken should be recorded. Once the PMS is up and running, the maintenance work done to the roads should also be recorded (see Figure 3-2).

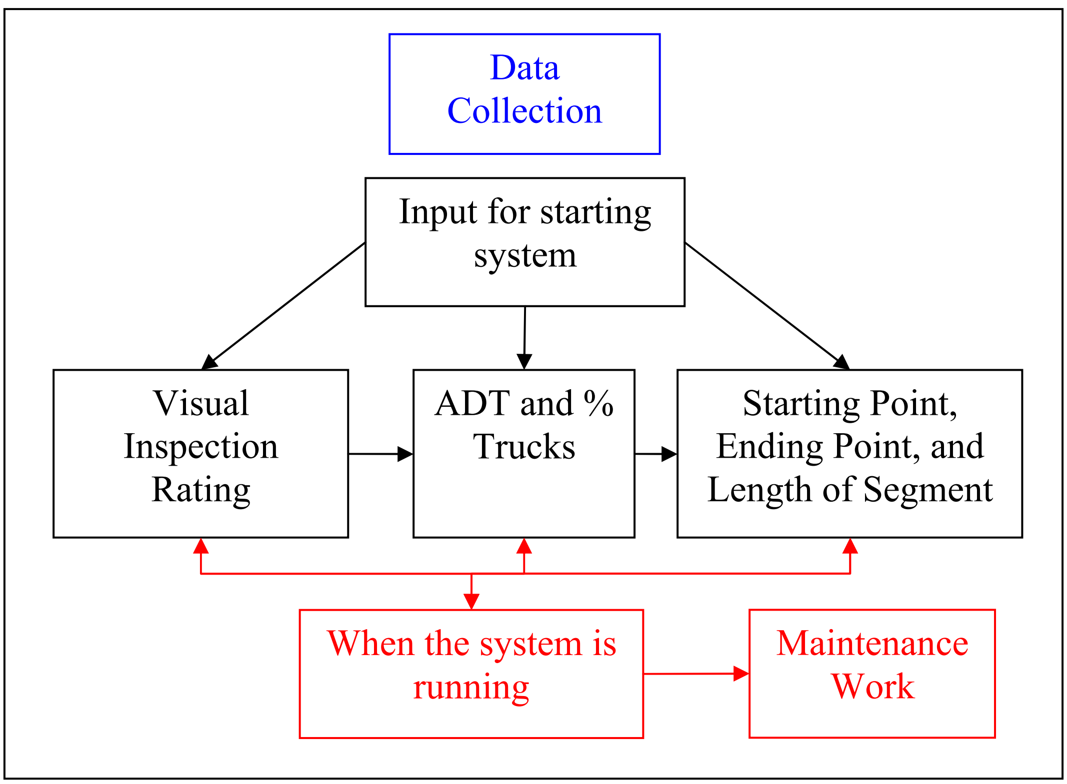

Figure 3-2. Data collection flow chart

The PCI is the most time consuming piece of data to collect. A PCI is an evaluation of the current state of the pavement and it is rated on a scale such as excellent to poor. Obtaining the condition rating could be an intensive evaluation of the road where everything from cracks to potholes are hand measured. The other end of the spectrum on rating pavement is a windshield survey, also known as a visual inspection rating, where a vehicle is driven at 20 mph and the road is evaluated on how it looks from the cab of the truck. The latter form of rating pavement is the easiest and cheapest way to collect the needed information. For purposes of this PMS, the visual inspection method was selected to obtain the condition rating for the road because of its simplicity.

A VSR was developed for use with Alabama's county roads. It is similar to the University of Wisconsin–Madison Pavement Surface Evaluation and Rating Manual (PASSER 2002). The photographs shown in Alabama's VSR system are taken directly from roads in this state. Instead of having a consecutive count from one to ten the values are lumped in groups of two from one to ten. For example, a rating for excellent condition would be grouped with numbers nine and ten. The person evaluating the road should decide if the rating value is a nine or a ten. Grouping values like this will cause the visual inspection of the road to be faster and easier.

Collecting ADT and the amount of tractor-trailer traffic for the entire road network is the next step in the process of data collection. Since both of these have a direct impact on the deterioration of the road they need to be accurately recorded. Having these two values in the database will help with predicting how fast the road deteriorates.

After all the data has been collected for the roads and the PMS is up and running, it is important to begin recording maintenance data. Every time some form of road maintenance is performed, it shall be input to the PMS, whether it is a hot mix asphalt overlay or ditch cleaning. Keeping good maintenance records will reveal which maintenance activities are the best and which ones have little effect on the condition or deterioration of the road.

3.3 PMS Computer Software Design and Usage

A computer software package was designed at the University of Alabama in Huntsville along the lines of the methodology presented in this chapter. It was developed from scratch using Microsoft Visual Basic and C^{++} programming code. Engineers at Shelby County, Alabama provided input about the program to make it more useful to county engineering applications. The program went through a number of revisions before the final version was obtained. The PMS computer software package that was created for Alabama's county roads facilitates input given in the categories shown in Figure 3-3).

As can be seen in Figure 3-3 the input screen is setup to collect all the data that has been mentioned. The Input Screen follows the flowcharts of Figures 3-1 and 3-2. This is where all the information is entered to be put into the database.

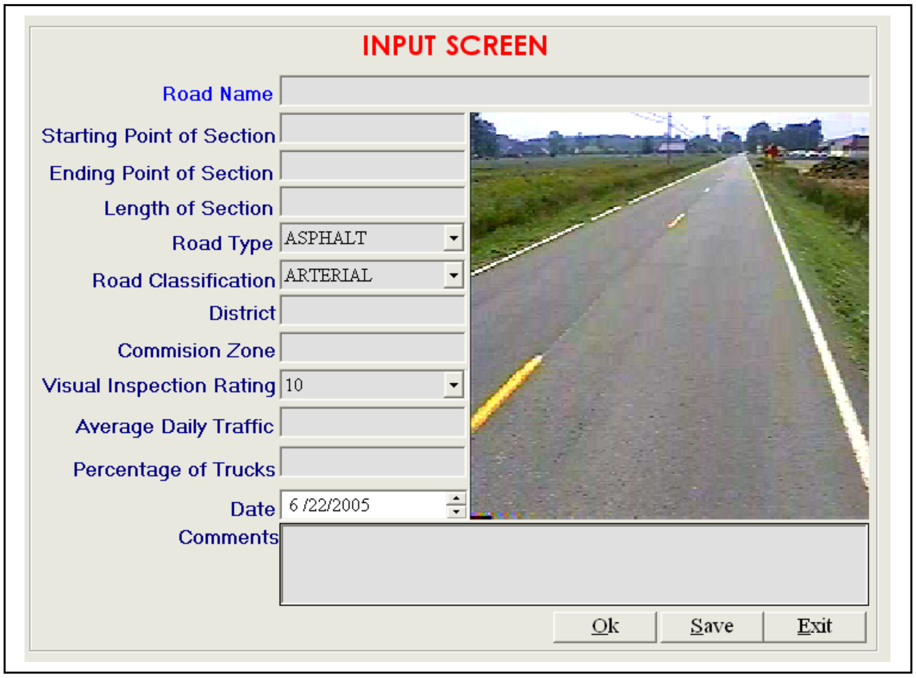

Figure 3-3. Snapshot of PMS program input screen

There are two items on the menu have not been mentioned yet. They are the road type and the road classification. The road type is found on a drop down menu with three choices: asphalt, chip seal, and gravel, corresponding to the road surface. The road classification deals with the design of the roadway. The drop down menu reveals a selection of urban arterial, urban collector, arterial, collector, and local. The road type and classification are there to help identify the road.

The visual inspection rating is a drop down list that reveals a scale of one to ten. When a VSR value is selected the picture of the road on the right hand of the screen changes to reflect the chosen rating. If the incorrect rating value is entered the error can quickly be seen because the picture of the road will not match the desired condition rating. This will help to keep the user from accidentally selecting the wrong value.

There is a comment box at the bottom of the screen. It allows the user to enter information that is not otherwise covered in the input screen, such as a noticeable drainage problem at a specific location.

To keep in line with the flowchart on Figure 3-1, a maintenance entry screen is included in the program (see Figure 3-4)

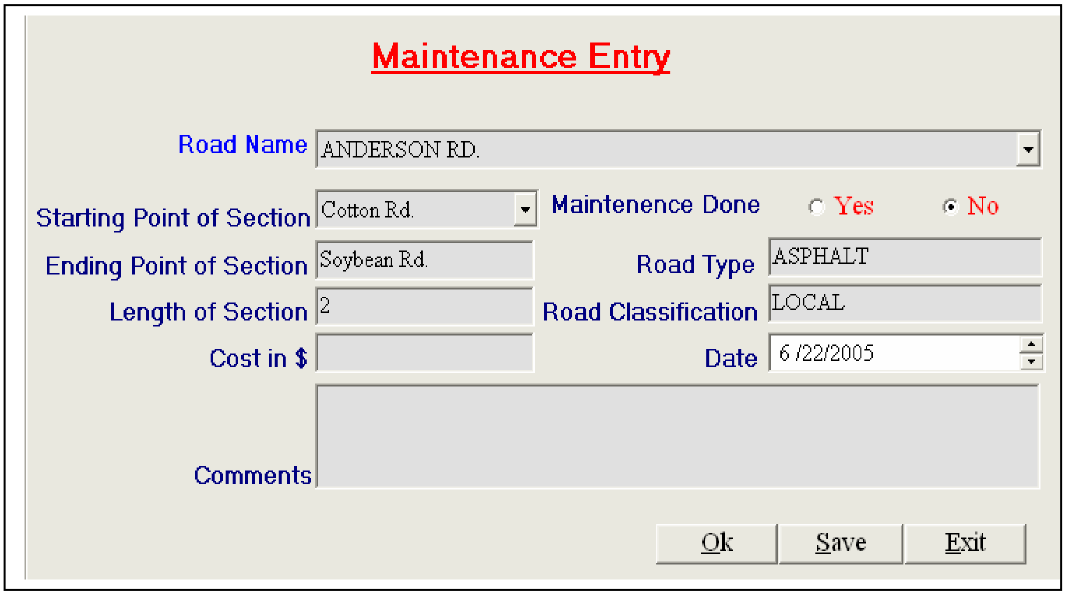

Figure 3-4. Snapshot of PMS program maintenance entry screen

Since the road information has already been entered, all that needs to be done to enter the maintenance information is to select the desired road and then choose the starting point of the section. Once this is done the rest of the information is automatically displayed. All that needs to be entered by the user is the cost and whether or not the maintenance has already been performed. The comment box allows the user to enter what type of maintenance will be done and other pertinent information.

3.5 Database

The database is the heart of the PMS and stores all the data that has been collected. But more importantly the program allows data extraction techniques. Data extraction uses queries to take the information that is stored in the database and to output it in a user defined understandable format. Having the wealth of knowledge that was collected for the entire county at the tips of your fingers is a powerful thing. The program allows three types of database queries: simple, complex, and decision support queries (see Figure 3-5).

Simple queries are designed for asking short general questions. A simple query will display all the information for the one topic that was specified. For example, a question such as, where is the ADT less than 1000, will output a display that shows every road segment in the specified ADT range.

