Flexible Pavement Condition-Rating Model for Maintenance and Rehabilitation Selection

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ABSTRACT

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Keeping asphalt-surfaced highways and roads in an acceptable condition is the major goal that departments of transportation and pavement engineers always strive to achieve. According to ASCE 2009 report card, an estimated spending of $186 billion is needed annually to substantially improve highways conditions. Hence, prediction models of current and future pavement condition should be rationalized and studied from cost effective perspective. In modeling the pavement condition, two major categories of models have been used: (1) deterministic and (2) stochastic. Existing models consider some factors that might be more critical than others, such as roughness measurements and distress information. They ignore other factors that could have a real effect on the accuracy of the pavement performance model(s), such as climate conditions.

Therefore, the current research aims at developing a comprehensive condition-rating model that incorporates a wider range of possible factors significantly affecting flexible pavement performance. Data for this research were collected from the records of Nebraska Department of Roads (NDOR) called "Tab Files". In addition to a questionnaire that was designed and sent to pavement engineers and experts in North America. An integrated model was developed using Multi-Attribute Utility Theory (MAUT) and multiple regression analysis. Sensitivity analysis of the developed regression models is done using Monte-Carlo simulation to quickly identify the high-

impact factors. Models' validation shows robust results with an average validity percent of 94% in which they can be utilized by Departments of Transportation (DOT) and/or Pavement Management Systems (PMS) as a useful tool for assessing and predicting pavement conditions.

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CHAPTER 1: INTRODUCTION

1.1 Problem Statement:

In today's transport systems, only marine and pipeline transportation do not make use of pavement, which justifies the importance of pavement as one of the major components of transportation and infrastructure systems. Although the function of the pavement varies with the specific user, the purpose of pavement remains the provision of a safe, reliable, efficient, and comfortable driving environment in the highway and roadway systems. Highway agencies are facing challenges to keep serviceability of their pavements to an acceptable level due to the expansion of ground transportation systems and higher costs of construction, maintenance, and rehabilitation of pavement. During the last two decades, the issue of proper design, high-quality construction, optimum maintenance and rehabilitation of pavement have been the focus of highway agencies, contractors, consulting engineers, and researchers.

According to ASCE 2009 report card, America's major roads are assessed with a grade of (D-) which clearly indicates that they are in poor or mediocre condition. Roads in poor conditions lead to severe wear and tear on motor vehicles and can also lead to an increased number of crashes and delays. The current spending level of $70.3 billion per year for highway capital improvements is well below the estimated $186 billion needed annually to substantially improve highway conditions. Therefore, knowing the current condition of pavement is essential to departments of transportation (DOT) because it assists them in predicting the performance of pavement and in optimizing maintenance and rehabilitation activities.

Deterioration of flexible pavement is neither uniform nor identical in which it varies based on different environmental, physical, and operational factors. Thus, it is crucial to inspect and assess most of these factors in order to effectively study their impact on pavement condition and overall performance.

The available prediction models of the current condition of flexible pavement are either of deterministic or stochastic nature. But in modeling the pavement condition, these models are only based on some factors that might be more critical than others, such as roughness measurements and distresses information (i.e. longitudinal cracking, transverse cracking, and rutting). However, the impact of other factors, such as climate conditions (temperature and rainfall), has been clearly neglected. Previous research works are only limited to the causes of surface distress without considering the direct effect they might have on pavement condition. Therefore, the main objective of the current study is to provide the municipalities and DOT with an effective and practical model that incorporates a wider range of possible factors that significantly impact flexible pavement condition.

1.2 Research Objectives:

The objectives of the current research can be summarized as follows:

- Develop a condition-rating model to assess the condition of existing flexible pavement.
- Build deterioration curves for flexible pavement.
- Design a condition rating scale for flexible pavement.

- Develop a web-based automated tool that helps decision makers in their management plans.

1.3 Research Methodology:

In order to meet the aforementioned objectives, the current research methodology was adopted. It consists of many stages as follows:

(1) A comprehensive literature review of the flexible pavement condition-rating protocols.

(2) The data collection phase (includes data for both model development and validation process).

(3) Based on the collected data an integrated MAUT/Regression condition-rating model is developed.

(4) Results of the developed models are tested and validated using Monte-Carlo simulation.

(5) A web-based automated application is built to allow the developed model to be used by DOT and other authorities in managing their highways and road networks.

1.3.1 Literature Review:

A comprehensive literature review is carried out in all the areas related to modeling flexible pavement condition. The topics included in the current literature are: development of pavement management systems, current evaluation processes used to assess the condition of flexible pavement, condition-rating and performance models, and the applied techniques in the current study (Multi-Attribute Utility Theory MAUT, Analytical Hierarchy Process AHP, Multiple regression, and Monte-Carlo simulation).

1.3.2 Data Collection:

The data-collection process consists of two parts required to run and build the integrated MAUT/Regression model. In part one, a questionnaire is designed and sent to sixty pavement engineers and experts mainly in Canada and the US to collect the data related to MAUT model development. In part two, historical data are collected from the records of the Nebraska Department of Roads (NDOR) to obtain real network data, which are used in building and verifying the integrated MAUT/Regression model.

1.3.3 Model Development:

The development of the proposed condition-rating model consists of four major phases as follows: (1) developing a MAUT condition-rating model, (2) developing an integrated MAUT/Regression condition-rating model, (3) testing the model applications using the Monte-Carlo simulation technique, (4) designing a web-based tool to predict the condition-rating values.

1.4 Thesis Organization

In order to achieve the objectives of this research, the thesis is organized according to the following structure: Chapter 2 presents a comprehensive literature review that covers different topics, such as development of pavement management systems (PMS), major criteria for condition assessment, current condition-assessment models, in addition to a detailed description of the applied techniques that include; Multi-Attribute Utility

Theory (MAUT), Analytic Hierarchy Process (AHP), Multiple Regression, and Monte-Carlo Simulation.

Chapter 3 provides an overview of the proposed research methodology adopted in this study, including a brief description of every phase from literature review to model development and web-based application.

Chapter 4 describes the data-collection process, and includes the real data obtained from NDOR files, and the data collected via questionnaires from pavement engineers and experts.

Chapter 5 illustrates the model-development process divided into three main parts. Part one describes the MAUT implementation framework, which includes the steps for building the MAUT condition-rating model and its application results. Part two presents the integrated MAUT/Regression model design and validation processes, including the different statistical tests and diagnostics applied during these processes. Finally, in Part three the application of Monte-Carlo simulation on the developed models is presented, in addition to discussions of results and sensitivity analysis.

Chapter 6 contains the methodology of developing a web-based application for condition-rating of existing flexible pavement. The step-by-step process of the web application is described in detail.

Chapter 7 presents conclusions, limitations of the developed models, research contributions, and recommendations for future work.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction:

This chapter consists of four main sections as follows: Section 2-2 provides a literature review of the development of pavement management systems and their applications. Section 2-3 illustrates the concept of pavement-condition assessment and the four main procedures for assessing the current condition of any road segment, which are: surface distress, structural capacity, ride quality, and skid resistance. Section 2-4 provides a literature review of the existing condition-rating and performance prediction models, including distress-based models, roughness-based models, and composite indices.

The last section, Section 2-5 presents an overview of the adopted techniques in this study, which are: Multi-Attribute Utility Theory (MAUT), Analytic Hierarchy Process (AHP), Multiple Regression, and Monte-Carlo Simulation.

2.2 Development of Pavement Systems Methodology:

In the late 1960s and early 1970s two groups of researchers in USA; the American Association of State Highway Officials (AASHO), and the Texas Transportation Institute of Texas A&M University (Scrivner, 1968) initiated a study to make new breakthroughs in the design of pavement using a systems approach. At the same time in Canada a third group of researchers was conducting a similar independent study about the need to link all the planning, designing, constructing and maintaining activities together forming a unified pavement system (Hutchinson *et al.,* 1968).

In fact, the effort of these three groups of researchers was the foundation of the development of pavement management systems.

2.2.1 Pavement Management Systems (PMS):

ASSHTO has defined PMS as a set of methods and tools used to help decision-makers in finding the optimal strategies for providing and maintaining pavement at an adequate level of service over a period of time. (ASSHTO, 2001, 1993) and (Delaware DOT, 2000). A total Pavement Management System (PMS) must serve different management needs or levels and must interface with any sort of transportation management system involved. Figure 2-1 shows the major components of PMS.

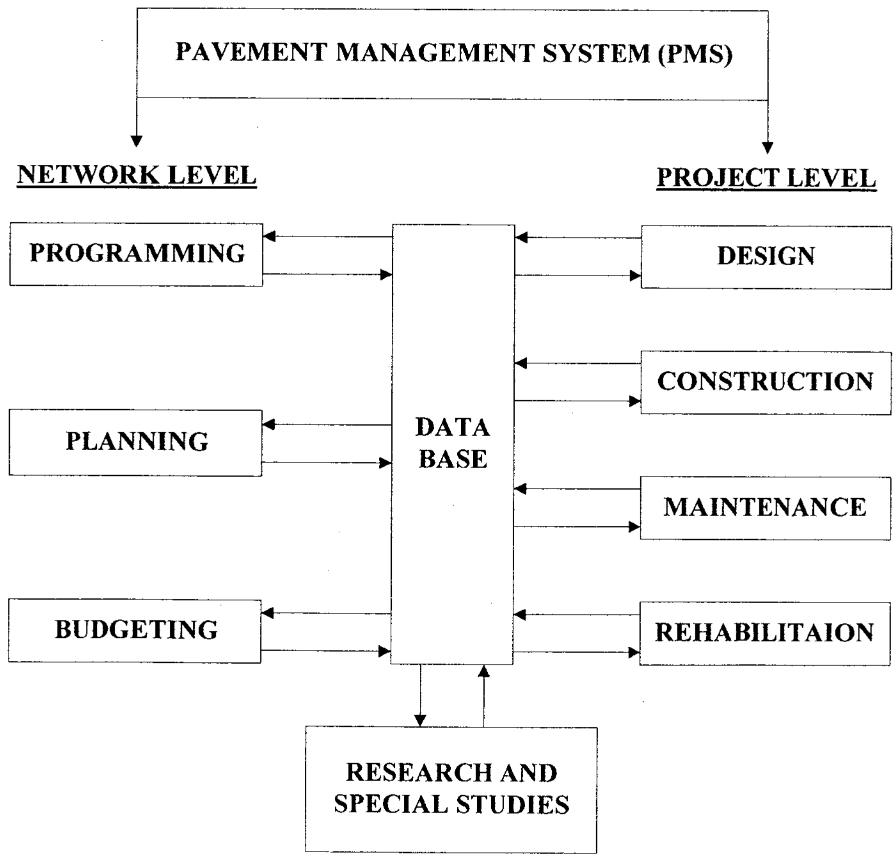


Figure 2-1: Major Components of a Pavement Management System (Hass *et al.*, 1994).

The coordinated set of activities that PMS consists of can be classified into two distinctive levels: the network level and the project level (Hass *et al.,* 1994).

The network level is more like a wider view of the pavement infrastructure and normally more related to the overall budget and planning issues, while the project level has a direct focus on a particular section or project within the whole network system. Figure 2- lists the major activities occurring at each level.

In 1986, Roger Smith conducted an interesting survey to determine the importance of the various management activities (which PMS assists on both network and project levels). The respondent agencies indicated that the following three PMS activities would be the most useful to them (Smith, 1986):

1. A feasible tool to objectively quantify the pavement condition.
2. A list of maintenance and rehabilitation treatments which are most cost-effective.
3. Means of matching problems to suitable treatments.

In part one of the survey, a list of network-level activities were given to the agencies and they were asked to rank them from most to least useful (importance) on a scale of 1-10, with 1 = most useful and 10 = least useful. Table 2-1 provides the importance of network-level PMS components.

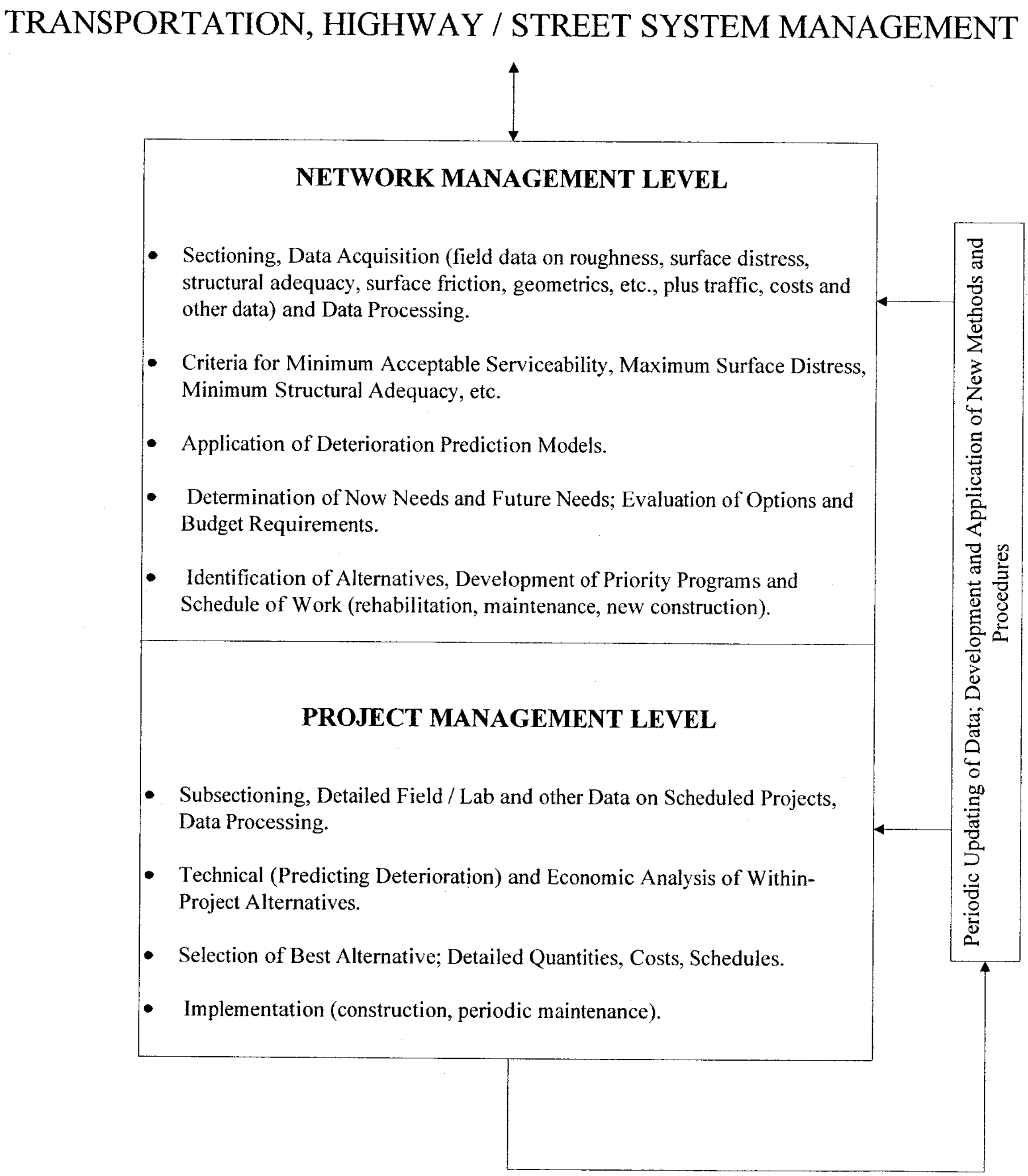


Figure 2-2: Basic Operating Levels of Pavement Management and Major Component Activities (Hass *et al.,* 1994).

Table 2-1: Importance of Network-Level PMS Components (Smith, 1986).

Item	Rating
1. Present overall condition	3.0
2. Prioritization of projects requiring major or preventive maintenance	3.0
3. Identification of projects requiring major rehabilitation	3.1
4. Identification of projects requiring preventive maintenance	3.1
5. Budget needs	3.3
6. Future overall condition	4.3

In a similar manner, part two of the survey repeats the same procedure as part one, but this time in order to investigate the importance of project-level activities. Table 2-2 provides the importance of project-level PMS components.

Table 2-2: Importance of Project-Level PMS Components (Smith, 1986).

Item	Rating
1. Identify feasible major maintenance alternatives	2.6
2. Identify feasible preventive maintenance alternatives	2.8
3. Provide present condition	2.9
4. Determine cause of deterioration	3.9
5. Perform economic analysis of selected alternatives	4.1
6. Project future conditions	4.4

In another part of the survey, the DOT and highways agencies were asked to rank the level of importance of data components that (PMS) usually collect and keep in their data-bases. The ranking scale was from 1 to 10, with 1 indicating the highest level of importance and 10 no importance. Table 2-3 provides the order and ranking of importance of inventory data.

Table 2-3: Importance of Inventory Data (Smith, 1986).

Item	Rating
1. Pavement condition	1.5
2. Maintenance history	2.7
3. Design and construction information	3.5
4. Structural capacity	3.6
5. ADT and functional class	4.6
6. Ride quality	4.8
7. Skid resistance	6.0

From the previous surveys, we can see that providing evidence of the pavement's present condition is one of the most important activities that any department of transportation (DOT), highway agency, and road management system should identify in a precise and reliable way, because all the future work, such as maintenance and rehabilitation selection, budget allocation…etc, will be totally dependent on the condition assessment results and its level of accuracy and validity.

2.3 Pavement Condition Assessment:

One of the most common questions that people ask is: "For any specific facility or infrastructure asset such as highways, bridges, or water mains, what is the present condition or current status?" When this question is applied to the departments of transportation, the pavement management engineer should be able to respond with solid helpful information, which in most cases depends on the pavement condition assessment analysis. According to (Hass *et al.*, 1997) pavement evaluation begins with data collection of the following aspects: type and severity of surface distress, structural capacity, ride quality, and skid resistance of a specific road or a highway section.

Table 2-4 lists different evaluation measures affecting the overall performance and condition of the pavement.

Table 2-4: Concepts for In-Service Monitoring and Evaluation of Road Pavements (Hass *et al.*, 1997).

Monitoring	Evaluation
Longitudinal roughness	Serviceability
Surface distress and defects (cracking, deformation, patches, disintegration, surface defects)	Deterioration, overall composite index, and maintenance needs
Deflection testing	Material properties and structural capacity
Skid resistance or surface friction	Safety against skidding
Ride quality	User evaluation of overall pavement quality
Appearance	Aesthetics
Traffic	Performance and remaining life
Costs (construction, maintenance, user)	Unit-cost summaries for economic evaluation
Location reference, geometric and structure data, longitudinal and cross-fall deficiency, coring for layer thickness	Verification of inventory database, inputs for structural evaluation, safety against potential hydroplaning
Environment (climate, pavement temperature, drainage, water below surface, freeze/thaw)	Material degradation, distress and defects progression, structural integrity, performance

2.3.1 Surface Distress:

Distress evaluation is an important consideration of any pavement management system, by which the selection of the most effective maintenance and rehabilitation strategies can be determined. A comprehensive description of each instance of pavement distress including its general mechanism, level of severity (low, medium, and high), and measurement methods, can be found in the *Highway Pavement Distress Identification*

Manual published by the Federal Highway Administration (Smith, 1986). The types of distress or failures in asphalt-pavement can be classified as follows: (1) Structural failure which is associated with the pavement ability to carry the design load. (2) Functional failure which is associated with ride quality and safety of the pavement. (3) Load-associated distress which is caused mainly by traffic. (4) Non load-associated distress which is caused by climate, materials or deficiencies in design or construction. Table 2-5 lists all the possible types of distress in asphalt-pavement as follows:

Table 2-5: Distresses Types in Asphalt Pavements (Yang, 2004).

Types of Distress	Structural	Functional	Load Associated	Non-load Associated
Alligator or fatigue cracking	x		x	
Bleeding		x		x
Block cracking	x			x
Corrugation		x		x
Depression		x		x
Joint reflection cracking	x			x
Lane/shoulder dropoff or heave		x		x
Lane/shoulder separation		x		x
Longitudinal and Transverse cracking	x			x
Patch deterioration	x	x	x	
Polished aggregate		x	x	
Potholes	x	x	x	
Pumping and water bleeding	x	x	x	x
Raveling and weathering		x		x
Rutting		x	x	
Slippage cracking	x			
Swell	x	x		x

Among the previous several distresses in asphalt-pavement, two types only will be explained in detail in this study, namely, rutting and transverse cracking.

2.3.1.a Rutting:

A typical pattern of deformation in asphalt pavement is rutting as shown in Figure 2-3, which during the first few years of construction develops at a somewhat rapid rate and then decreases to a much slower rate. A rut, by definition, is a surface depression in the wheel paths, and it becomes more noticeable after a rainfall when they are filled with water. Pavement uplift may occur along the sides of the rut, in addition to the fact that ruts filled with water can cause vehicle hydroplaning and lead to major structural failures. There are two basic types of rutting that take place either in any of the pavement layers (mix rutting) or in sub-grade (sub-grade rutting). Figure 2-3 shows an example of the surface distress (rutting) (WSDOT, 2009).

Figure 2-3: Surface Distress (Rutting) (WSDOT, 2009).

Rutting can be usually caused by: (1) Consolidation or lateral movement of the materials due to traffic loading, (2) Inadequate compaction of HMA layers during construction.

Rutting is measured in square feet or square meters of surface area, and the severity is determined by the mean depth of the rut. Usual treatments for repair are: in the case of Low ruts (L) ¼ to ½ in: can generally be left untreated. Medium ruts (M) greater than ½ in. up to 1 in: shallow, partial or full-depth patching. High ruts (H) greater than 1 in: full-depth patching or milling and overlaying.

2.3.1.b Longitudinal and Transverse (Thermal) Cracking:

These two types of cracks are usually not caused by loads. Longitudinal cracks are cracks parallel to the pavement's centerline or lay-down direction and can be caused by a reflective crack from an underlying layer, or the poor construction of a lane joint, whereas, on the contrary, transverse (thermal) cracks extend in a perpendicular way to the pavement's centerline or lay-down direction and can be caused as well by a reflective crack from an underlying layer beneath the asphalt surface. However shrinkage of the HMA surface due to low temperatures or asphalt binder hardening is considered the main cause of transverse cracks. Both kinds of cracks are shown in Figures 2-4 and 2-5 (WSDOT, 2009).

Longitudinal and transverse cracks are measured in linear feet or meters. Furthermore, in the SHRP manual the longitudinal is divided into wheel path longitudinal cracking and non-wheel path longitudinal cracking.

For the repair of the cracks, strategies are determined on the basis of the severity and extent of cracks, and for the both types (longitudinal and transverse cracking) a quite similar procedure of treatment is followed: In the case of Low severity cracks (< ½ inch wide) the perfect solution for preventing the penetration of moisture into the sub-grade through the cracks is the crack seal. On the other hand, removing and replacing the cracked pavement layer with an overlay is the preferred solution in the case of high severity cracks (> ½ inch wide).

Figure 2-4: Surface Distress (Longitudinal Cracking) (WSDOT, 2009).

Figure 2-5: Surface Distress (Transverse Cracking) (WSDOT, 2009).

2.3.2 Structural Capacity:

By definition, structural capacity is the ability of pavement to safely carry the projected traffic load. It is usually determined by any of the structural test methods, which are categorized as destructive or nondestructive methods. The major difference relates to whether or not physical disturbance of materials is allowed to occur or not.

The *destructive method* of evaluation is usually in-place testing of component materials using a test pit. A *non-destructive method* is used when no major disruption of structure of the pavement is required, and it involves many techniques. However, the most effective and widely used ones are surface deflection measurement techniques.

Normally, non-destructive testing methods (NDT) are preferable to destructive ones due to: (1) Less damage to pavement structure. (2) A lower cost for testing. (3) Less interruption to traffic. (4) These tests are relatively quicker than the destructive ones, allowing more evaluations to be completed in less time.

Consequently, the required overlay thickness design, the elastic modulus of each of the structural layers and the permissible loads for a specified number of load applications are determined using the NDT methods on Asphalt pavements.

2.3.3 Ride Quality:

The general public perception of a good road is one that provides a smooth ride. Consequently, a major focus of state highway agencies in management of their highway networks has been to determine the ride quality of the pavement deriving from roughness characteristics. Usually, to auto drivers and passengers, rough roads mean discomfort, decreased speed, and potential vehicle damage.

According to (Hass *et al.,* 1994), roughness can be defined as irregularities in the pavement surface that affect the ride quality of the pavement, and are often experienced by the operator or passenger of a vehicle travelling over the surface. These irregularities can be divided into three profile components of distortion: transversal, longitudinal, and horizontal profiles. They are mainly caused by factors such as: traffic loading, environmental effects, construction materials, and built-in construction deficiencies.

Highway agencies use many devices for roughness evaluation; these devices are based either on measuring the surface profile of the pavement, or on a response-type road-roughness measuring system (RTRRMS) (Shahin, 2005). The latter is very popular due to the historical cost of profile-measuring devices. A survey of 48 states in the USA shows that (RTRRMS) are the most used devices for roughness measurements in 22 states (Epps *et al.,* 1986).

In order to compare the different measures of roughness on a common quantitative scale, the International Roughness Index (IRI) was developed by the World Bank at the International Road Roughness Experiment held in Brazil in 1982. IRI is used to define the longitudinal surface profile in the wheel-path and constitutes a standardized roughness measurement. It is expressed in units of inches per mile (in/m), meters per kilometer (m/km), or millimeters per meter (mm/m). More description of the relationship between roughness and serviceability will be discussed in the following sections.

Figure 2-6 shows the IRI roughness scale developed by (Sayers *et al.,* 1986).

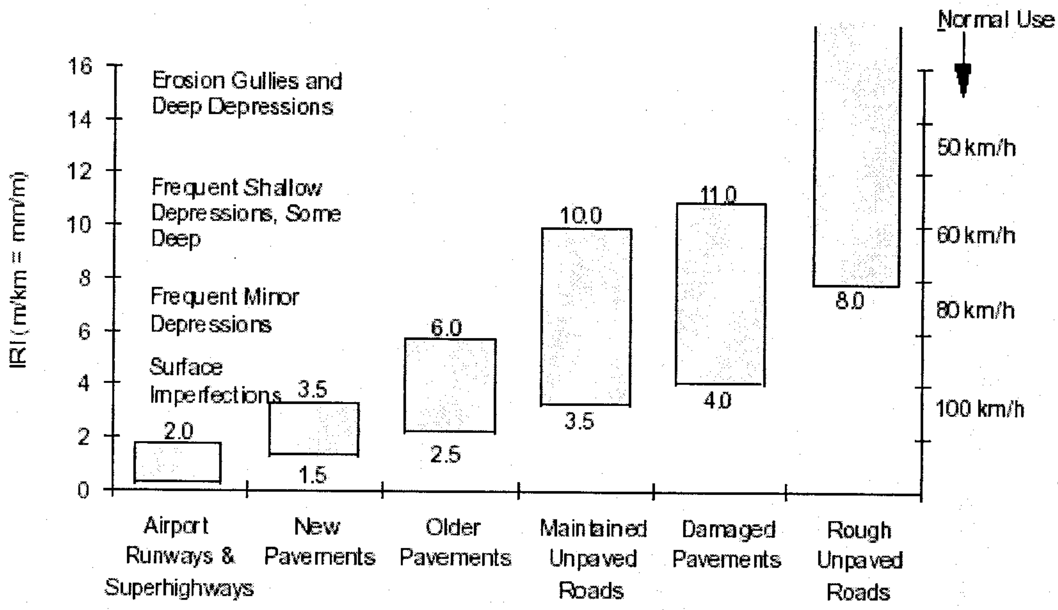


Figure 2-6: International Roughness Index (IRI) Roughness Scale (Sayers *et al.,* 1986).

2.3.4 Skid Resistance:

Most DOT and road agencies have an obligation to provide users with a roadway that is "reasonably" safe. In addition, inadequate skid-resistance evaluation will lead to higher incidences of skid-related accidents. That explains why skid resistance is an important pavement evaluation parameter.

Skid resistance changes over time. Typically, it increases in the first two years following construction as the roadway is worn away by traffic and rough aggregate surfaces become exposed. Then it decreases over the remaining pavement life as aggregates become more polished. Skid resistance is also typically higher in the fall and winter and lower in the spring and summer.

The phenomenon of skidding involves a complex interrelationship between four major elements, namely, the roadway (characteristics of the pavement), the vehicle (mainly tires), the driver, and the weather. In reality, the pavement characteristic which dominates the measurement of skid resistance is the *friction* of the pavement surface.

According to (HRB, 1972) surface friction is defined as the force developed when a tire that is prevented from rotating slides along the pavement surface. Skid resistance is generally quantified using some form of friction measurement, such as a friction factor or skid number.

Friction Factor: $$f = \frac{F}{L} \qquad \text{Eq: (2-1)}$$

Skid number: $$SN = 100 \times f = 100 \times \left(\frac{F}{L}\right) \qquad \text{Eq: (2-2)}$$

Where:

- F = frictional resistance to motion in the plane of the interface.
- L = load acting perpendicular to the interface.

For measuring the pavement friction the best known standard is the locked wheel skid trailer as specified in (ASTM, 1991) "Standard Test Method for Skid Resistance of Paved Surfaces Using a Full-Scale Tire".

Both traffic speed and the method of measurement play a major role in determining the minimum skid resistance required for a pavement. Table 2-6 shows the minimum skid numbers measured according to ASTM E950 (ASTM, 1991).

Table 2-6: Recommended Minimum Skid Number for Main Rural Highways (Yang, 2004).

Traffic Speed (mph)	SN measured at traffic speed	SN measured at 40 mph
30	36	31
40	33	33
50	32	37
60	31	41
70	31	46

Note.1 mph = 1.6 km/h.

It is clear from Table 2-6 that for a mean traffic speed of 50 mph (80 km/h), the NCHRP Report 37 recommended a SN of 37 measured at 40 mph (64 km/h), as the minimum permissible for standard main rural highways. And since there are no definite federal and state standards on the minimum SN required, most highways agencies follow the guidelines recommended by NCHRP Report 37 (NCHRP, 1972).

2.4 Existing Condition Rating Models:

Due to the critical role that pavement condition data (surface distress, structural capacity, ride quality, and skid resistance) play in performing any PMS functions, especially those related to project the present and future condition of the pavement and determine maintenance and rehabilitations needs, strategies, and budget allocations (Smith, 1986) . Therefore, several condition-rating indices and prediction models have been developed in order to quantify these vital measures and the overall performance of a roadway or highway section.

In 1994, the National Cooperative Highway Research Program (NCHRP) conducted a survey of 50 states in the USA, the District of Columbia, and 9 Canadian provinces, giving a total of 60 agencies to determine the common practices in pavement condition rating and predicting performance. The survey results showed that it was not a prevailing practice to use structural adequacy and skid resistance in routine evaluation of pavement because of the high costs. However, regarding the other two criteria (surface distress and ride quality) there was a clear consensus about their major roles in pavement evaluation (NCHRP, 1994).

In modeling the pavement performance, three common types of prediction indicators can be summarized as:

- ***Distress-Based*:** in which the information on distress (such as type, severity, and extent of the observable surface distress) is combined in a single numeric statistic, such as a Pavement Condition Index (PCI) on a scale of 0 to 100 (Shahin, 2005).
- ***Roughness-Based:*** in which roughness information is converted into an index such as the international roughness index (IRI) or the Present Serviceability Rating (PSR).
- ***Composite indices:*** in which both distress conditions and pavement roughness are combined to form panel-rating indices such as the Present Serviceability index (PSI) created by (ASSHO, 1960).

Table 2-7 shows specific examples of common indicators related to the above categories. A detailed explanation of the models will be presented in the following sections.

Table 2-7: Examples of Performance Indicators (Hass *et al.*, 1997).

Facility	Service and user rating	Safety and sufficiency	Physical condition	Structural integrity/ load capacity
Highways, roads, streets, parking areas	Present Serviceability Rating (PSR), ride quality, vehicle operating costs	Ratings based on skid resistance, accidents, congestion, and pollution	Present Serviceability Index (PSI), International Roughness Index (IRI), Pavement Condition Index (PCI)	Structural rating based on deflection testing, remaining life, load capacity

2.4.1 Distress Based Models:

The main causes of observable deterioration and disintegration of asphalt-pavement are: excessive loads, environmental impact, age, inadequate pavement design and material degradation. The information regarding the type, severity, and extent of this distress is usually collected from deterioration inspection reports and surveys. Then a composite index combining the various kinds of distress is developed.

In Washington State, an early procedure for determining a composite index of pavement distresses was introduced involving the use of deducted values. This approach of deducted values was further developed for PAVER (Shahin, 2005) and has been widely implemented in other systems derived from the PAVER method.

In the deducted value approach, an index of 100 is assigned to a perfect pavement (newly constructed, reconstructed, overlaid pavement surface prior to the development of the first crack or other distress). Subsequently, a cumulative deducted value is generated based on the level and severity of observed distress and subtracted from the index of 100.

In the PAVER system, deduct value curves were developed for each of the distress types such as those shown in Figure 2-7, in which the X axis represents the density or extent of the distress ,the Y axis represents the deducted value, and three curves correspond to the severity of the distress (High, Medium, Low). Afterwards, the total deducted value is computed by adding the individual distress-type deducted values.

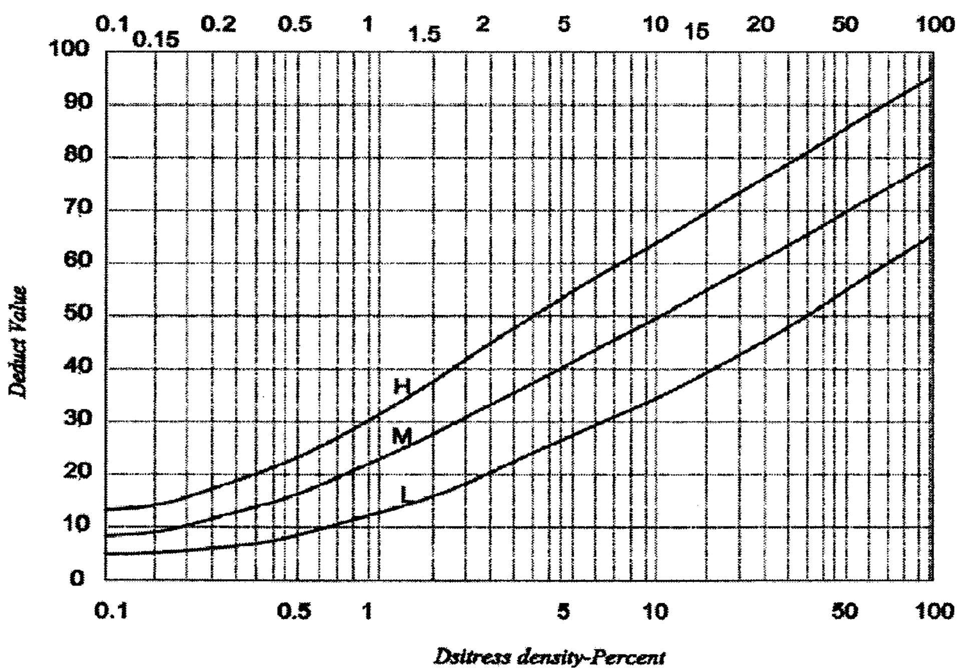


Figure 2-7: Example of a Deduct Value Curve for Alligator Cracking (Hass *et al.,* 1994).

To overcome some of the deficiencies of the previous charts, a series of curves were established to correct the total deduct value. It was called Corrected Deduct Value (CDV) as shown in Figure 2-8.

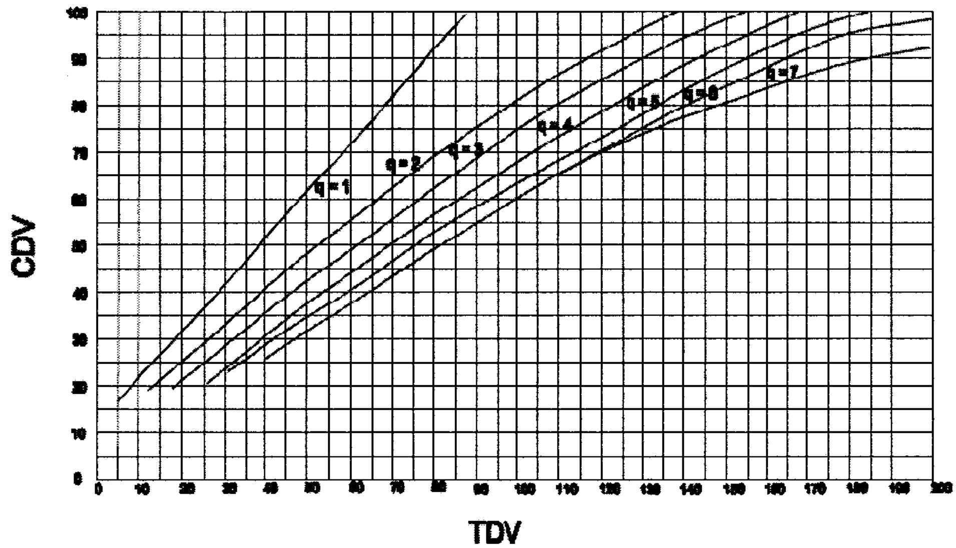


Figure 2-8: Corrected Deduct Value Curves (Hass *et al.,* 1994).

This value is then subtracted from 100 to define the composite distress index called the Pavement Condition Index (PCI) on a scale of 100 to 0, where 100 means a road in excellent condition and 0 one in poor condition. The PCI is calculated using the following equation (Shahin, 2005):

$$PCI = 100 - SCDV \qquad \text{Eq: (2-3)}$$

Where:

- SCDV: Sum of corrected deduct value of each surface distress.

The PCI for each pavement section is computed as the average of the PCI of each sample unit observed for the pavement section. Figure 2-9 shows the PCI scale associated with qualitative descriptions for PCI ranges.

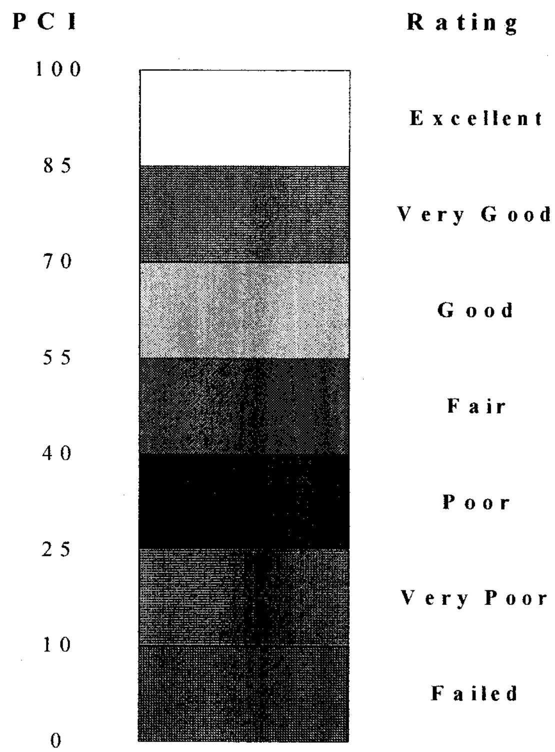


Figure 2-9: Pavement Quality versus Pavement Condition Index (Hass *et al.,* 1994).

Although the PCI concept is widely applied, major disadvantages of using it as the only performance indicator can be recognized. One of the limitations is that the deduct value curves were developed for a certain set of values for distress type and severity level. If the user agency tried to modify these values, especially the ones regarding the severity level, then the deduct value curves would have to be carefully examined and modified in an appropriate manner, which could be not applicable and would be time-consuming (Hass *et al.,* 1994).

Another limitation that could be found is that a distressed pavement with low PCI will often have poor ride quality as well. In this case, the problem is usually solved by applying the rehabilitation for the pavement to address the low PCI, which will also improve the ride quality indirectly. But a more problematic situation would be, when a pavement has an acceptable PCI but has a poor ride quality. The current DOT procedures do not have suitable provisions for identifying pavement in a similar condition for the correct rehabilitation and maintenance remedies. Thus, a pavement in that condition would continue to be in service with a low ride quality and increased public dissatisfaction.