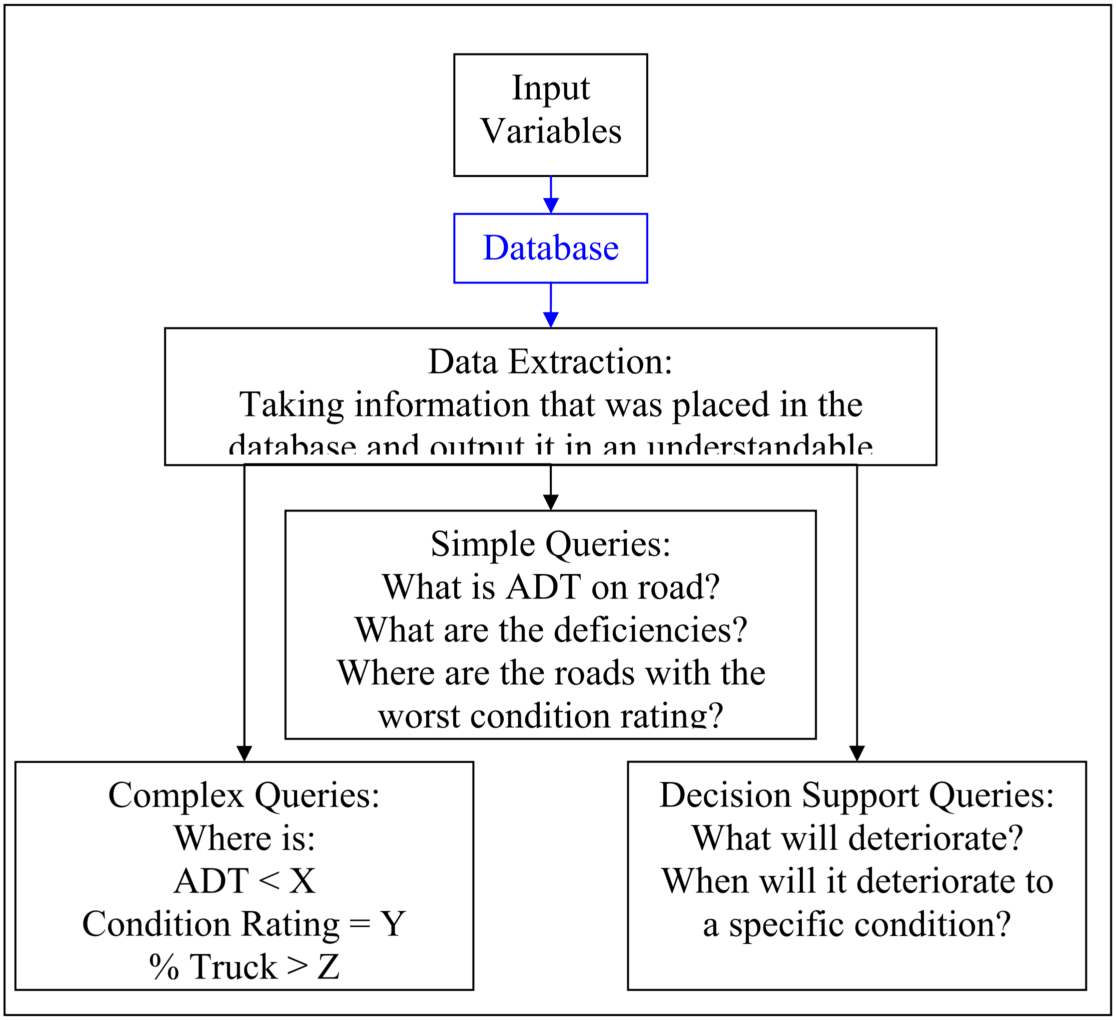

Figure 3-5. Database flow chart

A complex query will allow much greater scrutiny than a simple query. It will let the user make a very specific question. It works by allowing more than one question to be input at the same time. For example, questions like where is the ADT less than 1000 and where is the percentage trucks greater than or equal to 5 and where is the condition rating less than 5, will output a display that shows every road segment that matches the three question in the search criteria (see Figure 3-6 and Figure 3-7).

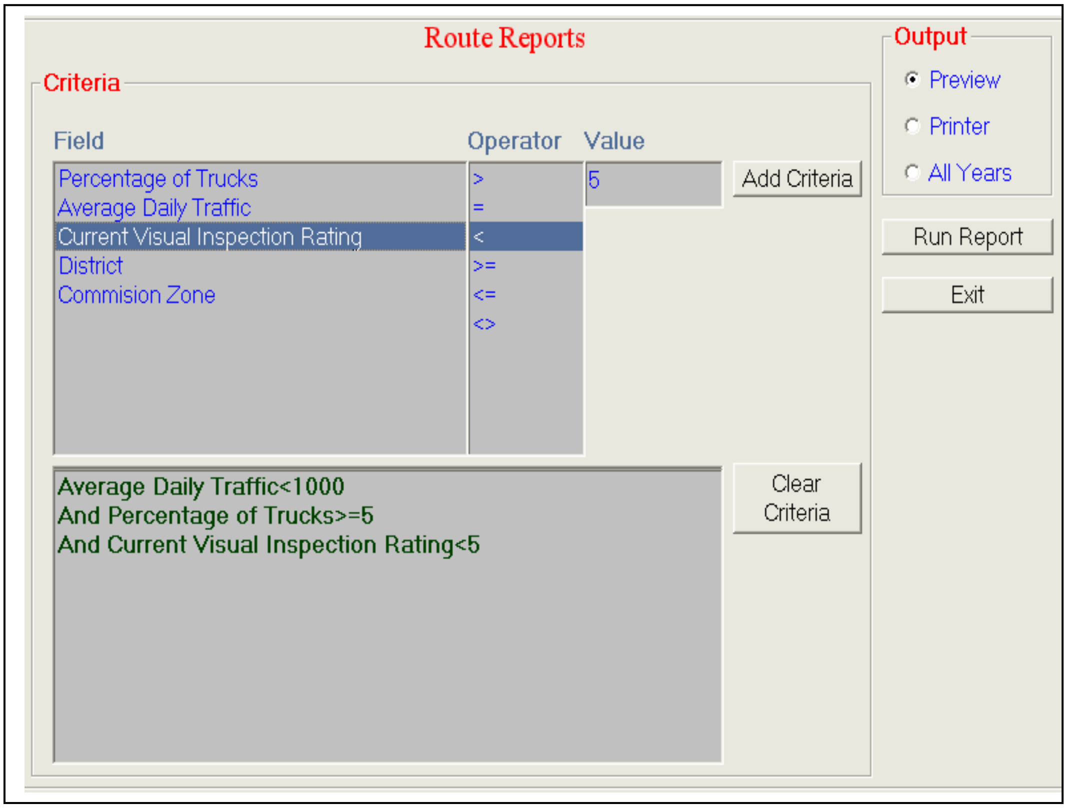

Figure 3-6. Snapshot of PMS program complex query

Road Condition Report

Route Name	Starting Point	Ending Point	No of Years	ADT	% of Trucks	Projected ADT	Current Rating
RACEWAY RD.	John	Cotton Rd.	1	1000	5	1020	9.00
RACEWAY RD.	Test City	John	1	1100	5	1122	9.00
REMINGTON	Pie Rd.	Deer Run	1	50	0	51	10.00
SOYBEAN RD.	Cotton Rd.	Anderson	1	800	4	816	9.00
ZEPHYR	Fishline	The	1	50	0	51	10.00

Figure 3-7. Snapshot of PMS program complex query solution

The final type of query is decision support. This query is used in conjunction with an equation that was developed for this PMS that predicts the deterioration of a road segment based on four factors. These factors are the VSR, ADT, percent of tractor-trailer traffic, and the length of time in years since the road was paved. This equation is moderately accurate. It is useful in giving a county engineer an estimate of what the deterioration of the road will be in a given number of years. This query asks when the road will deteriorate to a specified condition rating. For example, a question like what will the condition of a certain road be like in four years will output an answer in the form of the current rating, the loss of rating over the years, and the condition rating in year four. It could also be used to ask where will the condition ratings be less than six in the next three years for all roads in the county, and the output will display every road segment that matches the search criteria. This query could also be used in conjunction with a complex query. For example, a question like where will the condition rating be less than or equal to four in three years and where is the ADT greater than 500 and where is the percent of trucks less than three will display every road segment that matches these questions. As can be seen from these examples the decision support query is very helpful. It allows the engineer to spend money as wisely as possible because the roads that will most need maintenance can be taken care of before they fall below a desirable level.

Some of the statistics about the roads can be determined through of the Road History Screen. All that has to be done is enter the road name and the starting point of the section and the database automatically fills in the rest. All the maintenance work that has ever been done to the road will by displayed at the bottom of the screen. This screen is helpful when information about one road is all that is needed (see Figure 3-8).

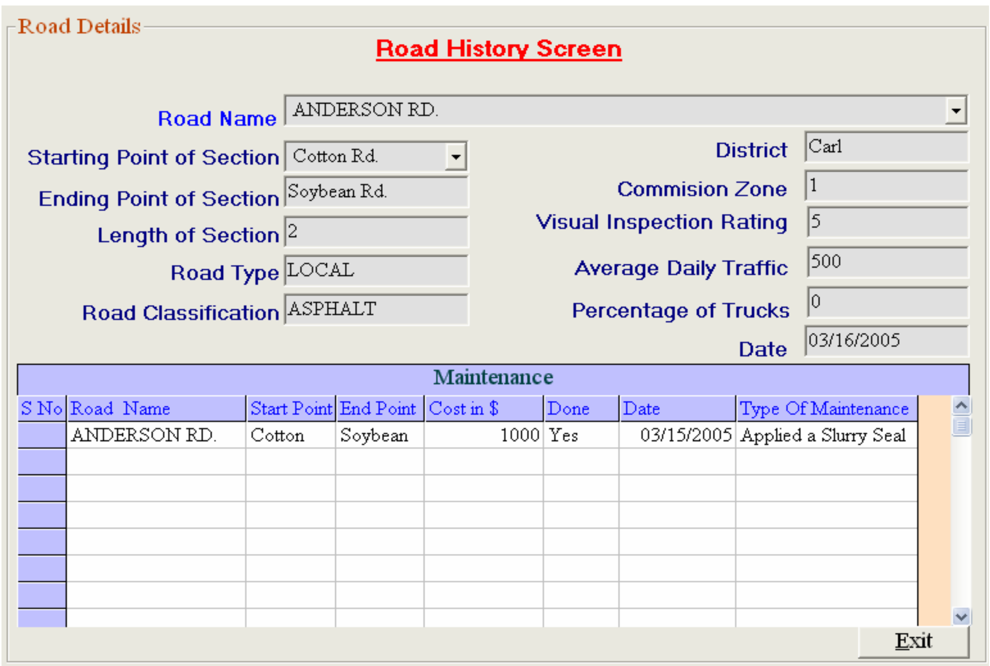

Figure 3-8. Snapshot of PMS program road history screen

The Road Inquiry Screen is another simple tool in the program. All that has to be done is to enter the road name and the starting point and the database automatically fills in the rest. It shows all the information in the database and can predict the deterioration of the road out to 25 years in the future. It also has gives the projected ADT for the road at a default growth rate of 2 percent per year (see Figure 3-9).

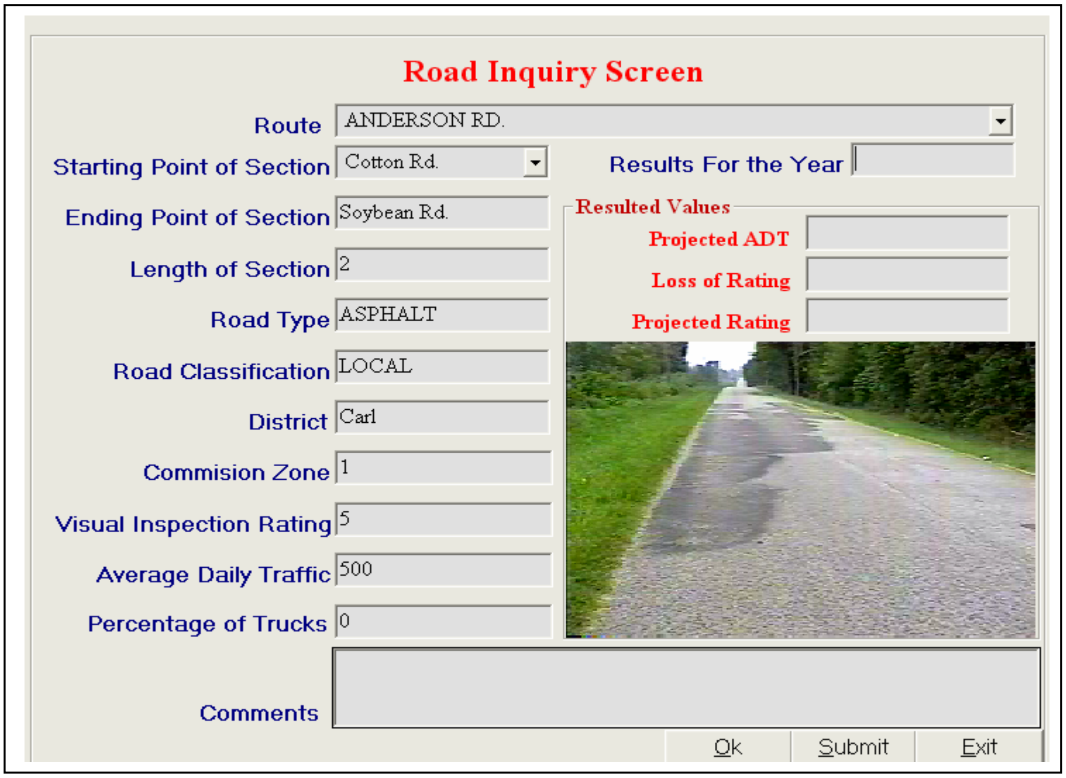

Figure 3-9. Snapshot PMS program road inquiry screen

The PMS computer program follows the flow charts and the methodology that has been presented in this chapter. It was designed to be easy to use and use data that is inexpensive to collect. It has met this intended purpose.