A neural-network system for the determination of condition rating for flexible pavement was developed by (Eldin *et al.,* 1995). The proposed neural-network system was based on the condition-rating scheme established by the Oregon Department of Transportation (ODOT). In this computational scheme, the pavement condition rating is computed on the basis of the cracking and rutting indices. The lower of these two indices is then transformed into a global condition rating on a range from 0 to 5, where larger index values indicate better pavement conditions.

(Paramapathy *et al.,* 2000) developed a Monte-Carlo simulation model to study the time-dependent uncertain deterioration of a pavement section. The distributions of the pavement condition index (PCI) were estimated and compared against results from a non-homogeneous Markov model. In the proposed model, four independent variables were considered and randomized, which are annual average daily traffic (AADT), subgrade deflection (w), initial pavement condition index (Po), and traffic growth rate (R).

Although the predicted cumulative distribution of time to pavement failure can be used as a useful decision-making tool by pavement engineers, the uncertainties related to the components of both environmental and construction deterioration were not accommodated in the proposed model.

A pavement rehabilitation prioritization model was developed by (Bandara *et al.,* 2001). It was formulated by incorporating experienced highway maintenance engineers' subjective assessments regarding pavement condition deterioration rates in the Markov transition process. Fuzzy set mathematics was used in quantifying the rapidly adjusted severity levels and extensive subjective evaluations of four different distress types (alligator cracking, potholes, edge failures, and raveling). The proposed model is limited only to the impact of distress on pavement conditions, without taking into consideration other environmental impacts and the impact of traffic conditions.

2.4.2 Roughness Based Models:

The main use of the objective roughness measurements is to identify the pavement serviceability, which can be defined as "the ability of a specific section of pavement to serve traffic in its existing conditions". Thus, in order to correlate the subjective (i.e., user) rating of pavement ride quality (serviceability) with objective measurements (roughness) a Present Serviceability Rating (PSR) was developed in the American Association of State Highway Officials (AASHO) Road Test (Highway Research Board, 1962).

The PSR is the mean of independent ratings of the present serviceability of a specific section of a roadway, made by individual raters who drove around the test track and rated their ride on a scale from 0 to 5 as shown in Figure 2-10, which is the rating form used during the AASHO Road Test. Since PSR is based on passenger interpretations of ride quality, it generally reflects road roughness because roughness largely determines ride quality.

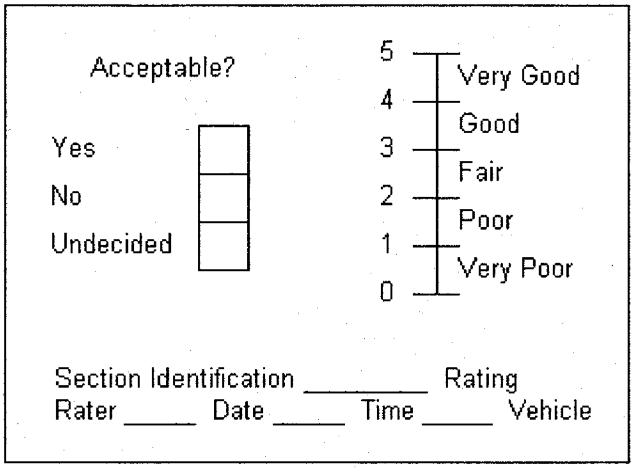

Acceptable?
Yes
No
Undecided
5
4
3
2
1
0
Very Good
Good
Fair
Poor
Very Poor
Section Identification ________ Rating
Rater _____ Date _____ Time _____ Vehicle

Figure 2-10: Individual Present Serviceability Rating Form (after Carey *et al.,* 1960).

According to (Hass *et al.,* 1994), in modeling user observations as in the PSR model of the AASHO Road Test, some assumptions are involved in the development of rating scales. These assumptions neglect certain systematic problems, especially those related to rater behavior, which must be anticipated and probably accounted for in the development of rating procedure. Such problems are: (1) Leniency, the tendency of a rater to consistently rate too high or too low. (2) Central tendency, the tendency of a rater to hesitate in giving extreme ratings. (3) Considering the raters capable of providing ratings on a direct interval scale.

In 1994, relationships between PSR and IRI were developed by Al-Omari and Darter for the three pavement types: flexible, rigid and composite. This study used data from the states of Louisiana, Michigan, New Mexico, New Jersey and Indiana, and suggested the following nonlinear model (Al-Omari *et al.,* 1994):

$$PSR = 5 \times e^{(-0.0041 \times IRI)} \qquad \text{Eq: (2-4)}$$

Where:

PSR: present serviceability index.

IRI: international roughness index in inch/mile.

In the previous equation, if IRI = 0 the equation is forced to pass through PSR = 5, which clearly indicates that the equation is biased and not statistically correct (Gulen *et al.*, 1994).

2.4.3 Composite Indices:

The composite indicators are based on the combination of two or more pavement condition attributes using appropriate weights for the attributes and reliable modeling techniques. As mentioned before, using the roughness information only is the best way to predict PSR for a given pavement. However, to relate serviceability to physical deterioration, which can be modeled mechanistically, a PSR model based on certain distress types is desirable.

An example of a composite indicator is the Present Serviceability Index (PSI) developed at the AASHO Road Test (Carey *et al.,* 1960), which is based both on pavement roughness and on distress conditions, such as cracking, rutting, and patching. The original functional form of the PSI equation is (Highway Research Board, 1962):

$$PSI = C + (A_1R_1 + \ldots) + (B_1D_1 + B_2D_2 + \ldots) \qquad \text{Eq: (2-5)}$$

Where:

- R_1: function of profile roughness $[\log(1+\overline{SV})]$, where $\overline{SV}$ = mean slope variance obtained from the CHLOE profilometer.
- D_1: function of surface rutting $[\overline{RD}^2]$, where $\overline{RD}$ = mean rut depth as measured by simple rut-depth indicator.
- D_2: function of surface deterioration $[\sqrt{(C+P)}]$, where $C+P$ = amount of cracking and patching determined by procedures developed at the AASHO Road Test.

After the determinations of coefficients (C, A_1, B_1, and B_2) using multiple linear regressions applied by the AASHO Road Test on 74 flexible sections, the final PSI equation will be (Highway Research Board, 1962):

$$PSI = 5.03 - 1.91\log(1+\overline{SV}) - 1.38\,\overline{RD}^2 - 0.01\sqrt{(C+P)} \qquad \text{Eq: (2-6)}$$

Two major shortcomings can be noticed in the previous PSI equation:

1. Since PSI is based on the evaluations of the Road Test rating panel, the question to be asked is whether the public's perception of serviceability is the same today as it was 30 years ago, especially since vehicle properties, travel speeds and highway characteristics have changed significantly.

2. Although the distress data (cracking amount, rut depth, and patching) are used for computing PSI, it is the roughness information that provides the major correlation variable. According to (Zaniewski *et al.,* 1985), after the addition of distress data to PSR, an increment of only about 5% was added to the correlation coefficient between PSR and PSI. In other words, the contribution of the physical distress to PSI is relatively small and can be neglected. That explains why many agencies rely only on roughness to estimate PSI.

Another example of composite indicator is the Riding Comfort Index (RCI) developed in Alberta (Karan *et al.,* 1983), in which up to 25 years of data on roughness, surface distress, traffic, deflection and other factors were used.

For conventional granular base pavements the following regression equation was proposed (Karan *et al.,* 1983):

$$RCI = -5.998 + 6.870*Log\ (RCI_B) - 0.162*Log\ (AGE^2 + 1) + 0.185*AGE - 0.084*AGE*Log\ (RCI_B) - 0.093*\Delta AGE \quad \text{Eq: (2-7)}$$

Where:

RCI = Riding Comfort Index (scale of 0 to 10) at any AGE.

RCI_B = previous RCI.

AGE = age in years.

ΔAGE = 4 years (particularly for this equation)

For the previous equation, the standard error of estimate is 0.38 with a squared correlation coefficient (R^2) of 0.84.

It was found that the equation was biased to only two variables (AGE, and RCI_B) while a number of variables were considered, such as traffic in terms of $ESAL_S$, climate zone, sub-grade soil type, and others. The reason for this bias is that the pavement was primarily designed for environmental deterioration, with structural layers significantly thicker than required by traffic alone. A plot of the RCI equation is shown in Figure 2-11.

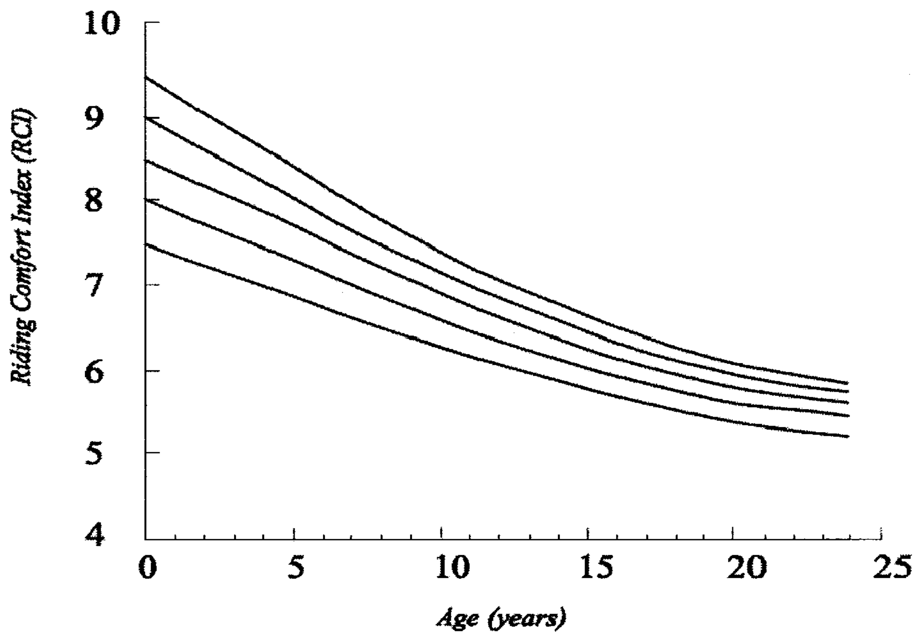


Figure 2-11: Performance Prediction from RCI Equation (Karan *et al.,* 1983).

A pavement performance index called the Pavement Quality Index (PQI) was developed by (Reza *et al.,* 2005). The proposed composite index incorporates ride quality together with distress surface by combining the Pavement Condition Rating (PCR) with the International Roughness Index (IRI) in one equation. The PQI treats IRI as a deduction from PCR, which gives a primary control to PCR and prevents PQI from being greater than PCR. This guarantees that pavements rated poor by just using the PCR would still be poor under the proposed model, and pavements that have little distress would be considered in a good condition although they might have a bad ride quality.

Moreover, (Ruotoistenmäki *et al.,* 2007) developed a road condition-rating tool to calculate values for existing or newly constructed roads. The model is based on a factor analysis of three measured road condition variables: structural factor, roughness factor and transversal unevenness factor. Factor final scores are calculated as the means of the log-transformed variables in each factor. Condition rating is conducted as the weighted sum of the factor scores and used as an input in strategic level decision-making.

In this study the rating scale extended from ∞ (poor condition) to $-\infty$ (excellent condition), thus there are no theoretical limits to the rating values, which means that it cannot be used for practical purposes where the rating values need to be transformed into a finite scale divided into certain categories. In addition, variables describing surface texture and surface distress (i.e. cracking) were not included in this model.

2.5 An Overview of the Applied Techniques in the Current Research:

2.5.1 Multi-Attribute Utility Theory (MAUT):

In its basic form, MAUT assumes that a decision maker is to choose among a set of alternatives whose objective function values or attributes are known with the presence of risk or uncertainty. It focuses on the structure of multi-criteria or multi-attribute alternatives, and on methodologies for assessing individual values and subjective probabilities. MAUT embraces both a large body of mathematical theory for utility models and a wide range of practical assessment techniques that pay attention to limited abilities of assessors. Information obtained from assessment usually feeds into the parent problem to rank alternatives, make a choice, or otherwise clarify a situation for the decision-maker (Hammond *et al.,* 1999).

The foundation of MAUT is the use of utility functions, which represent the assessor's preferences, given a certain set of decision attributes. The utility functions transform an attribute's raw score (i.e. dimensioned such as; feet, pounds, gallons, per minute, dollars, etc.) to a dimensionless utility score between 0 and 1. The utility scores are then multiplied by the weight of the decision attributes, and aggregated (linearly or non-linearly) to calculate the total score for each alternative (Keeney *et al.,* 1993).

The MAUT evaluation method is suitable for complex decisions with multiple criteria and many alternatives. Additional alternatives can be added to MAUT analysis. Once the utility functions have been developed, any number of alternatives can scored against them.

2.5.2 Analytic Hierarch Process (AHP):

The Analytic Hierarch Process (AHP) is one multi-criteria decision-making method that was originally developed by Prof. Thomas L. Saaty in the 1970s. The AHP provides a comprehensive and rational framework for structuring a decision problem, for representing and quantifying its elements, for relating those elements to overall goals, and for evaluating alternative solutions. It is used around the world in a wide variety of decision situations, in fields such as government, business, industry, healthcare and education. Decision situations to which the AHP can be applied include: (1) the selection of one alternative from a given set of alternatives, usually where there are multiple decision criteria involved. (2) Ranking of alternatives from most to least desirable.

Using the AHP, the procedure for modeling a multi-criteria decision problem can be summarized as:

1. Model the problem as a hierarchy containing the decision goal, the criteria for reaching it, and the sub-criteria for evaluating the criteria, as shown in Figure 2-12.

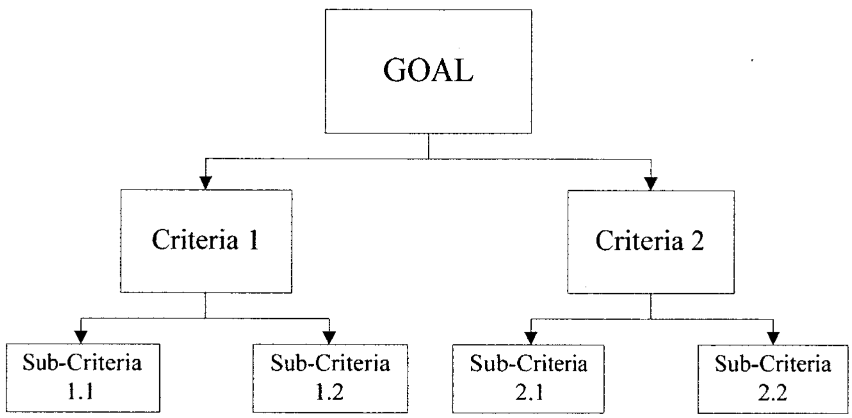


Figure 2-12: Hierarchy of Three Levels.

2. In order for the participants to incorporate their judgments about the various elements in the hierarchy, decision-makers use pair-wise comparison matrices to compare the elements two by two.
3. Establish priorities among the elements of the hierarchy by filing the pair-wise matrices with numerical values from a scale of (1-9), which represent the relative importance or likelihood of one sub-criteria /sub-factor over another. The scale of (1-9) with its linguistic meanings is shown in Table 2-8.

4. Synthesize these judgments to yield a set of overall priorities for the hierarchy. These overall priorities are called priority vectors, and calculated for each reciprocal matrix (from paired comparison).

Table 2-8: Pair-wise Comparison Scale (Saaty, 1995).

Intensity of Importance	Definition	Explanation
1.0	Equal importance	Two elements contribute equally to the objective
2.0	Weak	Between equal and moderate
3.0	Moderate importance	Experience and judgment slightly favor one element over another
4.0	Slightly more than Moderate	Between moderate and strong
5.0	Strong importance	Experience and judgment strongly favor one element over another
6.0	Slightly more than Strong	Between strong and very strong
7.0	Very strong	An element is favored very strongly over another; its dominance demonstrated in practice
8.0	Approximately Extreme importance	Between very strong and extremely strong
9.0	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation

5. Check the consistency of the judgments by calculating Consistency Ratio (CR). Prof. Saaty proved that for a consistent reciprocal matrix, the largest eigen value is equal to the size of the comparison matrix, or $\lambda_{max} = n$. Then he gave a measure of consistency, called Consistency Index (CI) as deviation or degree of consistency using the following formula (Saaty, 1982):

$$CI = \frac{\lambda max - n}{n-1} \qquad \text{Eq: (2-8)}$$

Where: λ_{max}: is the maximum eigen-value of the reciprocal matrix. And n: is the matrix size.

Then, he proposed what is called Consistency Ratio (CR), which is a ratio between Consistency Index (CI), and the average Random Consistency Index (RI) for random comparisons for a matrix of the same size from a 1 to 9 scale. The following equation is used to calculate (CR) (Saaty, 1982):

$$CR = \frac{CI}{RI} \qquad \text{Eq: (2-9)}$$

If the value of consistency ratio (CR) is smaller or equal to 10%, the inconsistency is acceptable. On the contrary, if the (CR) is greater than 10%, a revision of the subjective judgment needs to be applied.

6. Come to a final decision based on the results of the previous process. The final overall ranking output for each element (sub-factor) is calculated based on combining its consistent priority vector (weight V_i) with the weight of its criteria (main factor- weight W_i). A detailed explanation of the previous steps is presented in Section 5.1 (MAUT Condition-Rating Model).

2.5.3 Multiple Regression Analysis:

Multiple regression analysis is one of the most widely used of all statistical methods. The general purpose of multiple regression (the term was first used by Pearson, 1908) is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. An experimenter typically will wish to investigate a number of predictor variables (independent) simultaneously, because almost always more than one key predictor variable influences the response (dependent). Applications of multiple-regression exist in almost every field, especially in the pavement field where the dependent variable is a quantitative measure of some condition or behavior. A good example of regression equations developed from the performance of the existing pavements, are those equations used in the pavement evaluation systems COPES (Daretr *et al.,* 1985) and EXPEAR (Hall *et al.,* 1989). Although these equations illustrated the effect of various factors on pavement performance, the materials and construction of the pavements that were studied were not well controlled; therefore a wide scatter of data and a large standard error were found.

The general response function for linear regression model is as follows:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_{p-1} X_{ip-1} + \varepsilon_i \qquad \text{Eq: (2-10)}$$

Where Y_i is the value of the response variable (dependent) in the i^{th} trial, β_0, β_1, β_2, and β_{p-1} are regression parameters, X_{i1}, X_{i2} and X_{ip-1} are the value of the predictor variables (independent) in the i^{th} trail, and ε_i is the random error. Ordinarily, the values of the regression parameters β_0, β_1, β_2 and β_{p-1} are not known and need to be estimated from relevant data. According to (Kutner *et al.,* 2005) multiple regression requires a large number of observations. The number of cases (participants) must substantially exceed the number of predictor variables that are used in the regression model. The absolute minimum number of observations is five times as many data points as predictor variables. A more acceptable ratio is 10:1.

A major limitation of observational data is that they often do not provide adequate information about cause and effect relationships. That's why an initial examination of relationships and interactions between predictor variables must be applied before we begin modeling the data at hand. It is recommended that we first plot the data points, then by examining these initial plots we can easily assess whether the data have linear relationships or interactions are present, and whether transformation of predictor variables should be taken into consideration or not.

According to (Kutner *et al.,* 2005) models with transformed variables involve complex, curvilinear response functions, yet still are special cases of the general linear regression model, and the regression assumptions still applied on them.

After the application of preliminary diagnostics for relationships and interactions, and the definition of different functional forms of predictor variables (inputs), the multiple regression model development process can be started. The following steps summarize this process:

1. Fitting the regression model with VIF (Variance Inflation Factor) values.
2. If any VIF > 5, then the variable with highest VIF should be eliminated, if all VIF values ≤ 5, then we can proceed to step 4.
3. Fitting the regression model with VIF values for the new model (without the deleted variable).
4. Performing best-subset analysis with the remaining predictor variables.
5. Listing all models that have $C_P \leq (P + 1)$, where P is the number of predictor variables in the model.

6. Among models listed in step 5, the best model using the best-subset criteria ($C_P \leq P + 1$, lowest standard deviation S, and the highest R^2 adj) should be chosen.
7. Performing a complete analysis for the chosen model including:
   - Determining the goodness of fit (Coefficient of determination R^2 and R^2 (adj), F-test, and t-test).
   - The residual analysis which examines the regression's assumptions, it includes (Normality Test, Independency Test, and Homoscedasticity Test).

A detailed explanation of the previous steps is presented in Section 5.2 (Integrated MAUT/Regression Model) and Appendix (B).

2.5.4 Monte-Carlo Simulation:

The Monte-Carlo method was invented by scientists working on the atomic bomb in the 1940s, who named it for the city in Monaco famed for its casinos and games of chance. Its core idea is to use random samples of parameters or inputs to explore the behavior of a complex system or process. The scientists faced physics problems, such as models of neutron diffusion that were too complex for an analytical solution, so they had to be evaluated numerically. The Monte-Carlo simulation proved to be surprisingly effective at finding solutions to these problems. Since that time, Monte-Carlo methods have been applied to an incredibly diverse range of problems in science, engineering, finance and business applications in virtually every domain of industry.

The Monte-Carlo simulation is categorized as a sampling method because the inputs are randomly generated from probability distributions to simulate the process of sampling from an actual population. The Monte-Carlo sample uses always a new random number between 0 and 1. There is no single Monte-Carlo method; instead, the term describes a large and widely used class of approaches. However, these approaches tend to follow a particular scheme as follows:

- Creating a parametric model where [y = f(x)], followed by a definition of possible uncertain inputs.
- Each uncertain parameter is defined by the most fitting probability distribution function.
- Random numbers range from 0 to 1 start to be generated by Monte-Carlo simulation.
- These random numbers are then used to generate values randomly for the uncertain parameters from the predefined probability distributions.
- This step is repeated for several iterations, and results of each iteration are aggregated into final simulated output.

A detailed explanation of the previous steps is presented in Section 5.3 (Monte-Carlo Simulation) and Appendix (C).

2.6 SUMMARY:

A comprehensive literature review was carried out in this chapter to test the available literature in the intended subject. Several topics were reviewed, such as:

1. The development of Pavement Management System (PMS),
2. Major components of a PMS,
3. Why does the pavement condition-assessment is considered as one of the most important activities of a PMS,
4. A detailed explanation of the four major procedures used for assessing the current condition of any road segment, which are (surface distress, structural capacity, ride quality, and skid resistance),
5. An overview of the existing condition-rating and performance prediction models including distress-based models,
6. Roughness-based models, and
7. Composite indices.
8. A brief explanation of the four techniques used in this study, which are Multi-Attribute Utility Theory (MAUT), Analytic Hierarchy Process (AHP), Multiple Regression, and Monte-Carlo Simulation.

Based on the literature review, it is clear that the deterioration of flexible-pavement is a complex phenomenon that depends on many factors. Therefore, several condition-rating indices and prediction models have been developed. However, these indices and models are only based on several factors, which might be more critical than others such as, the roughness measurements, the distress information, or a combination of both of them without considering other factors that could have a real impact on the accuracy of the condition-assessment model(s). Therefore, the current study proposes a new condition-rating model that incorporates a wider range of possible factors such as environmental and traffic factors.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction:

The methodology of the current study is illustrated in Figure 3-1. It comprises the following steps: a comprehensive literature review, a data-collection phase that consists of two parts, a MAUT condition-rating model, an Integrated MAUT/Regression Model, an application of the Monte-Carlo Simulation, a web-based condition-rating tool, and finally conclusions and recommendations. A summarized description of the previous steps is given below:

3.2 Literature Review:

Chapter 2 of the current thesis describes in detail the relevant literature and presents it in different sections. In Section 2-2, an overview of the development of pavement management systems and the different PMS activities on both the project and the network level is presented.

Section 2-3 illustrates the concept of the pavement condition-assessment that begins with major evaluation measures (*surface distress, structural capacity, ride quality and surface friction)* affecting the present condition and future performance of the pavement.

Section 2-4 presents comprehensively the existing condition-rating and deterioration models, such as the Pavement Condition Rating (PCR), the International Roughness Index (IRI), and the Present Serviceability Index (PSI).

Finally, the techniques used in the current study for developing the condition-rating models are explained in detail in Section 2-5. These techniques are *the Multi-attribute*

Utility Theory (MAUT), the Analytic Hierarchy Process (AHP), the Multiple-Regression, and the Monte-Carlo simulation.

3.3 Data Collection:

The collected data for this research consists of two parts. The first part is the data received from the records of the *Nebraska Department of Roads* (NDOR) called "Tab Files". The NDOR has grouped the "Tab files" on a yearly basis and the data at hand are limited to a period of eight years from 1997 to 2003. They include information on highway sections, such as an assigned code to each highway section, the beginning and the ending reference post, the pavement age, the distress amount (rutting, transverse cracking…etc), and the average daily traffic (ADT). The data were sufficient to build and verify the model. Eighty percent of the data-points were used to build the proposed integrated MAUT/Regression models, while the rest twenty percent were used in verifying the models. The second part involves the data collected by a designed questionnaire sent to pavement engineers and experts in the municipalities and the departments of transportation in Canada, the USA, and worldwide. The main goal of sending the questionnaire was to collect the missing information that "Tab files" did not include, especially those regarding the condition-rating score of each highway section.

Sixty questionnaires were sent to DOT experts and engineers by emails, telephone and direct interviews. In return, *ten* questionnaires only were received, and on the basis of their data the global weights of each main factor and sub-factor were developed in addition to the final condition-rating index.

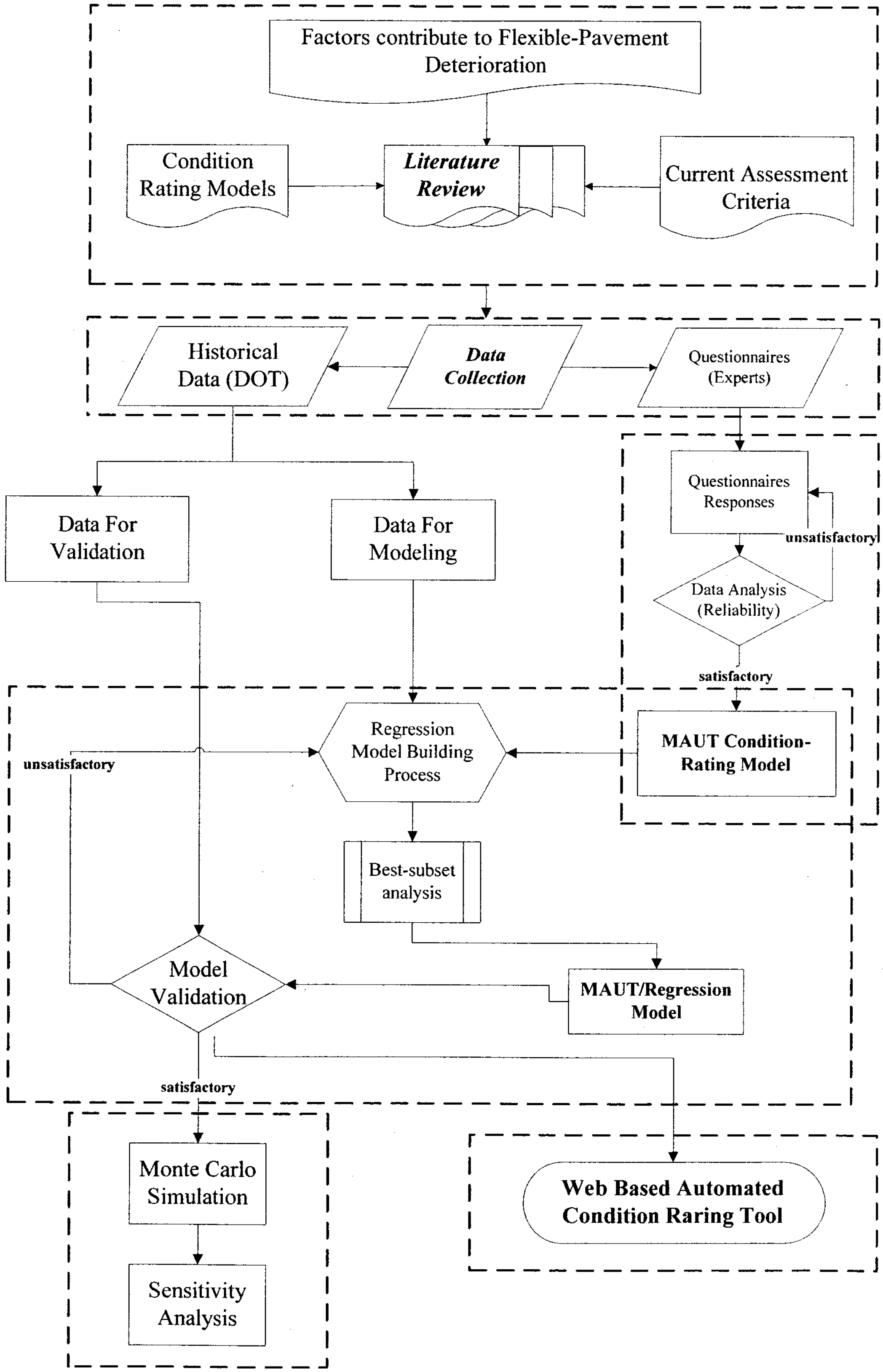


Figure 3-1: Research Methodology.

3.4 The MAUT Condition-Rating Model:

To fill the gap of the historical data "Tab files", a condition-rating model was built using the Multi-Attribute Utility Theory (MAUT). The main reason for the selection of MAUT is that, it is very useful when the decision-making process is complex, for instance, when it is unstructured.

The (MAUT) is concerned with expressing the utilities of multiple-attribute outcomes or consequences as a function of the utilities of each attribute taken singly. Applying the MAUT, the condition-rating score (CR) of each highway section is obtained by multiplying the importance weight of each factor (W_i) by its attribute's utility scores (U_i) as follows:

$$CR = \sum_{i=1}^{n} Wi * Ui \qquad \text{Eq: (3-1)}$$

Where:

- n: is the number of considered factors affecting flexible-pavement condition.
- W_i: importance weight of each factor.
- U_i: attribute's utility score of each factor.

The importance weights (W_i) were calculated using the Analytical Hierarchy Process (AHP). The AHP is used because, when the decision cycle involves a variety of multiple-criteria whose rating is based on a multiple-value choice, it splits the overall problem into as many evaluations of lesser importance, while keeping at the same time their part in the global decision. On the other hand, the attribute's utility scores (U_i) were extracted from the utility-scoring functions. These utility-scoring functions are constructed based on the experts' preferences collected from the questionnaires. Figure 3-2 illustrates the general framework of the MAUT. The first step was to set the selected factors of this study (that have a direct impact on the flexible-pavement condition) in a hierarchy-level structure. The main categories (Climate Conditions, Physical Properties, and Operational Factors) and their sub-factors that were included in the proposed model are described in the following Table:

Table 3-1: Description of Sub-Factors Included in the Developed Model.

Category	Sub-Factor	Description
Climate Conditions	Air Temperature	Average air temperature readings collected annually in summer seasons (June, July, and August) of years 1997 to 2003
	Pavement Temperature	Average pavement temperature readings collected annually in summer and winter seasons of years 1997 to 2003.
	Rainfall Amount	Average rainfall amounts collected annually in summer seasons (June, July, and August) of years 1997 to 2003.
	Freezing Temperature	Average freezing temperature readings collected annually in winter seasons (December, January, and February) of years 1997 to 2003.
Physical Properties	Surface Layer Depth	The thickness of the top layer of a full-depth asphalt pavement in inches.
	Base Layer Depth	The thickness of the bottom layer of a full-depth asphalt pavement in inches
	Pavement Age	Number of years since the first construction of pavement segments.
Operational Factors	Average Daily Traffic (ADT)	The average number of vehicles passing a specific point (two ways) in a 24-hour period.
	Roughness Measurements	Measuring the texture of a pavement surface to determine the ride quality.
	Transverse Cracking Amount	Cracks perpendicular to the pavement centerline or lay-down direction (Pavement Distress)
	Rutting Amount	A surface depression in the wheel paths (Pavement Distress).

Four pair-wise comparison matrices between the main factors and their sub-factors are constructed. These matrices have to be filled by the participants with numbers on a scale of (1-9). A reliability test using the cronbach's coefficient alpha is then performed on these numbers to test whether or not they are reliable in building the importance weights of the studied factors. Afterwards, the importance weight of each sub-factor is calculated mathematically.

Subsequently, the logical consistency of the final weights is verified based on the consistency ratio (CR). The consistency ratio (CR) should be less than 10%, in order for the results to be consistent. Finally, a condition-assessment value is generated by combining the attribute's utility score with the importance weight of each sub-factor.

3.5 Integrated MAUT/Regression Model:

The real data received from the NDOR records along with the condition-rating values of the MAUT model are both tabulated for each highway section. Then, multiple regression technique is applied using Minitab ® 15 statistical software. The integrated MAUT/Regression model development process adopted in the current study consists of four major phases: (1) preliminary examinations for possible correlations between the variables, (2) building the model, (3) statistical tests for model adequacy, and (4) residual analysis such as the normality test, the independency test, and the homoscedasticity test...etc. Figure 3-3 shows these four phases, which are explained in detail in Section 5.2 and Appendix B.

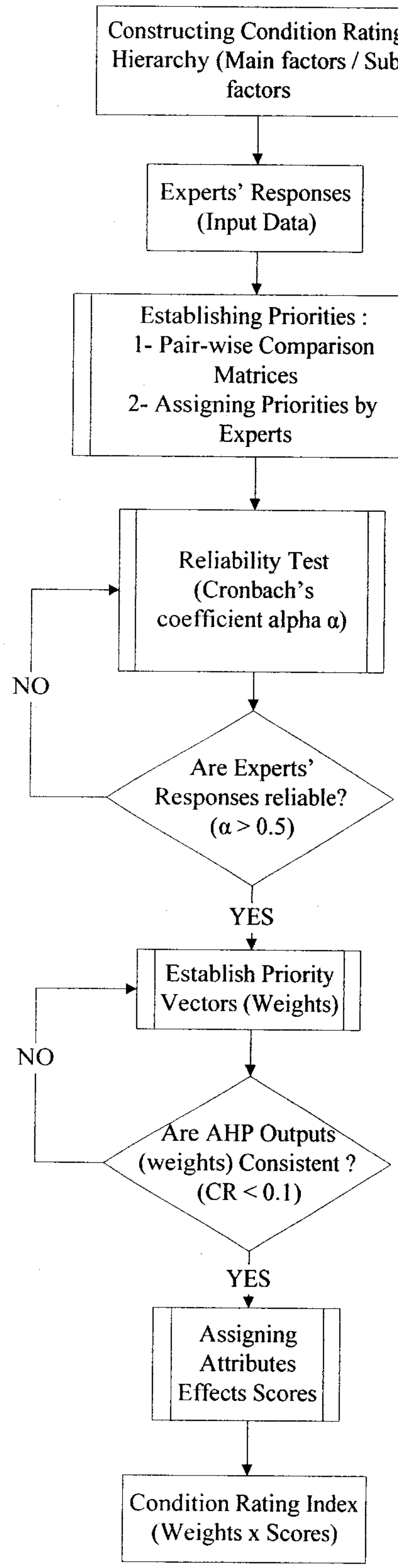


Figure 3-2: MAUT Condition-Rating Model Methodology Framework.

Consequently, the most appropriate regression models are selected for the validation process. Figure 3-4 presents an overview of the methodology of the validation process. As shown in Figure 3-4, the validation process includes four procedures as follows: (1) plot of actual vs predicted outputs, (2) descriptive statistics, (3) mathematical measures (AIP-Average Invalidity Percentage, AVP- Average Validity Percentage, RMS-Root Mean Square Error, and MAE-Mean Absolute Error), and (4) a comparison between the proposed model and the existing condition-rating models. The calculations and the values of these procedures are shown in detail in Section 5.2 and Appendix B.

3.6 Deterioration Curves:

In the current study the deterioration curves are built on the basis of the proposed integrated MAUT/Regression condition-rating models. These curves are constructed by building the relationship between the condition-rating of the pavement and its age. This relationship is based on different climatic, physical, and operational factors. The curves are intended to assist the decision-makers in managing their maintenance and rehabilitation programs. The curves are presented in Section 5.2 and Appendix B.

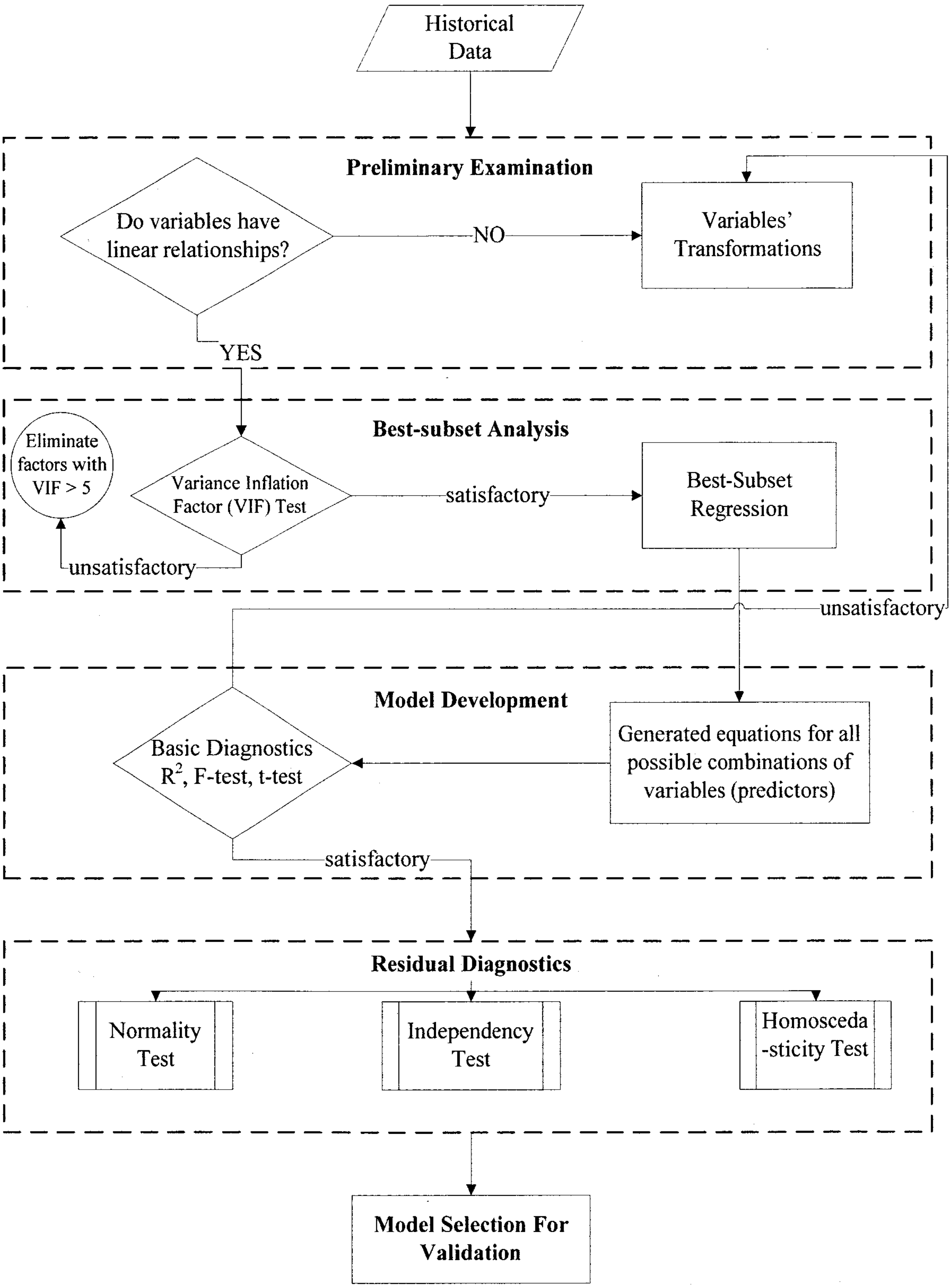


Figure 3-3: Regression Model Building Methodology.