3.6 Summary of Chapter

A PMS is very beneficial to Alabama's county engineers because it allows them to store all the necessary information about their roads and to interpret that information by using queries. This PMS will help them spend the taxpayer's money as wisely as possible.

Section 4
Regression Analysis and Model Development

Regression analysis is a vital tool for modeling. Applying regression analysis to roadway characteristics can be used to predict the deterioration of roads for individual and network applications. The application of regression analysis in this chapter focuses on predicting the future pavement condition index for individual roads based on current traffic and maintenance history. The model will be used to predict the length of time it takes for a road to reach a point of failure. The failure point of a road can be loosely defined as the situation where the only way to increase the PCI is through total reconstruction. The photographs in Figure 4.1 help illustrate a road that has failed. The use of regression analysis helps the user decide the best time to perform maintenance to keep the road from falling below a desired level (see Figure 4-1).

Figure 4-1. Photographs of failed roads with PCI equal to one

4.1 Initial Data Collection

The first step to building a regression model is to collect representative data. The desired equation was a time model for the length of time it takes for an asphalt road to progress from a new overlay to the point where it fails. It was presumed that the main factors in the deterioration of a road are average daily traffic (ADT) and the percentage of tractor-trailers using the roadway. Since a time model was desired, a method was needed for calculating the length of time since the road had been resurfaced. The factor representing this time was how many years ago the road was resurfaced.

Data were collected in two counties in Alabama, Franklin and Shelby. Franklin County is rural with a low population and low ADTs on its roads. Shelby County on the other hand, is an urban county with a high population and one of the highest growth rates in Alabama. The ADTs on the roads are very high with some values being above 25,000 vehicles a day.

To build a prediction model for PCI, the first item collected was the current PCI. This was done through a visual inspection survey. The roads were evaluated visually and compared to pictures in the PASER manual. In Franklin County 30 sections of road were assessed and given the appropriate rating, likewise, 30 sections of roads in Shelby County were reviewed. The ADT and percentage of tractor-trailers were already on file in Franklin County. In Shelby County traffic counters were used to collect the traffic information. The number of years since last resurfacing was obtained from the county engineers. The data were imported into Minitab Statistical Analysis Software, Release 14 so that the regression analysis could be executed (MINITAB). The collected data can be seen in Appendix 1.

4.2 Regression Analysis and Model Creation

Statistical regression analysis was run on the 60 collected data points to build a deterioration model. One data point was deleted because it was an outlier. It was a road that had been resurfaced two years ago but it had a visual inspection rating (VSR) of only three. Upon further review, this roadway was inconsistent with other roads in the county and was removed as a two-year old road would be unlikely to have a VSR of three, which is a road on the verge of failing structurally.

Since VSR is used to determine PCI, VSR was chosen as the response variable. The variables ADT, percentage of tractor-trailers, and number of years since last resurfaced were chosen predictors. Combinations of the predictor variables were made and tested to see how the model would react (see Table 4-1).

Table 4-1. Complete set of variables for regression analysis

Variables for Regression Analysis
Visual Inspection Rating
ADT
%Trucks
Years Ago Resurfaced
Average Daily Cars
Average Daily Trucks
Total Cars
Total Trucks
Total Cars *K
Total Trucks *K
Yearly Passenger Cars

A correlation test was done on the variables to see if there was any correlation between them. Data is interpreted from the correlation test by looking at the Pearson Correlation Coefficient and the P-Value. The correlation coefficient establishes linear relationship between variables. The correlation coefficient has a range from negative one to positive one. The sign of the number indicates how the variables move together. If the sign is positive the variables either increase or decrease together. If the sign is negative, one variable will increase while another variable will decrease. The closer the value is to either positive one or negative one the stronger the linear relationship is between them. A value of zero indicates that there is no linear relationship between the variables (MINITAB). If variables other than the response have a high linear relationship, the regression model is not able to accurately explain the data (see Table 4-2, Table 4-3 and Table 4-4)

Table 4-2. Correlation test results

Cell Contents: Pearson correlation P-Value	ADT	% Trucks	Years Ago Resurfaced	Average Daily Trucks
% Trucks	0.277 0.034			
Years Ago Resurfaced	0.207 0.116	0.216 0.100		
Average Daily Trucks	0.838 0.000	0.563 0.000	0.141 0.288	
Average Daily Cars	0.998 0.000	0.235 0.074	0.210 0.110	0.799 0.000
Yearly Passenger Cars	.882 0.000	0.222 0.091	0.418 0.001	0.654 0.000
Total Trucks	0.850 0.000	0.552 0.000	0.313 0.016	0.913 0.000
Total Cars *K	0.882 0.000	0.222 0.091	0.418 0.001	0.654 0.000
Visual Inspection Rating	-0.286 0.028	-0.332 0.010	-0.813 0.000	-0.211 0.108
Total Cars	0.882 0.000	0.222 0.091	0.418 0.001	0.654 0.000
Total Trucks	0.850 0.000	0.552 0.000	0.313 0.016	0.913 0.000

Table 4-3. Correlation test results continued

Cell Contents: Pearson correlation P-Value	Average Daily Cars	Annual Passenger Cars	Total Trucks	Total Cars *K
Yearly Passenger Cars	0.890 0.000			
Total Trucks	0.823 0.000	0.843 0.000		
Total Cars *K	0.890 0.000	1.000 0.000	0.843 0.000	
Visual Inspection Rating	-0.289 0.026	-0.471 0.000	-0.387 0.002	-0.471 0.000
Total Cars	0.890 0.000	1.000 0.000	0.843 0.000	1.000 0.000
Total Trucks	0.823 0.000	0.843 0.000	1.000 0.000	0.843 0.000

Table 4-4. Correlation test results continued

Cell Contents: Pearson correlation P-Value	Visual Inspection Rating	Total Cars
Total Cars	-0.471 0.000	
Total Trucks	-0.387 0.002	0.843 0.000

The data shows some interesting results. The VSR is correlated with the variable years ago resurfaced at -0.813. This infers that as the number of years since last the resurfacing increases the condition of the road decreases.

Stepwise regression analysis was the next thing to be run on the variables. Stepwise regression either includes or excludes variables from a generated model based on a set alpha value (MINITAB). If the P-Value for a variable is above the set alpha value, the variable will not be included in the model (see Figure 4-2).

Stepwise Regression

Alpha-to-Enter: 0.15 Alpha-to-Remove: 0.15

Response is Visual Inspection Rating on 9 predictors, with N = 59.
*The 9 predictors are: ADT '% Trucks' 'Years Ago Resurfaced' 'Avg. Daily Trucks' 'Avg. Daily Cars' 'Yearly Trucks' 'Yearly Passenger Cars' 'Total Cars *k' 'Total Trucks *k'*

Step	1	2	3
Constant	8.965	9.329	9.330
Years Ago Resurfaced	-0.250	-0.240	-0.223
T-Value	-10.55	-10.16	-8.86
P-Value	0.000	0.000	0.000
% Trucks		-0.078	-0.069
T-Value		-2.13	-1.90
P-Value		0.037	0.063
Yearly Passenger Cars			-0.00000
T-Value			-1.65
P-Value			0.104

S	1.05	1.02	1.00
R-Sq	66.14	68.69	70.17
R-Sq(adj)	65.55	67.57	68.54
PRESS	68.2272	65.4702	63.6021
R-Sq(pred)	63.25	64.73	65.74

Figure 4-2. Stepwise regression analyses on variables

The stepwise regression shown in figure 4-2 reveals that the best predictors of pavement deterioration are Years Ago Resurfaced, Yearly Passenger Cars, and % Trucks. The P-Values for these variables are all less than the alpha value of 0.15. Even though this model is the best statistically, it does not make sense in application. The variable Yearly Passenger Cars is not logical in conjunction with % Trucks as this variable is related to ADT. It is the percentage of the ADT that is comprised of tractor-trailers. Yearly Passenger Cars and % Trucks cannot be used in the same regression equation for this reason.

Since it is not possible to have both Yearly Passenger Cars and % Trucks in the same regression equation, then one or the other could be included in the model along with Years Ago Resurfaced. However, the regression equation that contained % Trucks and Years Ago Resurfaced would not practically explain the data. The % Trucks variable is too ambiguous. % Trucks has to be tied to ADT for it to be understandable.

The stepwise regression did show that Years Ago Resurfaced had a P-Value of less than 0.001. This means that Years Ago Resurfaced is very helpful in explaining the data. A scatter plot of years Ago Resurfaced versus VSR was made. It can be seen that Years Ago Resurfaced does have a linear effect on VSR. The point at 25 years and VSR of 4 is a real value so it cannot be thrown out even though it has a large influence on the regression line (see Figure 4-2).

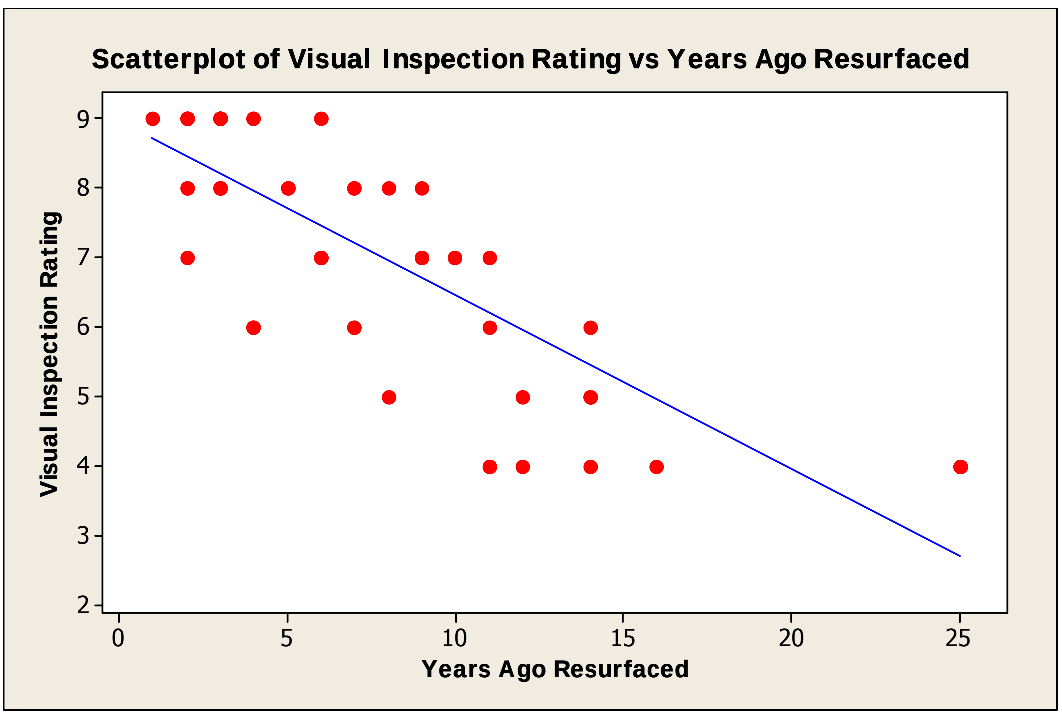

Figure 4-3. Scatter plot of VSR vs. years ago resurfaced

Since the stepwise regression did not reveal much, it was decided to build regression models that made sense application wise. This involved building models and looking at the appropriate values to determine which model was the best. The values consist of P-Values, R^2, and PRESS. There are three separate R^2 items to observe but the $R^2_{(adj)}$ and the $R^2_{(pred)}$ are the most important. The $R^2_{(adj)}$ value calculates how well the model embodies the data. The higher the $R^2_{(adj)}$ value, the better the model explains the data (Montgomery 2001). The $R^2_{(pred)}$ value describes the prediction capabilities of the model. PRESS stands for prediction sum of squares. It evaluates the models predictive capability and the lower the value the better the model is at prediction (MINITAB). PRESS is used to calculate $R^2_{(pred)}$.

The first model that was built consisted of the variables Years Ago Resurfaced, ADT, and % Trucks. This is the data that was obtained in the field (see Figure 4-4).