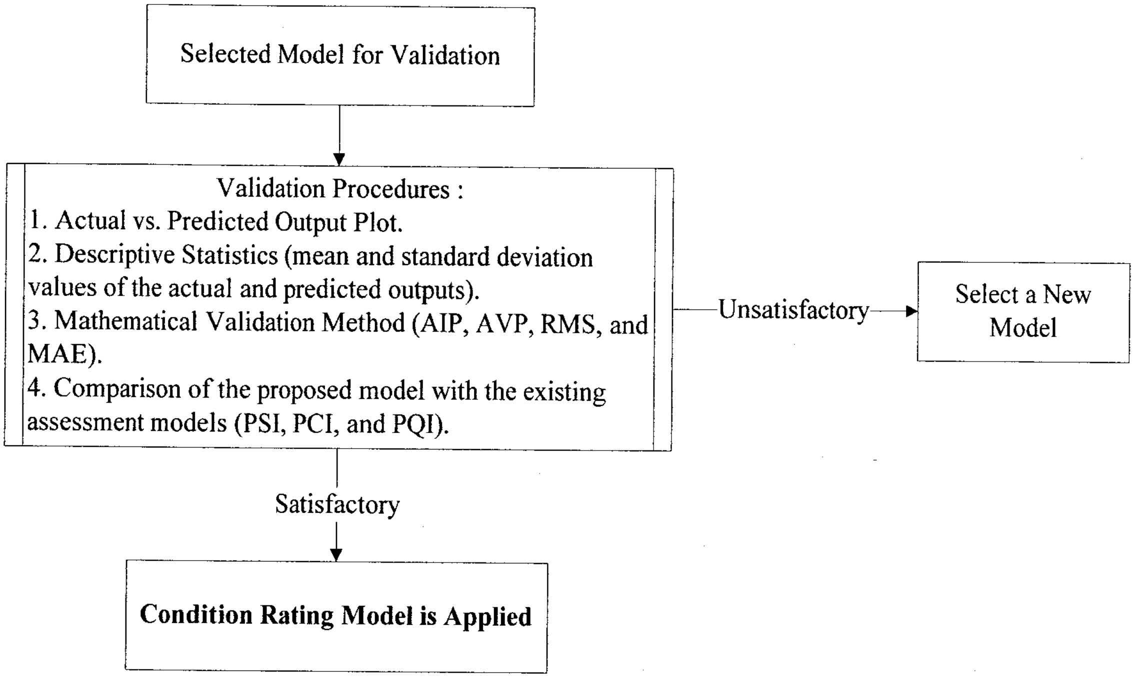


Figure 3-4: Regression Model Validation Methodology.

3.7 Monte-Carlo Simulation:

Since the developed regression models are based on several uncertain parameters interacting to produce the condition-rating outcome, the Monte-Carlo simulation is used. The main purpose of the application of the Monte-Carlo simulation is to deal with the uncertainty propagation. The Monte-Carlo simulation application consists of four main phases: (1) model preparation by defining distributions for inputs and outputs, (2) determining the required number of iterations and simulations, (3) conducting the simulation results, and (4) performing a sensitivity analysis. Figure 3-5 shows these four phases presented in more detail in Section 5.3 and Appendix C.

3.8 Web-based Automated Condition-Rating Tool:

After building the MAUT/Regression condition-rating models, a web-based automated tool is developed using the C# programming language. The tool will help pavement engineers and experts to predict the condition-rating scores of existing road/highway segments, which will assist them in their management plans regarding assigning maintenance and rehabilitation treatments.

3.9 SUMMARY:

This chapter presented the adapted methodology in the current study. The methodology includes literature review, data collection (which consists of model information and validation data), the MAUT condition-rating model, the integrated MAUT/Regression condition-rating model, the application of the Monte-Carlo simulation, and the development of web-based flexible pavement condition-rating tool.

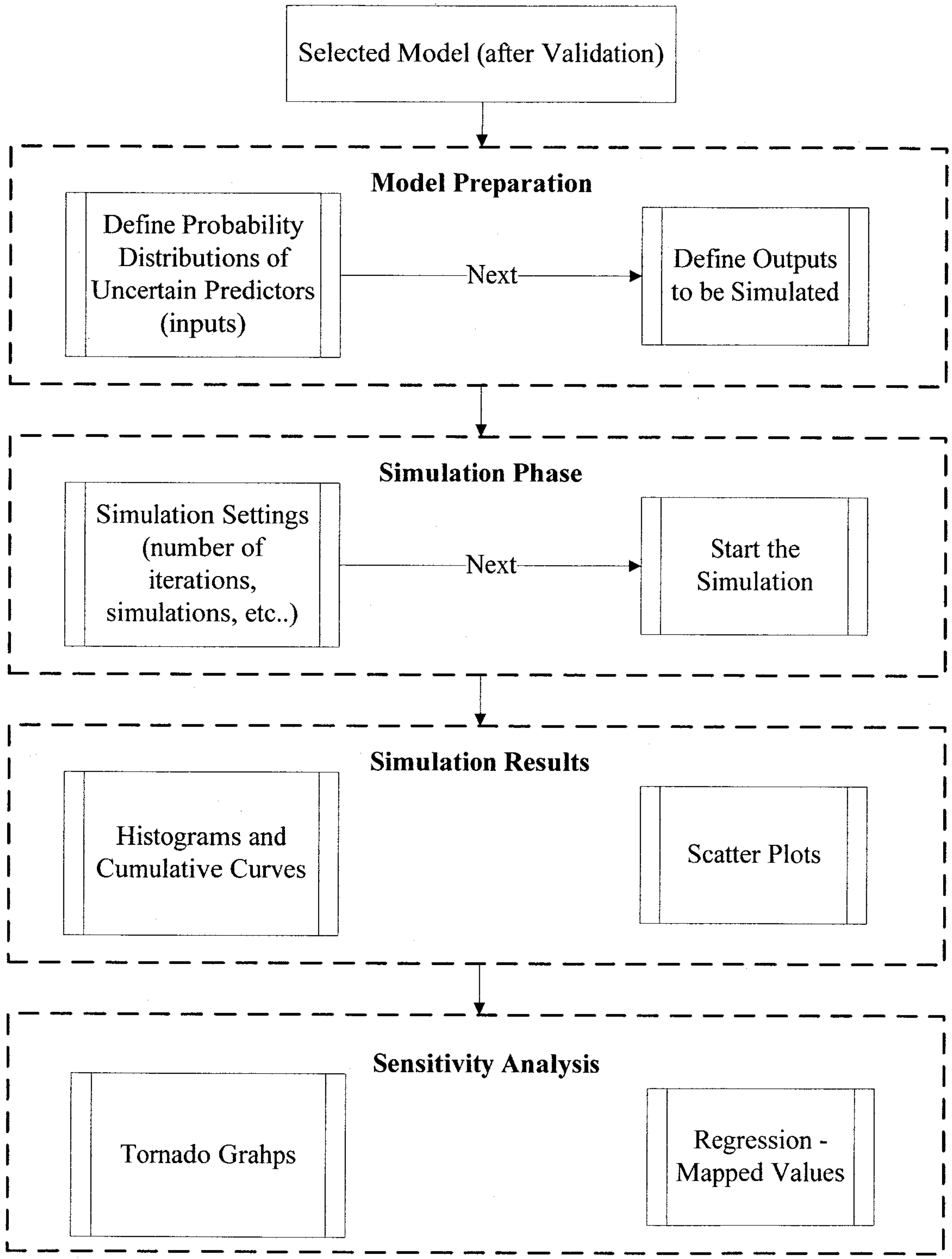


Figure 3-5: Monte-Carlo Simulation Methodology.

CHAPTER 4: DATA COLLECTION

4.1 Introduction:

This chapter describes the data-collection process required to build and run the integrated MAUT/Regression model. This process consists of two parts as follows: Part One, in which the information needed to build the MAUT model is collected by questionnaires; Part Two, which contains real-network characteristics data. These data are then combined with the data of the MAUT model to develop the integrated MAUT/Regression model. Figure 4-1 shows the data-collection process and its two parts.

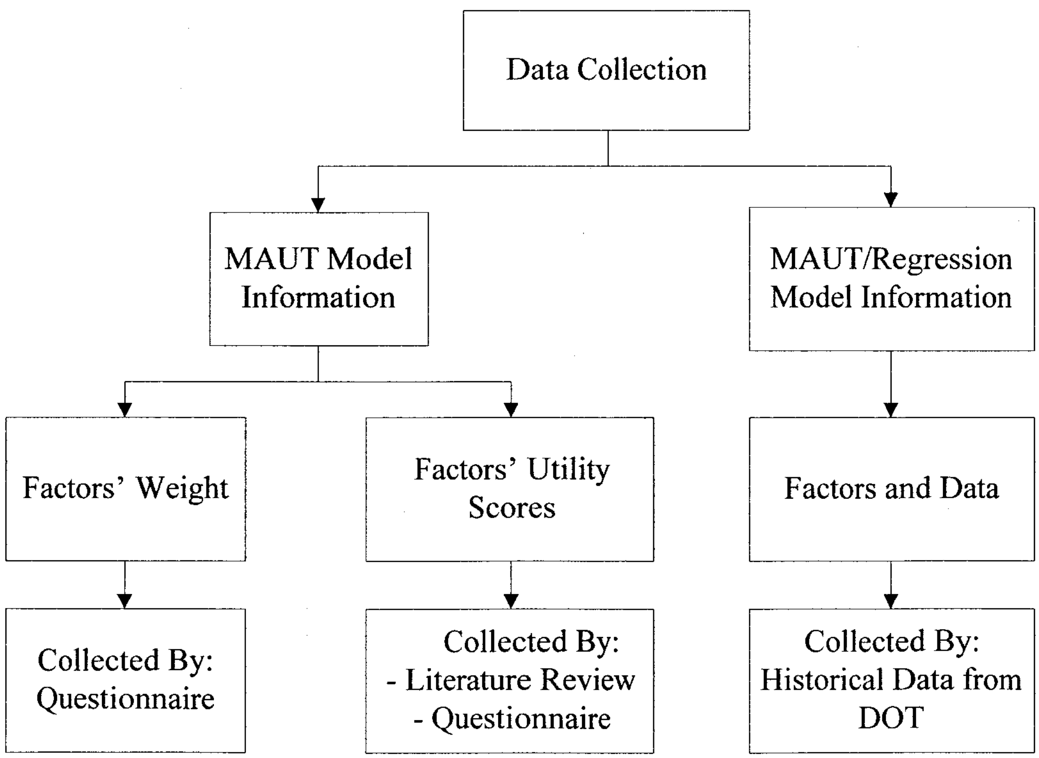


Figure 4-1: Data Collection Process.

4.2 The MAUT Model Information:

The MAUT model development process requires two sets of information: factor weight and factor performance impact (utility scores). Accordingly, a questionnaire was designed and sent to practicing pavement engineers and experts in the municipalities and the departments of transportation in Canada, the USA and Worldwide (a copy of the questionnaire is attached in Appendix D). The primary mission of the questionnaire is to collect data regarding the factors' weights, factors' impact criteria and the required maintenance and rehabilitation (M&R) actions.

In the second part of the designed questionnaire, the AHP pair-wise comparison matrices are founded. By filling the cells of each pair-wise comparison matrix with numbers on a scale of 1-9 by the expert respondent, the relative weight of each factor at each level of the constructed hierarchy is calculated mathematically.

4.2.1 Factors Weights:

A total of sixty questionnaires were sent to DOT experts and engineers by emails, telephone and direct interviews. In return, *ten* questionnaires were only received and they can be summarized according to their locations as follows: State of Nebraska: seven responses, Ontario: two responses, and Alberta: one response.

The results of the main factors' pair-wise comparison matrix showed that (80%) of the participating experts considered the "Operational factors" to have the highest priority and impact on the condition-rating model, while (10%) of the experts selected the "Physical Properties" as having the highest priority and impact on the condition-rating model. The remaining (10%) ranked equally the "Operational and Physical factors" as having the highest priority and impact on the condition-rating model. These results are shown in Figure 4-2.

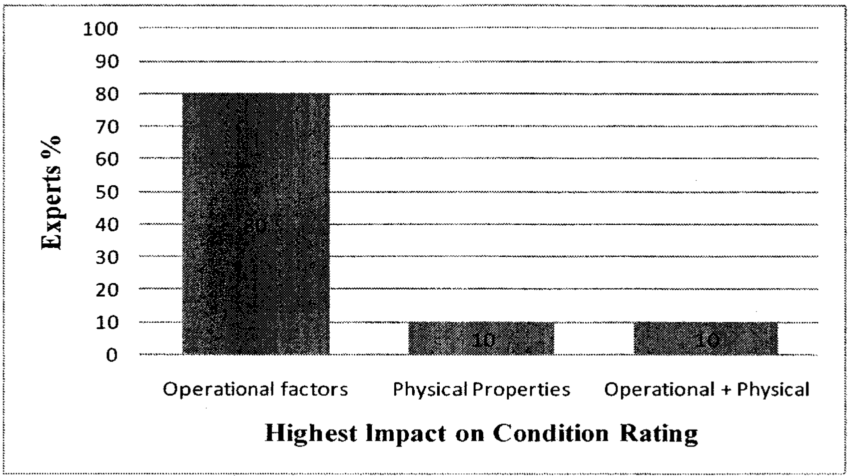
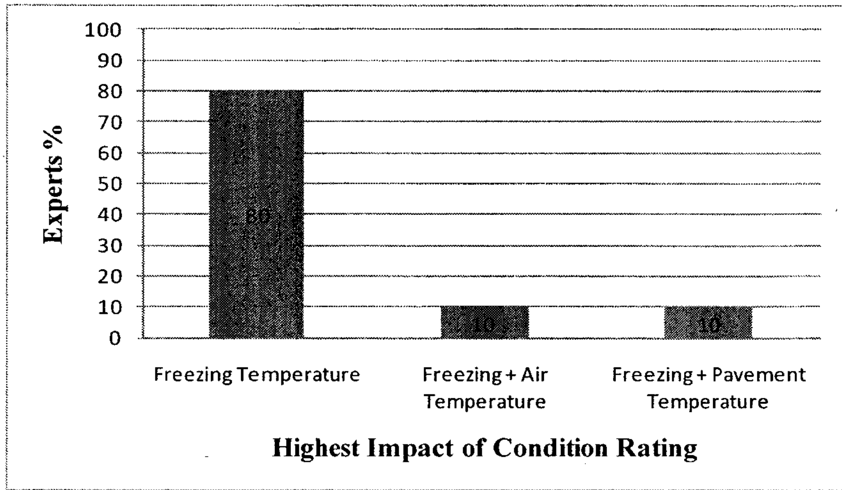


Figure 4-2: Results of Experts' Preferences for the Main-Factors Impact.

Regarding the **Climate Conditions'** pair-wise comparison matrix, results showed that (80%) of the participating experts considered the sub-factor "Freezing Temperature" to have the highest priority among sub-factors of the climate conditions. However, (10%) of the experts stated that "Freezing Temperature" and "Air Temperature" have the same highest priority rating. The remaining (10%) stated that "Freezing Temperature" and "Pavement Temperature" have the same highest priority rating. On the other hand, (40%) of the participating experts considered the sub-factor "Air Temperature" as having the lowest priority among the climate conditions sub-factors. A similar percentage of (40%) selected the sub-factor "Rainfall Amount" as the lowest priority sub-factor. The remaining (20%) ranked equally "Air Temperature" and "Rainfall Amount" as having the lowest priority and impact on the condition-rating model. These results are shown in Figure 4-3.



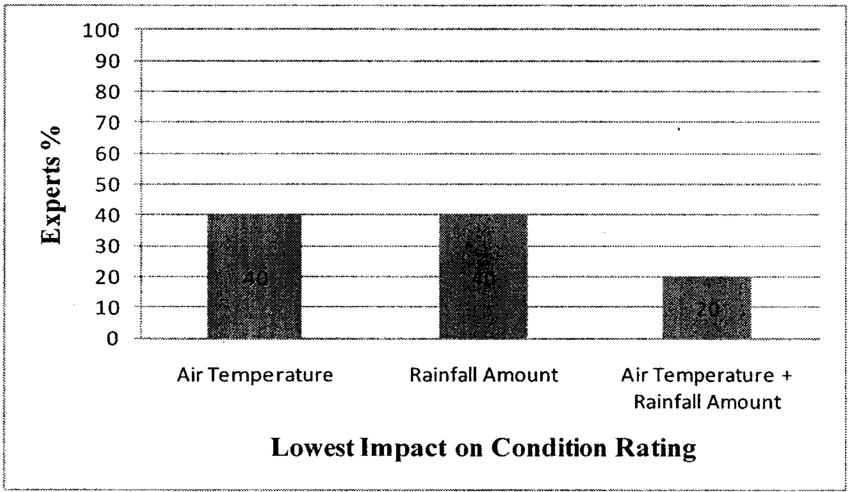


Figure 4-3: Results of Experts' Preferences for the "Climate Conditions" Impact.

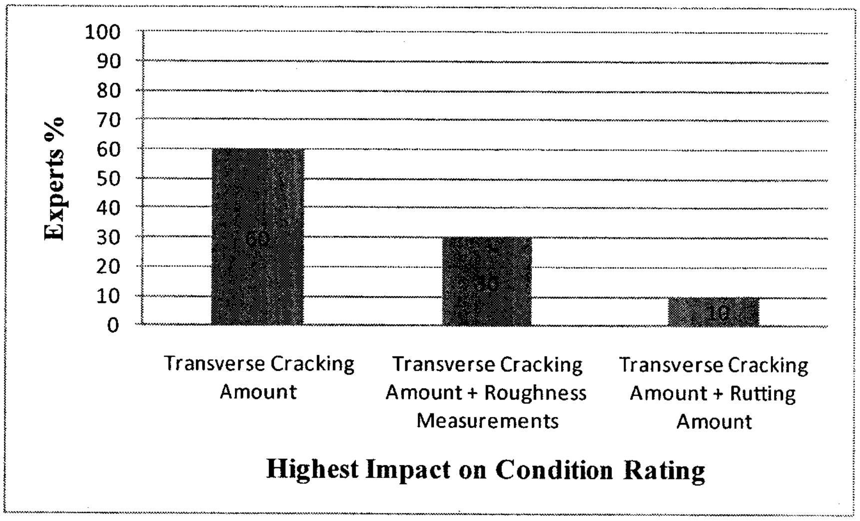
The results from the **Physical Properties'** pair-wise comparison matrix showed that (40%) of the participating experts considered the sub-factor "Pavement Age" as having the highest priority among sub-factors of the physical properties. On the contrary, a similar percentage of (40%) of the experts considered "Pavement Age" as the lowest priority sub-factor. The remaining (20%) ranked equally "Pavement Age" and "Surface Layer Depth" as having the highest priority and impact on the condition-rating model.

Finally, the results from the **Operational Factors'** pair-wise comparison matrix showed that (60%) of the participating experts considered the sub-factor "Transverse Cracking Amount" as having the highest priority among sub-factors of the operational factors. However, (30%) of the experts stated that "Transverse Cracking Amount" and "Roughness Measurements" have the same highest priority rating. The remaining (10%) stated that "Transverse Cracking Amount" and "Rutting Amount" have the same highest priority rating. On the other hand, (70%) of the participating experts considered the sub-factor "Average Daily Traffic-ADT" as having the lowest priority among sub-factors of the operational factors. A percentage of (20%) of the experts state that "ADT" and "Rutting Amount" have the same lowest priority rating. The remaining (10%) ranked equally "ADT" and "Roughness Measurements" as having the lowest priority and impact on the condition-rating model. These results are shown in Figure 4-4.

The final weights of each main factor and its sub-factors are presented in detail in Section 5.1 (Table 5-9).

4.2.2 Factors Performance Impact:

Although the final collected relative weights are essential components in the building process of the MAUT model, they only represent the general impact of the sub-factors on the flexible-pavement condition. Each sub-factor may have different attributes that vary in their impact on the condition of the pavement. Therefore, to better represent this impact, specific scores should be assigned to the different attributes.



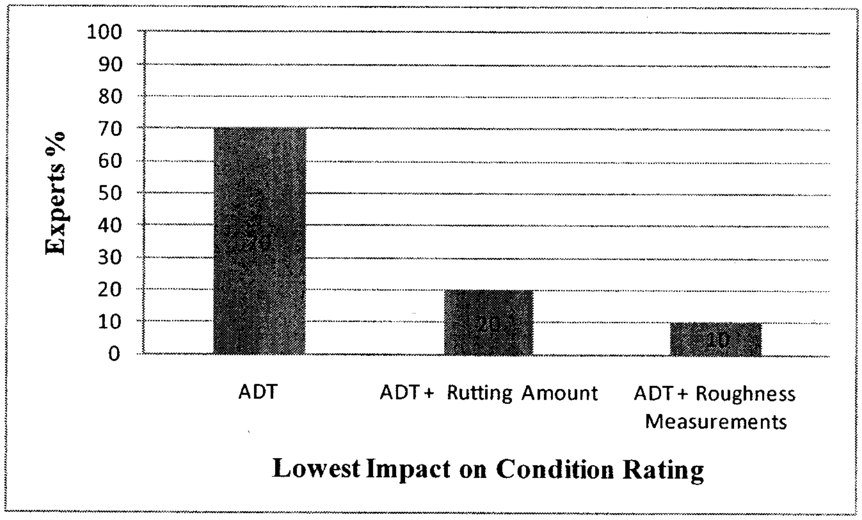


Figure 4-4: Results of Experts' Preferences for the "Operational Factors" Impact.

For example, the sub-factor "Average Daily Traffic-ADT" is studied in the current research with three different attributes. These attributes are Low, Moderate and Heavy.

In the third part of the designed questionnaire, the respondent is asked from his/her expertise to assign the corresponding score to each attribute, by answering the following question: "On a scale of 0-10, how do you rate the *impact* of the sub factor (x) on the condition of the flexible-pavement of a road section." The proposed scale with the linguistic meaning of each numeric score is shown in Figure 4-5.

0	2	3	4	5	6	7	8	10
Extremely Neg	Very Neg	Moderately Neg	Neg	Even Impact	Pos	Moderately Pos	Very Pos	Extremely Pos

Neg: Negative impact on flexible pavement condition.
Pos: Positive impact on flexible pavement condition.
Even: Neither negative nor positive impact on flexible pavement condition.

Figure 4-5: The Scoring Scale of the Sub-Factors' Attributes.

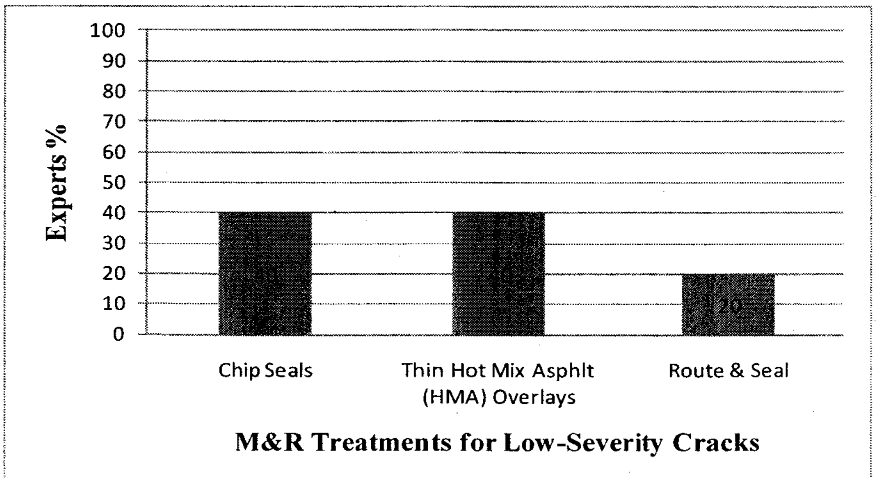
4.2.3 Selection of Maintenance and Rehabilitation Treatments:

In order to determine the required maintenance and rehabilitation (M&R) treatments, the experts' feedback are obtained in the last part of the designed questionnaire. A list of the common M&R treatments are suggested based on the severity level of two types of distress (transverse cracking and rutting). And on the basis of his/her experience, the participating expert has to select the most suitable M&R treatment that corresponds to the distress type and severity.

In the case of transverse cracking distress, two levels of severity were investigated as follows: low-severity cracks (< 13 mm wide) and high-severity cracks (≥ 13 mm wide). Five M&R treatments were proposed which are: chip seals, thin hot mix asphalt (HMA) overlays, hot in-place recycling, full-depth reclamation, and slurry seals.

In the case of rutting distress, two levels of severity were investigated as well: slight ruts (< 9 mm deep) and severe ruts (≥ 9 mm deep). Three M&R treatments were proposed: doing nothing, micro-surfacing, milling-off and replacement.

Data from the ten received questionnaires showed that, regarding the **low-severity** cracks (< 13 mm wide), (40%) of the participating experts selected the chip seals as a suitable treatment for this case. A similar percentage of (40%) went with the thin hot mix asphalt (HMA) overlays as a better treatment for low cracks. The remaining (20%) suggested a new treatment (route & seal) that was not included in our list, to be the best one for low cracks. Moreover, in the case of **high-severity** cracks (≥ 13 mm wide), a percentage of (50%) of the participating experts selected hot in-place recycling as a suitable treatment for this case. (30%) of the experts went with full-depth reclamation as a better treatment for high-severity cracks. (10%) of them suggested a new treatment not included in our list, which is cold in-place recycling. The remaining (10%) of the participating experts proposed two new alternatives, cold in-place recycling and route & seal treatments, as the best solutions for this particular kind of high-severity cracks. These results are shown in Figure 4-6.



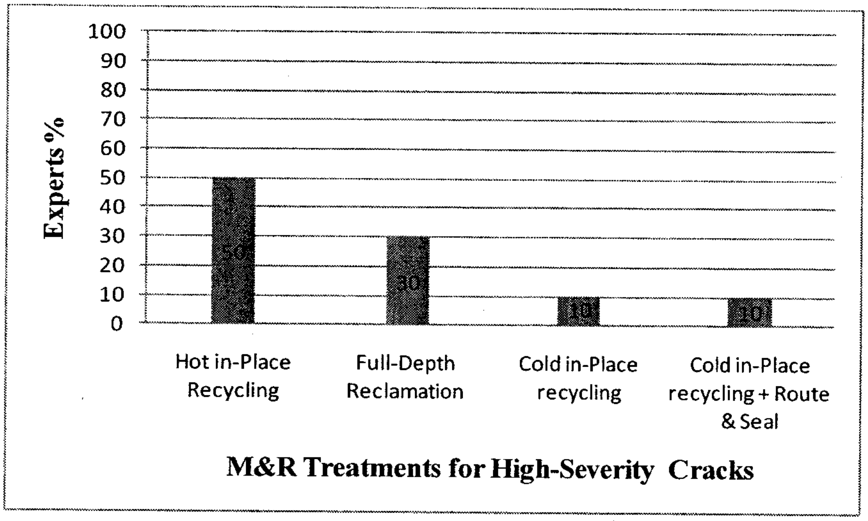


Figure 4-6: Results of Experts' Selection for the "Transverse Cracking" Distress.

On the other hand, the received data regarding the rutting levels showed the following results: In the case of **slight-ruts** (< 9 mm deep), (60%) of the participating experts chose micro-surfacing as the most suitable solution for the slight ruts and (40%) chose to do nothing about the slight ruts. For the **severe-ruts** (≥ 9 mm deep), all the participating experts selected the milling off and replacement as the best treatment for severe ruts. These results are shown in Figure 4-7.

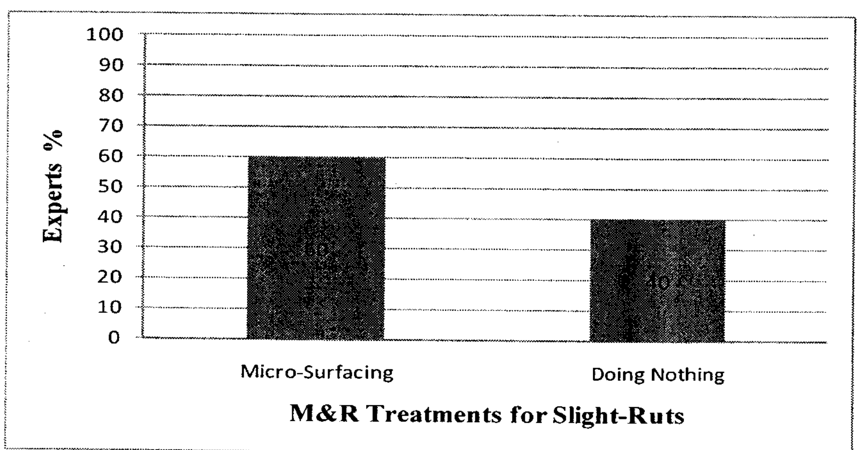


Figure 4-7: Results of Experts' Selection for the "Rutting" Distress.

4.3 Integrated MAUT/Regression Model Information:

The integrated MAUT/Regression model development-process required two parts of information as well. The first part consists of the real values of the sub factors' attributes collected from the historical records of the Nebraska Department of Road (NDOR) called "Tab files". The second part consists of the MAUT model outputs of condition ratings. The MAUT model information was explained earlier in the sections above. The real values of the attributes of sub-factors will be presented in the following section:

The Nebraska Pavement Management System (NPMS) manages all rural and urban-marked maintained highways and recreation roads. Its records include all highways and roads on the National Highway System. The information used in NPMS includes pavement inventory data, historical and current pavement condition data, pertinent traffic characteristics information, and construction and maintenance cost information. The NPMS database is structured on a milepost basis. The pavement data are stored for each milepost in the system. The data is collected for network level sections, which are listed in order by highway number and reference post number. Contests are validated by the personnel in the pavement management department. These network pavement sections were specified using geographical, geometrical, traffic, and pavement design information. An example of the collected information is the pavement condition data that is used to describe the surface condition of each segment of the highways within the state. The historical condition data and performance measures are used to monitor and evaluate maintenance, rehabilitation, and reconstruction designs and techniques, calibrate performance prediction curves and design procedures, and provide information for special research purposes.

The NDOR conducts condition surveys on the paved road network, which includes a uniform pavement rating system for highways throughout the state on an annual basis.

The available "Tab files" data were grouped according to year and contained information on highway sections, such as beginning reference post, ending reference post, district number, state functional code, county code, national functional code, rural-urban code, the completed date of a strategy, and accident data along with detailed information on geometry, distress amount, traffic, pavement design, etc.

The geometrical information includes lane direction, centerline mile amount, and shoulder width. The distress information consists of values for different distresses, such as rutting, slab cracking, transverse cracking and joint cracking. It also includes values for performance indicators, such as the International Roughness Index (IRI), restoration index, cracking index, etc.

The information regarding traffic contains the average daily traffic (ADT) of vehicles, truck ADT, and the growth of the number of vehicles after 20 years. The pavement design data include; the thickness of the base and the surface course layer, the roadway material type, the pavement age, etc.

The NDOR has classified pavements into three categories: rigid pavements, bituminous pavements and full-depth asphalt pavements. In the current study, the analysis was limited to the records of the full-depth asphalt pavements. and the "Tab files" had only been acquired for a period of eight years from (1997-2003).

Table 4-1 shows an example of a "Tab file" for the year 1997. Not all the data in the tab files were used in this research. Some information, such as beginning reference post, ending reference post, number of lanes, all performance indicators (IRI, PSI, cracking index, etc.) were eliminated from this study.

On the other hand, some modifications were made to the information used in this study. For example, the pavement distresses were limited to only two distress types "transverse cracking and rutting", the traffic information was limited to only the Average Daily Traffic (ADT), and the pavement age was limited to a maximum of 15 years as a threshold for applying maintenance and rehabilitation treatments. For example, a road segment of 16 years of age will be considered in a good condition because the age of 15 years is the threshold for M&R treatment application as an obligatory procedure, not only as a necessary one.

Information on surface and base course layer depth was used as it is without any modifications, but the International Roughness Index (IRI) was replaced by roughness measurements to prevent the correlation and the calibration procedures between the developed model and the (IRI).

After applying suitable modifications to the collected data, a new data set was available for model development. However, the new data set is still missing the climate data taken into consideration in the current research. The considered climate data include the air temperature, pavement temperature, rainfall amount, and freezing temperature.

4.4 Climate Conditions:

Both the pavement surface and the underlying supporting layers are exposed to continuous changeable climate influences. For this reason, statistical data and general information on the following climate variables were gathered before starting the model development process:

4.4.1 Air Temperature:

The air temperature has a direct influence on the strength of the supporting layers, the type and amount of the bitumen that should be used in the flexible-pavement and, as a result, on the overall performance of the pavement. Also, sudden variations in temperature between the top and the bottom surfaces of the pavement affect its deflection and load-bearing capacity, which may result in cracking, spalling, or even the blow-out of some slabs.

In the current research, based on the temperature variations between the yearly seasons, two sets of data were developed. The first data set accounts for **summer** with climate conditions of air temperature, pavement temperature, and amount of rainfall. The second data set accounts for **winter** with climate conditions of freezing and pavement temperature.

The North-American regional weather networks collect and archive hourly weather information in an accessible database. Each highway segment in the "Tab files" was located in its climatic zone, and on that basis climate information was obtained for each specific climatic zone (NARWN, 2009).

In this study, the readings of the air temperature covered the months of June, July, and August from 1997 to 2003. These readings of air temperature were recorded for each day and averaged on a yearly basis.

4.4.2 Pavement Temperature:

According to (Solaimanian *et al.,* 1993), during the winter season, the minimum pavement temperature is in most cases one or two degrees Fahrenheit (°F) higher than the minimum air temperature. Therefore, the asphalt institute provides the following equation for determining the low pavement temperature (AI, 1995):

$$T_{min} = 0.859\ T_{air} + 1.7 \qquad \text{Eq: (4-1)}$$

Where: T_{min} is the minimum pavement temperature (°C) and T_{air} is the minimum air temperature (°C).

The previous equation is applied in the current study for calculating the pavement temperature of each highway segment for both summer and winter data sets.

4.4.3 Rainfall Amount:

The rainfall has an influence on the stability and strength of the supporting layers because it affects the moisture content of the sub-grade and sub-base. In cold regions where the pavement is exposed to freezing temperatures, the moisture content acts as a supply, which causes the growth of ice lenses under the pavement and may contribute to frost damage. Also, where the frost problem is absent, the moisture content will vary with rainfall and this will in turn affect the expansion and contraction of the pavement.

The rainfall amounts for each climatic zone were collected from the archive of the North-American regional weather networks for the years between (1997 and 2003) and were determined for each highway section within its specific climatic zone (NARWN, 2009).

4.4.4 Freezing Temperature:

Most researchers refer to the effect of freezing temperature by using the "Frost" terminology. This term generally involves two concepts: (1) the existence of freezing temperature below 32 °F (0 °C). (2) The action of the freezing temperatures upon the soil, which leads to the state of frozen soils. When the pavement is subjected to freezing temperatures, several phenomena occur, such as the rapid freezing of the water film on the pavement's surface, which leads to skid-related accidents, and layers or lenses of a clear ice of several inches in thickness are built up under the pavement system.

In a similar way, the readings of the freezing temperature covered the months of December, January, and February from 1997 to 2003. These readings were recorded for each day and averaged on a yearly basis. Also, the pavement temperatures for winter data set were extracted from the Equation (4-1) in a similar manner, and then used for analysis and model development processes.

4.5 SUMMARY:

This chapter presented a detailed discussion regarding the collection process of the required data. Two parts of data were collected; one part via a designed questionnaire for the MAUT condition-rating model. The other part was collected from the records of the NDOR called "Tab Files" for the building and validation of the integrated MAUT/Regression condition-rating model; in addition to the collection of the climate data from the archive of the North-American regional weather networks.

Table 4-1: Sample “Tab File” from Year 1997.

Highway Number	Section	Air Temp ^0C	Pav Temp ^0C	Rainfall Amount (mm/hr)	Surface Layer Depth (inch)	Base Layer Depth (inch)	AGE (years)	ADT (vch/dy)	Rough Amount (mm/m)	Trans Crack Amount (mm)	Rutting Amount (mm)
L 01 E	1	29.44	26.99	1.13	3.0	8.5	4	25	3.55	0.20	5.0
L 02 C	1	30.56	27.95	1.15	2.0	5.0	19	20	1.38	27.30	3.0
	2	30.56	27.95	1.15	2.0	5.0	18	20	3.31	27.30	5.0
L 05 B	1	30.56	27.95	0.93	4.0	8.0	5	15	1.09	0.70	13.0
L 06 A	1	28.89	26.52	1.14	2.0	10.0	22	15	4.29	0.00	0.0
L 10 B	1	29.44	26.99	0.77	2.0	4.0	34	125	3.18	0.00	3.0
	2	29.44	26.99	0.77	2.0	4.0	34	125	3.43	51.80	6.0
L 10 C	1	28.89	26.52	0.77	4.0	12.0	34	130	3.18	0.00	3.0
	2	28.89	26.52	0.77	4.0	12.0	10	130	1.64	10.20	6.0
	3	28.89	26.52	0.77	4.0	12.0	14	140	2.07	0.00	3.0
L 10 D	1	29.44	26.99	1.25	3.0	8.0	24	80	4.30	4.40	3.0
	2	29.44	26.99	1.25	3.0	8.0	24	80	3.20	37.00	8.0
L 14 D	1	29.44	26.99	1.28	3.0	8.0	5	50	2.13	16.70	14.0
	2	29.44	26.99	1.28	3.0	8.0	27	50	3.52	0.00	15.0
L 17 B	1	30.00	27.47	0.94	2.0	4.0	23	40	2.86	0.00	1.0
	2	30.00	27.47	0.94	2.0	4.0	23	40	0.00	0.00	0.0
L 17 C	1	29.44	26.99	0.80	2.0	6.0	23	30	2.89	0.00	2.0
	2	29.44	26.99	0.80	2.0	6.0	23	30	2.34	17.30	6.0

CHAPTER 5: DEVELOPMENT OF FLEXIBLE PAVEMENT CONDITION-RATING MODEL

Keeping asphalt-surfaced highways and roads in an acceptable condition is the major goal that departments of transportation and pavement engineers always try to achieve. This requires a reliable tool for predicting the performance of pavements in a network. The objective of the current study is to develop simplified pavement condition-rating models that can be used for various pavement management purposes. These models predict the present condition rating based upon knowledge of different climatic, physical, and operational factors. The model-building procedure requires a detailed analysis of historical data. In the following sections, the development of a flexible pavement condition-rating model is comprehensively explained and discussed.

5.1 THE MAUT CONDITION-RATING MODEL

5.1.1 Application of AHP in MAUT Model:

The AHP technique is used in order to assess each factor's relative weight in the MAUT model, which represents the relative importance of this factor among other factors towards the goal decision of flexible pavement condition-rating. The procedure for using the AHP (Saaty, 1982; 1995) can be summarized as follows:

5.1.2 Model the Problem as a Hierarchy:

The goal is to structure the problem into humanly-manageable sub-problems. To do so, iterating from top (the more general) to bottom (the more specific), splits the problem into sub-modules that will become sub-hierarchies. Navigating through the hierarchy from top to bottom, the AHP structure of the MAUT model comprises:

Level 1: contains the ***Goal*** (Condition-Rating value ranging from 0-10). *Level 2*: contains the ***Criteria*** (main factors: climate conditions, physical properties, and operational factors.) *Level 3*: contains the ***Sub-criteria*** (sub-factor evaluation parameters such as: air temperature, pavement age, average daily traffic ADT....etc).

Figure 5-1 shows the constructed hierarchy of the proposed model.