Regression Analysis: Visual Inspection Rating versus Years Ago Resurfaced, ADT, % Trucks

The regression equation is
Visual Inspection Rating = 9.37 - 0.235 Years Ago Resurfaced - 0.000026 ADT - 0.0679 % Trucks

Predictor	Coef	SE Coef	T	P
Constant	9.3721	0.2746	34.12	0.000
Years Ago Resurfaced	-0.23539	0.02382	-9.88	0.000
ADT	-0.00002589	0.00002290	-1.13	0.263
% Trucks	-0.06791	0.03769	-1.80	0.077

S = 1.01624   R-Sq = 69.4%   R-Sq(adj) = 67.7%

PRESS = 66.6731   R-Sq(pred) = 64.08%

Figure 4-4. Regression analysis (1)

The data in Figure 4-4 can now be analyzed. The $R^2_{(adj)}$ is 67.7% which means that 67% of the data has been explained. The $R^2_{(pred)}$ is 64.08% which means that 64% of the data will be correctly explained in values beyond the collected data. The closer a variable's P-Value is to zero the more influence it has on the regression equation. The P-Value for Years Ago Resurfaced and % Trucks look fine. The P-Value for ADT is 26.3% which could be considered large depending on the desired confidence interval. The regression equation does not start at ten and decline rather, it starts at 9.37. This is because there is a lack of data for roads starting at ten. All of the variables in the equation are negative because the VSR is deteriorating. Negative variables are good because this shows that the roads are deteriorating which is what is happening in real life.

The next regression model that was run was made up of the variables Years Ago Resurfaced and ADT. The reason for doing this is to see how ADT will change in the regression equation. The percent of tractor-trailers is part of the ADT value. So, ADT by itself might yield a better equation.

Analysis of the results reveals that the P-Value for the ADT did drop to 11.9% from 26.3%. The $R^2_{(adj)}$ is 66.4% which is just a little below the previous value. $R^2_{(pred)}$ rose slightly by 0.11% to 66.19%. The equation started at 9.09 and all the variables were negative (see Figure 4-5).

Regression Analysis: Visual Inspection Rating versus Years Ago Resurfaced, ADT

The regression equation is
Visual Inspection Rating = 9.09 - 0.243 Years Ago Resurfaced - 0.000036 ADT

Predictor	Coef	SE Coef	T	P
Constant	9.0922	0.2310	39.36	0.000
Years Ago Resurfaced	-0.24265	0.02395	-10.13	0.000
ADT	-0.00003591	0.00002266	-1.58	0.119

S = 1.03642   R-Sq = 67.6%   R-Sq(adj) = 66.4%

PRESS = 66.4746   R-Sq(pred) = 64.19%

Figure 4-5. Regression analysis (2)

The next model undertaken was with the variables ADT and %Trucks. This was done to see how much of the data was explained by these two variables (see Figure 4-6).

Regression Analysis: Visual Inspection Rating versus ADT, % Trucks

The regression equation is
Visual Inspection Rating = 8.21 - 0.000061 ADT - 0.131 % Trucks

Predictor	Coef	SE Coef	T	P
Constant	8.2054	0.4094	20.04	0.000
ADT	-0.00006133	0.00003734	-1.64	0.106
% Trucks	-0.13087	0.06132	-2.13	0.037

S = 1.67767   R-Sq = 15.1%   R-Sq(adj) = 12.1%

PRESS = 180.745   R-Sq(pred) = 2.63%

Figure 4-6. Regression analysis (3)

The regression analysis in figure 4.6 brings to light some interesting results. The P-Values for both variables are acceptable. The $R^2_{(adj)}$ is 12.1% which was unacceptable. This model does not explain the data. Likewise, the $R^2_{(pred)}$ is 2.63% because the data is not accurately being explained. Contrary to previous belief, these two variables help very little with predicting the behavior of the data.

Since the results for the previous regression model show that the data is not being explained very well by ADT and % Trucks, a model with only the variable Years Ago Resurfaced was generated.

The results of the regression analysis can be viewed in figure 4.7. The $R^2_{(adj)}$ is 65.5%. When this value is compared to the previous model where the $R^2_{(adj)}$ is 12.1%, it shows that Years Ago Resurfaced is explaining most of the data. The $R^2_{(pred)}$ is 63.25% so, Years Ago Resurfaced is predicting the future values better than ADT and % Trucks.

When this model is compared to the model that contains ADT, % Trucks and Years Ago Resurfaced it can be seen that Years Ago Resurfaced is the main predicting factor. The $R^2_{(adj)}$ is 65.5% with just Years Ago Resurfaced but with the addition of the variables ADT and % Trucks it rose slightly to 67.7%. The $R^2_{(pred)}$ is 63.25% and it climbed to 64.08% with ADT and % Trucks. The variables ADT and % Trucks slightly help the regression model (see Figure 4-7).

Regression Analysis: Visual Inspection Rating versus Years Ago Resurfaced

The regression equation is
Visual Inspection Rating = 8.97 - 0.250 Years Ago Resurfaced

Predictor	Coef	SE Coef	T	P
Constant	8.9654	0.2196	40.83	0.000
Years Ago Resurfaced	-0.25049	0.02374	-10.55	0.000

S = 1.05007   R-Sq = 66.1%   R-Sq(adj) = 65.5%

PRESS = 68.2272   R-Sq(pred) = 63.25%

Figure 4-7. Regression analysis (4)

One possible reason for ADT and % Trucks not explaining the data very well is that the depth of the asphalt on each road is not the same. An equivalent single-axle loading (ESAL) takes into account ADT and percentage of tractor-trailers. The ESAL factor is the number of repetitions of an 18,000 pound single axle load applied to the pavement on two sets of dual tires (Garber and Hoel 2002). When a road is being designed a predicted amount of ESALs is selected and applied over the service life of the road. The number of ESALs a road must support is taken into account and the depth of the asphalt layer is designed. Also a road could experience a periodic increase in the amount of tractor-trailer traffic due to logging or agricultural reasons, such crop harvests. This large temporary truck traffic increase could attribute to road failure.

The variable ADT and % Trucks may be indirectly affecting the results of the regression analysis because the asphalt was designed to support the traffic. Years Ago Resurfaced is explained more of the data because of possible other factors that may be affecting the road, such as the weather.

The next regression model used the variables Total Cars and Total Trucks. The Total Cars variable was made by multiplying ADT by the number of days in a year and the number of years since the road was last resurfaced. This yields the cumulative amount of cars that have driven over the current asphalt layer. The Total Trucks variable was made by multiplying the percentage of tractor-trailers by ADT. This gives the number of trucks that are on a road in one day. It was then multiplied by the number of days in a year and then multiplied by the number of years since the road was last resurfaced. This yields the cumulative amount of tractor-trailers that have driven over the current asphalt layer. This was done to incorporate the Years Ago Resurfaced variable into ADT and % Trucks.

The regression analysis was performed and can be seen in figure 4.8. The P-Value for Total Trucks appears to be large. By looking in table 4.4 it can be seen that Total Trucks and Total Cars correlated at a value of 0.843. The $R^2_{(adj)}$ came out to be 19.4% which means that these two variables did not explain much of the data. The $R^2_{(pred)}$ is low at a value of 13.76%. The regression equation shows a value of zero for Total Cars and Total Trucks. This actually means that the values were below 0.000001. The equation also shows that Total Trucks is positive which means that it adds the equation. This model is not helpful at all. It does not reveal any useful information (see Figure 4-8).

Regression Analysis: Visual Inspection Rating versus Total Cars, Total Trucks

The regression equation is
Visual Inspection Rating = 7.74 - 0.000000 Total Cars + 0.000000 Total Trucks

Predictor	Coef	SE Coef	T	P
Constant	7.7426	0.2563	30.21	0.000
Total Cars	-0.00000004	0.00000002	-2.29	0.026
Total Trucks	0.00000003	0.00000019	0.16	0.875

S = 1.60581 R-Sq = 22.2% R-Sq(adj) = 19.4%

PRESS = 160.093 R-Sq(pred) = 13.76%

Figure 4-8. Regression analysis (5)

The models shown in this chapter were those that made the most sense to present. There were other regression models generated and they can be viewed in Appendix A along with a full display of the regression models shown in this chapter. A full display shows the regression model, analysis of variance, and unusual observations.

4.3 Model Selection and Validation

The model that was partially accepted contained the variables Years Ago Resurfaced, ADT, and % Trucks. For a model to be fully accepted it must pass the model validation tests. The reason this model was chosen is that it explained the highest amount of data. The ADT and % Trucks variables did not contribute a lot to the model but they slightly increased the accuracy of the model. The equation obtained in the regression analysis is equation 4.1.

$$\text{Visual Inspection Rating} = 9.37 - 0.235\ \text{Years Ago Resurfaced} - 0.000026\ \text{ADT} - 0.0679\ \%\ \text{Trucks} \qquad \text{Eq. (4.1)}$$

The next thing that was done was to validate the selected regression model. Validating the model means to make sure that the model makes sense scientifically and statistically. The scientific part of validation is make sure the variables in the model are correct for the application and that putting them in the regression model makes sense. One example of this is using the variables Years Ago Resurfaced and % Trucks in the same regression mode. These two variables are correct application wise to pavement deterioration. The problem here is that % Trucks is obtained from ADT and including it in a model without ADT would not make sense scientifically.

To validate the model, statistical tests have to run on the three basic assumptions of linear regression. The three assumptions are that the errors are normally distributed, the variability of the errors is constant, and the regression is significant.

To run the first statistical test a normal probability plot of the residuals is made. If a distribution is normal, the points will fall along a straight line. The normal probability plot can be seen in Figure 4.9. It can be seen that the points do not form a straight line. This is an indication that the error is not normally distributed (see Figure 4-9).

To further examine the situation of whether or not the error is normally distributed an Anderson-Darling test was performed. If the P-Value is less than a desired alpha value then it must be concluded that the distribution is not normal. By looking in table 4-5 it can be seen that the P-Value is less than 0.005 which means that the error is not normally distributed (see Table 4-5).

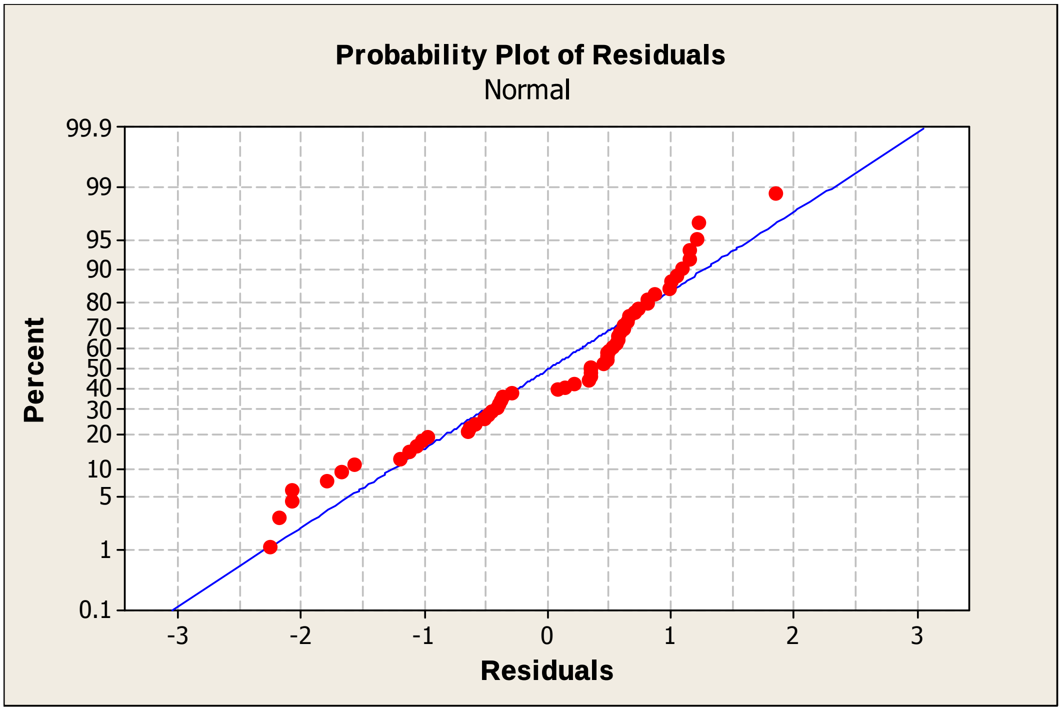

Figure 4-9. Normal probability plot of residuals

Table 4-5. Anderson-Darling test results

Mean	**-2.40862×10^{-15}**
Standard Deviation	0.9896
N	59
Anderson-Darling	1.721
P-Value	<0.005

Because the assumption that the errors are normally distributed failed a transformation of some of the data is required. Transforming data refers to multiplying a variable by a certain value found from a lambda value. This lambda value is obtained through a Box-Cox Plot produced in Minitab Software. Finding which variables need to be transformed is a trial and error process (Chatterjee et al 2000).

The analysis was done and the best model was attained by transforming the variables ADT and Years Ago Resurfaced. The variables Visual Inspection Rating and % Trucks were best left alone. The Box-Cox Plot shown in figure 4-10 reveals that the best lambda value for the transformation is zero. This corresponds to using a log base ten transformation on the ADT variables (see Figure 4-10).

A Box-Cox Plot of Years Ago Resurfaced can be seen in Figure 4-11. The best lambda value is zero. Just like the variable ADT the Years Ago Resurfaced variable is transformed using log base ten (see Figure 4-11).

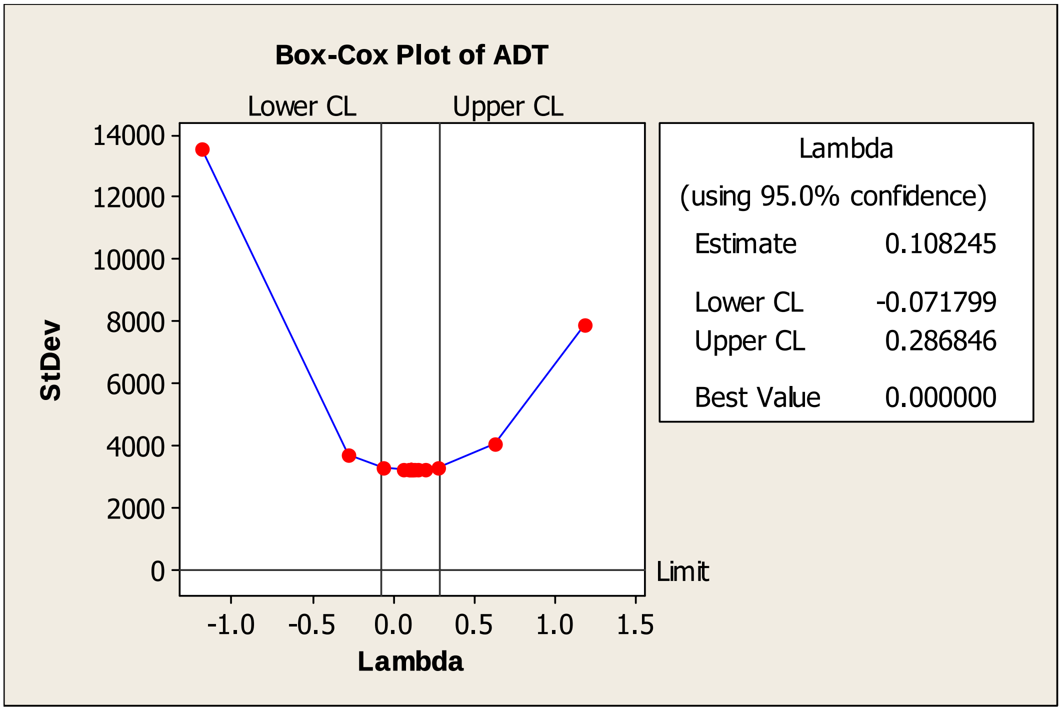

Figure 4-10. Box-Cox plot of ADT

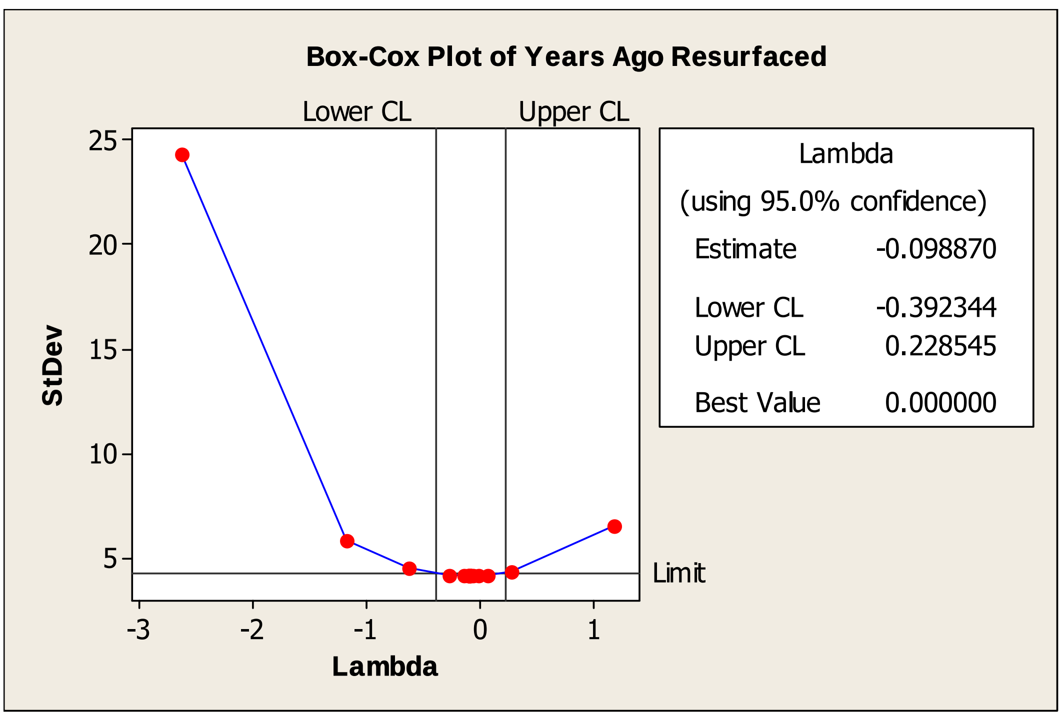

Figure 4-11. Box-Cox plot of years ago resurfaced

Now that the transformations have been performed the errors can again be checked for normality. Figure 4-12 shows the Normal Probability Plot of the residuals after the transformation. The points are better clustered along a straight line than the previous attempt. The graph does show some tailing on the left hand side. This could be a concern so an Anderson-Darling test was performed to check the normality. The Anderson-Darling test results are shown in Table 4-6. The P-Value is much better than before at 0.345. Depending on the chosen alpha value the errors are normally distributed (see Figure 4-12 and Table 4-6).

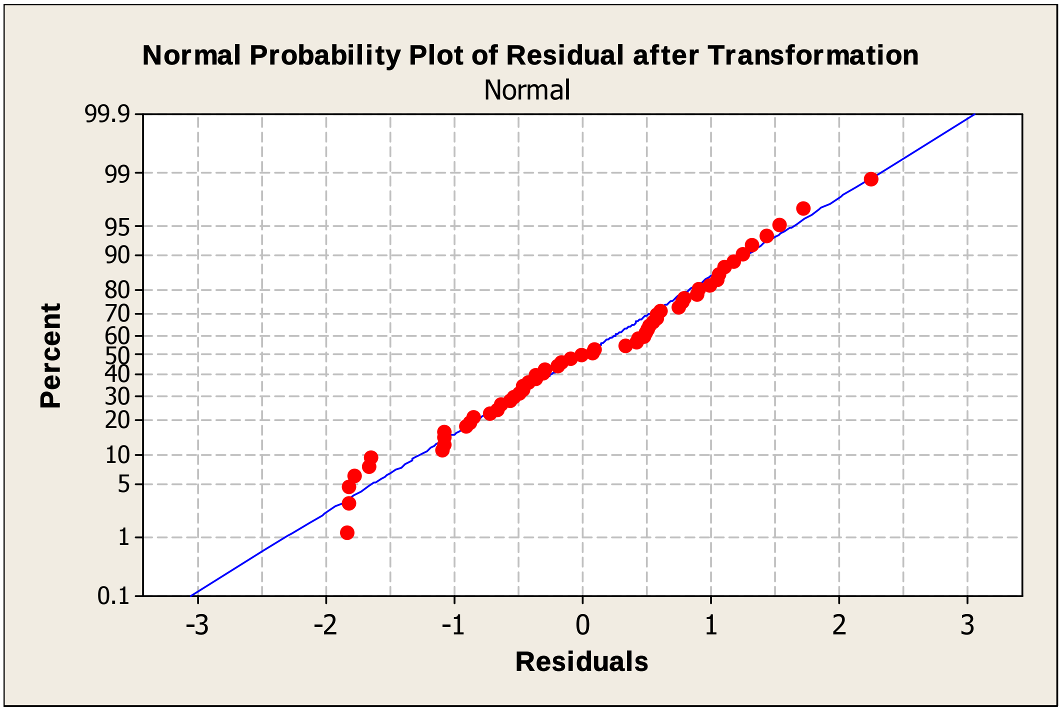

Figure 4-12. Normal probability plot of residuals after transformation

Table 4.6 Anderson-Darling test results after transformation

Mean	**-2.78497×10^{-15}**
Standard Deviation	0.9907
N	59
Anderson-Darling	0.404
P-Value	0.345

The next test is to check the variability of the errors with the transformed variables still in effect. To do this a plot of the residuals versus the fitted values must be made. The plot is read by looking for obvious patterns. The plot is shown in figure 4-13. The points in the plot look pretty well scattered. They may seem to appear a little diagonal but this may be due to the fact that Visual Inspection Rating values are integers (see Figure 4-13).

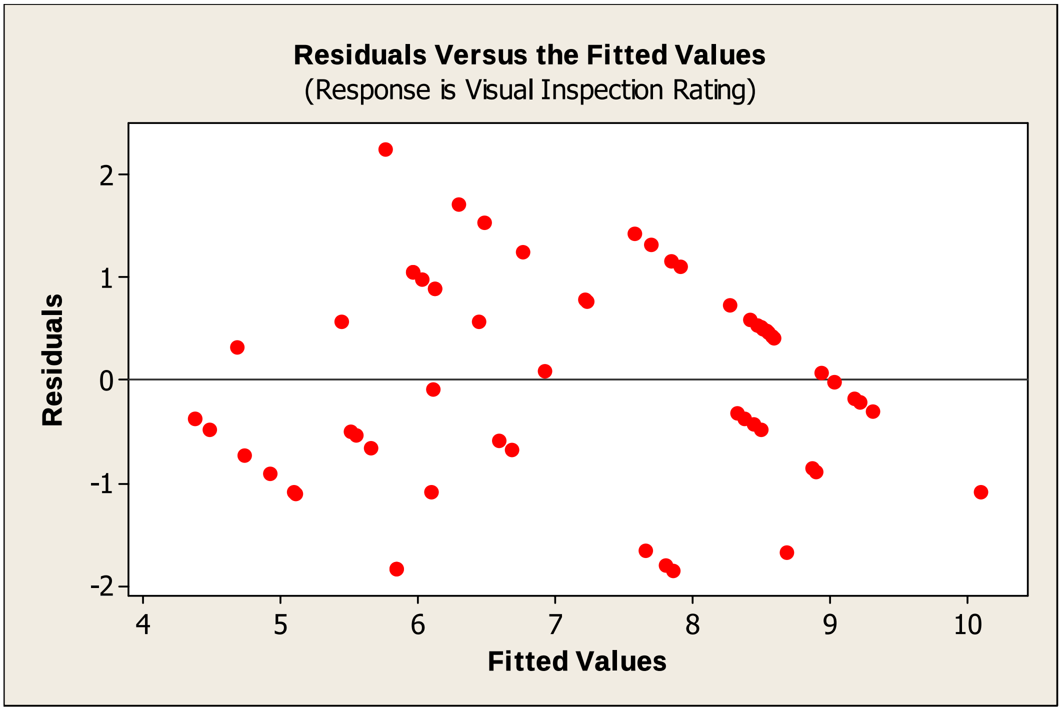

Figure 4-13. Residuals vs. fitted values after transformation

The last test on the assumptions is the significance of regression test. This test looks at the P-Value in the analysis of variance done during regression analysis. If the P-Value is below a desired alpha value, conclude that the regression analysis is significant. The P-Value given in Table 4-7 is less than 0.001 (see Table 4-7).