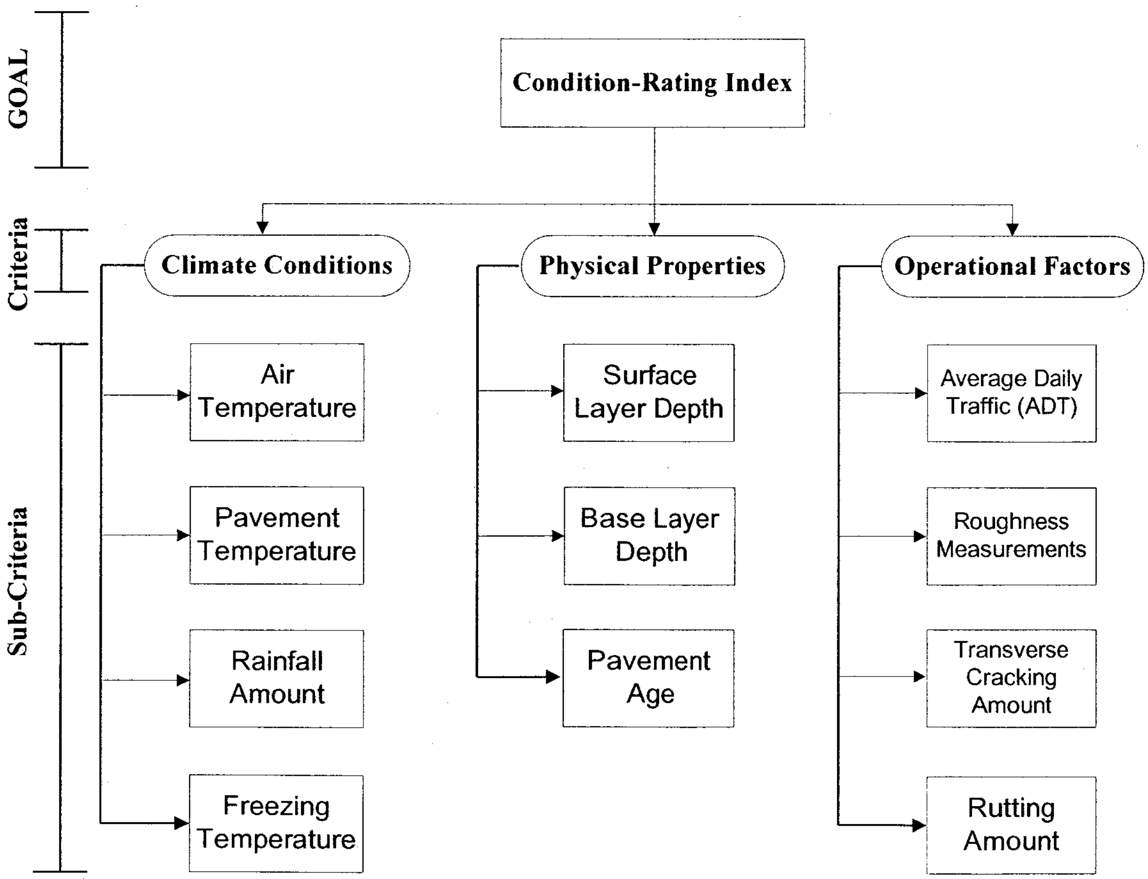


Figure 5-1: Hierarchy of the Developed Model.

5.1.3 Pair-wise Comparison Matrices:

In this step, four pair-wise comparison matrices were developed, one among the main factors of the second level: (Climate conditions, Physical properties, and Operational factors) and the other three among the sub-factors of the third level.

5.1.4 Assign Priorities:

Once the matrices have been constructed, the participants use AHP to establish priorities for all its main factors and sub-factors. In doing so, information is elicited from the participants and processed mathematically. Consequently, filling the cells of each pair-wise comparison matrix with numbers on a scale of (1-9) by the expert respondent, will lead to calculating the relative weights of each sub-factor in its group. Tables 5-1, 5-2, 5-3, and 5-4 present an example of assigning priorities by "Respondent No.1".

Table 5-1: Main Factors Pair-wise Comparison Matrix (Respondent No.1).

Main Factors	Climate Conditions	Physical Properties	Operational Factors
Climate Conditions	1	1/2	1/4
Physical Properties	2	1	1/2
Operational Factors	4	2	1

Table 5-2: Physical' Sub-Factors Pair-wise Comparison Matrix (Respondent No.1).

Sub-Factors	Surface Layer Depth	Base Layer Depth	Pavement Age
Surface Layer Depth	1	1	1/2
Base Layer Depth	1	1	1/2
Pavement Age	2	2	1

Table 5-3: Climate' Sub-Factors Pair-wise Comparison Matrix (Respondent No.1).

Sub-Factors	Air Temperature	Pavement Temperature	Rainfall Amount	Freezing Temperature
Air Temperature	1	1	2	1/3
Pavement Temperature	1	1	2	1/3
Rainfall Amount	1/2	1/2	1	1/6
Freezing Temperature	3	3	6	1

Table 5-4: Operational' Sub-Factors Pair-wise Comparison Matrix (Respondent No.1).

Sub-Factors	Average Daily Traffic (ADT)	Roughness Measuremen ts	Transverse Cracking Amount	Rutting Amount
Average Daily Traffic (ADT)	1	1/2	1/3	1
Roughness Measurements	2	1	2/3	2
Transverse Cracking Amount	3	3/2	1	3
Rutting Amount	1	1/2	1/3	1

5.1.5 Reliability Test:

After filling the matrices with numerical values based on a scale of relative importance (1-9), this scale was tested to see whether its measuring values were reliable or not. In other words, can we rely on these scores in building our model or not?

The reliability of the nine-point scale used in this study was determined by applying Cronbach's alpha test, which is a widely used measure of reliability (Wei *et al.,* 2007).

Cronbach's alpha (α) is an index with values between (0-1) for estimating the reliability of a scale containing several items.

According to (Kaplan *et at.*, 1993) the lowest acceptable limits of (α) are 0.50 -0.60, and the closer (α) is to 1.00, the better the internal consistency of the items in the scale being assessed. Table 5-5 shows the results of the reliability analysis, Physical properties has the lowest reliability coefficient ($\alpha = 0.552$) but within the acceptable range (0.5-0.6); thus their results were included in the model.

Table 5-5: Reliability Results of the Measuring Scale.

Variable	Cronbach's (α)	Reliability
Main Factors	0.998	High
Climate Conditions	0.781	High
Physical Properties	0.552	Low (acceptable)
Operational Factors	0.957	High

Since all the reliability results range between 0.552 – 0.998, the scale can be considered reliable with the sample and priority vectors can now be calculated based on the values in the matrices.

5.1.6 Establish Priority Vector:

Having a comparison matrix filled with priority values ranging from 1-9, we can now perform the computing of priority vectors. The priority vector is the normalized eigen vector of the matrix using Saaty's methodology (1982). Since it is normalized, the sum of all elements in each comparison matrix is equal to 1. The priority vector (weighting vector W_i) shows relative weights among the factors that we compare. In our study, Table 5-6 shows those weights (W_i) in which the **Operational** factors have the highest effect on the condition of flexible-pavement with a weight of **(0.571)**, followed by the **Physical** properties with a weight of **(0.286),** and at last the **Climate** conditions with a weight of **(0.143)**. On the other hand, within the Climate conditions, freezing temperature has the highest weight of (0.545); pavement age weight is also the highest in Physical properties (0.500); and finally Transverse Cracking Amount has the highest weight of (0.428) in Operational factors.

5.1.7 Checking the Consistency of the Judgments:

In this step the Consistency Index (CI) and the Consistency Ratio (CR) are both used to verify the logical consistency of the priority weights. Table 5-6 presents the values of CI and CR for all main and sub factors.

Table 5-6: Weighting Vector; Consistency Index; Consistency Ratio Values for Pair-wise Matrices, (Table 5-1 to 5-4), filled by "Respondent No.1".

Factors	Weights (W_i)	C.I	C.R (%)
Climate Conditions	0.143	0.00	0.00
Physical Properties	0.286		
Operational Factors	0.571		
Air Temperature	0.182	0.00	0.00
Pavement Temperature	0.182		
Rainfall Amount	0.091		
Freezing Temperature	0.545		
Surface Layer Depth	0.250	0.00	0.00
Base Layer Depth	0.250		
Pavement Age	0.500		

Factors	Weights (W_i)	C.I	C.R (%)
Average Daily Traffic (ADT)	0.142	0.00	0.00
Roughness Measurements	0.287		
Transverse Cracking Amount	0.428		
Rutting Amount	0.143		

The previous results show values of CR ≤ 10%, which means that all the matrices received from practitioners were consistent, and thus the weight vectors are accepted and can be incorporated in the proposed model.

In Table 5-7, the final weighting vectors (W_i) for the ten questionnaires are presented.

Table 5-7: Weighting Vectors Values (W_i) of the Ten Received Questionnaires.

Factors	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Climate Conditions	**0.143**	**0.111**	**0.100**	**0.100**	**0.125**	**0.100**	**0.143**	**0.100**	**0.100**	**0.167**
Air Temperature	0.182	0.125	0.143	0.307	0.125	0.222	0.223	0.167	0.111	0.105
Pavement Temperature	0.182	0.125	0.286	0.308	0.250	0.223	0.222	0.167	0.111	0.053
Rainfall Amount	0.091	0.250	0.143	0.077	0.125	0.111	0.111	0.333	0.222	0.316
Freezing Temperature	0.545	0.500	0.428	0.308	0.500	0.444	0.444	0.333	0.556	0.526
Physical Properties	**0.286**	**0.333**	**0.300**	**0.300**	**0.250**	**0.300**	**0.286**	**0.201**	**0.300**	**0.333**
Surface Layer Depth	0.250	0.400	0.322	0.333	0.571	0.462	0.200	0.322	0.222	0.333
Base Layer Depth	0.250	0.400	0.194	0.333	0.286	0.308	0.400	0.484	0.111	0.333
Pavement Age	0.500	0.200	0.484	0.334	0.143	0.230	0.400	0.194	0.667	0.334
Operational Factors	**0.571**	**0.556**	**0.600**	**0.600**	**0.625**	**0.600**	**0.571**	**0.699**	**0.600**	**0.500**
Average Daily Traffic (ADT)	0.142	0.143	0.100	0.083	0.111	0.100	0.100	0.077	0.125	0.083
Roughness Measurements	0.287	0.286	0.200	0.333	0.111	0.200	0.300	0.384	0.125	0.167
Transverse Cracking Amount	0.428	0.286	0.400	0.334	0.556	0.400	0.500	0.385	0.500	0.333
Rutting Amount	0.143	0.285	0.300	0.250	0.222	0.300	0.100	0.154	0.250	0.417

5.1.8 Decomposed Priority Weights:

In this step, the decomposed weight of each sub-factor (which represents its overall weight among its group) will be calculated. Equation (5-1) shows the calculation of the decomposed weight of a sub-factor by multiplying the main factor weight by its sub-factor weight (Al-Barqawi and Zayed, 2006).

$$SDW_{ij} = W_i * V_{ij} \qquad \text{Eq: (5-1)}$$

Where: SDW_{ij}: sub-factor decomposed weight. W_i: weight of main factor i. V_{ij}: weight of sub-factor j within the main factor i.

As an example, Equation (5-1) is applied to the "Respondent No.1" and the results with the overall weights for sub-factors are shown in Table 5-8.

Table 5-8: Sub-factors Decomposed Weights.

Sub-Factor	W_i	V_{ij}	SDW_{ij}
Air Temperature	0.143	0.182	0.026
Pavement Temperature	0.143	0.182	0.026
Rainfall Amount	0.143	0.091	0.013
Freezing Temperature	0.143	0.545	0.078
Surface Layer Depth	0.286	0.250	0.072
Base Layer Depth	0.286	0.250	0.072
Pavement Age	0.286	0.500	0.143
Average Daily Traffic (ADT)	0.571	0.142	0.081
Roughness Measurements	0.571	0.287	0.164
Transverse Cracking Amount	0.571	0.428	0.244
Rutting Amount	0.571	0.143	0.082

A similar application of Equation (5-1) was repeated for all of the 10 received respondents, and as a result, the final weight of each main factor with its sub-factors was determined as the average of the ten values. Table 5-9 shows the values of the final weights, in which it is noticed that ***Operational factors*** contribute in condition assessment of flexible-pavement with (59%), ***Physical Properties*** with (29%), and finally ***Climate Conditions*** with (12%). Figure 5-2 graphically presents the final weights of the three main factors in condition-rating assessment.

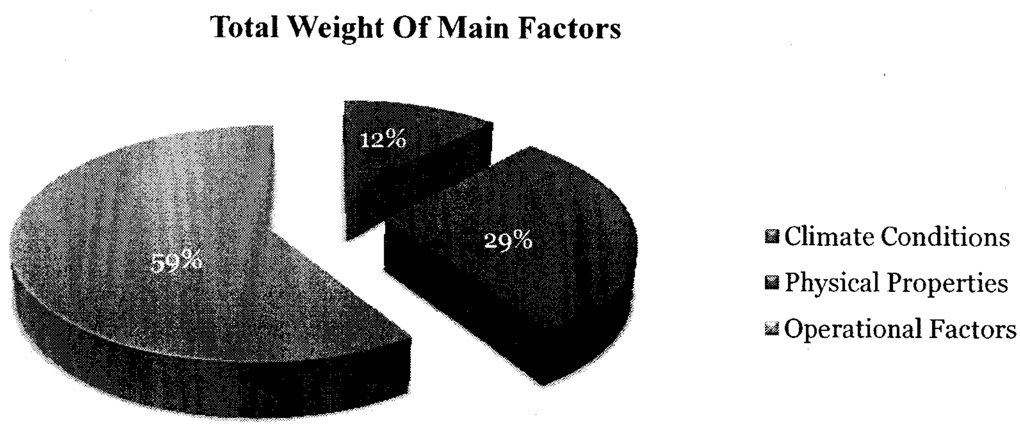


Figure 5-2: Total Weights of Main Factors in Condition-Rating Assessment.

Accordingly, the final contribution of each main factor and sub-factor to the condition of flexible-pavement is shown in Table 5-9. The weight of each main-factor and sub-factor is calculated by taking the average (mean) of the ten received questionnaires. Computing the average value is valid since no outliers were found in the ten observations. Along with the average (mean) values, both the variance and the standard deviation are calculated as well. The minimum standard deviation value is (0.007), corresponding to the sub-factor "Air Temperature" which means that the air temperature data (ten values) is more clustered together around the average. On the other hand, the maximum standard deviation value is (0.062), corresponding to the sub-factor "Roughness Measurements" which means that the roughness measurements data (ten values) is more spread out from the average. The highest contributing sub-factor is "Transverse Cracking Amount" (Operational-24.40%); then "Rutting Amount" (Operational-14.30%) with approximately the same contribution of "Roughness Measurements" (Operational-14.20%). On the other hand, the least sub-factor is "Air Temperature" (Climate-2.00%).

Figure 5-3 graphically presents the final weights of sub-factors in the MAUT condition-rating model.

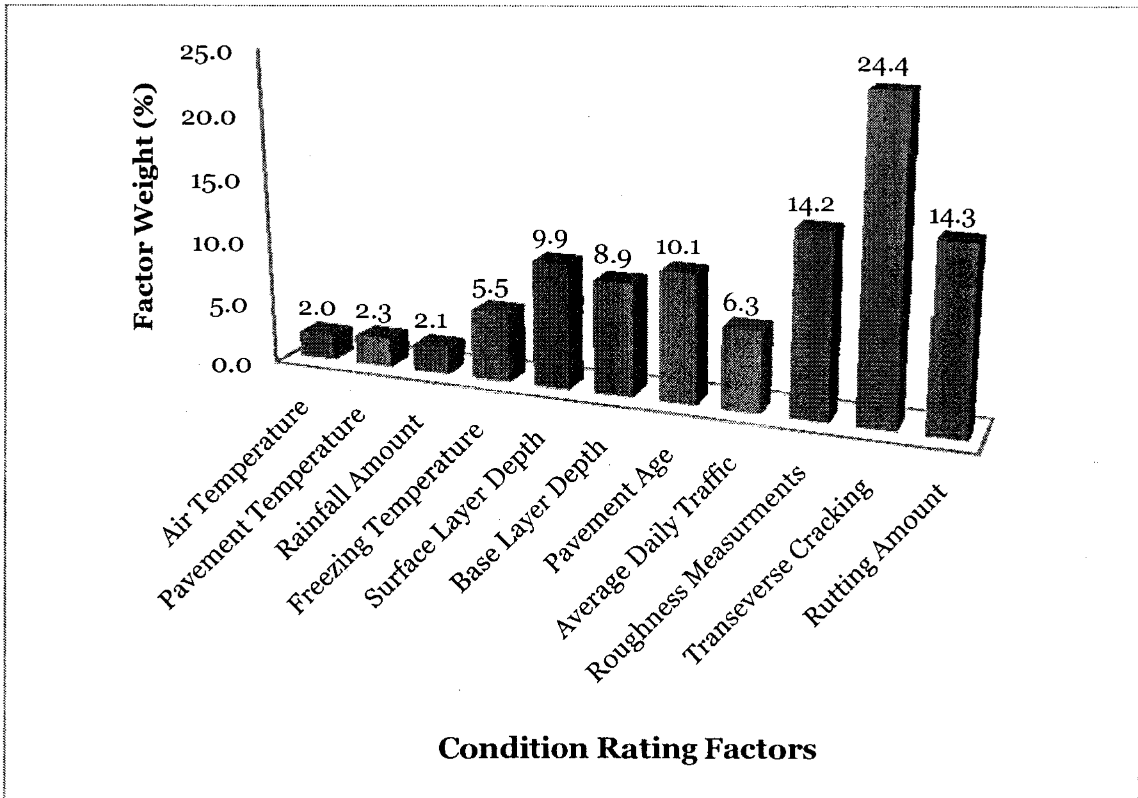


Figure 5-3: Total Weights of Sub-Factors Included in MAUT Model.

Table 5-9: The Final Weights of Main and Sub-Factors in the MAUT Condition-Rating Model.

Factors	Average (W_i)	Variance	Std. Dev
Climate Conditions	**0.119**	**0.00060**	**0.024**
Air Temperature	0.020	0.00005	0.007
Pavement Temperature	0.023	0.00008	0.009
Rainfall amount	0.021	0.00018	0.014
Freezing Temperature	0.055	0.00034	0.018
Physical Properties	**0.289**	**0.00152**	**0.039**
Surface Layer Depth	0.099	0.00106	0.033
Base Layer Depth	0.089	0.00088	0.030
Pavement Age	0.101	0.00267	0.052
Operational Factors	**0.592**	**0.00260**	**0.051**
Average Daily Traffic (ADT)	0.063	0.00016	0.013
Roughness Measurements	0.142	0.00038	0.062
Transverse Cracking Amount	0.244	0.00349	0.059
Rutting Amount	0.143	0.00219	0.047

5.1.9 Attributes Utility Functions (U_{ij}):

Owing to the fact that each sub-factor may have several attributes that differ in their impact on flexible-pavement condition, the utility score (U_{ij}) of each attribute was used. The modeling survey was designed to provide preference scores for selected sub-factors required to estimate the utility-scoring functions. Respondents were asked to evaluate the impact of each sub-factor by assessing its different attributes. The respondents had provided scores for each level (attribute) of a particular sub-factor. These scores were provided on a scale of 0 to 10, where (0) means the lowest negative effect of an attribute and (10) means the highest positive effect. Moreover, given that the objectives are to obtain multi-attribute utility functions based on experts' preferences, a mean-score approach was adopted. The mean-score approach of each attribute is based on averaging scores derived from several respondents, which represents the single-attribute utility function for that attribute.

A sample of the received data (scores) from experts (respondents) is presented in Table 5-10, in which a utility score is assigned for each attribute's value of sub-factor (Roughness Measurements).

Table 5-10: Utility Values of Sub-Factor's (Roughness Measurements) Attributes.

Roughness Measurements (mm/m)	Response 1	Response 2	Response 3	Response 4	Response 5	Response 6	Response 7	Response 8	Response 9	Response 10	Average
Smooth ($R_M \leq 2.48$)	8	8	7	9	7	8	7	8	9	8	7.9
Moderate ($2.49 \leq R_M \leq 3.33$)	4	5	5	6	4	5	5	5	6	5	5.0
Rough ($3.34 \leq R_M \leq 6.18$)	3	1	2	1	2	2	2	1	2	2	1.8

Table 5-11 shows the final averaged utility scores for all the sub-factors' attributes, based on the proposed scale.

Table 5-11: Utility Scores (U_{ij}) for Sub-Factors' Attributes.

Attribute	Utility	Attribute	Utility
1.1 Air Temperature (T_a)		**2.2 Surface Layer Depth (SDL)**	
$0\,^\circ C \leq T_a < 10\,^\circ C$	5.2	SDL < 2 in	2.1
$10\,^\circ C \leq T_a < 22\,^\circ C$	7.9	SDL ≥ 2 in	5.8
$T_a \geq 22\,^\circ C$	3.5		
1.2 Pavement Temperature (T_P)		**2.3 Base Layer Depth (BDL)**	
$T_P \geq \lvert -22\,^\circ C \rvert$	0.8	BDL ≥ 4 in	3.5
$\lvert -22\,^\circ C \rvert > T_P \geq \lvert -10\,^\circ C \rvert$	1.3	BDL ≥ 4 in	7.0
$\lvert -10\,^\circ C \rvert > T_P > \lvert 0\,^\circ C \rvert$	2.3		
$0\,^\circ C \leq T_P < 10\,^\circ C$	3.6	**3.1 Average Daily Traffic (ADT)**	
$10\,^\circ C \leq T_P < 22\,^\circ C$	7.0	Low (ADT < 20 vch/day)	8.2
$T_P \geq 22\,^\circ C$	4.1	Moderate (20 ≤ ADT ≤ 100)	4.8
		Heavy (ADT > 100 vch/day)	1.9
1.3 Rainfall Amount (R_F)		**3.2 Transverse Cracking Amount (Crk)**	
Low: $R_f < 0.5$ mm/hr	7.1	Low (Crk < 13 mm)	8.2
Moderate: $0.5 \leq R_f < 3$ mm/hr	5.4	High (Crk ≥ 13 mm)	3.3
High: $R_f \geq 3$ mm/hr	2.5		
1.4 Freezing Temperature (T_F)		**3.3 Roughness Measurements (R_M)**	
$T_F \geq \lvert -22\,^\circ C \rvert$	0.7	Smooth ($R_M \leq 2.48$ mm/m)	7.9
$\lvert -22\,^\circ C \rvert > T_F \geq \lvert -10\,^\circ C \rvert$	1.4	Moderate ($2.49 \leq R_M \leq 3.33$)	5.0
$\lvert -10\,^\circ C \rvert > T_F > \lvert 0\,^\circ C \rvert$	2.6	Rough ($3.34 \leq R_M \leq 6.18$ mm/m)	1.8
2.1 Pavement Age		**3.4 Rutting Amount (Rut)**	
Less than 5 yrs	8.6	Low (Rut ≤ 9 mm)	7.7
5 yrs ≤ Age < 9 yrs	7.9	Moderate (10 mm ≤ Rut ≤ 13 mm)	6.9
9 yrs ≤ Age < 12 yrs	6.2	High (14 mm ≤ Rut ≤ 20 mm)	3.8
12 yrs ≤ Age < 14 yrs	4.2	Critical (Rut > 20 mm)	1.5
Equal to 15 yrs	1.5		
16 yrs ≤ Age < 19 yrs	7.8		
19 yrs ≤ Age < 22 yrs	5.0		
22 yrs ≤ Age < 26 yrs	4.4		
26 yrs ≤ Age < 30 yrs	1.9		
More than 30 yrs	1.2		

°C: degree Celsius.
mm/hr: millimeters per hour
in: inch.
yrs: years.

vch/dy: vehicles per day.
mm/m: millimeters per meter.
mm: millimeters.

Accordingly, in order to represent the relationship between the values of attributes and utility scores, utility functions were constructed. Scores of the different attributes obtained from the responses were used to model the utility functions. A wide variety of functional forms and transformations were investigated. Models were fitted using mean-scores and individual-level scores. The ability of each function to reproduce utility scores directly was assessed. After all the investigations, the following functions emerged as the best functional form for converting attributes values into utility scores. (An example of one of the sub-factor's utility functions will be explained here; the rest will be illustrated in Appendix E).

Figure 5-4 shows the Average Daily Traffic (ADT) utility scores (0-10) towards its range of attributes values (ADT in vehicles per day) based on collected questionnaires. A quadratic function does exist, and tells that the greater the ADT value is, the smaller the utility score is, and the more negative impact the ADT have on the pavement condition.

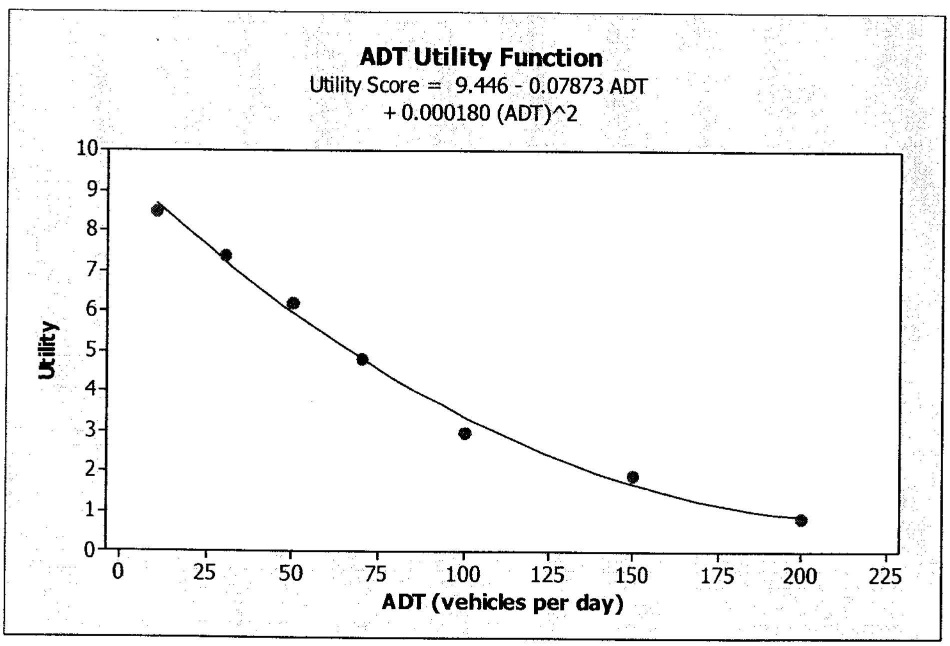


Figure 5-4: Utility Function of the Sub-factor (ADT) Attributes.

5.1.10 Condition Rating Scores:

Finally, the overall condition-rating score is generated mathematically by multiplying the decomposed weight of each sub-factor (Table 5-9) with the utility score of each sub-factor attribute (Table 5-11), followed by a summation of results of each criterion within the road segment. The following Equation was used for both summer and winter cases:

$$\mathrm{CR} = \sum_{j=1}^{m} \mathrm{SDWij} * \mathrm{Uij} \qquad \text{Eq: (5-2)}$$

Where:

m: number of sub-factors *j*.

SDW_{ij}: sub-factor decomposed weight.

U_{ij}: utility score of each sub-factor *j* within the main factor *i*.

5.1.11 The MAUT Model Application:

Based on the developed MAUT model (Equation 5-2) condition-rating scores of each highway segment are calculated for the available data sets (NDOR "Tab files") as shown in Table 5-12. Once the condition of each pavement section has been defined, multiple regression analysis is applied in order to build the most appropriate condition-rating models for flexible pavement.

Table 5-12: Sample of Condition Rating Results for Summer Model for Year 1997.

Highway Number	Section	Air Temp ^0C	Pav Temp ^0C	Rainfall Amount (mm/hr)	Surface Layer Depth (inch)	Base Layer Depth (inch)	AGE (years)	ADT (vch/dy)	Rough Amount (mm/m)	Trans Crack Amount (mm)	Rutting Amount (mm)	Condition Rating
L 01 E	1	29.44	26.99	1.13	3.0	8.5	4	25	3.55	0.20	5.0	6.3
L 02 C	1	30.56	27.95	1.15	2.0	5.0	19	20	1.38	27.30	3.0	5.2
	2	30.56	27.95	1.15	2.0	5.0	18	20	3.31	27.30	5.0	4.8
L 05 B	1	30.56	27.95	0.93	4.0	8.0	5	15	1.09	0.70	13.0	6.3
L 06 A	1	28.89	26.52	1.14	2.0	10.0	22	15	4.29	0.00	0.0	5.8
L 10 B	1	29.44	26.99	0.77	2.0	4.0	34	125	3.18	0.00	3.0	5.8
	2	29.44	26.99	0.77	2.0	4.0	34	125	3.43	51.80	6.0	3.8
L 10 C	1	28.89	26.52	0.77	4.0	12.0	34	130	3.18	0.00	3.0	5.8
	2	28.89	26.52	0.77	4.0	12.0	10	130	1.64	10.20	6.0	6.3
	3	28.89	26.52	0.77	4.0	12.0	14	140	2.07	0.00	3.0	6.3
L 10 D	1	29.44	26.99	1.25	3.0	8.0	24	80	4.30	4.40	3.0	5.8
	2	29.44	26.99	1.25	3.0	8.0	24	80	3.20	37.00	8.0	4.4
L 14 D	1	29.44	26.99	1.28	3.0	8.0	5	50	2.13	16.70	14.0	4.7
	2	29.44	26.99	1.28	3.0	8.0	27	50	3.52	0.00	15.0	4.9
L 17 B	1	30.00	27.47	0.94	2.0	4.0	23	40	2.86	0.00	1.0	6.1
	2	30.00	27.47	0.94	2.0	4.0	23	40	0.00	0.00	0.0	6.4
L 17 C	1	29.44	26.99	0.80	2.0	6.0	23	30	2.89	0.00	2.0	6.1
	2	29.44	26.99	0.80	2.0	6.0	23	30	2.34	17.30	6.0	4.6

5.2 INTEGRATED MAUT/REGRESSION MODEL

5.2.1 Introduction:

This chapter presents an integrated MAUT/Regression model for evaluating the condition of flexible-pavement. It considers the impact of different climate condition, physical properties, and operational factors on the overall condition of flexible pavement. As mentioned before, the output (condition-rating score) was not included in the received historical data; therefore the MAUT model was developed to provide this missing value. However, the application of multiple regression analysis is focused on building the most appropriate models for condition assessment of flexible-pavement. Figures 3-3 and 3-4 presented the applied methodologies for building and validating the proposed model. The detailed explanation of these methodologies will be described in the following sections.

5.2.2 Model Development Process:

As stated earlier, the current research deals with two sets of data. One set is based on the NDOR "Tab files" contains the real values of the considered sub-factors in this study. Yet another set consists of the questionnaires' responses corresponding to the MAUT condition-rating model. The two sets of data were combined and stored in Microsoft Excel because of its capability of turning easily among various tasks. Then, for data processing and the model development phase, Minitab ® 15 statistical software is used. According to (Kulandaivel, 2004) Minitab ® 15 is one of the most powerful, flexible, and easy to use statistical software packages.

Many regression models are designed in order to cover the wide range of influence that predictor variables (sub-factors) have on response output (condition-rating score).

Based on temperature variations between the yearly seasons, two models were built (for summer and winter seasons). Only the building process of the summer model is presented in detail (the winter model can be found in Appendix B). The model development steps are as follows:

5.2.2.a Initial examination of relationships and interactions:

Prior to modeling the data in hand, it is recommended that we first plot the data points. Then by examining these initial plots we can easily assess whether the data have linear relationships or interactions are present.

An X variable (e.g. ADT) that has a linear relationship with Y (condition-rating) will produce a plot close to a straight line, as shown in Figure B-1a (Appendix B), which is the ideal case. However, some exceptions may come across our own modeling, such as in Figure B-1b, c, and d (Appendix B), where transformation of variables should be taken into consideration in order to get better results.

In the current study, plotting each input variable (sub-factor) against the output variable (condition rating-CR) resulted in three patterns of figures:

Pattern One, in which the data plot looks like Figure B-1b (Appendix B), and a transformation of variable X to ($\sqrt{X}$) was applied. Six sub-factors followed pattern one in their relation with the output CR (condition rating), which are (rainfall amount, pavement age, ADT, roughness measurements, transverse cracking amount, and rutting amount). Figure 5-5 is an example of pattern one between the sub-factor "Transverse cracking-Tran Crak" and the output (CR).

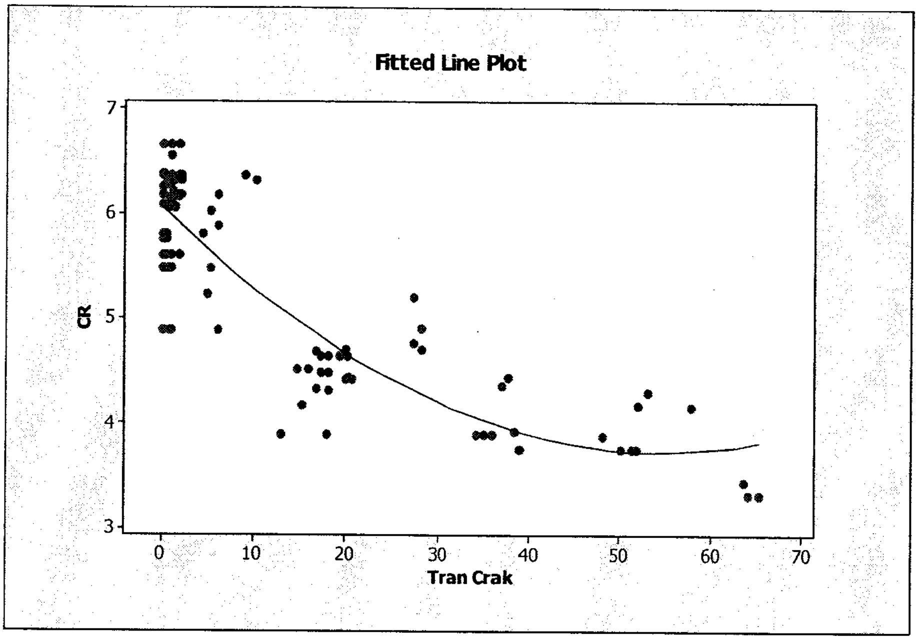


Figure 5-5: Plot of Transverse Cracking (Tran Crak) against Condition Rating (CR).

Pattern Two, in which the data plot looks like Figure B-1d (Appendix B), and it is recommended to transform the variable X to Log X. Two sub-factors followed pattern two in their relation with the output CR (condition-rating), which are (Air Temperature and Pavement Temperature). Figure 5-6 is an example of pattern two between the sub-factor "Air Temperature-Air Temp" and the output (CR).

Pattern Three, in which the data plot looks like Figure B-1a (Appendix B), which is the ideal case, and there is no need for any transformation to be applied. Two sub-factors followed pattern three in their relation with the output CR (condition-rating), which are (Surface Layer Depth, and Base Layer Depth). Figure 5-7 is an example of pattern three between the sub-factor "Surface Layer Depth-SLD" and the output (CR).

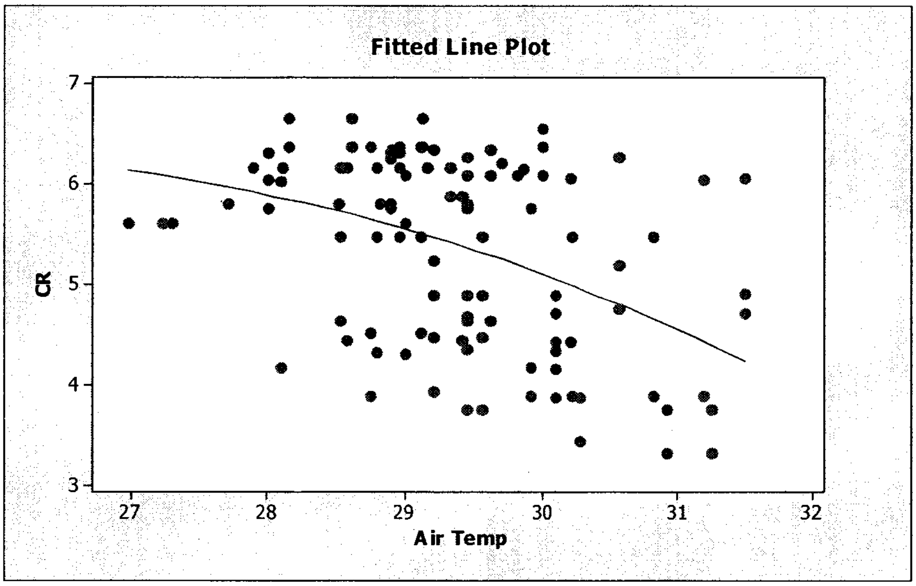


Figure 5-6: Plot of Air Temperature (Air Temp) against Condition Rating (CR).

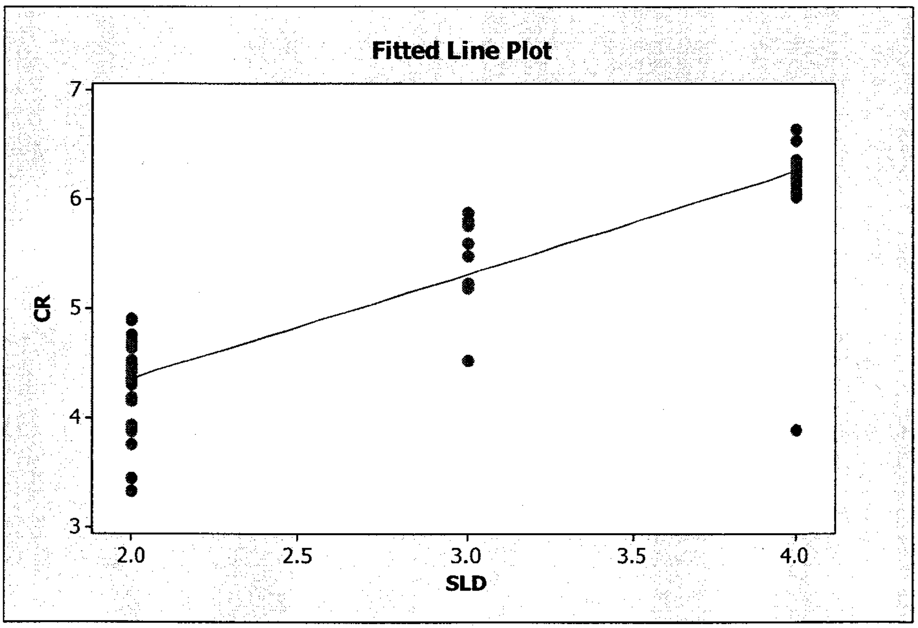


Figure 5-7: Plot of Surface Layer Depth (SLD) against Condition Rating (CR).

5.2.2.b Testing for Multi-colinearity:

The statistical phenomenon (multi-colinearity) refers to a situation in which two or more predictor variables are highly correlated in a multiple regression model. A perfect multi-colinearity between two or more independent variables means a correlation value equal to 1 or -1. The multi-colinearity presence leads to some of the following consequences; the estimation of the impact of an explanatory variable X on its dependent variable Y tends to be less accurate and precise than if independent variables were not correlated with one another, which means that the two independent variables with high correlation will contribute redundant information to the multiple regression models. Another consequence will be the producing of unstable coefficients for the model (large standard error and low t values.)

In the current study, multi-collinearity will be investigated by calculating the sample correlation matrix for the independent variables. The correlation matrix for the summer model with its ten independent variables before and after transformation is constructed as shown in Figures 5-8 and 5-9.

Correlations: Air Temp, Pav Temp, Rain, AGE, SLD, BLD, ADT, Rough, ...

	Air Temp	Pav Temp	Rain	AGE	SLD	BLD
Pav Temp	0.764					
Rain	0.275	0.183				
AGE	0.062	0.157	-0.281			
SLD	-0.061	-0.115	-0.118	-0.300		
BLD	-0.361	-0.345	-0.118	-0.293	0.849	
ADT	-0.098	0.020	-0.201	0.181	0.362	0.289
Rough	0.254	0.230	0.301	0.302	0.015	0.128
Tran Crak	0.484	0.383	0.285	0.219	-0.042	-0.143
Rutt	0.300	0.118	0.369	-0.368	0.332	0.151

	ADT	Rough	Tran Crak
Rough	0.033		
Tran Crak	0.058	0.274	
Rutt	-0.171	0.000	0.291

Cell Contents: Pearson correlation

Matrix Plot of Air Temp, Pav Temp, Rain, AGE, SLD, BLD, ADT, ...