Table 4-7. Analysis of variance table

Source	DF	SS	MS	F	P
Regression	3	128.697	42.899	41.44	<0.001
Residual Error	55	56.930	1.035		
Total	58	185.627			

The regression analysis on the data with the transformed variables has passed the tests on the three basic assumptions. A new equation was developed to go along with the transformed ADT and Years Ago Resurfaced variables. Equation 4.2 is shown below. The equation starts out at 11.2 because of the transformations. All the variables are negative meaning that the equation depicts deterioration.

$$\text{Visual Inspection Rating} = 11.2 - 0.0911\ \text{T ADT} - 1.76\ \text{T YAR} - 0.0711\ \%\ \text{Trucks} \qquad \text{Eq. (4.2)}$$

The P-Value for the variable T ADT is high at 0.341 but appropriate so the variable % Trucks will make sense application wise. The $R^2_{(adj)}$ is 67.7% and $R^2_{(pred)}$ is 64.5%. These values are close to the values for the equation without the transformed variables. The $R^2_{(adj)}$ value for the regression analysis without the transformed variables is 67.7% and the $R^2_{(pred)}$ 64.08%.

At this point, he regression analysis and model validation were successfully been completed, and the researchers moved to the next task.

4.4 Summary of Chapter

This chapter began with explaining how and where the data was collected. It then went into the regression analysis that was used to create different models. From there it went into model selection where the model that appeared to be the best was chosen and then validated. However, the validation for the model failed because the error was not normally distributed. To combat this problem a transformation was performed for the variables ADT and Years Ago Resurfaced. The model with the transformed variables passed the validation stage and was selected to represent the data. The selected model is equation 4.2 and it will be implemented into the PMS computer software package developed for this report.

Section 5
Conclusions

The successful development of a pavement management system and a computer software package has enabled Alabama's county engineers to effectively store, maintain, and analyze roads within their jurisdictions. They can now go into the field and collect data for all their roads, and store it in a database. Once this information is in the database, they can use queries to make better management decisions pertaining to their roadway network by printing and viewing the easy to understand output.

The introduction of a pavement deterioration equation will allow county engineers to make decisions that pertain to the future condition of their roads. They can decide what roads need immediate attention and which ones can be left alone for a longer period of time.

5.1 PMS Database Conclusion

The database is the heart of the PMS. It is important to note that a database is only as good as the information put into it. The PMS computer program designed for this report is user friendly. The input screen is set up to clearly guide the user on what information is required and how it is to be inserted into the database. The program is straight forward and the query functions allow easy access to the stored data. The output from the queries is designed to be clear and understandable to aid the engineer in making instantly recognizable and concise decisions.

One recommendation would be the implementation of geographical information systems into the PMS computer software. This would enable the user to not only view the data empirically but also graphically. This would be a big step forward because the engineer could print maps to show the county commissioners and public what roads need maintenance and where they are located. It could also be used to print maps to give to maintenance crews to directly relay which roads and what parts of the roads need work.

5.2 Model Conclusion

A pavement deterioration equation will be helpful to county engineers. The model is reasonably accurate and it should allow engineers to make more informed decisions on when a road will need maintenance. The model may not be valid for counties across the entire state. The terrain of Franklin and Shelby County is rolling hills. The southern portion of Alabama is flat and contains more sand than the northern region. This could affect the behavior of the roads.

The model that was selected is based on the variables ADT, Percent Trucks, and Years Ago Resurfaced with Visual Inspection Rating being the response variable. However, to meet the requirement of the errors being normally distributed for regression analysis the variables ADT and Years Ago Resurfaced required logarithmic transformations. The model presented in equation 4.2 is statistically valid and can now be used to predict the future condition of roads.

One thing that the model lacked was data on which roads had recently been paved and would have a VSR of 10. It was shown that ADT and % Trucks only slightly increased the model's ability to explain the data. This is probably due to the fact that they are taken into account when a road is being designed. It may prove useful to collect the depth of the asphalt for each road and see what affect this has on the model. It would also be helpful for engineers to keep their PMS program up-to-date so that five years from now the model could be reevaluated and updated.

5.3 Closure

A PMS computer program was designed as a helpful and efficient tool for Alabama's county engineers. Engineers no longer have to guess or get by using spreadsheets as a database tool. The new program provides summaries, future predictions, and pavement condition ratings in digital or paper format, simplifying the process of maintaining, upgrading, analyzing, and accessing the asset data.

Section 6
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Appendix
Collected data and Regression Analysis

A.1 Collected County Road Data

Table A-1. Franklin County collected road data

Road Name	ADT	% Trucks	Date Resurfaced	Rating Number
County Rd. 84	155	7.50	2003	9
County Rd. 81 (East Side Section 1)	700	6.80	2003	9
County Rd. 81 (West Side Section 3)	785	3.30	2003	9
County Rd. 81 (East Side Section 2)	635	3.10	2003	9
County Rd. 81 (West Side Section 4)	986	1.20	2003	9
County Rd. 90	300	5.20	2002	9
County Rd. 21	205	4.10	2002	9
County Rd. 34	200	3.30	2002	9
County Rd. 172 (Hodges Main St.)	570	3.10	2002	9
County Rd. 49	410	3.00	2002	9
Washington St.	770	1.70	2002	9
South Jackson Ave.	2525	1.40	2002	9
Jackson Ave.	4360	1.00	2002	9
Cotton Gin Rd.	100	9.60	2001	9
County Rd. 524	340	6.00	2001	9
County Rd. 41	270	0.00*	1999	9
County Rd. 724 (Section 2)	438	11.90	2002	9
County Rd. 724 (Section 1)	1300	5.40	2002	9
Walnut Gate Rd.	1160	3.15	2002	8
Waterloo Rd.	4800	2.20	2002	8
Lawrence St.	1800	1.90	2002	8
Underwood Rd.	1125	7.50	2000	8
County Rd. 75	1100	9.80	2003	7
County Rd. 48	3700	0.00*	1995	7
Gravel Hill Rd. (Section 1)	205	9.20	2001	6
Gravel Hill Rd. (Section 2)	675	4.90	2001	6
Gravel Hill Rd. (Section 3)	2000	4.30	2001	6
County Rd. 22 (Section 1)	130	9.20	1980	4
County Rd. 22 (Section 2)	890	8.10	1980	4
Duncan Creek Rd.	380	4.15	1980	4
County Rd. 63	305	1.90	2003	3

*Note: A value of zero in the % Trucks column indicates that there is no data for that particular section

Table A-2. Shelby County collected road data

Road Name	ADT	% Trucks	Date Resurfaced	Rating Number
County Road 93	2750	5.9	2004	9
Heatherwood Road	3783	4.2	1998	8
County Road 44 (Alabaster to County Road 95)	5552	5.2	2003	8
County Road 66	17037	13.1	1997	8
County Road 58	10385	3.9	2003	8
County Road 264 (CR 44 to ST 119)	7515	3.8	1996	8
County Road 35 (CR 52 to CR-33)	6232	5.5	2000	8
Caldwell Mill Road (South)	8733	7.2	1998	8
County Road 14	7815	2.4	2002	8
County Road 17-Valleydale Rd. (I-65 to U.S. 31)	25146	5.9	1996	7
County Road 275	10605	3.2	1995	7
County Road 52 (U.S. 31 to I-65)	26480	16.8	1999	7
County Road 95 (CR-44 to CR-52)	14387	5.3	1996	7
County Road 13 (CR 93 to CR-52	2301	6.5	1999	7
County Road 44 (CR 17 to CR-95	6620	3.7	1994	7
Caldwell Mill Road (North)	12939	3.9	1998	6
County Road 52 (State 261 to Jefferson Co. Line)	11388	5.3	1998	6
County Road 17 (CR 58 to CR 44)	7832	4.8	1991	6
County Road 263 (CR-26 to U.S. 31)	1952	3.2	1994	6
County Road 105	4877	10.1	1997	5
County Road 52 (U.S. 31 to State 261)	11315	2.8	1991	5
County Road 26 (St. 119 to CR-263) Sect. 1	4176	16.2	1991	5
County Road 26 (St. 119 to CR-263) Sect. 2	4082	4.7	1991	5
County Road 68	6369	5.8	1993	5
County Road 17-Valleydale Rd. at Rite Aid	18052	8.5	1991	4
Indian Valley Road	3580	3.9	1993	4
County Road 52 (I-65 to CR-11)	16869	7.8	1989	4
County Road 11 (I-65 bridge to U.S. 31)	5625	5.5	1994	4
County Road 263 (U.S. 31 to CR-26)	4176	16.2	1994	4