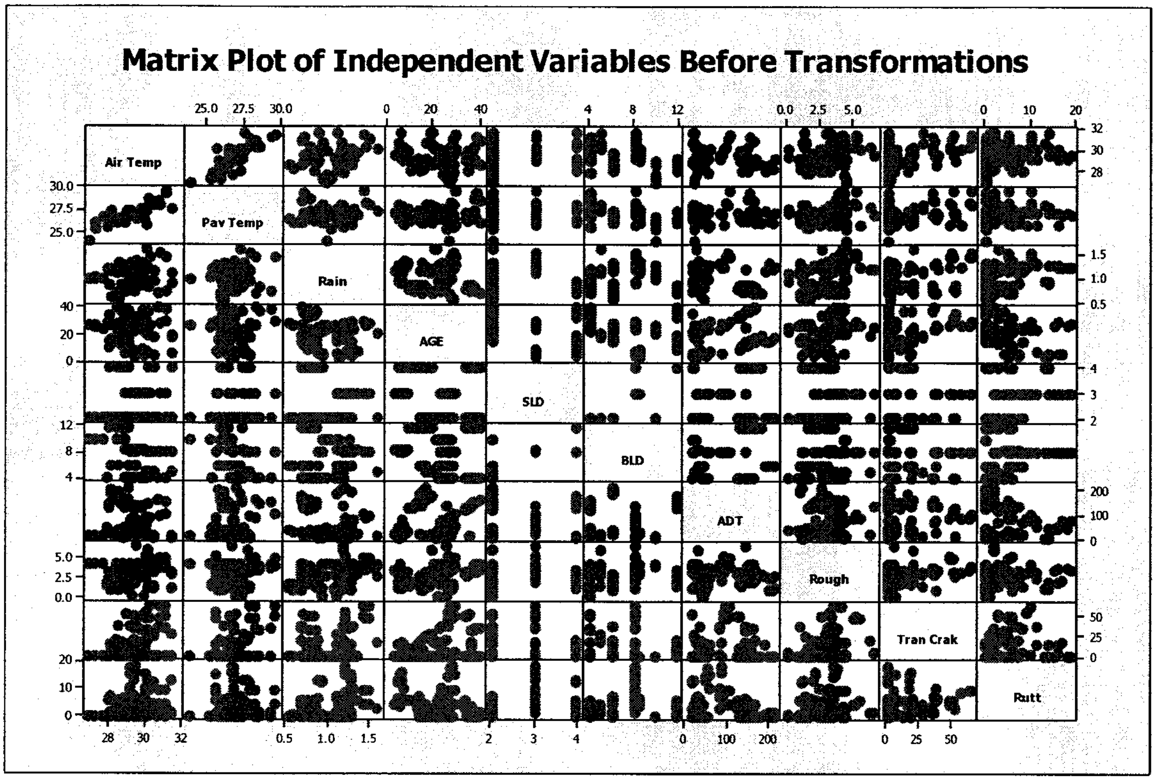


Figure 5-8: Correlation Matrix Plot of Summer Model Input Variables before Transformation.

Correlations: Log Air Temp, Log Pav Temp, √Rain, √AGE, SLD, BLD, √ADT,

	Log Air Temp	Log Pav Temp	√Rain	√AGE
Log Pav Temp	0.763			
√Rain	0.267	-0.174		
√AGE	0.024	0.123	-0.267	
SLD	-0.059	-0.114	-0.119	-0.332
BLD	-0.362	-0.347	-0.118	-0.296
√ADT	-0.074	0.028	-0.194	0.206
√Rough	0.210	0.180	0.243	0.249
√Tran Crak	0.466	0.341	0.255	0.148
√Rutt	0.376	0.183	0.391	-0.430

	SLD	BLD	√ADT	√Rough
BLD	0.849			
√ADT	0.383	0.284		
√Rough	0.053	0.165	0.067	
√Tran Crak	-0.040	-0.147	0.077	0.221
√Rutt	0.304	0.119	-0.111	0.071

	√Tran Crak
√Rutt	0.462

Cell Contents: Pearson correlation

Matrix Plot of Log Air Temp, Log Pav Temp, √Rain, √AGE, SLD, BLD, ...

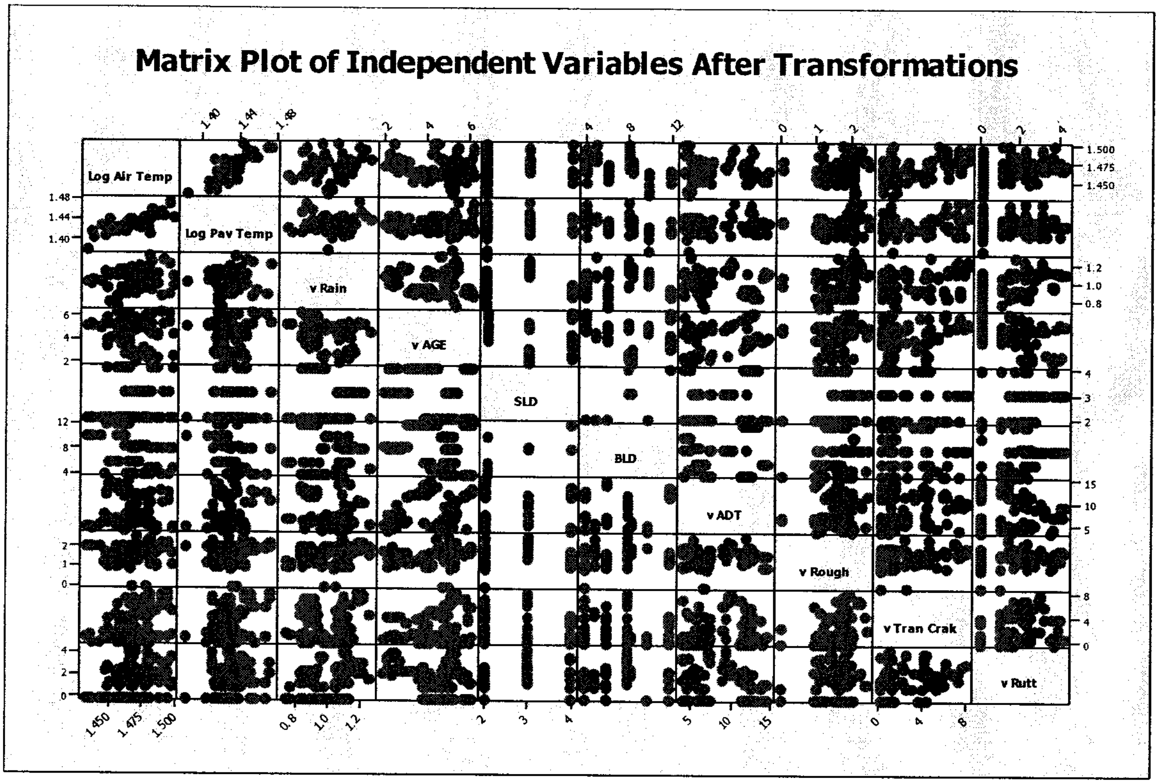


Figure 5-9: Correlation Matrix Plot of Summer Model Input Variables after Transformation.

Recall that a correlation value greater than 0.7 (in absolute value) generally indicates multi-collinearity is a problem. Both Figures (5-8 and 5-9) show existing relationships and interactions between some variables. However, they are weak relationships based on the weak (positive and negative) correlation values in both cases (before and after transformation). The only two exceptions are the positive correlation coefficient between the two variables (Air Temperature and Pavement Temperature) before (0.764) and after (0.763) transformation, and the positive correlation coefficient (0.849 before and after) between (Surface Layer Depth and Base Layer Depth).

Usually, in similar cases when two variables are highly correlated, a decision should be made to eliminate the one that is "logically" less important.

For this study, a statistical parameter called variance inflation factor (VIF) is used to determine the severity of multi-colinearity and which variables should be eliminated.

5.2.2.c Variance Inflation Factor (VIF):

By definition, VIF is a statistical index that measures how much the variance of an estimated regression coefficient (square of the standard deviation) is increased because of colinearity. In other words, VIF quantifies the severity of multi-colinearity.

For example, if the variance inflation factor of an independent variable equals 9, it means that the standard error of the coefficient of this independent variable is ($\sqrt{9} = 3$) times larger than it would be if the mentioned independent variable was not correlated with another independent variable.

A common rule of thumb is that, if any independent variable's VIF > 5 then multi-colinearity is high, and the variable should be eliminated from the regression model. Also the value of 10 has been proposed by (Kutner *et al.*, 2005) as a cut off value.

In the current study, the following steps regarding VIF are applied:

1. Fit regression model with VIF values for the set of selected independent variables.
2. If any VIF > 5, then we have to eliminate the variable with highest VIF, or in case of all VIF $\leq$ 5 then we have to proceed directly to step 4.

3. Fit regression model with VIF values for the new model without the deleted variable.

4. Perform best-subsets regression with remaining explanatory variables.

Figures 5-10 and 5-11 show an example of Minitab output for VIF.

- Fit regression model with VIF values for the set of selected independent variables.

Regression Analysis: CR versus Log Air Temp, Log Pav Temp, ...

Predictor	Coef	SE Coef	T	P	VIF
Constant	11.823	5.638	2.10	0.038	
Log Air Temp	0.933	4.887	0.19	0.849	3.877
Log Pav Temp	-3.519	3.829	-0.92	0.360	2.551
√Rain	-0.0126	0.3245	-0.04	0.969	1.522
√AGE	-0.26426	0.04578	-5.77	0.000	2.041
SLD	0.1089	0.1166	0.93	0.352	7.427
BLD	-0.05375	0.03376	-1.59	0.114	7.678
√ADT	0.00343	0.01282	0.27	0.790	1.524
√Rough	-0.2896	0.1062	-2.73	0.007	1.652
√Tran Crak	-0.27242	0.01921	-14.18	0.000	1.844
√Rutt	-0.18654	0.03988	-4.68	0.000	2.386

Highest VIF > 5

S = 0.370945   R-Sq = 86.1%   R-Sq(adj) = 84.8%

Figure 5-10: Minitab Output of VIF Test for all Independent Variables versus the Output CR.

- The independent variable (Base Layer Depth-BLD) is eliminated from the model, and step one is repeated with the new data set.

Regression Analysis: CR versus Log Air Temp, Log Pav Temp, ...

Predictor	Coef	SE Coef	T	P	VIF
Constant	6.118	4.383	1.40	0.166	
Log Air Temp	4.627	4.332	1.07	0.288	3.003
Log Pav Temp	-3.269	3.853	-0.85	0.038	2.547
√Rain	-0.0242	0.3267	-0.07	0.041	1.522
√AGE	-0.25079	0.04531	-5.54	0.000	1.971
SLD	-0.05188	0.05867	-0.88	0.047	1.854
√ADT	0.00699	0.01271	0.55	0.054	1.478
√Rough	-0.36730	0.09494	-3.87	0.000	1.303
√Tran Crak	-0.27707	0.01912	-14.49	0.000	1.801
√Rutt	-0.17380	0.03935	-4.42	0.000	2.290

```
S = 0.373547   R-Sq = 85.8%   R-Sq(adj) = 84.6%
```

Figure 5-11: Minitab Output of VIF Test for all Independent Variables except (BLD) versus the Output CR.

- All VIF ≤ 5, now we can proceed to the next step, which is best-subset analysis.

5.2.2.d Best-Subset Analysis:

Upon concluding that the variance inflation factor VIF for all the selected variables is ≤ 5, the best-subset analysis can be applied. Best-subset analysis is defined as the process of constructing the best fit regression model with the best possible combinations of the selected variables.

In best-subset regression, three statistics should be investigated as follows:

1. **The Measure of the fit of the model (C_p),** calculated using the following equation:

$$Cp = \frac{SSEp}{MSE(X_1 \ldots . X_{p-1})} - (n - 2p) \qquad \text{Eq: (5-3)}$$

Where:

- SSEp: is the error sum of squares for the fitted subset regression model with p parameter (p-1).
- n: is the number of observations.
- MSE ($X_1 \ldots\ldots X_{p-1}$): is an unbiased estimate of variance.

It is recommended that the value of C_p be less than or equal to p + 1, where p is the number of variables in the model.

2. **Standard deviation of residuals (S),** (where S=√MSE: Mean standard Error) the estimation of the standard deviation is preferred to be as low as possible, so when S is large, the denominator of F-ratio, $F = \frac{MSR}{MSE}$ is also large, which makes the F-ratio smaller and possibly statistically insignificant.
3. **R^2 (adj)**, the closer the value of R^2 (adj) to 1 (100%) the better the results are, without creating other problems such as multi-colinearity.

Figure 5-12 presents an example of Minitab output for best-subset analysis.

Best Subsets Regression: CR versus Log Air Temp, Log Pav Temp, ...

Response is CR

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Log Air Temp	Log Pav Temp	√Rain	√AGE	SLD	√ADT	√Rough	√Tran Crak	√Rutt
1	76.2	76.0	67.8	0.46692								X	
1	20.9	20.3	491.9	0.85078									X
2	80.6	80.3	35.9	0.42318							X	X	
2	79.3	79.0	45.6	0.43683				X				X	
3	83.2	82.8	18.0	0.39561				X				X	X
3	82.4	81.9	24.2	0.40498				X			X	X	
4	85.5	85.0	1.9	0.36851				X			X	X	X
4	83.4	82.8	18.2	0.39460				X	X			X	X
5	85.6	85.0	3.3	0.37909				X	X		X	X	X
5	85.6	85.0	3.4	0.37923	X			X			X	X	X
6	85.7	84.9	4.8	0.37991	X	X		X			X	X	X
6	85.7	84.9	4.9	0.36205	X			X	X		X	X	X
7	85.8	84.9	6.3	0.36169	X	X		X	X		X	X	X
7	85.7	84.8	6.7	0.36140	X			X	X	X	X	X	X
8	85.8	84.8	8.0	0.36185	X	X		X	X	X	X	X	X
8	85.8	84.7	8.3	0.36236	X	X	X	X	X		X	X	X
9	85.8	85.6	10.0	0.36094	X	X	X	X	X	X	X	X	X

Figure 5-12: Minitab Output for Best-Subset Analysis for Summer Condition-Rating Trial Model.

From Figure 5-12 the selected model is the most appropriate combination of variables, as it satisfies the previous three statistics, with $C_p = 10 \leq p + 1 = 9 + 1 = 10$, the lowest S value = 0.36094, and the highest R^2 (adj) = 85.6.

5.2.2.e Model Development:

After determining the most appropriate combination of variables based on best-subset analysis, the next step will be building a multiple regression model for both summer and winter cases using Minitab ® 15 statistical software. Figure 5-13 presents the Minitab output that includes a regression equation of all the selected variables with their estimated coefficients "β_k", the coefficient of determination R^2 and R^2 (adjusted) , and the overall significance of the regression (P value).

Regression Analysis: CR versus Log Air Temp, Log Pav Temp, ...

```
The regression equation is
CR = 6.12 + 4.63 Log Air Temp - 3.27 Log Pav Temp - 0.024 √Rain - 0.251 √AGE
     - 0.0519 SLD + 0.0070 √ADT - 0.367 √Rough - 0.277 √Tran Crak - 0.174 √Rutt
```

Predictor	Coef	SE Coef	T	P
Constant	6.118	4.383	1.40	0.166
Log Air Temp	4.627	4.332	1.07	0.288
Log Pav Temp	-3.269	3.853	-0.85	0.038
√Rain	-0.0242	0.3267	-0.07	0.041
√AGE	-0.25079	0.04531	-5.54	0.000
SLD	-0.05188	0.05867	-0.88	0.047
√ADT	0.00699	0.01271	0.55	0.054
√Rough	-0.36730	0.09494	-3.87	0.000
√Tran Crak	-0.27707	0.01912	-14.49	0.000
√Rutt	-0.17380	0.03935	-4.42	0.000

```
S = 0.373547    R-Sq = 85.8%    R-Sq(adj) = 84.6%
```

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	9	91.896	10.211	73.18	0.000
Residual Error	109	15.210	0.140		
Total	118	107.106			

Figure 5-13: Minitab Output of Regression Equation for Summer Condition-Rating Trial Model.

In order to determine the goodness of the developed regression model, three statistics should be examined as follows:

1. **Coefficient of determination R^2 and R^2 (adjusted):** The higher these two values, the better the model is. An R^2 of 70% or higher is generally accepted as good. In our model R^2 and R^2 (adjusted) values are 85.8% and 84.6% respectively. Both values indicate that the model fits the data well.

2. **F test**: we have to prove that at least one coefficient "β_k" in the regression equation is not equal to zero. Therefore, a P (F) test of the whole model is carried out based on a hypothesis test. The null hypothesis (H_0) assumes that all coefficients are equal to zero (i.e. $\beta_0 = \beta_1 = \beta_{p-1} = 0$). The alternate hypothesis (H_a) assumes that at least one of the coefficients is not equal to zero (i.e. $\beta_k \neq 0$). The table of analysis of variance in Figure 5-13 shows a value of $P = 0.000 \leq 0.05$, which means that (H_0) is rejected with 95% confidence. Therefore, (H_a) is accepted and at least one coefficient in the estimated regression equation is not equal to zero.

3. **t test**: we have to test whether all predictor variables are significantly related to the response variable or not. Therefore, a "t-test" is performed for each of the coefficients β_0, $\beta_1 \ldots \beta_{p-1}$ in a similar way to (F test). The null hypothesis of each coefficient will be as follows:

$$H_0\colon \beta_k = 0 \qquad ; H_1\colon \beta_k \neq 0$$

Figure 5-13 shows that the p-value of the estimated coefficients for predictors ($\sqrt{\text{AGE}}$, $\sqrt{\text{Rough}}$, $\sqrt{\text{Tran Crak}}$, and $\sqrt{\text{Rutt}}$) is 0.000. Similarly, the p-value of predictors (Log Pave Temp, $\sqrt{\text{Rain}}$, and SLD) is 0.038, 0.041, and 0.047 respectively. As a result, the alternate hypothesis is accepted and the previous predictor variables are significantly related to the response variable (Condition Rating-CR) at α–level of 0.05 (95% confidence). However, the case is different for the remaining two predictors. The p-value of the estimated coefficients for predictor ($\sqrt{\text{ADT}}$) is 0.054, which is slightly greater than $\alpha = 0.05$, but can be accepted. The one that does not have a significant relation with the response variable (CR) is the predictor (Log Air Temp) with a p-value equals to 0.288 >> $\alpha = 0.05$.

5.2.2.f Residuals Analysis:

Although the previous preliminary tests are always considered important indicators for verifying the goodness of the model, the essential validating procedure will be the testing of the linear regression assumptions. Rather than checking the linear regression assumptions directly on the response variables, it is recommended to re-express these assumptions in terms of the random errors, and then check them on the random errors instead. The following three assumptions about the random errors are equivalent to the assumptions about the response variables:

- The random errors ε_i are normally distributed.
- The random errors ε_i are independent.
- The random errors ε_i have a constant variance σ^2 (homoscedasticity).

Moreover, by definition *Residuals* are estimates of experimental error obtained by subtracting the observed responses from the predicted responses, and can be thought of as elements of variation unexplained by the fitted model. Since this is a form of error, the same previous liner regression assumptions that apply to errors can be applied to the residuals. This is the basic idea underlying residual analysis, which is a highly useful tool for examining the aptness of a regression model.

These assumptions are described below as follows:

I. Normality of Residuals:

Although many statisticians recommend using skewness and kurtosis for examining normality (Looney, 1995) and (Wilkinson *et al.,* 1999) argue that skewness and kurtosis often fail to detect distributional irregularities in the residuals. Therefore, *graphical methods* can be considered as a better way for examining the normality assumption. The *normal probability plot* of the residuals is used, in which each residual is plotted against its expected value under normality. A plot that is nearly linear suggests normal distribution of the residuals. A plot that obviously departs from linearity suggests that the error distribution is not normal.

Consider the Minitab output for normal probability and frequency plots of residuals for the selected model (Figure 5-14). In the normal probability plot, the normal distribution is represented by a straight line angled at 45 degrees. The standard residuals are compared against the diagonal line to show the departure. In our case, it is clear that the residuals follow the straight line; which means that the departure from normality is slight.

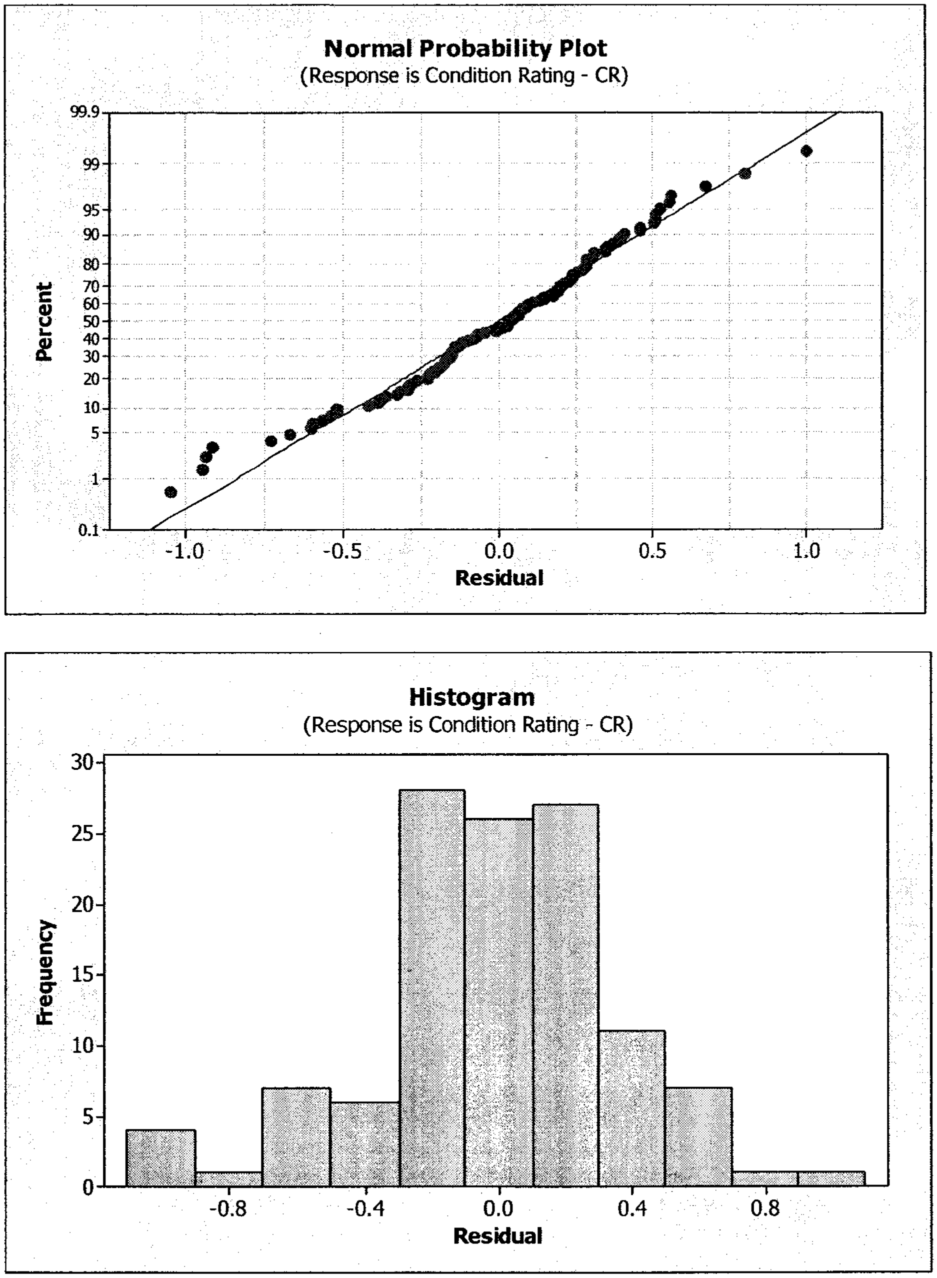


Figure 5-14: Normal Probability and Histogram of Residual Plots for the Summer Condition-Rating Model.

Furthermore, in order to ensure the normality results, additional test statistics were performed. Some researchers argue that the Shapiro-Wilk (Shapiro & Wilk, 1965) test was originally constructed to test a sample size carrying up to 50 subjects. However, to examine normality for a sample size between 51 and 1999 subjects (119 subjects in our study), other statistical tests such as the Anderson-Darling test are more recommended. The null hypothesis (H_0) of the normality test assumes that there is no significant departure from normality, while the alternate hypothesis (H_a) assumes that a significant departure from normality does exist.

In Table 5-13 a p-value of $0.054 > 0.05$ for the Shapiro-Wilk test, and $0.070 > 0.05$ for the Anderson-Darling test, means that the null hypothesis cannot be rejected and the assumption that there is no significant departure from normality holds with a 95% confidence level.

Table 5-13: Test Statistics Results for Normality Check.

Test Statistic	**Test Value**	**P-Value**	**Decision (95% confidence)**
Shapiro-Wilk	0.989	0.054	Accept Normality
Anderson-Darling	0.689	0.070	Accept Normality

II. Independence of Residuals:

A regression model requires independence of erroneous terms. Again, a residuals plot can be used to check this assumption. Whenever data observations are obtained in a time sequence or any other type of sequence, it is better to prepare a *sequence plot of the residuals*. Plotting the residuals of those observations versus the case order or time order of the observations will test for any correlation between errors that are close to each other in the sequence.

When the residuals are independent, we expect them to fluctuate in a more or less random scatter around the base line 0. Consider the Minitab output for residuals versus the order of the data plot for the selected model (Figure 5-15). The residuals scatter around the regression line in a random and patternless manner, which implies independent errors.

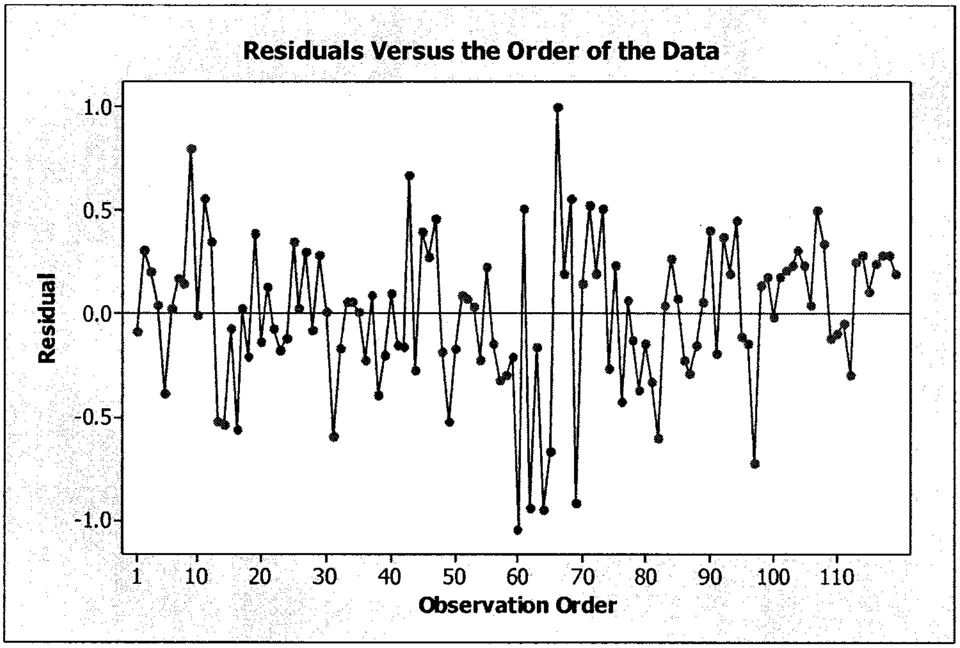


Figure 5-15: Residuals vs. Order of Data Plot for the Summer Condition-Rating Model.

Moreover, a test called the Durbin–Watson statistic is used to detect the presence of autocorrelation in the residuals from a regression analysis. In other words, it is used to statistically examine whether the residuals are independent or not.

Because most regression problems involving time series data exhibit positive autocorrelation, the hypotheses usually considered in the Durbin–Watson test are:

H_0: $\rho = 0$ (Error terms are independent).

H_1: $\rho > 0$ (Error terms are positively correlated).

For upper and lower critical values, d_U and d_L have been tabulated for different values of k (the number of predictor variables) and n (the number of observations).

If $D < d_L$ reject H_0: $\rho = 0$

If $D > d_U$ do not reject H_0: $\rho = 0$

If $d_L < D < d_U$ the test is inconclusive.

For the model under consideration, where k = 9 and n = 119, the Durbin–Watson tables indicate the following values; for k = 9, n = 150 (since 119 is not included in the tables the values at n = 150 were taken instead), and the level of significance $\alpha = 0.05$. The critical values are $d_L = 1.60$ and $d_U = 1.86$.

The Minitab output for the same model for Durbin–Watson statistics is:

$D = 1.91 > d_U = 1.86$ thus, the (H_0) is not rejected and the error terms are statistically proven to be independent.

III. Homoscedasticity:

Homoscedasticity means that the variance of errors is the same across all levels of the independent variables. When the variance of errors differs at different values of the independent variables, **heteroscedasticity** is indicated, which means that the residuals are not evenly scattered around 0 (the horizontal line). According to (Berry *et al.*, 1985), slight heteroscedasticity has little effect on significance tests; however, when heteroscedasticity is marked, it can lead to serious distortion of findings and seriously weaken the analysis.

Scatter plots of the residuals versus the fitted values from the model allow comparison of the amount of random variation in different parts of the data.

In Figure 5-16, the residuals vary around the zero line in a constant pattern without any high concentration above or under it. This implies that the assumption of homoscedasticity is not violated, and the test's results are considered satisfactory.

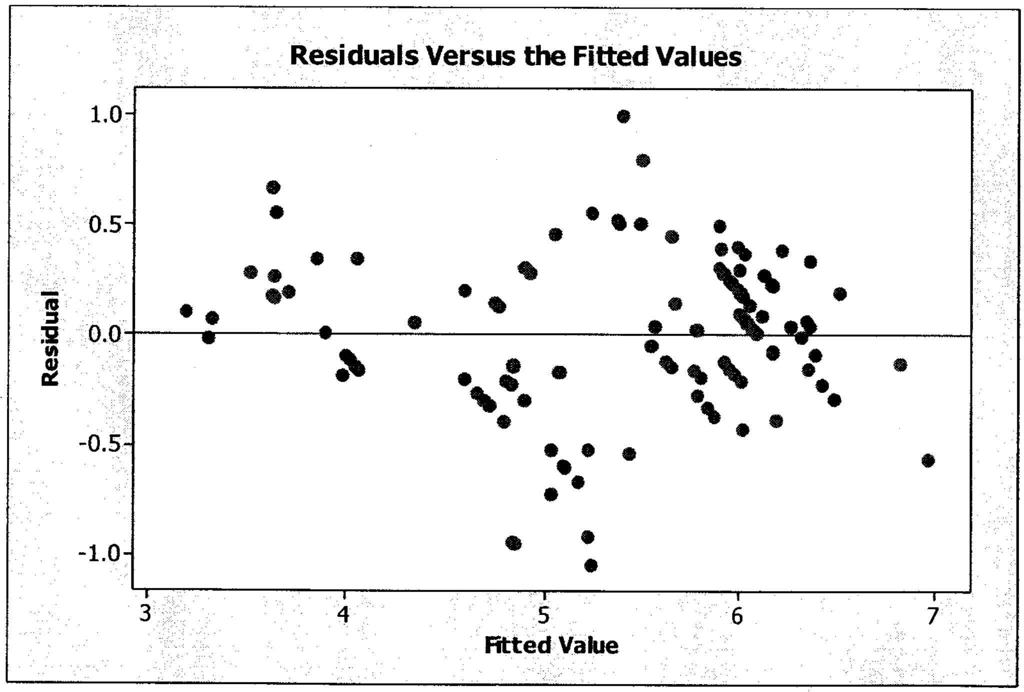


Figure 5-16: Residuals vs. Fitted Values Plot for the Summer Condition-Rating Model.

5.2.3 The Proposed Condition Rating Scale:

Different rating scales for condition assessment of flexible-pavements have been developed in the US and Canada. The most common ones are the scales of Pavement Condition Index (PCI) and Pavement Serviceability Index (PSI). The rating scale of PCI is a (0-100) scale, where the higher value (100) means a road in excellent condition, and (0) in a poor condition (Shahin, 2005). The rating scale of PSI is a (1-5) scale, where the higher value (5) indicates that the pavement is in a very good condition, whereas (1) refers to a pavement in a poor condition (Carey *et al.,* 1960).

In the current study, the overall condition-rating is measured on a scale of 0 to 10, divided into five condition states corresponding to five ranges of numerical scores. These condition states are: Critical, Poor, Fair, Good, and Excellent. In addition, for each condition state a required M&R action is suggested based on the overall condition-rating score and the distress levels. For example, on the basis of the proposed scale, a road segment with an overall CR of (3.5) falls under the state of (Poor condition) and the required M&R action could be a heavy rehabilitation strategy.

The developed condition-rating scale will be able to provide guidance for practicing pavement engineers and managers to plan and maintain their pavement networks. The proposed condition-rating scale with its numerical (scores), linguistic (states), required actions (M&R strategies), and additional recommendations for specific distress types are all presented in Figure 5-17.

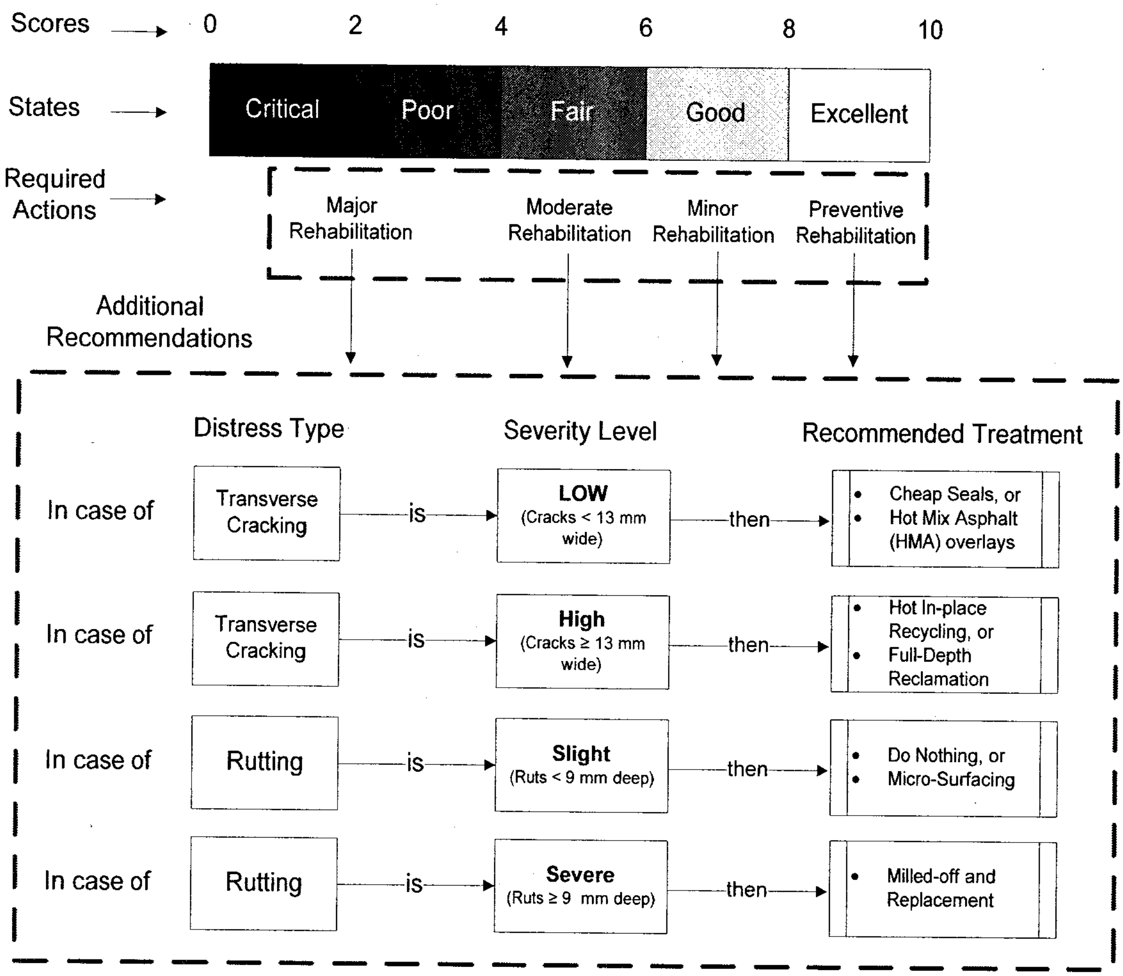


Figure 5-17: Proposed Condition Rating Scale.

5.2.4 Model Validation:

Although the previous statistical diagnostics that were described above are enough to check the adequacy of the developed model, they cannot be considered at all as accurate alternatives of the validation process. Most of the researchers consider the validation step as possibly the most important and overlooked step in the model building sequence. The ultimate goal of model validation is to make the model useful in the sense that the model addresses the right problem, provide accurate information about the system being modeled, and make the model be actually used.

Therefore a comprehensive model validation procedure is applied on the selected models. The validation data consist of thirty-two observations embedded into the regression model to compare its results with the actual results using a Microsoft Excel spread sheet. Furthermore, descriptive statistics and plots of the actual and predicted outputs are obtained using Minitab ® 15 statistical software. A detailed explanation of the previous steps follows:

5.2.4.a Actual vs. Predicted Output Plot:

In this step, a comparison between the actual values of condition ratings and the predicted values obtained from the regression model is conducted, using a scatter plot as the one shown in Figure 5-18. The Figure shows that there is no significant departure between the actual values plot and the predicted values plot, and the predicted values scatter around the actual values in acceptable ranges. Therefore, the first validation test results are considered satisfactory.

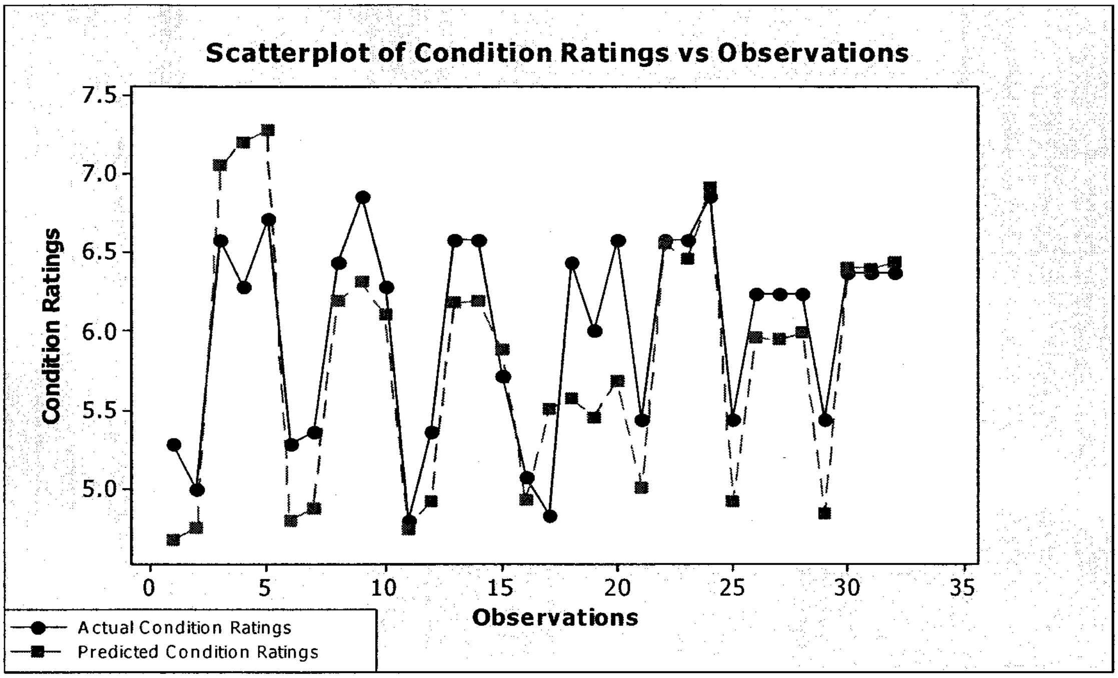


Figure 5-18: Minitab Output of Validation Plot for Summer Condition-Rating Model.

5.2.4.b Descriptive Statistics:

The descriptive statistics of the actual and predicted values of condition ratings will be checked in this step. The results showing in Figure 5-19 and Table 5-14 tell that the mean and standard deviation values of the actual and predicted outputs are close to each other, in spite of the fact that the predicted output has a slightly lesser value of mean and a greater value of standard deviation than the actual output. Therefore, the second validation test results are considered satisfactory.

Table 5-14: Descriptive Statistics for Actual and Predicted Values of Validation Data.

Descriptive Statistics	Actual CR	Predicted CR
Mean	6.005	5.817
Standard Deviation	0.639	0.791
No. of Observations	32	32

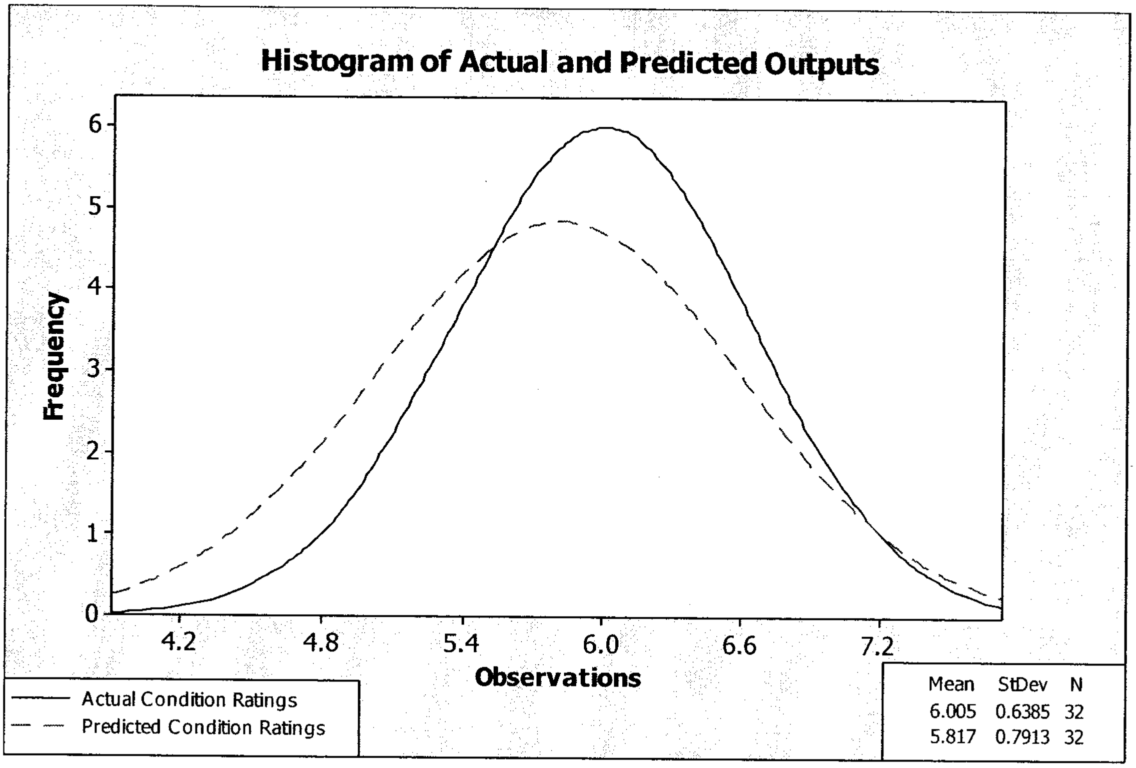


Figure 5-19: Minitab Output of Histogram of Validation Data for Summer Condition-Rating Model.

5.2.4.c Mathematical Validation Method:

The final step in the validation process is the application of mathematical equations. Based on (Zayed *et al.,* 2005) two equations (5-4) & (5-5) are used to validate the developed model. Equation (5-4) represents the average invalidity percent (AIP), which shows the error of prediction. On the other hand, Equation (5-5) represents the average validity percent (AVP), which shows the validation percentage out of 100. Both (AIP) and (AVP) values are determined as follows:

$$AIP = \left(\sum_{i=1}^{n} \frac{|1-(^{Ei}/_{Ci})|}{n}\right) \qquad \text{Eq: (5-4)}$$

$$AVP = 1 - AIP \qquad \text{Eq: (5-5)}$$

Where: (AIP): Average Invalidity Percent. (AVP): Average validity Percent.

(E_i): Estimated/Predicted Value. (C_i): Actual Value. (n): Number of Observations.

The AIP value varies from 0 to 1. The closer the value of AIP to 0, the more the model fits the validation data. In contrast, the closer the value of AIP to 1, the more inappropriate the model is. In addition, two error terms are used to investigate the performance of the developed model (Dikmen *et al.*, 2005), namely, root square error (RMS) and mean absolute error (MAE), which can be estimated using the following formulas:

$$RMS = \frac{\sqrt{\sum_{i=1}^{n}(Actual - Predicted)^2}}{n} \qquad \text{Eq: (5-6)}$$

$$MAE = \frac{\sum_{i=1}^{n}|Actual - Predicted|}{n} \qquad \text{Eq: (5-7)}$$

The MAE value varies from 0 to infinity (∞). The closer the MAE value to 0, the better the validation results are. By applying the previous four equations to the model under consideration, we obtained the following results:

- AIP = 0.0631
- AVP = 0.9369
- RMS = 0.0798
- MAE = 0.3727

The results show that the predicted outputs are almost 94% accurate, with RMS and MAE values close to zero. Thus the validation results are considered satisfactory and the selected model does fit the validation data.

5.2.4.d Comparison of the Proposed Model with the Existing Assessment Models:

To illustrate the validity of the proposed model in estimating the condition of a flexible-pavement segment, a comparison was carried out between the developed model and three common assessment-indices which are (PCI, PSR, and PQI). The four models were applied on (32) road segments, and the results are tabulated and plotted on one graph. Using the Pavement Condition Index (PCI), a flexible-pavement is usually rated by assigning an index of 100 to a perfect pavement, then on the basis of the level and severity of the observed distresses a cumulative corrected deduct value is generated and subtracted from the index of 100 (Shahin, 2005). In the case of using the Present Serviceability Rating (PSR), an equation (Eq: 2-5) between PSR and IRI was developed by (Al-Omari *et al.,* 1994) for three pavement types including flexible pavement. Moreover, in the case of the Pavement Quality Index (PQI), the PQI treats the international roughness index (IRI) as a deduction value from the present condition rating (PCR) as follows: [$PQI = PCR - a\ (IRI)^{b}$], where (a) and (b) are constants given for interstates, freeways, and multi-lane roads (Reza *et al.,* 2005).

As the rating scale of PCI is (0-100), that of PSR is (1-5), and that of PQI is (0-100). Therefore, the values of the computed PCI, PSR, and PQI were all adjusted to become on the same scale of the proposed model, which is from (0-10).

Figure 5-20 shows the values of the four indices plotted against the (32) data observations. It is clear that the ratings of the two indices (PSR and PQI) are quite high and distributed in the range of (CR = 8 to 10), whereas the ratings of the (PCI) are less high than (PSR and PQI) and distributed in a wider range of (CR = 2 to 9). Finally, the proposed MAUT/Regression model rates the data observations in an approximate similar pattern to the (PCI) but within a smaller range of (CR = 4 to 8). Thus, the proposed model can be considered valid in predicting the condition ratings of flexible pavement.

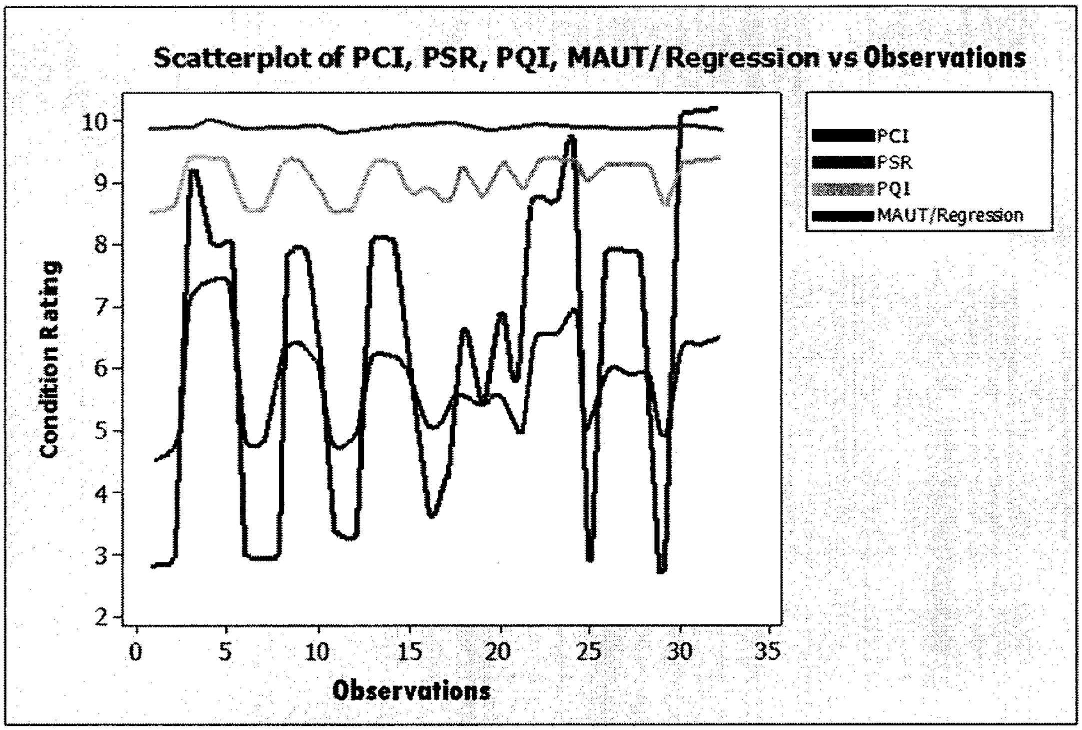


Figure 5-20: Scatterplot of MAUT/Regression,PCI,PSR, and POI.

5.2.5 Summary of Developed Models:

All the above-mentioned methodology for model developing and validating processes had been explained only for the summer condition-rating model. As has already been stated, two data sets were prepared to build two different models (summer and winter seasons). Therefore, all the models are developed and tested based on the same adopted methodology. The number of predictors and their transformation functions may differ from one model to another, due to available input data and results of different statistical tests. The regression equations for the developed models are listed below, in addition to the results of validation and different statistical tests applied to all the developed models as shown in Table 5-15.

5.2.5.a Summer Season Condition-Rating Model:

The developed regression equation is:

$$\mathbf{CR = 6.12 + 4.63\ Log\ Air\ Temp - 3.27\ Log\ Pav\ Temp - 0.024\ \sqrt{Rain} - 0.251\ \sqrt{AGE} - 0.0519\ SLD + 0.0070\ \sqrt{ADT} - 0.367\ \sqrt{Rough} - 0.277\ \sqrt{Tran\ Crak} - 0.174\ \sqrt{Rutt}}$$

The units of all variables are the same as described in Table 5-11.

5.2.5.b Winter Season Condition-Rating Model:

The developed regression equation is:

$$\mathbf{CR = 8.09 + 0.0198\ Freezing\ Temp + 0.0025\ Pav\ Temp - 0.232\ \sqrt{AGE} - 0.0377\ SLD + 0.0032\ \sqrt{ADT} - 0.363\ \sqrt{Rough} - 0.271\ \sqrt{Tran\ Crak} - 0.162\ \sqrt{Rutt}}$$

The units of all variables are the same as described in Table 5-11.

Table 5-15: Summary of Statistical and Validation Results for Condition-Rating Models.

Model	R^2 %	R^2 (adj) %	P(F)	Durbin-Watson Statistics	AIP	AVP
Summer	85.80	84.60	0.00	D > du 1.9114	0.064	0.936
Winter	86.00	85.00	0.00	D > du 1.8745	0.066	0.934

5.2.6 Deterioration Curves:

In order to predict the condition ratings (CR) of flexible pavement based on different climate, physical, and operational factors, a relationship between (CR) and age is built using the developed MAUT/Regression model. The deterioration curves are built by varying one or two attributes of the regression model at a time, while keeping other attributes constant. Figure 5-21 to Figure 5-24 represent condition deterioration of flexible pavement with respect to ADT (Average Daily Traffic), Roughness measurements, Transverse Cracking amount, and Rutting amount respectively.

As shown in Figure 5-21 prediction curves are developed for each of the traffic levels (Low, Moderate, and Heavy), the X-axis represents the pavement age, and the Y-axis is the condition-rating (CR) score. For example, if the pavement age and level of traffic for a specific road segment are known, under the same conditions of the proposed model, a user can easily obtain the condition-rating score by plotting the corresponding value from the chart on the Y-axis (CR-axis).

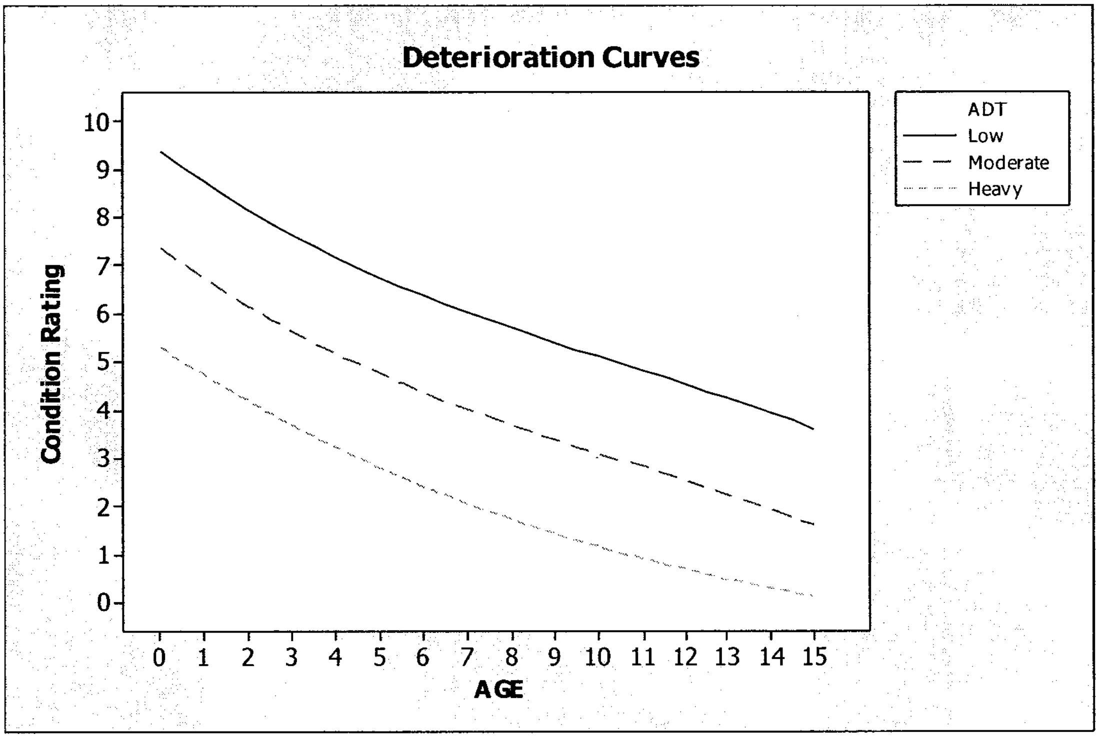


Figure 5-21: Minitab Output of Deterioration Curves for Average Daily Traffic (ADT).

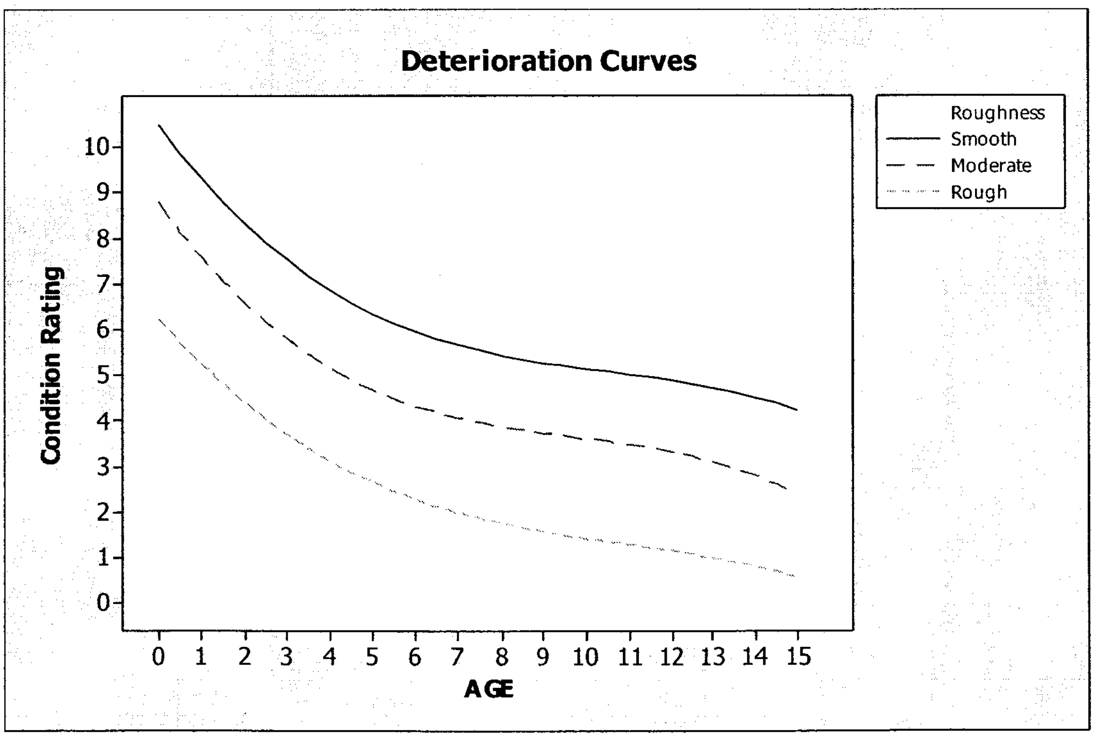


Figure 5-22: Minitab Output of Deterioration Curves for Roughness Measurements.

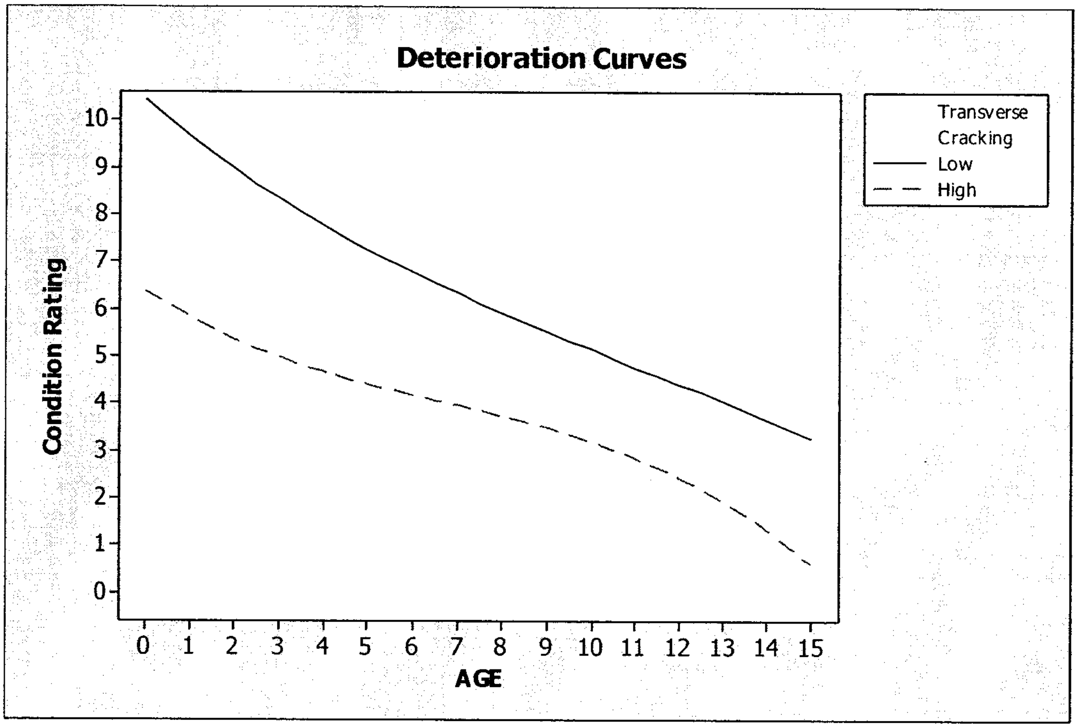


Figure 5-23: Minitab Output of Deterioration Curves for Transverse Cracking Amount.

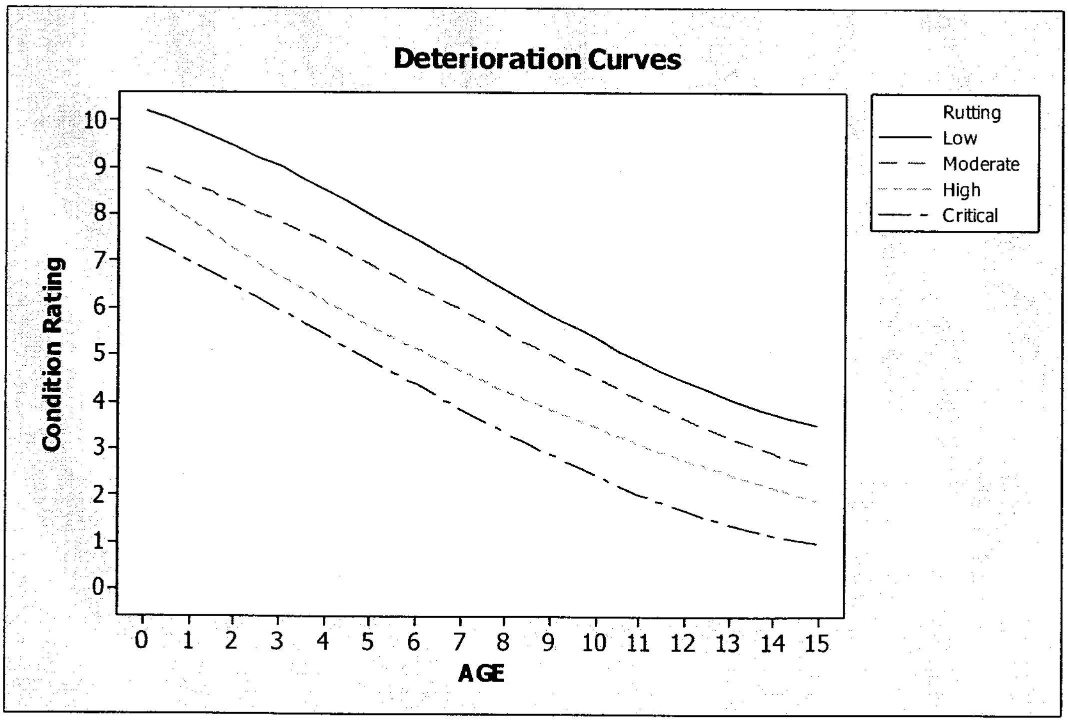


Figure 5-24: Minitab Output of Deterioration Curves for Rutting Amount.

From Figure 5-21 to Figure 5-24 it is clear that the rate of pavement deterioration is significantly less whenever the traffic level is lower, and the distress severity is less. We can also notice that an inverse polynomial relation of third degree does exist between the condition value and age of pavement. Tables 5-16 to 5-19 show the third degree equations between (Age) and (CR), which represent the deterioration curves of Figure 5-21 to 5-24.

Table 5-16: Deterioration Models for Average Daily Traffic.

ADT (vehicles/day)	Traffic Level	Model	R^2 (%)	R^2 (adj)	Std. Error	P-Value
< 20	Low	$Y = 0.0018\ x^3 - 0.0154\ x^2 - 0.4531\ x + 9.2230$	86.50	84.60	0.5526	0.0255
$20 \leq ADT \leq 100$	Moderate	$Y = 0.0040\ x^3 - 0.0664\ x^2 - 0.1630\ x + 7.2130$	89.50	88.00	0.5166	0.0120
> 100	Heavy	$Y = 0.0006\ x^3 - 0.0111\ x^2 - 0.2570\ x + 5.2060$	93.90	93.00	0.3412	0.0160

Y = Condition Rating, x = Pavement Age

Table 5-17: Deterioration Models for Roughness Measurements.

Roughness (mm/m)	Severity Level	Model	R^2 (%)	R^2 (adj)	Std. Error	P-Value
$RM \leq 2.48$	Smooth	$Y = -\ 0.0037\ x^3 + 0.1224\ x^2 - 1.4190\ x + 10.810$	88.70	87.00	0.5878	0.0380
$2.49 \leq RM \leq 3.33$	Moderate	$Y = -\ 0.0036\ x^3 + 0.1151\ x^2 - 1.3030\ x + 8.760$	83.00	80.50	0.6972	0.0410
$3.34 \leq R_M \leq 6.18$	Rough	$Y = -\ 0.0019\ x^3 + 0.0752\ x^2 - 1.0330\ x + 6.179$	85.10	83.00	0.6115	0.0250

Y = Condition Rating, x = Pavement Age

Table 5-18: Deterioration Models for Transverse Cracking Amount.

Transverse Cracking (mm)	Severity Level	Model	R^2 (%)	R^2 (adj)	Std. Error	P-Value
cracks < 13.00	Low	$Y = 0.0013\, x^3 - 0.0036\, x^2 - 0.6152\, x + 10.290$	94.60	93.30	0.4304	0.0010
cracks ≥ 13.00	High	$Y = - 0.0029\, x^3 + 0.0588\, x^2 - 0.6172\, x + 6.373$	91.30	90.00	0.4998	0.0030

Y = Condition Rating, x = Pavement Age

Table 5-19: Deterioration Models for Rutting Amount.

Rutting (mm)	Severity Level	Model	R^2 (%)	R^2 (adj)	Std. Error	P-Value
$R \leq 9.00$	Low	$Y = 0.0028\, x^3 - 0.0463\, x^2 - 0.3018\, x + 10.290$	91.20	90.00	0.5819	0.0130
$10.00 \leq R \leq 13.00$	Moderate	$Y = 0.0026\, x^3 - 0.0430\, x^2 - 0.2608\, x + 8.965$	88.10	86.40	0.6194	0.0320
$14.00 \leq R \leq 20.00$	High	$Y = 0.0010\, x^3 - 0.0033\, x^2 - 0.5753\, x + 8.456$	86.60	84.70	0.7217	0.0000
$R > 20.00$	Critical	$Y = 0.0011\, x^3 - 0.0112\, x^2 - 0.4999\, x + 7.500$	88.50	86.90	0.6976	0.0440

Y = Condition Rating, x = Pavement Age

It can be noticed from the results of (R^2, adjusted R^2, standard error, and P-value) that the developed deterioration models are robust and reliable. Therefore the deterioration curves can be used by the DOT to determine the condition-rating score of an existing flexible pavement road/highway, under the same conditions of the proposed models.

5.3 MONTE-CARLO SIMULATION

5.3.1 Introduction:

In order for the proposed integrated MAUT/Regression model to be more efficient in describing the real world with all the uncertainty involved, in addition to exploring thousands of combinations for "what-if" factors and analyzing the full range of possible outcomes, the Monte-Carlo simulation is used.

The Monte-Carlo method is one of many methods for analyzing *uncertainty* propagation, where the goal is to determine how random variation, lack of knowledge, or error values affects the sensitivity, performance, or reliability of the system that is being modeled. The Monte-Carlo simulation can be defined as a method of generating random sample data based on some known distribution for numerical experiments. This method is often used when the model is complex, or involves more than just a couple of uncertain parameters. By using random inputs, we are essentially turning the deterministic model into a stochastic one. Figure 3-5 presents the steps of Monte-Carlo Simulation Methodology as follows:

1. Setting up the developed model (defining a probability distribution function for inputs and identify outputs).
2. Determining the required number of iterations and then running the simulation.
3. Analyzing the generated results (histograms and cumulative curves).
4. Performing a sensitivity analysis to display the impact of each input variable on the output variable.

The previous steps were executed using a risk analysis software called"@ Risk 5.5" which shows many possible outcomes and how likely they are to occur in a convenient Microsoft Excel spreadsheet. The detailed explanation of the previous steps will be described in the following sections.

5.3.2 Model Preparation:

A probability distribution of each uncertain input parameter should be defined, in order to cover the range of all possible values that the input variable may have and the probability that the input's value is within any measurable subset of that range.

Based on the collected data and by using @ Risk software, distributions that best fit the selected input variables are chosen as the first option and ranked along with other distributions that may fit the data as well. The ranking of the distributions is based on three statistical tests (Chi-Squared statistic, Anderson- Darling statistic, Kolmogorov-Smirnov statistic).

Figure 5-25 shows an example of defining probability distributions that best fits the inputs of the summer model, in which a fit comparison is used for sub-factor "Pavement Temperature - Pave Temp". The mean and std. deviation values are quite the same for both the normal fitting line and the data histogram, which means that the normal distribution does fit the sub-factor "Pave Temp".

In addition to the graphical justification, three statistical tests are used to select the best probability fit for each sub-factor; Chi-Square (Chi-Sq), Kolmogorov-Smirnov (KS) and Anderson-Darling (AD). Table 5-20 illustrates the test statistics, critical values, and P-value for Chi-Sq, KS, and AD. On the basis of these results the normal probability distribution could not be rejected as the best fit for all the sub-factors at a significance level $\alpha = 0.05$.

For example, the critical value for the sub-factor "Pave Temp" at 5% significance level is 31.58 using the Chi-Sq test, 0.6831 using the AD test, and 0.0367 using the KS test; however the test statistics are 28.92, 0.2926, and 0.018 for Chi-Sq, AD, and KS respectively. Because the test statistics are less than critical values for the three tests, a null hypothesis (in which the best probability fit is normal distribution) cannot be rejected. Similarly, the rest of the sub-factors are analyzed; where the majority shows a normal distribution to be the best fit (Appendix C).

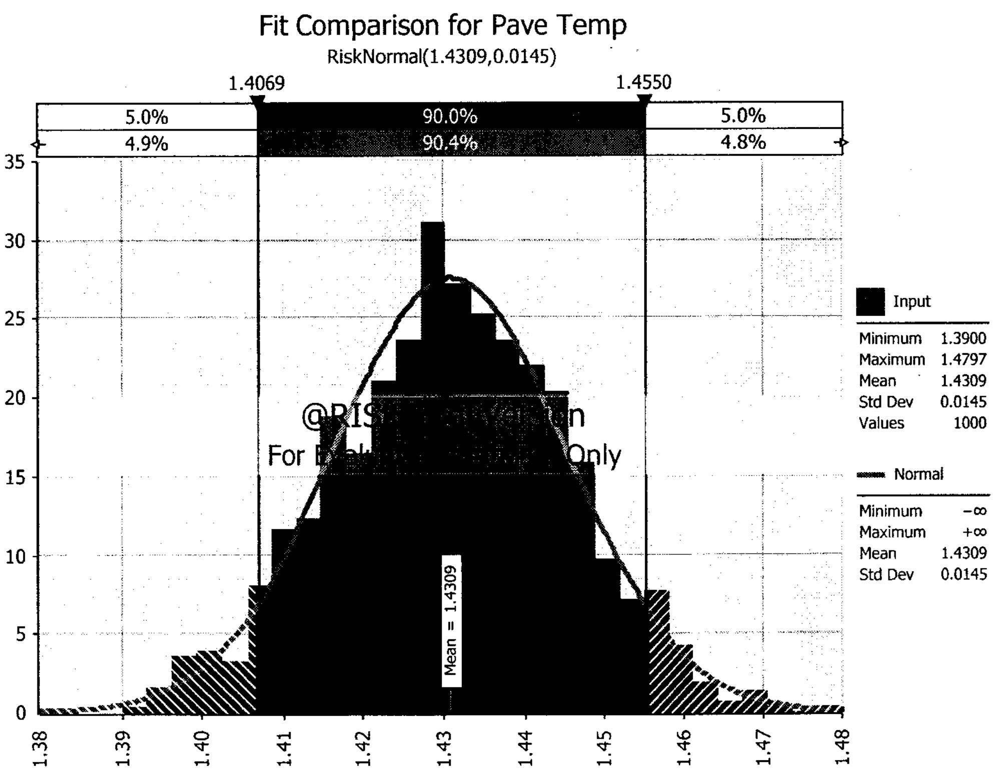


Figure 5-25: @ RISK Output for Defining Distributions that Best Fit the Sub-Factor "Pave Temp".

Table 5-20: Fitted Normal Probability Distributions for Summer Model Sub-Factors.

Sub-Factor		Air Temp	Pave Temp	Rain Amt	AGE	SLD	ADT	Rough	Trans Crak	Rutt
Mean	μ	1.467	1.430	1.002	4.733	2.66	8.643	1.662	2.498	1.396
Standard Deviation	σ (%)	0.013	0.014	0.127	1.033	0.782	3.173	0.416	2.301	1.284
Normal Distribution	Skewnes	0	0	0	0	0	0	0	0	0
	Kurtosis	3	3	3	3	3	3	3	3	3
Chi-Sq* Test	Test Value	16.68	28.92	29.50	36.22	28.80	13.43	44.46	29.2	22.07
	Critical Value	41.33	31.58	33.45	46.81	32.94	22.72	48.27	37.9	44.46
	P - Value	0.95	0.41	0.38	0.13	0.42	0.91	0.02	0.39	0.77
	Reject H0?	No	No	No	No	No	No	No	No	No
A-D Test**	Test Value	0.22	0.29	0.25	0.55	0.49	0.22	0.34	0.24	0.34
	Critical Value	0.75	0.68	0.82	0.61	0.71	0.52	0.63	0.56	0.87
	P - Value	> 0.25	0.53	0.45	0.35	0.86	0.61	0.67	0.45	> 0.25
	Reject H0?	No	No	No	No	No	No	No	No	No
K-S*** Test	Test Value	0.015	0.018	0.018	0.017	0.017	0.015	0.016	0.019	0.016
	Critical Value	0.028	0.036	0.045	0.027	0.019	0.064	0.031	0.031	0.0327
	P - Value	> 0.15	0.26	0.31	0.18	0.28	0.13	0.72	> 0.15	0.41
	Reject H0?	No	No	No	No	No	No	No	No	No

H_0: the data follow a normal distribution; H_a: the data do not follow a normal distribution.
Chi-Square statistic test for a normal distribution = the P-value should be close to 1 to have the most confidence level that the data follow a normal distribution.
** Anderson-Darling statistic test for a normal distribution = the P-value should be close to 1 to have the most confidence level that the data follow a normal distribution.
*** Kolmogorov-Smirnov statistic test for a normal distribution = the P-value should be close to 1 to have the most confidence level that the data follow a normal distribution.

After defining the probability distribution of each input variable, the output parameter which @ Risk will track during each iteration or re-calculation of a simulation should also be clearly identified. Figure 5-26 shows the calculation of the condition rating-CR (summer model) using the Monte-Carlo simulation.

$$CR_S = 6.12 + 4.63\boxed{\text{Log Air Temp}} - 3.27\boxed{\text{Log Pave Temp}} - 0.024\boxed{\sqrt{\text{Rain}}} - 0.251\boxed{\sqrt{\text{AGE}}} - 0.0519\boxed{\text{SLD}} + 0.0070\boxed{\sqrt{\text{ADT}}} - 0.367\boxed{\sqrt{\text{Rough}}} - 0.277\boxed{\sqrt{\text{Tran Crak}}} - 0.174\boxed{\sqrt{\text{Rutt}}}$$

Figure 5-26: Calculating Condition Rating for Summer Model using Monte-Carlo Simulation.

5.3.3 Run the Simulation:

Prior to running the simulation, the number of required iterations should be determined. By increasing the number of iterations in your model, you will increase the accuracy of your results. However, the question that always arises is how many iterations are enough?

Best practices suggest performing a “test” with a small (e.g. 10-100) number of iterations first, to check the performance of the procedure. Then make a large number of (100-1000) of iterations. The previous procedure was adopted and applied in the proposed model (summer case) and the results of running the simulation are shown in Figure 5-27, in which the simulation ran for 1000 iterations giving us a look at 1000 different scenarios and the likelihood of each occurring for the data in hand. For example, in the cumulative curve of the same data we can see that there is a 5% chance of CR value exceeding the rating value of 6.73, and a 5% chance of CR value being less than the rating value of 3.97.

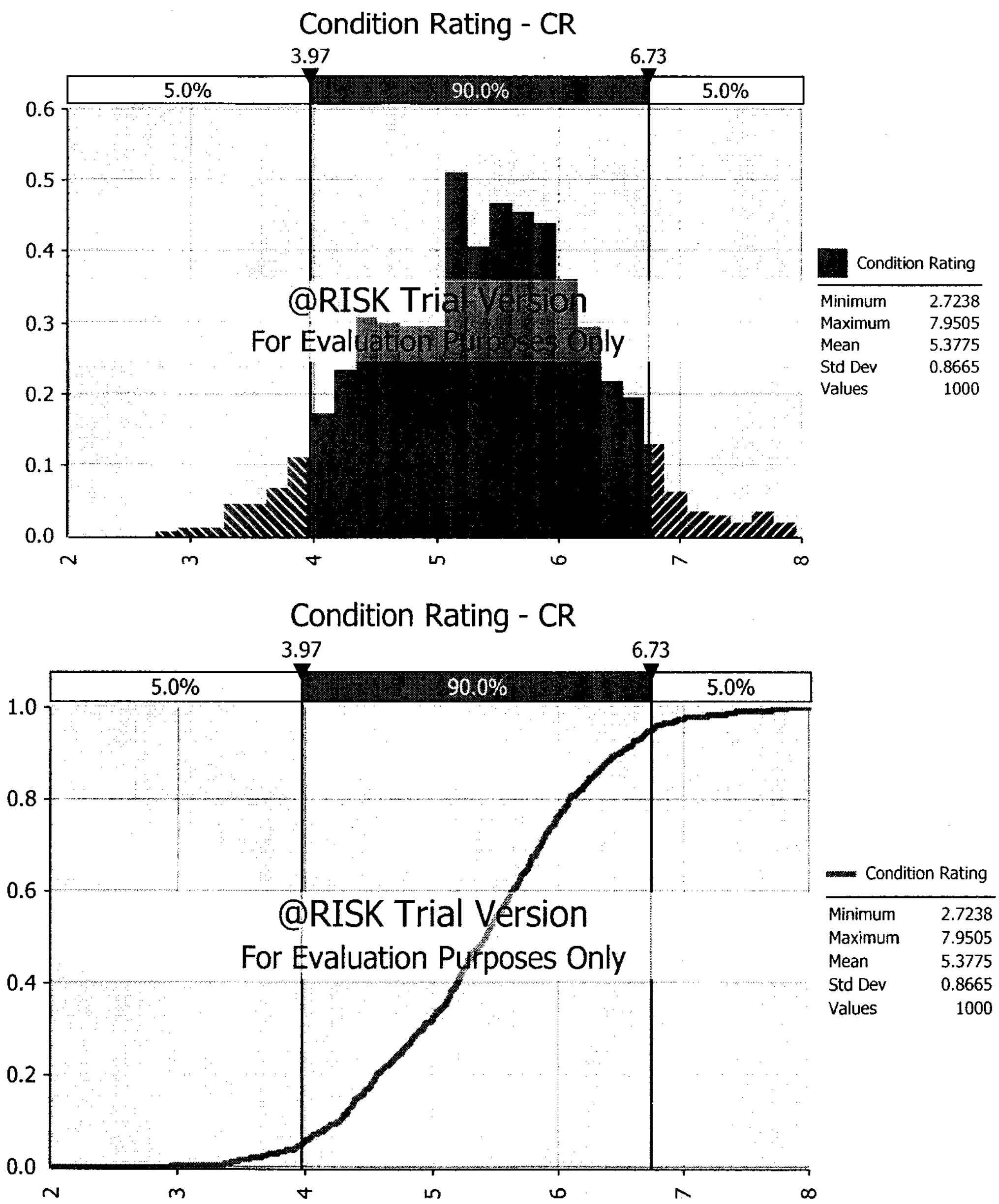


Figure 5-27: @ RISK Output for Simulation Results of Summer Model.