A.2 Linear Regression Model Development

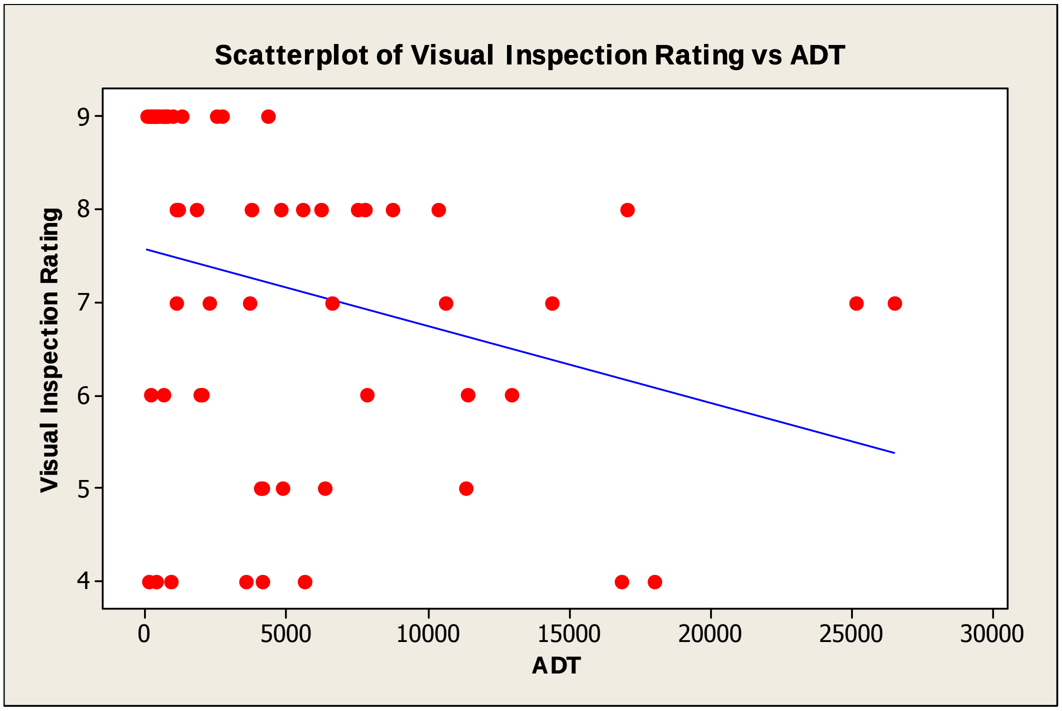

Figure A-1. Scatterplot of VSR vs. ADT

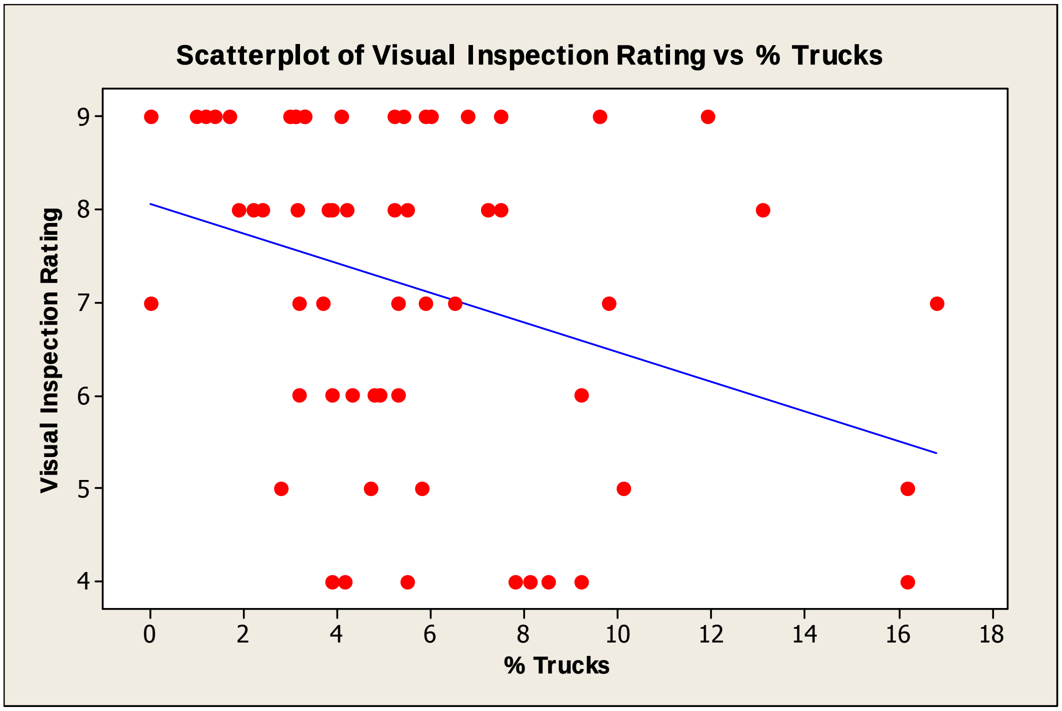

Figure A-2. Scatterplot of VSR vs. % trucks

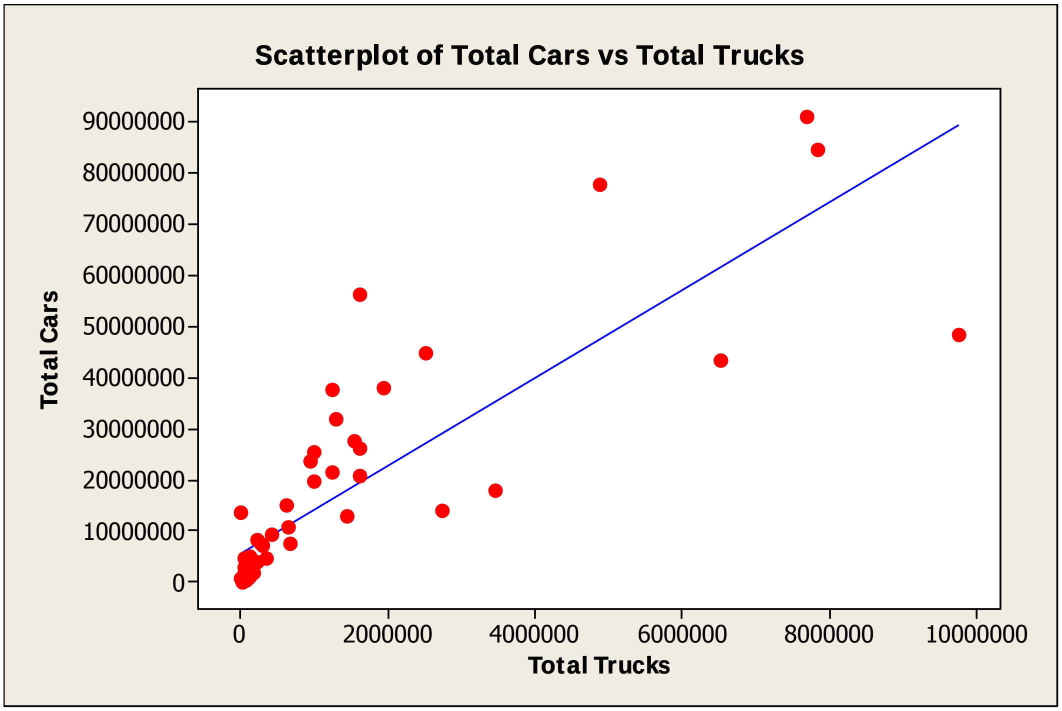

Figure A-3. Scatterplot of total cars vs. total trucks

Regression Analysis: Visual Inspection Rating versus Years Ago Resurfaced, ADT, % Trucks

```
The regression equation is
Visual Inspection Rating = 9.37 - 0.235 Years Ago Resurfaced
                           -0.000026 ADT - 0.0679 % Trucks


Predictor                    Coef     SE Coef      T      P
Constant                   9.3721      0.2746  34.12  0.000
Years Ago Resurfaced     -0.23539     0.02382  -9.88  0.000
ADT                   -0.00002589  0.00002290  -1.13  0.263
% Trucks                 -0.06791     0.03769  -1.80  0.077


S = 1.01624   R-Sq = 69.4%   R-Sq(adj) = 67.7%

PRESS = 66.6731   R-Sq(pred) = 64.08%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       3  128.826  42.942  41.58  0.000
Residual Error  55   56.801   1.033
Total           58  185.627


Source                DF   Seq SS
Years Ago Resurfaced   1  122.776
ADT                    1    2.697
% Trucks               1    3.353


Unusual Observations

                        Visual
      Years Ago  Inspection
Obs  Resurfaced      Rating    Fit  SE Fit  Residual  St Resid
 26         4.0       6.000  8.080   0.173    -2.080     -2.08R
 27         4.0       6.000  8.087   0.162    -2.087     -2.08R
 28        25.0       4.000  2.859   0.481     1.141      1.27 X
 29        25.0       4.000  2.914   0.467     1.086      1.20 X
 30        25.0       4.000  3.196   0.481     0.804      0.90 X
 34        12.0       4.000  6.190   0.196    -2.190     -2.20R
 35         9.0       7.000  6.202   0.471     0.798      0.89 X
 38         6.0       7.000  6.133   0.586     0.867      1.04 X
 40        11.0       4.000  6.264   0.160    -2.264     -2.26R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-4. Model creation regression analysis Minitab output (1)

Regression Analysis: Visual Inspection Rating versus Years Ago Resurfaced, ADT

```
The regression equation is
Visual Inspection Rating = 9.09 - 0.243 Years Ago Resurfaced
                           -0.000036 ADT


Predictor                     Coef     SE Coef       T      P
Constant                    9.0922      0.2310   39.36  0.000
Years Ago Resurfaced      -0.24265     0.02395  -10.13  0.000
ADT                    -0.00003591  0.00002266   -1.58  0.119


S = 1.03642   R-Sq = 67.6%   R-Sq(adj) = 66.4%

PRESS = 66.4746   R-Sq(pred) = 64.19%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       2  125.473  62.737  58.40  0.000
Residual Error  56   60.154   1.074
Total           58  185.627


Source                DF   Seq SS
Years Ago Resurfaced   1  122.776
ADT                    1    2.697


Unusual Observations

                      Visual
      Years Ago  Inspection
Obs  Resurfaced      Rating    Fit  SE Fit  Residual  St Resid
 25         4.0       6.000  8.114   0.182    -2.114    -2.07R
 26         4.0       6.000  8.097   0.176    -2.097    -2.05R
 27         4.0       6.000  8.050   0.164    -2.050    -2.00R
 28        25.0       4.000  3.021   0.481     0.979     1.07 X
 29        25.0       4.000  2.994   0.474     1.006     1.09 X
 30        25.0       4.000  3.012   0.479     0.988     1.07 X
 34        12.0       4.000  6.052   0.185    -2.052    -2.01R
 35         9.0       7.000  6.005   0.467     0.995     1.07 X
 38         6.0       7.000  6.685   0.509     0.315     0.35 X
 40        11.0       4.000  6.221   0.161    -2.221    -2.17R
 54        11.0       4.000  6.273   0.166    -2.273    -2.22R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-5. Model creation regression analysis Minitab output (2)

Regression Analysis: Visual Inspection Rating versus Years Ago Resurfaced

```
The regression equation is
Visual Inspection Rating = 8.97 - 0.250 Years Ago Resurfaced


Predictor                 Coef  SE Coef       T      P
Constant                8.9654   0.2196   40.83  0.000
Years Ago Resurfaced  -0.25049  0.02374  -10.55  0.000


S = 1.05007   R-Sq = 66.1%   R-Sq(adj) = 65.5%

PRESS = 68.2272   R-Sq(pred) = 63.25%


Analysis of Variance

Source          DF      SS      MS       F      P
Regression       1  122.78  122.78  111.35  0.000
Residual Error  57   62.85    1.10
Total           58  185.63


Unusual Observations

                     Visual
      Years Ago  Inspection
Obs  Resurfaced      Rating    Fit  SE Fit  Residual  St Resid
 28        25.0       4.000  2.703   0.443     1.297      1.36 X
 29        25.0       4.000  2.703   0.443     1.297      1.36 X
 30        25.0       4.000  2.703   0.443     1.297      1.36 X
 40        11.0       4.000  6.210   0.163    -2.210     -2.13R
 54        11.0       4.000  6.210   0.163    -2.210     -2.13R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-6. Model creation regression analysis Minitab output (3)

Regression Analysis: Visual Inspection Rating versus ADT, % Trucks

```
The regression equation is
Visual Inspection Rating = 8.21 - 0.000061 ADT - 0.131 % Trucks


Predictor          Coef     SE Coef      T      P
Constant         8.2054      0.4094  20.04  0.000
ADT         -0.00006133  0.00003734  -1.64  0.106
% Trucks       -0.13087     0.06132  -2.13  0.037


S = 1.67767   R-Sq = 15.1%   R-Sq(adj) = 12.1%

PRESS = 180.745   R-Sq(pred) = 2.63%


Analysis of Variance

Source          DF       SS      MS     F      P
Regression       2   28.011  14.005  4.98  0.010
Residual Error  56  157.616   2.815
Total           58  185.627


Source    DF  Seq SS
ADT        1  15.191
% Trucks   1  12.820


Unusual Observations

                Visual
            Inspection
Obs    ADT      Rating    Fit  SE Fit  Residual  St Resid
 30    380       4.000  7.639   0.280    -3.639     -2.20R
 34   3580       4.000  7.475   0.243    -3.475     -2.09R
 35  25146       7.000  5.891   0.775     1.109      0.75 X
 38  26480       7.000  4.383   0.922     2.617      1.87 X
 52   4176       5.000  5.829   0.693    -0.829     -0.54 X
 54   4176       4.000  5.829   0.693    -1.829     -1.20 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-7. Model creation regression analysis Minitab output (4)

Regression Analysis: Visual Inspection Rating versus Years Ago Resurfaced, Avg. Daily Trucks, Avg. Daily Cars

```
The regression equation is
Visual Inspection Rating = 9.09 - 0.243 Years Ago Resurfaced
                           - 0.000015 Avg. Daily Trucks
                           - 0.000038 Avg. Daily Cars


Predictor                    Coef     SE Coef       T      P
Constant                   9.0946      0.2363   38.48  0.000
Years Ago Resurfaced     -0.24256     0.02421  -10.02  0.000
Avg. Daily Trucks      -0.0000154   0.0003300   -0.05  0.963
Avg. Daily Cars       -0.00003807  0.00004159   -0.92  0.364


S = 1.04577   R-Sq = 67.6%   R-Sq(adj) = 65.8%

PRESS = 68.9442   R-Sq(pred) = 62.86%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       3  125.478  41.826  38.24  0.000
Residual Error  55   60.150   1.094
Total           58  185.627


Source                DF   Seq SS
Years Ago Resurfaced   1  122.776
Avg. Daily Trucks      1    1.785
Avg. Daily Cars        1    0.916


Unusual Observations

                     Visual
      Years Ago  Inspection
Obs  Resurfaced      Rating    Fit  SE Fit  Residual  St Resid
 25         4.0       6.000  8.117   0.189    -2.117    -2.06R
 26         4.0       6.000  8.099   0.181    -2.099    -2.04R
 28        25.0       4.000  3.026   0.492     0.974     1.06 X
 29        25.0       4.000  2.998   0.484     1.002     1.08 X
 30        25.0       4.000  3.017   0.488     0.983     1.06 X
 35         9.0       7.000  5.988   0.549     1.012     1.14 X
 38         6.0       7.000  6.732   0.907     0.268     0.51 X
 40        11.0       4.000  6.219   0.165    -2.219    -2.15R
 54        11.0       4.000  6.283   0.229    -2.283    -2.24R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-8. Model creation regression analysis Minitab output (5)

Regression Analysis: Visual Inspection versus Avg. Daily Trucks, Avg. Daily Cars

```
The regression equation is
Visual Inspection Rating = 7.61 + 0.000139 Avg. Daily Trucks
                           - 0.000107 Avg. Daily Cars


Predictor                 Coef     SE Coef      T      P
Constant                7.6113      0.3068  24.81  0.000
Avg. Daily Trucks    0.0001393   0.0005491   0.25  0.801
Avg. Daily Cars    -0.00010665  0.00006833  -1.56  0.124


S = 1.74200   R-Sq = 8.5%   R-Sq(adj) = 5.2%

PRESS = 202.459   R-Sq(pred) = 0.00%


Analysis of Variance

Source          DF       SS     MS     F      P
Regression       2   15.692  7.846  2.59  0.084
Residual Error  56  169.935  3.035
Total           58  185.627


Source             DF  Seq SS
Avg. Daily Trucks   1   8.299
Avg. Daily Cars     1   7.392