5.3.4 Analysis of Results:

For a better understanding of the obtained results, three procedures were adopted as follows:

5.3.4.a Tornado Graphs:

Tornado Graphs are used to display the most important probability distribution of inputs in the proposed model. Figure 5-28 shows the sub-factor (input) distributions ranked by their impact on the condition rating-CR (output), in which the Transverse Cracking amount (Tran Crak) variable has the highest impact with a value of (0.72); then the Pavement Age (AGE) variable with an impact of (0.29); on the other hand, the Rainfall amount (Rain) variable almost has no impact on the model output with a value close to (0.00).

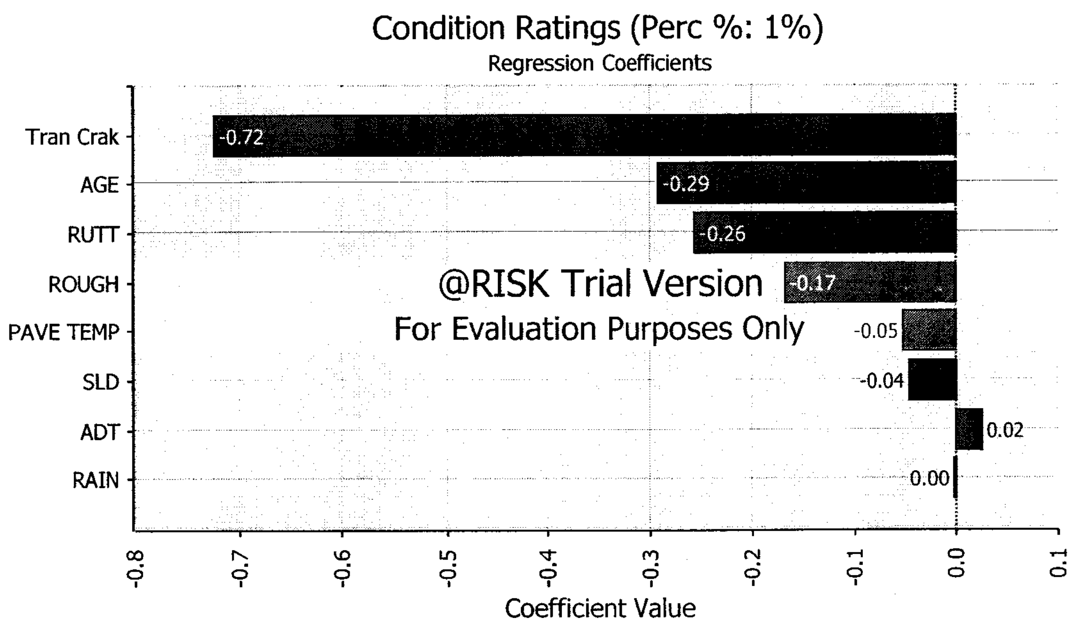


Figure 5-28: @ RISK Output of Tornado Graphs for Summer Model.

5.3.4.b Scatter Plots:

Scatter Plots are used to display the relationship between the simulated output (Condition-Rating) and the samples from an input distribution. Figure 5-29 shows the relationship between the simulated CR and the sub-factor "Transverse Cracking amount-Tran Crak", in which an inverse relationship clearly exists with a negative correlation value of (-0.94). In addition, condition ratings greater than 5.24 correspond to 45.5% of (Tran Crak) values less than 2.53; and condition ratings less than 5.24 correspond to 43.9% of (Tran Crak) values greater than 2.53. Similar scatter plots are conducted for all the model inputs and presented in Appendix C.

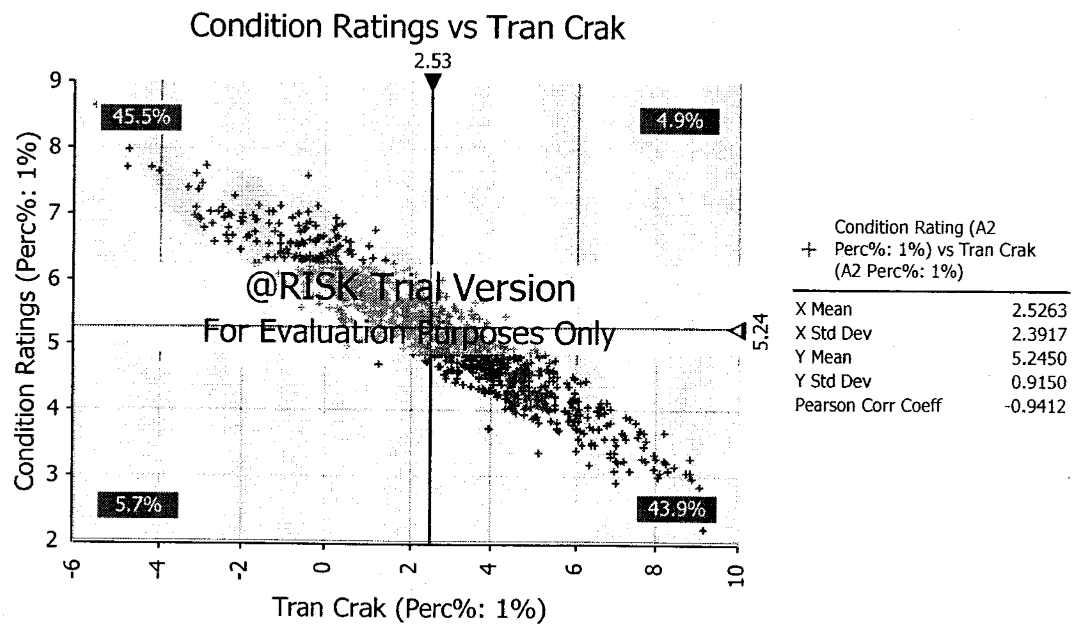
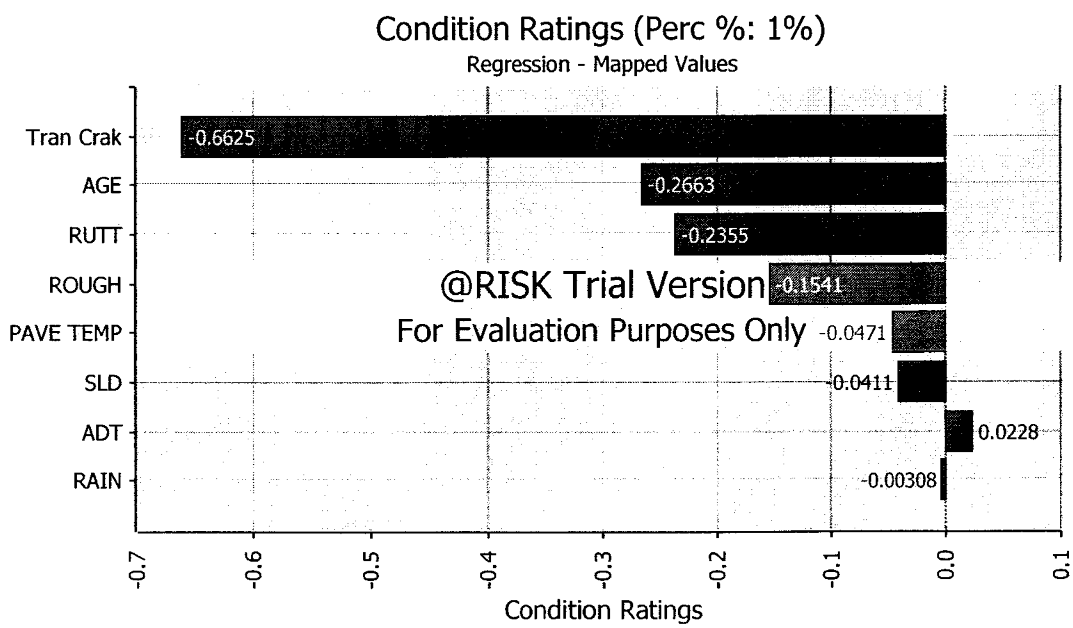


Figure 5-29: @ RISK Output of Scatter Plots for Summer Model.

5.3.4.c Sensitivity Analysis:

The main goal of any sensitivity analysis is to study how the uncertainty in the output of a model (numerical or otherwise) can be apportioned (qualitatively or quantitatively) to different sources of variation in the model input. Figure 5-30 represents a Regression-Mapped values graph that shows the actual change in condition ratings (output) for ± 1 standard deviation change in each sub-factor value (input).

It can be noticed that the sub-factor "Transverse Cracking amount-Tran Crak" is indeed the most important factor affecting the condition-rating (CR) output of this model; and when this variable changes by one standard deviation, the amount of change in the CR score from the x-axis will be equal to (-0.6225). This value (-0.6225) is shown in the bar corresponding to the (Tran Crak) variable. Similarly, all CR change values corresponding to each input variable are shown in Figure 5-30. Appendix (C) contains detailed reports and graphs of sensitivity analysis for both summer and winter models.



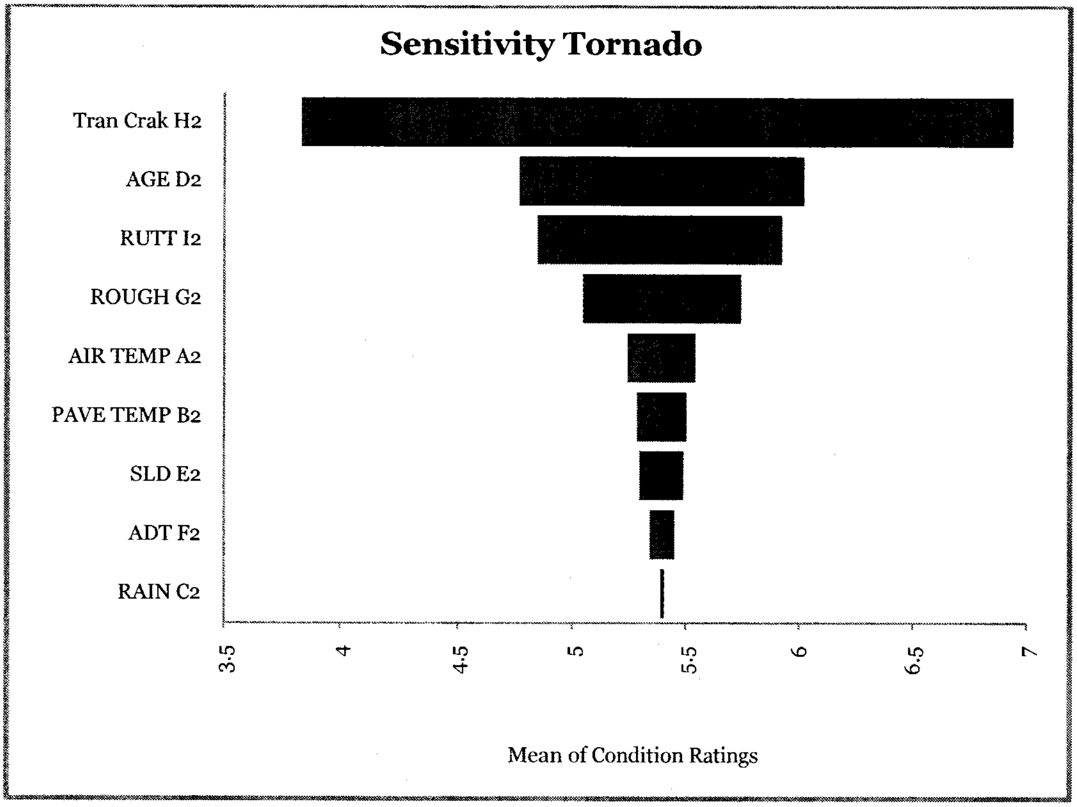


Figure 5-30: @ RISK Output of (Mapped Values + Sensitivity Tornado) for Summer Model.

5.4 SUMMARY:

This chapter presented the development of the flexible pavement condition-rating model. The chapter was divided into three parts as follows: Part one, in which the development of the MAUT condition-rating model was explained, including the application of the AHP technique to determine the relative weights of each sub-factor, and the use of the utility functions to determine the attribute scores of each sub-factor;

Part two, in which the development of the integrated MAUT/Regression condition-rating model was presented. The steps for building the integrated model were explained in detail and limited only to the summer season model. These steps are: (1) the initial examination of relationships and interactions (2) the multi-colinearity test (3) the variance inflation factor (VIF) (4) the best-subset analysis (5) generating the equation (model) and the preliminary examinations, and (6) the residual analysis. Moreover, the proposed condition-rating scale and the validation process were included in this part of the chapter. Four procedures for validating the integrated model (summer model) were used. These procedures are: (1) the plot of actual vs. predicted results (2) the descriptive statistics (3) the mathematical validation method, and (4) the comparison between the developed model and the existing condition-rating indices (i.e. PSI, PCI, and PQI). Finally, several deterioration curves were built based on four sub-factors: ADT (Average Daily Traffic), the roughness measurements, the transverse cracking amount, and the rutting amount.

Part three, in which the application of Monte-Carlo simulation was carried out on the integrated MAUT/Regression model (summer season). The simulation started with the preparation phase of the proposed model (defining the distributions of inputs and outputs), then running the simulation, and finally, conducting a sensitivity analysis.

CHAPTER 6: WEB-BASED CONDITION-RATING TOOL

6.1 Introduction:

To facilitate the usage of the developed integrated MAUT/Regression models of summer and winter conditions, an automated web-based tool is developed. The main reason behind selecting a web-based application is the ease in accessing this application via any web browser over a network such as the internet. Another reason can be the ability to update and maintain web applications without distributing software or installing it on potentially thousands of user computers.

This chapter describes the framework of a web-based decision support tool for condition rating of existing flexible pavement highways and roads. The tool is believed to assist practicing pavement engineers and experts in evaluating a specific pavement segment and selecting rehabilitation alternatives.

6.2 The Web-Based Tool System:

6.2.1 The Web-Based Tool Program:

The program of the web-based condition prediction tool is written in the C# language, using ASP.NET (Active Server Pages .NET) to create the online tool web pages. The ASP.NET is a very valuable tool for programmers and developers as it allows them to build dynamic, rich web sites and web applications. It is not limited to script languages but allows the user to make use of .NET languages like C#, Java, VB, etc. There were many reasons for using the ASP.NET web application framework, such as the fact that it is purely server-side technology, so the ASP.NET code executes on the server before it is sent to the browser; also the source code and HTML are together, therefore ASP.NET pages are easy to maintain and write. Finally, the web server continuously monitors the pages, components and applications running on it, and in case it notices any memory leaks, infinite loops, and other illegal activities, it immediately destroys those activities and restarts itself.

The web-based application program includes procedures that link different web-pages, perform calculations and interpretations, and finally generate and display the condition-rating results.

6.2.2 The Web-Based Tool Framework:

The web-based condition prediction tool employs the developed integrated MAUT/Regression models in predicting the current condition of any flexible pavement highway/road segment. For the pavement segment in question, the user has to prepare input data regarding all the sub-factors that were considered during the MAUT and multiple regression process. The following steps describe the framework of the web-based tool.

6.2.2.a Model Main Menu:

When the user opens the web page, he/she will be welcomed with a picture of a paved road and the "Model Main Menu" window display. The menu bar presents two options (*Summer* climate conditions *and Winter* climate conditions), which enable the user to select the climate conditions that correspond to the road or highway under consideration. The user can only select one option at a time. The first page of the web tool is shown in Figure 6-1.

Figure 6-1: The Web-based Tool Main Menu Window.

6.2.2.b Importing Input Data:

When the user selects one of the climate condition options, a new window opens, which is the "Input Menu". The "Input Menu" includes the main categories (Climate Conditions, Physical Properties, and Operational Factors). Under each category, the user has to fill the sub-factor cells with the values that he/she has from historical information.

The user has to pay attention to input data shown in specific units such as, degree Celsius (°C) for sub-factors of (air temperature, pavement temperature, and freezing temperature), millimeters per hour (mm/hr) for rainfall amount, inches (in.) for surface layer depth, years (yrs) for pavement age, vehicles per day (vch/dy) for average daily traffic, millimeters per meter (mm/m) for roughness measurements, and millimeters for distresses (transverse cracking amount and rutting amount).

However, the web application has additional features that enable the user to enter the input data in their original units without any need for the converting process. For example, if the user has air temperature data on the Fahrenheit scale (°F) he/she does not have to convert it to Celsius (°C); instead the user has to select the Fahrenheit option provided in the window beside the value entering field. These features are only provided for specific inputs which are: (1) air temperature, pavement temperature, and freezing temperature (selecting between the Fahrenheit and the Celsius scale), (2) surface layer depth (selecting between inches and millimeter units). Figure 6-2 shows the "Input Menu" window.

6.2.2.c Data Processing and Results:

After the input values have been entered by the user, the user then clicks on the "CR- Calculation" button to conduct the condition-rating result. The program executes all the required calculations using the integrated MAUT/Regression model. After completion the "CR- Calculation" the model outcome is shown in a new window called "Results" as shown in Figure 6-3, in which the outcome is described numerically in the Score field, linguistically in the Condition filed, in addition to the required Action for maintenance and rehabilitation treatments.

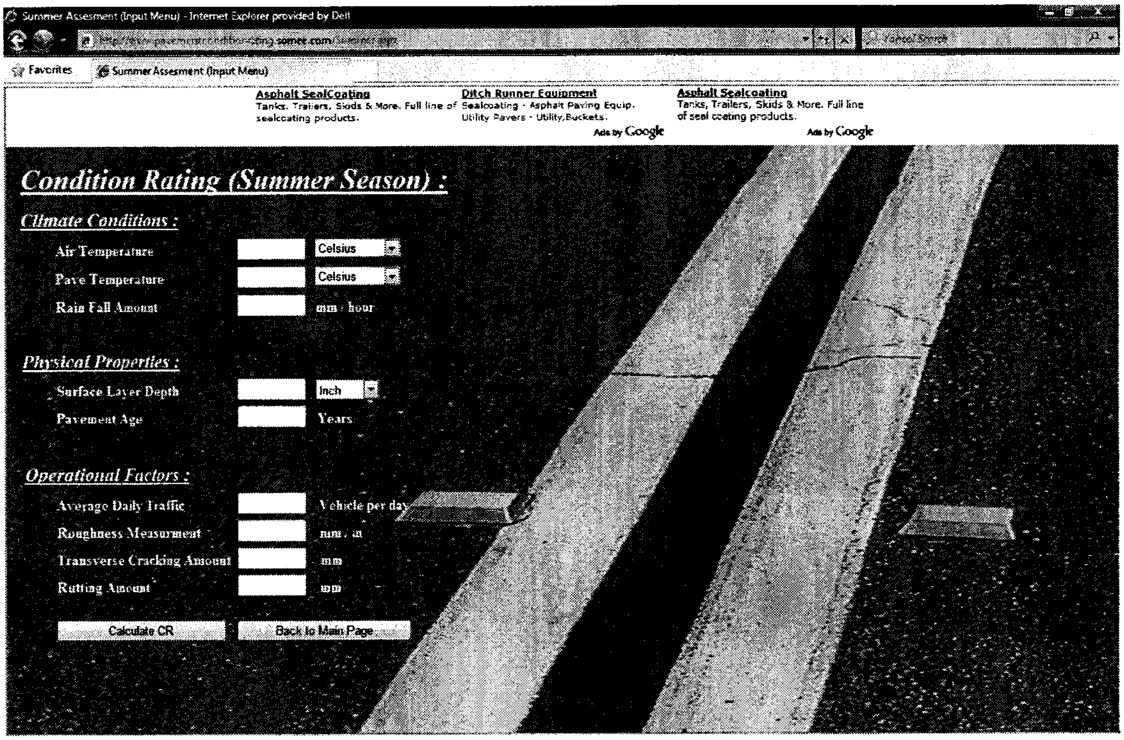


Figure 6-2: The Web-based Tool Input Menu Window.

Figure 6-3: The Web-based Tool Results Window.

6.3 SUMMARY:

This chapter presented the development of a web-based flexible pavement condition-rating tool. It is based on the proposed integrated MAUT/Regression models, for both summer and winter climate conditions. It is designed to provide practicing pavement engineers and experts with condition-rating scores of existing asphalt roads and highways and the required maintenance and rehabilitation actions.

CHAPTER 7: CONCLUSIONS AND RECOMMANDATIONS

7.1 Conclusions:

In the current research a new model is proposed to evaluate the condition of flexible pavement sections. Eleven factors are incorporated in the proposed model under three main categories: climate conditions, physical properties, and operational factors. Based on the different variations of climate characteristics within the four seasons of the year, two models are developed for summer and winter climate conditions.

As a result, a new flexible pavement condition-rating model with a numerical and linguistic condition scale is developed. Numerically, the scale ranges from 0 to 10, where 0 indicates a pavement in a critical condition and 10 a pavement in excellent condition. Linguistically, the scale is divided into five categories (critical, poor, fair, good, and excellent). The proposed scale is designed to provide an easy tool for pavement experts to plan the required rehabilitation and maintenance strategies of flexible pavements.

The findings of this research study can be summarized as follows:

- Based on the collected data, it can be concluded that the sub-factor "Transverse Cracking Amount" has the highest impact on flexible pavement condition with a weight of (24.52%), followed by the "Rutting Amount" (14.30%) and "Roughness Measurements" (14.20%).
- The results of best-subset analysis showed that the sub-factor (Base Layer Depth) has no effect on the pavement condition. Thus it was excluded from the multiple regression models for both summer and winter cases.

- The coefficient of determination (R^2) showed that 85.8% of the total variability in flexible pavement condition can be explained through the summer regression model and (R^2) of 86% in the winter regression model.
- Validation results show the robustness of the developed models, with an average validity percent of 94% for the summer model, and 93% for the winter model.
- On the basis of the developed models, the relationship between the condition-rating and age is represented by generating deterioration curves. These curves were developed with respect to Average Daily Traffic (ADT), Roughness measurements, Transverse Cracking amount, and Rutting amount, for both summer and winter cases.
- The sensitivity analysis showed that summer and winter models are more sensitive toward the sub-factor "Transverse Cracking Amount", and less sensitive toward the sub-factor "Rainfall Amount" and the "winter pavement temperature", respectively.
- By evaluating the condition of flexible pavement based on different climate, physical, and operational factors, the proposed web-based tool will assist decision makers prioritize inspection and rehabilitation to network sections that are in poor and critical conditions.

7.2 Contributions:

The current research contributed the following to the state of art of flexible pavement condition-rating:

- Identify and study a wider range of possible factors that significantly impact flexible pavement performance.
- Develop an integrated MAUT/Regression model for summer and winter climate conditions.
- Develop deterioration curves.
- Develop an automated web-based condition-rating tool to make the model accessible to different DOT and other transit authorities.

7.3 Limitations:

The developed models have several limitations, such as:

- The developed models are only appropriate for the condition prediction of full-depth asphalt pavement, that consists only of two layers (base and surface), and cannot be used for other kinds of flexible pavements.
- The MAUT model is built based on ten received questionnaires. The more experts involved in building the model, the more accurate the model will be.
- The developed multiple regression models are limited to a certain range of input data. These data are from the records of the NDOR called "Tab files".
- The developed multiple regression models are built on the assumption that a complete reconstruction is applied to each pavement segment after 15 years of service, which is the ideal case and can be violated.
- The web-based application for predicting the condition-rating of flexible pavements can only be run using the Internet Explorer web browser.

7.4 Recommendations and Future Work:

More efforts for the enhancement and extension of the current research can be summarized as follows:

- Current research enhancement areas:
  - More factors (predictors) can be included in the model, such as mix design, longitudinal cracking, sub-grade types, etc.
  - Acquiring more data from other DOT and transit authorities will lead to a better model-building process, more reliable validation results, and wider ranges for simulation outputs.
  - In addition to full-depth asphalt pavement, other types of flexible pavements could be analyzed using the developed models.
  - For the web-based automated tool, more enhancements should be added that enable the user to modify climate, physical, and operational factors, and to get better representation for the results (i.e. graphical deterioration curves).

- Current research extension areas:
  - Standardization of the data acquisition tool for DOT and other transit authorities, which will facilitate the collection of relevant climate, physical, and operational data.
  - Application of the condition-rating methodology to other pavement types, such as rigid and composite pavements.

- Integration of other performance models of flexible pavements with the developed condition-rating model.
- Linking of the web-based tool with web-GIS (Geographic Information System) so that the condition data of a specific road segment can be extracted and evaluated simultaneously.

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Appendices

Appendix A

A.1 Pavement Types:

In today's modern transport systems, except marine and pipelines transportation, pavement plays a major role as the basic structural element that carries the load of traffic in highways, urban and rural roads, and parking lots , as well as in the form of runways, taxiways, and parking aprons for air travel (Hass *et al.*, 1994).

It's safe to say that in the USA and Canada, pavement construction and maintenance cost represents approximately one-half of the total highway sector expenditures, which according to the US Federal Highway Administration exceeds $20 billion annually in the USA (FHWA, 2001).

Although the term pavement has many definitions in modern technology, the most straightforward one is by the pavement structural function or response which divides the pavement into three main categories:

1. **Flexible or asphalt pavements:** in which the asphaltic concrete is used mainly for the surface layer and sometimes for the underlying layers.
2. **Rigid or concrete pavements:** in this type of pavement, Portland Cement Concrete (PCC) is the principle material in use.
3. **Composite pavements:** it is the type of pavement that combines rigid and flexible elements, such as an asphalt concrete surface (top layer) and Portland Cement

Concrete (PCC) (bottom layer). But it is rarely used as a new construction because of its high expense.

A.2 Flexible-Pavement:

The first asphalt roadway was constructed in 1870 at Newark, New Jersey in the United States. However, the use of a hot mixture of asphalt (HMA) as the first pavement sheet-asphalt layer was introduced six years later in 1876 on Pennsylvania Avenue in Washington, DC.

Flexible pavement is mainly constructed of a bituminous surface course and a base course of suitable granular materials (Sargoius, 1975). As of 2001 (94%) of the 2.5 million miles of paved roads in the USA are asphalt surfaced (FHWA, 2001). The cross section of a conventional flexible pavement is shown in Figure A-1.

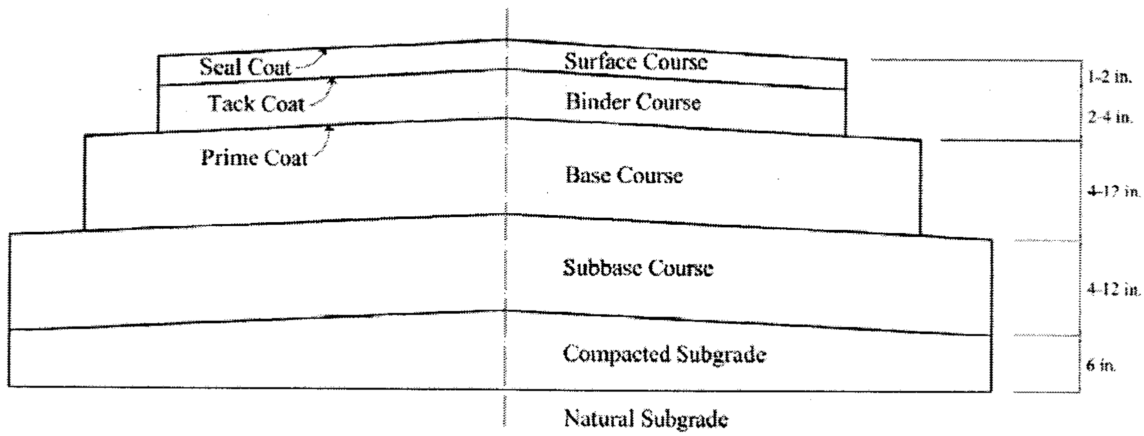


Figure A-1: Typical Cross Section of a Conventional Flexible Pavement.

Based on the base type used in the pavement system, flexible pavement can be divided into two main groups:

1. Flexible pavements with untreated granular bases:

This type is not highly recommended because of two facts:

- First, it always works as a moisture store keeping water in continuous contact with the sub-grade, causing eventually a gradual wane in its bearing strength.
- Second, when compared to asphalt bases, untreated granular bases withstand the tensile stresses in less-endure manner, which means a weaker and undependable pavement structure.

2. Full-depth asphalt pavements:

The concept of this type was first developed by the Asphalt Institute in 1960, which implies the placement of one or more layers of HMA directly on the treated sub-grade, and thus for heavy traffic the full-depth asphalt pavements are considered the most cost-effective and reliable kind of flexible pavements (AI, 1987).

Figure A-2 shows the typical cross section of a full-depth asphalt pavement.

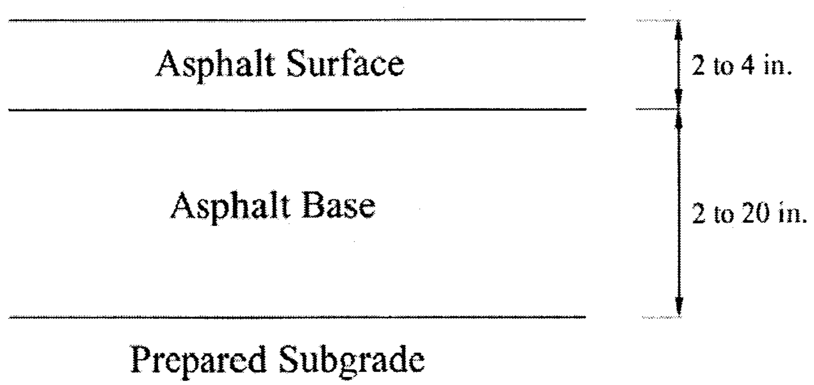


Figure A-2: A Typical Cross Section of a Full-Depth Asphalt Pavement.

According to the Asphalt institute (AI, 1987), the full-depth asphalt pavement has the following advantages:

1. Frost or moisture has no effect on asphalt bases.
2. They provide a retained uniformity in the structure of pavement.
3. Less pavement structure is required, since the asphalt base resists efficiently load tensile stresses.
4. Water entrapping has no chance of occurring since full-depth asphalt pavement has no permeable granular layers to hold water in.
5. According to previous studies, there is little or no reduction in sub-grade strength under full-depth asphalt pavement structures because they do not hold moisture contents.
6. The need for subsurface drainage is normally eliminated, unless the groundwater table is high and must be lowered.
7. Pavement riding quality is expected to improve with a properly constructed asphalt concrete base.

Appendix B

Integrated MAUT/Regression Model (Winter Season)

B.1 Model Development Process:

The following steps are applied in the building process of the winter model:

B.1.1 Initial Examination of Relationships and Interactions:

Prior to modeling the data in hand, it is recommended that we first plot the data points. Then by examining these initial plots we can easily assess whether the data have linear relationships or interactions are present. An X variable that has a linear relationship with Y will produce a plot close to a straight line, as shown in Figure B-1a (which is the ideal case). However, some exceptions may come across our own modeling, such as in Figure B-1b, c, and d, where transformation of variables should be taken into consideration in order to get better results.

According to (Leslie, 2001), if the data plot looks like Figure B-1b, it is recommended to transform the X variable in the model to 1/X, or exp (-X). If the data plot looks like Figure B-1c, consider transforming the X variable to X^2 or exp (X), and if it looks like Figure B-1d, Log X or $\sqrt{X}$ will be the suitable transformation of the variable X in our modeling.

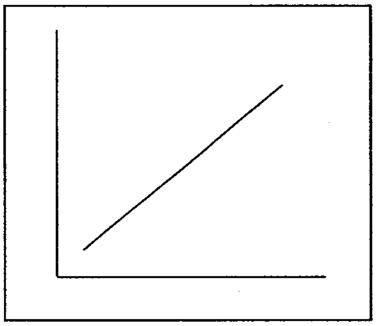


Figure B-1a: Relationship Plot.

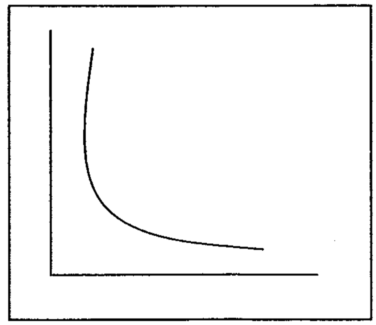


Figure B-1b: Relationship Plot.

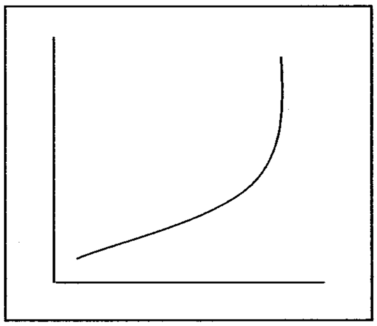


Figure B-1c: Relationship Plot.

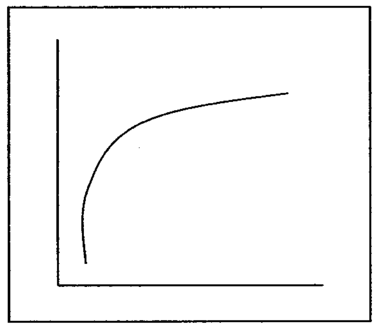


Figure B-1d: Relationship Plot.

In the winter model, plotting each input variable (sub-factor) against the output variable (condition rating-CR) resulted in two patterns of figures:

Pattern One, in which the data plot looks like Figure B-1b, and a transformation of variable X to SqRt of variable ($\sqrt{X}$) is recommended. Five sub-factors followed pattern one in their relation with the output CR (condition rating), which are (pavement age, ADT, roughness measurements, transverse cracking amount, and rutting amount).

Pattern Two, in which the data plot looks like Figure B-1a which is the ideal case, and there is no need for any transformation to be applied. Three sub-factors followed pattern two in their relation with the output CR (condition rating), which are (freezing temperature, pavement temperature, and Surface Layer Depth-SLD). Figure B-2 is an example of pattern two between sub-factor (freezing temperature) and the output (CR).

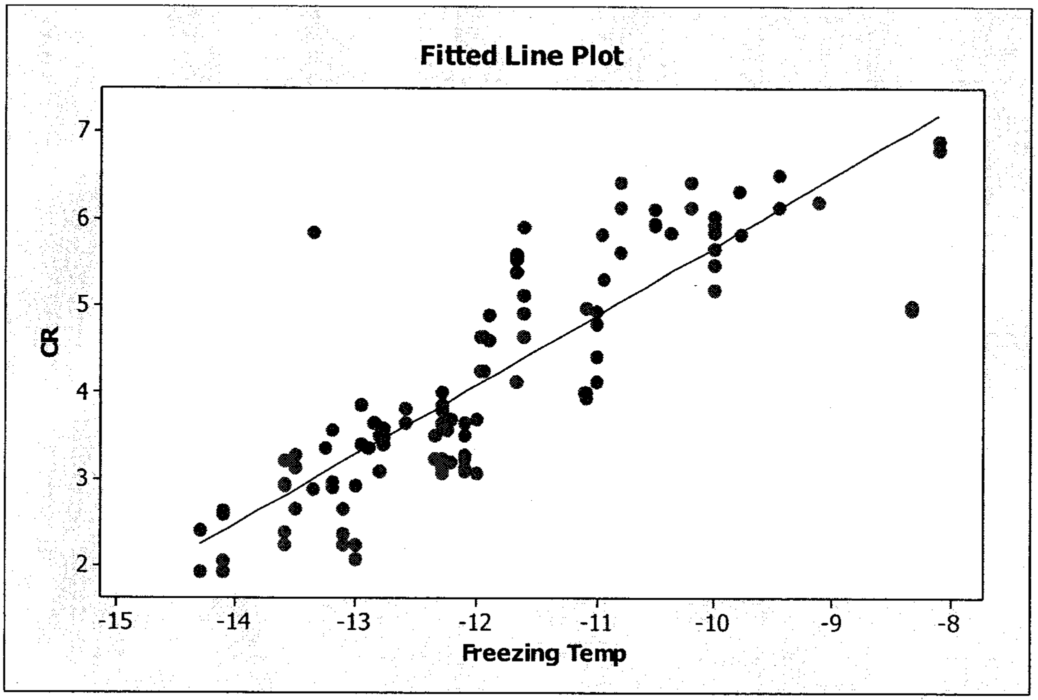


Figure B-2: Plot of Freezing Temperature against Condition Rating (CR).

B.1.2 Testing for Multi-colinearity:

The statistical phenomenon (multi-colinearity) will be investigated by calculating the sample correlation matrix for the independent variables. The correlation matrix for the winter model with its nine independent variables before and after transformation is constructed as shown in Figures B-3a and B-3b.

Correlations: Freezing Tem, Pav Temp, AGE, SLD, BLD, ADT, Rough, Tran Crak, ...

	Freezing Temp	Pav Temp	AGE	SLD
Pav Temp	0.784			
AGE	-0.378	-0.334		

SLD	-0.186	-0.051	-0.300	
BLD	-0.315	-0.155	-0.293	0.849
ADT	-0.234	-0.108	0.181	0.362
Rough	-0.085	-0.068	0.302	0.015
Tran Crak	-0.066	-0.094	0.219	-0.042
Rutt	0.009	-0.040	-0.368	0.332

	BLD	ADT	Rough	Tran Crak
ADT	0.289			
Rough	0.128	0.033		
Tran Crak	-0.143	0.058	0.274	
Rutt	0.151	-0.171	0.000	0.291

Cell Contents: Pearson correlation

Matrix Plot of Freezing Tem, Pav Temp, AGE, SLD, BLD, ADT, Rough, Tran Crak, ...

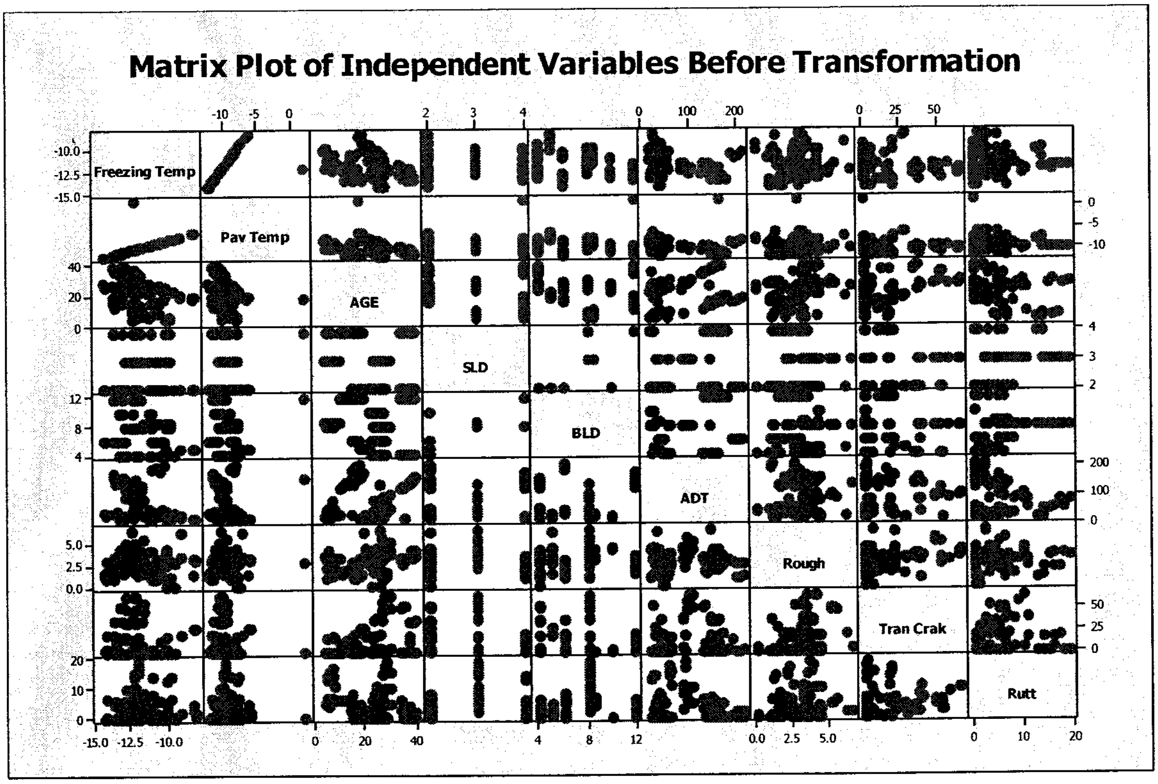


Figure B-3a: Correlation Matrix Plot of Winter Model Input Variables before Transformation.

Correlations: Freezing Tem, Pav Temp, √AGE, SLD, BLD, √ADT, √Rough, ...