Unusual Observations

       Avg.      Visual
      Daily  Inspection
Obs  Trucks      Rating    Fit  SE Fit  Residual  St Resid
 28      12       4.000  7.600   0.304    -3.600     -2.10R
 29      72       4.000  7.534   0.285    -3.534     -2.06R
 30      16       4.000  7.575   0.295    -3.575     -2.08R
 35    1484       7.000  5.294   0.907     1.706      1.15 X
 38    4449       7.000  5.881   1.504     1.119      1.27 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-9. Model creation regression analysis Minitab output (6)

Regression Analysis: Visual Inspection Rating versus Avg. Daily Trucks

```
The regression equation is
Visual Inspection Rating = 7.34 - 0.000546 Avg. Daily Trucks


Predictor                Coef    SE Coef      T      P
Constant               7.3442     0.2579  28.48  0.000
Avg. Daily Trucks  -0.0005457  0.0003341  -1.63  0.108


S = 1.76381   R-Sq = 4.5%   R-Sq(adj) = 2.8%

PRESS = 212.306   R-Sq(pred) = 0.00%


Analysis of Variance

Source          DF       SS     MS     F      P
Regression       1    8.299  8.299  2.67  0.108
Residual Error  57  177.328  3.111
Total           58  185.627


Unusual Observations

       Avg.      Visual
      Daily  Inspection
Obs  Trucks      Rating    Fit  SE Fit  Residual  St Resid
 38    4449       7.000  4.916   1.388     2.084      1.92 X
 43    2232       8.000  6.126   0.669     1.874      1.15 X

X denotes an observation whose X value gives it large influence.
```

Figure A-10. Model creation regression analysis Minitab output (7)

Regression Analysis: Visual Inspection Rating versus Avg. Daily Cars

```
The regression equation is
Visual Inspection Rating = 7.59 - 0.000093 Avg. Daily Cars


Predictor                Coef     SE Coef      T      P
Constant               7.5943      0.2969  25.58  0.000
Avg. Daily Cars  -0.00009280  0.00004073  -2.28  0.026


S = 1.72764   R-Sq = 8.3%   R-Sq(adj) = 6.7%

PRESS = 182.562   R-Sq(pred) = 1.65%


Analysis of Variance

Source          DF       SS      MS     F      P
Regression       1   15.497  15.497  5.19  0.026
Residual Error  57  170.131   2.985
Total           58  185.627


Unusual Observations

      Avg.      Visual
     Daily  Inspection
Obs   Cars      Rating    Fit  SE Fit  Residual  St Resid
 28    118       4.000  7.583   0.294    -3.583    -2.10R
 29    818       4.000  7.518   0.276    -3.518    -2.06R
 30    364       4.000  7.561   0.287    -3.561    -2.09R
 35  23662       7.000  5.399   0.802     1.601     1.05 X
 38  22031       7.000  5.550   0.738     1.450     0.93 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-11. Model creation regression analysis Minitab output (8)

Regression Analysis: Visual Inspection Rating versus Total Cars, Total Trucks

```
The regression equation is
Visual Inspection Rating = 7.74 - 0.000000 Total Cars + 0.000000 Total
Trucks


Predictor            Coef     SE Coef      T      P
Constant           7.7426      0.2563  30.21  0.000
Total Cars    -0.00000004  0.00000002  -2.29  0.026
Total Trucks   0.00000003  0.00000019   0.16  0.875


S = 1.60581   R-Sq = 22.2%   R-Sq(adj) = 19.4%

PRESS = 160.093   R-Sq(pred) = 13.76%


Analysis of Variance

Source          DF       SS      MS     F      P
Regression       2   41.225  20.612  7.99  0.001
Residual Error  56  144.403   2.579
Total           58  185.627


Source        DF  Seq SS
Total Cars     1  41.160
Total Trucks   1   0.064


Unusual Observations

                    Visual
                Inspection
Obs  Total Cars      Rating    Fit  SE Fit  Residual  St Resid
 28     1077115       4.000  7.701   0.251    -3.701    -2.33R
 29     7463429       4.000  7.452   0.223    -3.452    -2.17R
 30     3323599       4.000  7.609   0.238    -3.609    -2.27R
 31    84404834       4.000  4.470   0.734    -0.470    -0.33 X
 35    77730938       7.000  4.660   0.700     2.340     1.62 X
 38    48248678       7.000  6.026   1.159     0.974     0.88 X
 39    90830793       4.000  4.198   0.773    -0.198    -0.14 X
 43    43231047       8.000  6.140   0.667     1.860     1.27 X
 44    56200700       5.000  5.458   0.705    -0.458    -0.32 X
 54    14050444       4.000  7.239   0.374    -3.239    -2.07R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-12. Model creation regression analysis Minitab output (9)

Regression Analysis: Visual Inspection Rating versus Total Trucks *K, Total Cars *K

```
The regression equation is
Visual Inspection Rating = 7.74 + 0.000029 Total Trucks *k
                           - 0.000042 Total Cars *k


Predictor                Coef     SE Coef      T      P
Constant               7.7426      0.2563  30.21  0.000
Total Trucks *k     0.0000294   0.0001859   0.16  0.875
Total Cars *k     -0.00004151  0.00001816  -2.28  0.026


S = 1.60581   R-Sq = 22.2%   R-Sq(adj) = 19.4%

PRESS = 160.094   R-Sq(pred) = 13.76%


Analysis of Variance

Source          DF       SS      MS     F      P
Regression       2   41.224  20.612  7.99  0.001
Residual Error  56  144.403   2.579
Total           58  185.627


Source           DF  Seq SS
Total Trucks *k   1  27.761
Total Cars *k     1  13.463


Unusual Observations

      Total      Visual
     Trucks  Inspection
Obs      *k      Rating    Fit  SE Fit  Residual  St Resid
 28     109       4.000  7.701   0.251    -3.701    -2.33R
 29     658       4.000  7.452   0.223    -3.452    -2.17R
 30     144       4.000  7.609   0.238    -3.609    -2.27R
 31    7841       4.000  4.470   0.734    -0.470    -0.33 X
 35    4874       7.000  4.660   0.700     2.340     1.62 X
 38    9743       7.000  6.026   1.159     0.974     0.88 X
 39    7684       4.000  4.198   0.773    -0.198    -0.14 X
 43    6517       8.000  6.140   0.667     1.860     1.27 X
 44    1619       5.000  5.458   0.705    -0.458    -0.32 X
 54    2716       4.000  7.239   0.374    -3.239    -2.07R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-13. Model creation regression analysis Minitab output (10)

Regression Analysis: Visual Inspection Rating versus Total Trucks *k

```
The regression equation is
Visual Inspection Rating = 7.52 - 0.000329 Total Trucks *k


Predictor               Coef    SE Coef      T      P
Constant              7.5241     0.2464  30.54  0.000
Total Trucks *k   -0.0003286  0.0001038  -3.17  0.002


S = 1.66421   R-Sq = 15.0%   R-Sq(adj) = 13.5%

PRESS = 174.838   R-Sq(pred) = 5.81%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       1   27.761  27.761  10.02  0.002
Residual Error  57  157.866   2.770
Total           58  185.627


Unusual Observations

      Total      Visual
     Trucks  Inspection
Obs      *k      Rating    Fit  SE Fit  Residual  St Resid
 28     109       4.000  7.488   0.241    -3.488    -2.12R
 29     658       4.000  7.308   0.222    -3.308    -2.01R
 30     144       4.000  7.477   0.240    -3.477    -2.11R
 31    7841       4.000  4.948   0.729    -0.948    -0.63 X
 34     612       4.000  7.323   0.223    -3.323    -2.01R
 38    9743       7.000  4.323   0.920     2.677     1.93 X
 39    7684       4.000  4.999   0.714    -0.999    -0.66 X
 43    6517       8.000  5.383   0.599     2.617     1.69 X

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-14. Model creation regression analysis Minitab output (11)

Regression Analysis: Visual Inspection Rating versus Total Cars *k

```
The regression equation is
Visual Inspection Rating = 7.74 - 0.000039 Total Cars *k


Predictor             Coef     SE Coef      T      P
Constant            7.7395      0.2533  30.55  0.000
Total Cars *k  -0.00003909  0.00000970  -4.03  0.000


S = 1.59201   R-Sq = 22.2%   R-Sq(adj) = 20.8%

PRESS = 153.355   R-Sq(pred) = 17.39%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       1   41.160  41.160  16.24  0.000
Residual Error  57  144.467   2.535
Total           58  185.627


Unusual Observations

     Total      Visual
      Cars  Inspection
Obs     *k      Rating    Fit  SE Fit  Residual  St Resid
 28   1077       4.000  7.697   0.247    -3.697     -2.35R
 29   7463       4.000  7.448   0.220    -3.448     -2.19R
 30   3324       4.000  7.610   0.236    -3.610     -2.29R
 31  84405       4.000  4.440   0.704    -0.440     -0.31 X
 35  77731       7.000  4.701   0.643     2.299      1.58 X
 39  90831       4.000  4.189   0.764    -0.189     -0.14 X
 54  14050       4.000  7.190   0.207    -3.190     -2.02R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-15. Model creation regression analysis Minitab output (12)

Regression Analysis: Visual Inspection Rating versus Years Ago Resurfaced, % Trucks, Yearly Passenger Cars

```
The regression equation is
Visual Inspection Rating = 9.33 - 0.223 Years Ago Resurfaced - 0.0693
% Trucks
                           - 0.000004 Yearly Passenger Cars


Predictor                      Coef     SE Coef      T      P
Constant                     9.3297      0.2685  34.75  0.000
Years Ago Resurfaced       -0.22341     0.02522  -8.86  0.000
% Trucks                   -0.06929     0.03650  -1.90  0.063
Yearly Passenger Cars  -0.00000411  0.00000248  -1.65  0.104


S = 1.00336   R-Sq = 70.2%   R-Sq(adj) = 68.5%

PRESS = 63.6021   R-Sq(pred) = 65.74%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       3  130.256  43.419  43.13  0.000
Residual Error  55   55.371   1.007
Total           58  185.627


Source                 DF   Seq SS
Years Ago Resurfaced    1  122.776
% Trucks                1    4.730
Yearly Passenger Cars   1    2.750


Unusual Observations

                     Visual
      Years Ago  Inspection
Obs  Resurfaced      Rating    Fit  SE Fit  Residual  St Resid
 26         4.0       6.000  8.086   0.162    -2.086     -2.11R
 27         4.0       6.000  8.107   0.160    -2.107     -2.13R
 28        25.0       4.000  3.095   0.514     0.905      1.05 X
 29        25.0       4.000  3.099   0.486     0.901      1.03 X
 30        25.0       4.000  3.420   0.510     0.580      0.67 X
 34        12.0       4.000  6.209   0.194    -2.209     -2.24R
 38         6.0       7.000  6.283   0.465     0.717      0.81 X
 39        16.0       4.000  4.193   0.482    -0.193     -0.22 X
 40        11.0       4.000  6.251   0.158    -2.251     -2.27R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-16. Model creation regression analysis Minitab output (13)

Regression Analysis: Visual Inspection Rating versus T ADT, T YAR, % Trucks

```
The regression equation is
Visual Inspection Rating = 11.2 - 0.0911 T ADT - 1.76 T YAR - 0.0711 %
Trucks


Predictor       Coef  SE Coef      T      P
Constant     11.2287   0.7101  15.81  0.000
T ADT       -0.09110  0.09486  -0.96  0.341
T YAR        -1.7591   0.1897  -9.27  0.000
% Trucks    -0.07108  0.03675  -1.93  0.058


S = 1.01739   R-Sq = 69.3%   R-Sq(adj) = 67.7%

PRESS = 65.8900   R-Sq(pred) = 64.50%


Analysis of Variance

Source          DF       SS      MS      F      P
Regression       3  128.697  42.899  41.44  0.000
Residual Error  55   56.930   1.035
Total           58  185.627


Source    DF   Seq SS
T ADT      1   23.081
T YAR      1  101.744
% Trucks   1    3.872


Unusual Observations

                Visual
            Inspection
Obs  T ADT      Rating    Fit  SE Fit  Residual  St Resid
 28    4.9       4.000  4.469   0.476    -0.469     -0.52 X
 38   10.2       7.000  5.955   0.482     1.045      1.17 X
 43    9.7       8.000  5.752   0.341     2.248      2.34R

R denotes an observation with a large standardized residual.
X denotes an observation whose X value gives it large influence.
```

Figure A-17. Model creation regression analysis after transformation Minitab output