	Freezing Temp	Pav Temp	√AGE	SLD
Pav Temp	0.784			
√AGE	-0.359	-0.311		
SLD	-0.186	-0.051	-0.332	

BLD	-0.315	-0.155	-0.296	0.849
√ADT	-0.266	-0.137	0.206	0.383
√Rough	-0.129	-0.096	0.249	0.053
√Tran Crak	-0.051	-0.102	0.148	-0.040
√Rutt	0.058	-0.017	-0.430	0.304

	BLD	√ADT	√Rough	√Tran Crak
√ADT	0.284			
√Rough	0.165	0.067		
√Tran Crak	-0.147	0.077	0.221	
√Rutt	0.119	-0.111	0.071	0.462

Cell Contents: Pearson correlation

Matrix Plot of Freezing Tem, Pav Temp, AGE, SLD, BLD, ADT, Rough, Tran Crak, ...

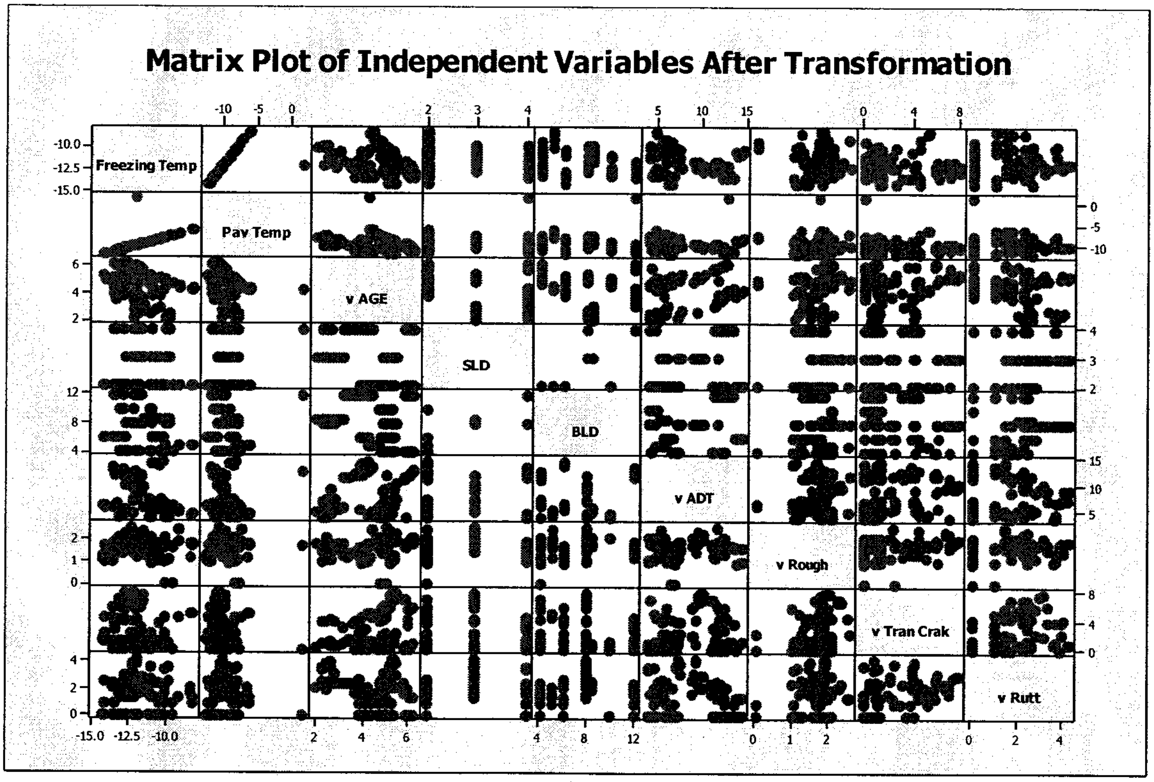


Figure B-3b: Correlation Matrix Plot of Winter Model Input Variables after Transformation.

Recall that a correlation value greater than 0.7 (in absolute value) generally indicates multi-colinearity is a problem. Both Figures (B-3a and B-3b) show existing relationships and interactions between some variables. However, they are weak relationships based on the weak (positive and negative) correlation values in both cases (before and after transformation). The only two exceptions are the positive correlation coefficient between the two variables (Freezing Temperature and Pavement Temperature) (0.784) before and after transformation, and the positive correlation coefficient (0.849 before and after) between (Surface Layer Depth and Base Layer Depth). Usually, in similar cases when two variables are highly correlated, a decision should be made to eliminate the one that is "logically" less important.

For this study, a statistical parameter called variance inflation factor (VIF) is used to determine the severity of multi-colinearity and which variables should be eliminated.

B.1.3 Variance Inflation Factor (VIF):

- Fit regression model with VIF values for the set of selected independent variables.

Regression Analysis: CR versus Freezing Temp, Pav Temp, ...

Predictor	Coef	SE Coef	T	P	VIF	
Constant	7.9729	0.3381	23.58	0.000		
Freezing Temp	0.00553	0.04325	0.13	0.898	3.358	
Pav Temp	0.00208	0.03109	0.07	0.947	2.739	
√AGE	-0.25126	0.04868	-5.16	0.000	2.393	
SLD	0.05593	0.09870	0.57	0.572	5.518	
BLD	-0.03248	0.02810	-1.16	0.250	5.520	Highest VIF > 5
√ADT	0.00096	0.01245	0.08	0.939	1.491	
√Rough	-0.32446	0.09298	-3.49	0.001	1.315	
√Tran Crak	-0.27179	0.01792	-15.17	0.000	1.665	
√Rutt	-0.17791	0.03938	-4.52	0.000	2.412	

S = 0.364223   R-Sq = 86.2%   R-Sq(adj) = 85.0%

Figure B-4a: Minitab Output of VIF Test for all Independent Variables versus the Output CR.

- The independent variable (Base Layer Depth-BLD) is eliminated from the model, and step one is repeated with the new data set.

Predictor	Coef	SE Coef	T	P	VIF
Constant	8.0851	0.3243	24.93	0.000	
Freezing Temp	0.01983	0.04151	0.48	0.634	3.084
Pav Temp	0.00254	0.03113	0.08	0.935	2.738
√AGE	-0.23180	0.04574	-5.07	0.000	2.107
SLD	-0.03774	0.05641	-0.67	0.505	1.798
√ADT	0.00316	0.01232	0.26	0.798	1.455
√Rough	-0.36295	0.08695	-4.17	0.000	1.146
√Tran Crak	-0.27103	0.01794	-15.11	0.000	1.663
√Rutt	-0.16224	0.03702	-4.38	0.000	2.126

S = 0.364779   R-Sq = 86.0%   R-Sq(adj) = 85.0%

Figure B-4b: Minitab Output of VIF Test for all Independent Variables except (BLD) versus the Output CR.

- All VIF ≤ 5, now we can proceed to the next step, which is best-subset analysis.

B.1.4 Best-Subset Analysis:

Upon concluding that the variance inflation factor VIF for all the selected variables is ≤ 5, the best-subset analysis can be applied. Best-subset analysis is defined as the process of constructing the best fit regression model with the best possible combinations of the selected variables. Figure B-5 presents an example of Minitab output for best-subset analysis.

Best Subsets Regression: CR versus Freezing Temp, Pav Temp, ...

Response is CR

Vars	R-Sq	R-Sq(adj)	Mallows Cp	S	Freezing Temp	Pav Temp	√AGE	SLD	√ADT	√Rough	√Tran Crack	√Rutt
1	76.4	76.2	70.9	0.45977							X	
1	20.9	20.2	507.2	0.84123								X
2	80.9	80.5	37.5	0.41554						X	X	
2	79.6	79.2	47.7	0.42931			X				X	
3	83.4	83.0	19.4	0.38849			X				X	X
3	82.7	82.2	25.2	0.39704			X			X	X	
4	85.8	84.9	2.6	0.36091			X			X	X	X
4	83.7	83.1	19.3	0.38691			X	X			X	X
5	86.0	84.8	3.5	0.36064	X		X			X	X	X
5	85.9	85.0	3.7	0.36110			X	X		X	X	X
6	86.0	84.3	5.1	0.36163	X		X	X		X	X	X
6	86.0	84.9	5.3	0.36196		X	X	X		X	X	X
7	86.0	84.9	7.0	0.36314	X		X	X	X	X	X	X
7	86.0	84.0	7.1	0.36324	X	X	X	X		X	X	X
8	86.0	85.0	9.0	0.36478	X	X	X	X	X	X	X	X

Figure B-5: Minitab Output for Best-Subset Analysis for Winter Condition-Rating Trial Model.

From Figure B-5 the selected model is the most appropriate combination of variables, as it satisfies the following three statistics, with $C_p = 9.0 \leq p + 1 = 8 + 1 = 9.0$, highest R^2 (adj) =85.00, but not the lowest S value = 0.36478.

B.1.5 Model Development:

After determining the most appropriate combination of variables based on best-subset analysis, the next step will be building a multiple regression model for winter climate conditions using Minitab ® 15 statistical software. Figure B-6 presents the

Minitab output that includes a regression equation of all the selected variables with their estimated coefficients "β_k", coefficient of determination R^2 and R^2 (adjusted) , and overall significance of the regression (P value).

Regression Analysis: CR versus Freezing Temp, Pav Temp, ...

```
The regression equation is
CR = 8.09 + 0.0198 Freezing Temp + 0.0025 Pav Temp - 0.232 √AGE - 0.0377 SLD
     + 0.0032 √ADT - 0.363 √Rough - 0.271 √Tran Crak - 0.162 √Rutt


Predictor          Coef  SE Coef       T      P
Constant         8.0851   0.3243   24.93  0.000
Freezing Temp   0.01983  0.04151    0.48  0.634
Pav Temp        0.00254  0.03113    0.08  0.035
√AGE           -0.23180  0.04574   -5.07  0.000
SLD            -0.03774  0.05641   -0.67  0.044
√ADT            0.00316  0.01232    0.26  0.058
√Rough         -0.36295  0.08695   -4.17  0.000
√Tran Crak     -0.27103  0.01794  -15.11  0.000
√Rutt          -0.16224  0.03702   -4.38  0.000


S = 0.364779   R-Sq = 86.0%    R-Sq(adj) = 85.0%


Analysis of Variance

Source           DF       SS      MS      F      P
Regression        8   90.000  11.250  84.55  0.000
Residual Error  110   14.637   0.133
Total           118  104.637
```

Figure B-6: Minitab Output of Regression Equation for Winter Condition-Rating Trial Model.

In order to determine the goodness of the developed regression model, three statistics should be examined as follows:

1. **Coefficient of determination R^2 and R^2 (adjusted):** the values R^2 and R^2 (adjusted) are 86.0% and 85.0% respectively. Both values indicate that the model fits the data well.

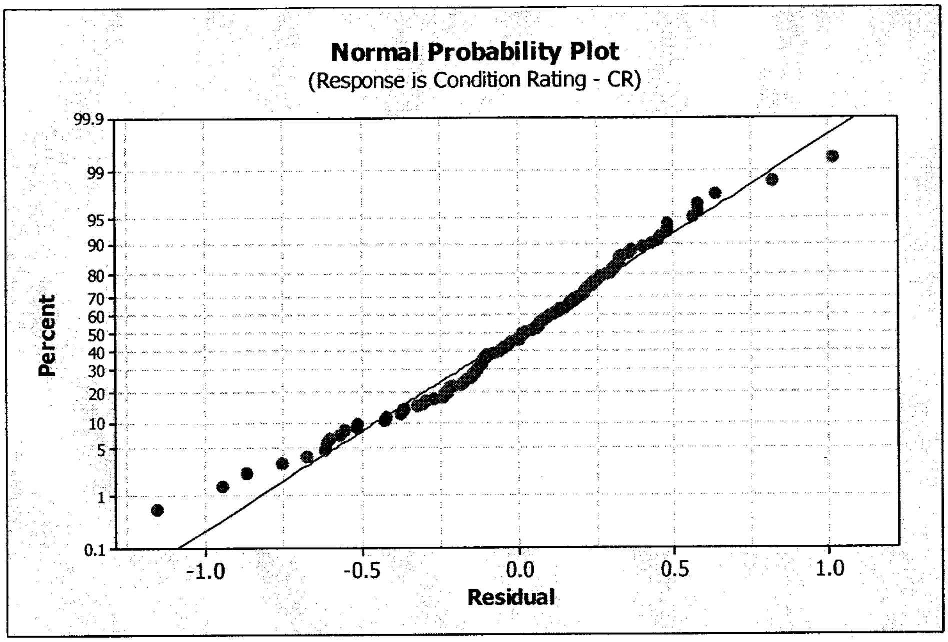
2. **F test:** The table of analysis of variance in Figure B-6 shows a value of P = 0.000 ≤ 0.05, which means that (H_0) is rejected with 95% confidence. Therefore, (H_a) is accepted and at least one coefficient in the estimated regression equation is not equal to zero.

3. **t test:** Figure B-6 shows that the p-value of the estimated coefficients for predictors ($\sqrt{\text{AGE}}$, $\sqrt{\text{Rough}}$, $\sqrt{\text{Tran Crak}}$, and $\sqrt{\text{Rutt}}$) is 0.000. Similarly, the p-value of predictors (Pave Temp and SLD) is 0.035 and 0.044 respectively. As a result, the alternate hypothesis is accepted and the previous predictor variables are significantly related to the response variable (Condition Rating-CR) at α – level of 0.05 (95% confidence). However, the case is different for the remaining two predictors. The p-value of the estimated coefficients for predictor ($\sqrt{\text{ADT}}$) is 0.058, which is slightly greater than $\alpha = 0.05$, but can be accepted. The one that does not have a significant relation with the response variable (CR) is the predictor (Freezing Tempe) with a p-value equals to 0.634 >> $\alpha = 0.05$.

B.1.6 Residuals Analysis:

I. Normality of Residuals:

In the normal probability plot, the normal distribution is represented by a straight line angled at 45 degrees. In our case (Figure B-7), the standard residuals are compared against the diagonal line to show the departure. It is clear that the residuals follow the straight line; which means that the departure from normality is slight.



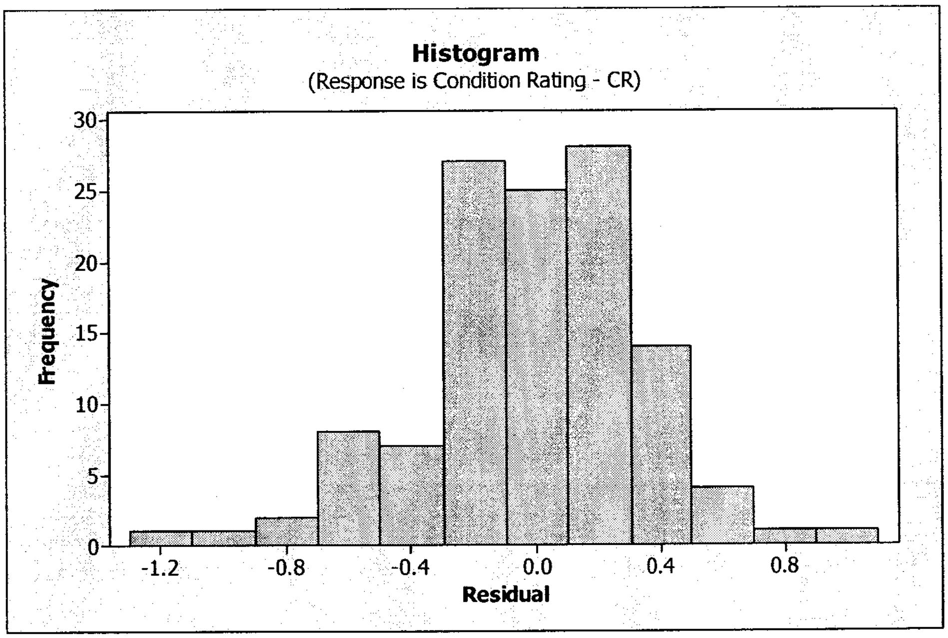


Figure B-7: Normal Probability and Histogram of Residual Plots for the Winter Condition-Rating Model.

Furthermore, in order to ensure the normality results, additional test statistics were performed. Two statistical tests are applied; Shapiro-Wilk and Anderson-Darling tests. In table B-1 a p-value of $0.056 > 0.05$ for the Shapiro-Wilk test, and $0.070 > 0.05$ for the

Anderson-Darling test, means that the null hypothesis cannot be rejected and the assumption that there is no significant departure from normality holds with a 95% confidence level.

Table B-1: Test Statistics Results for Normality Check.

Test Statistic	Test Value	P-Value	Decision (95% confidence)
Shapiro-Wilk	0.989	0.056	Accept Normality
Anderson-Darling	0.691	0.070	Accept Normality

II. Independence of Residuals:

When the residuals are independent, we expect them to fluctuate in a more or less random scatter around the base line 0. Consider the Minitab output for residuals versus the order of the data plot for the selected model (Figure B-8). The residuals scatter around the regression line in a random and patternless manner, which implies independent errors.

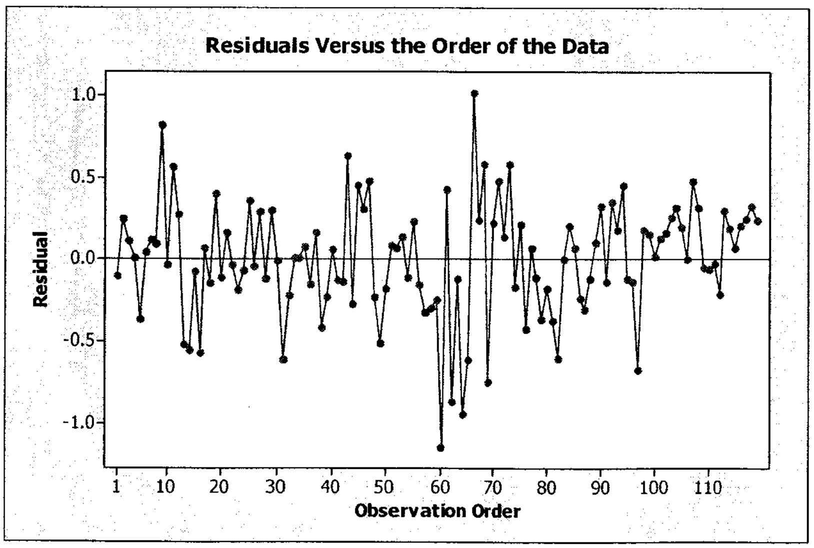


Figure B-8: Residuals vs. Order of Data Plot for the Winter Condition-Rating Model.

Moreover, a test called the Durbin–Watson statistic is used to detect the presence of autocorrelation in the residuals from a regression analysis.

$$\text{If } D < d_L \quad \text{reject } H_0\text{: } \rho = 0$$

$$\text{If } D > d_U \quad \text{do not reject } H_0\text{: } \rho = 0$$

$$\text{If } d_L < D < d_U \quad \text{the test is inconclusive.}$$

For the model under consideration, where k = 8 and n = 119, the Durbin-Watson tables indicate the following values; for k = 8, n = 150 (since 119 is not included in the tables the values at n = 150 were taken instead), and the level of significance $\alpha = 0.05$. The critical values are $d_L = 1.62$ and $d_U = 1.85$.

The Minitab output for the same model for Durbin-Watson statistics is:

$D = 1.87 > d_U = 1.85$ thus, the (H_0) is not rejected and the error terms are statistically proven to be independent.

III. Homoscedasticity:

Scatter plots of the residuals versus the fitted values from the model allow comparison of the amount of random variation in different parts of the data.

In Figure B-9, the residuals vary around the zero line in a constant pattern without any high concentration above or under it. This implies that the assumption of homoscedasticity is not violated, and the test's results are considered satisfactory.

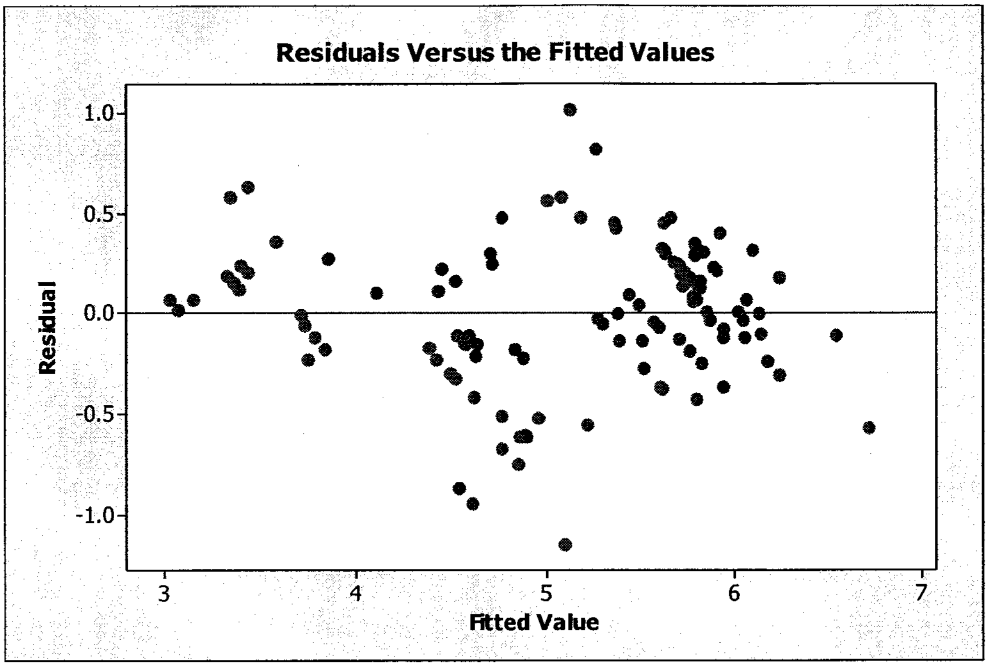


Figure B-9: Residuals vs. Fitted Values Plot for the Winter Condition-Rating Model.

B.2 Model Validation:

A comprehensive model validation procedure is applied on the selected models. The validation data consist of thirty-two observations embedded into the regression model to compare its results with the actual results using a Microsoft Excel spread sheet. Furthermore, descriptive statistics and plots of the actual and predicted outputs are obtained using Minitab ® 15 statistical software. A detailed explanation of the previous steps follows:

B.2.1 Actual vs. Predicted Output Plot:

In this step, a comparison between the actual values of condition ratings and the predicted values obtained from the regression model is conducted, using a scatter plot as the one shown in Figure B-10. The Figure shows that there is no significant departure between the actual values plot and the predicted values plot, and the predicted values scatter around the actual values in acceptable ranges. Therefore, the first validation test results are considered satisfactory.

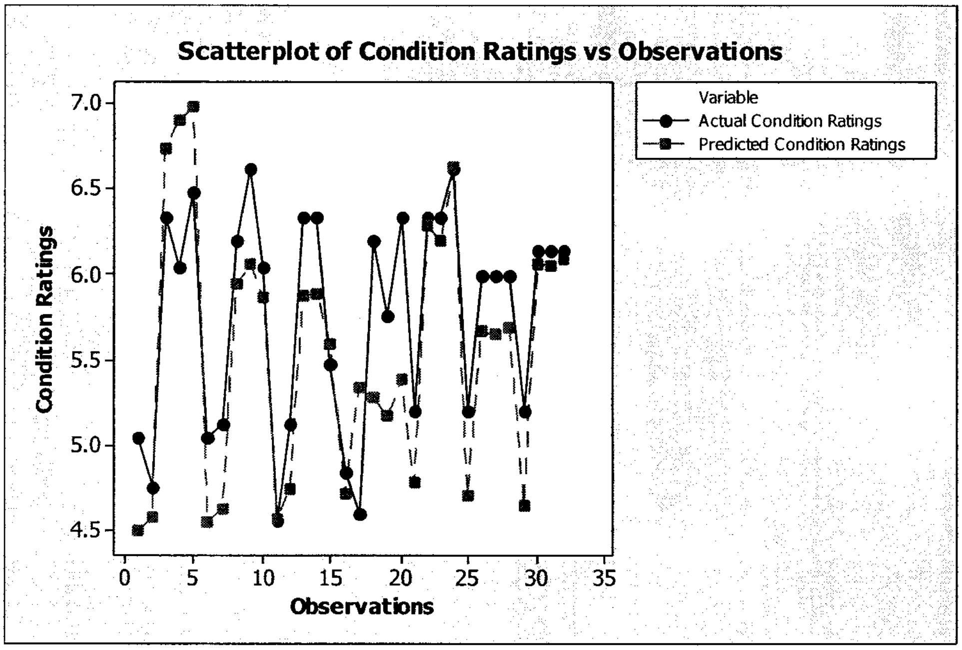


Figure B-10: Minitab Output of Validation Plot for Winter Condition-Rating Model.

B.2.2 Descriptive Statistics:

The descriptive statistics of the actual and predicted values of condition ratings will be checked in this step. The results showing in Figure B-11 and Table B-2 tell that the mean and standard deviation values of the actual and predicted outputs are close to each other, in spite of the fact that the predicted output has a slightly lesser value of mean and a greater value of standard deviation than the actual output. Therefore, the second validation test results are considered satisfactory.

Table B-2: Descriptive Statistics for Actual and Predicted Values of Validation Data.

Descriptive Statistics	Actual CR	Predicted CR
Mean	5.765	5.554
Standard Deviation	0.639	0.753
No. of Observations	32	32

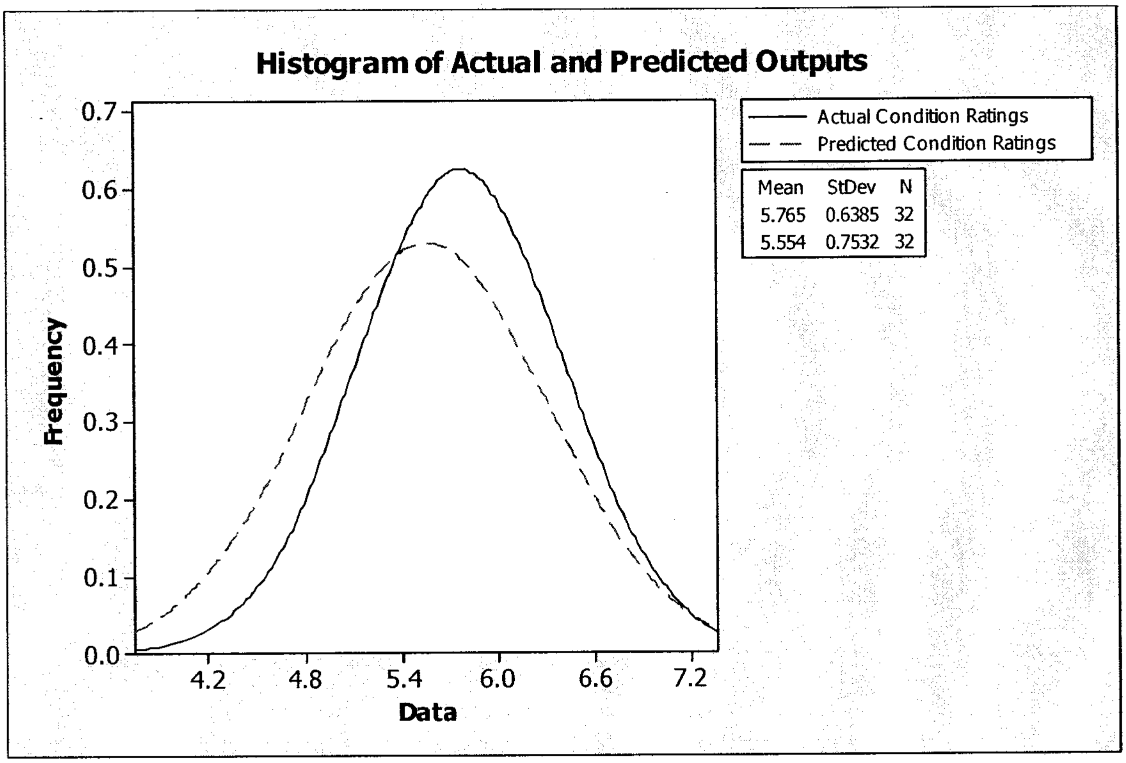


Figure B-11: Minitab Output of Histogram of Validation Data for Winter Condition-Rating Model.

B.2.3 Mathematical Validation Method:

The results show that the predicted outputs are 93% accurate, with RMS and MAE values close to zero. Thus the validation results are considered satisfactory and the selected model does fit the validation data.

AIP = 0.0660, AVP = 0.9340, RMS = 0.0806, MAE = 0.3756.

B.3 Deterioration Curves:

Figures B-12 to Figure B-15 represent condition deterioration of flexible pavement with respect to ADT (Average Daily Traffic), Roughness measurements, Transverse Cracking amount, and Rutting amount respectively. As shown in Figure B-12 prediction curves are developed for each of the traffic levels (Low, Moderate, and Heavy), the X-axis represents the pavement age, and the Y-axis is the condition rating (CR) score. For example, if the pavement age and level of traffic for a specific road segment are known, under the same conditions of the proposed model, a user can easily obtain the condition rating score by plotting the corresponding value from the chart on the Y-axis (CR-axis).

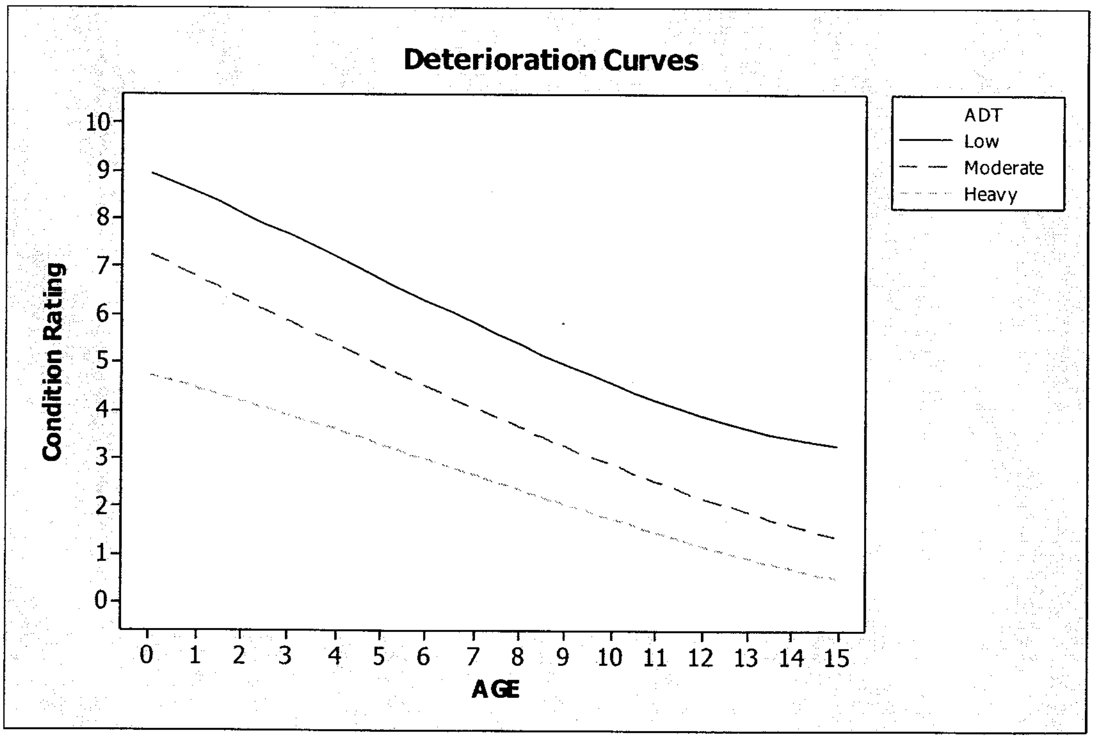


Figure B-12: Minitab Output of Deterioration Curves for Average Daily Traffic (ADT).

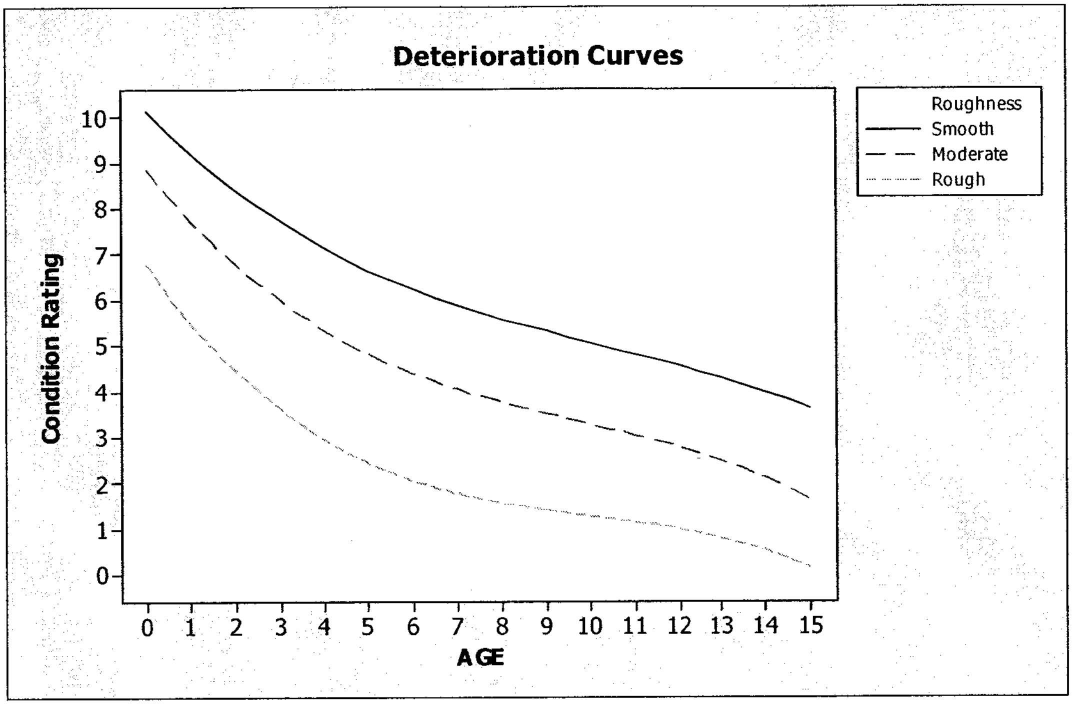


Figure B-13: Minitab Output of Deterioration Curves for Roughness Measurements.

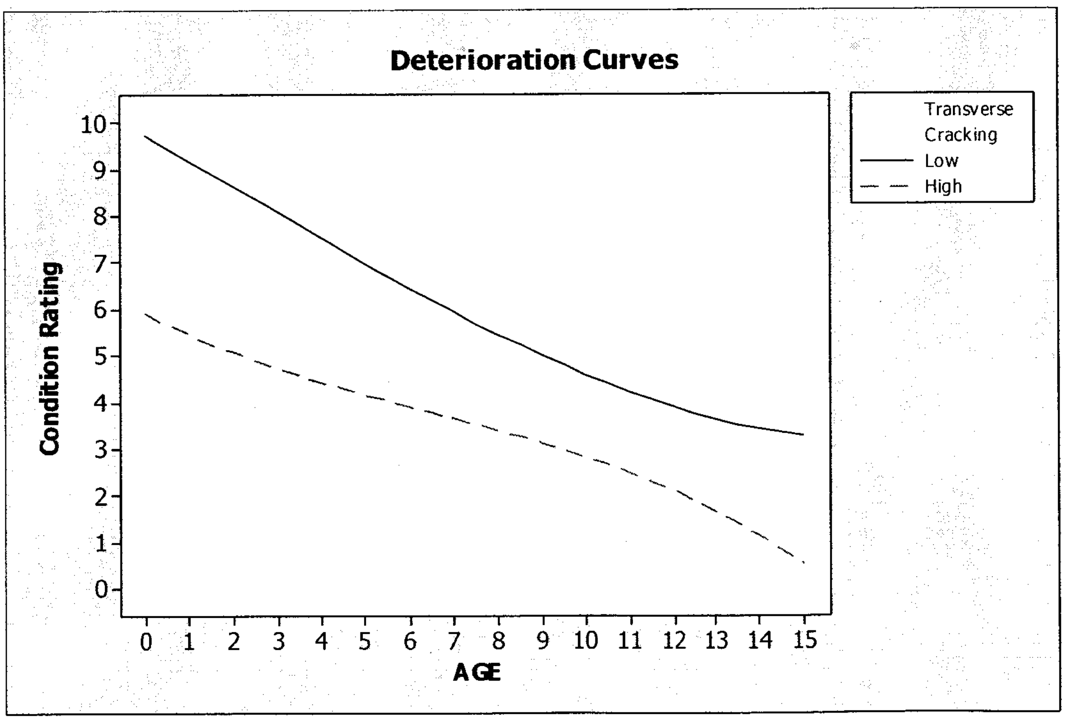


Figure B-14: Minitab Output of Deterioration Curves for Transverse Cracking Amount.

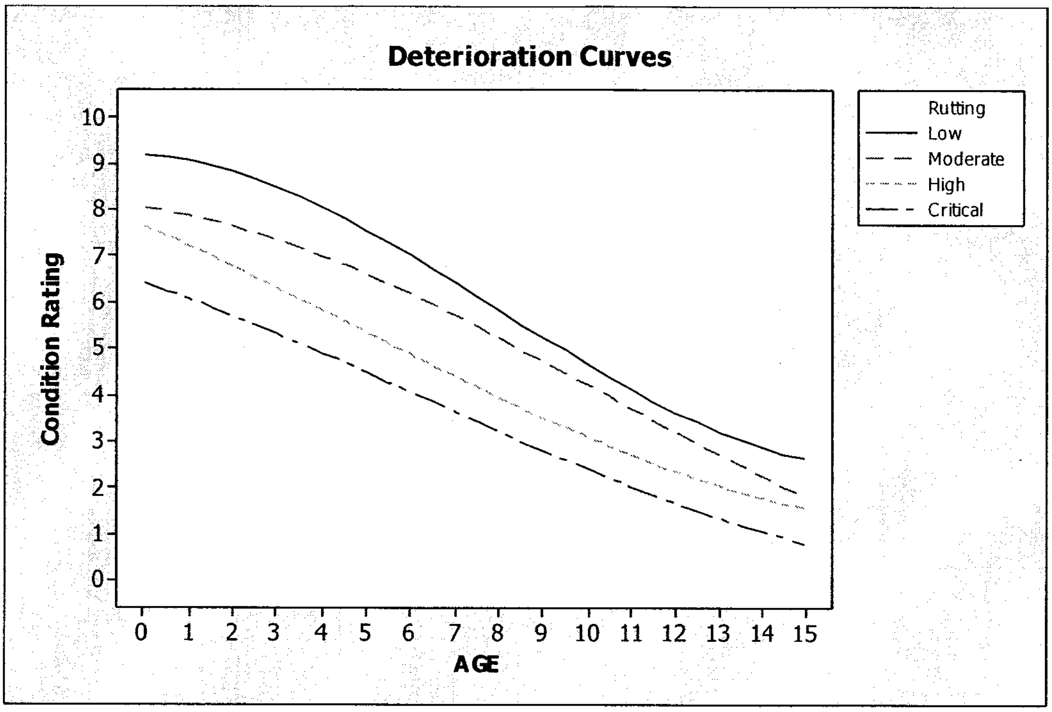


Figure B-15: Minitab Output of Deterioration Curves for Rutting Amount.

From Figure B-12 to Figure B-15, it is clear that the rate of pavement deterioration is significantly less whenever the traffic level is lower, and the distress severity is less. We can also notice that an inverse polynomial relation of third degree does exist between the condition value and age of pavement. Tables B-3 to B-6 show the third degree equations between (Age) and (CR), which represent the deterioration curves of Figure B-12 to B-15.

Table B-3: Deterioration Models for Average Daily Traffic.

ADT (vehicles/day)	Traffic Level	Model	R^2 (%)	R^2 (adj)	Std. Error	P-Value
< 20	Low	$Y = 0.0024\ x^3 - 0.0344\ x^2 - 0.3094\ x + 8.901$	94.10	93.30	0.3751	0.0360
$20 \leq ADT \leq 100$	Moderate	$Y = 0.0030\ x^3 - 0.0501\ x^2 - 0.2222\ x + 7.079$	94.80	94.10	0.3677	0.0080
> 100	Heavy	$Y = 0.0008\ x^3 - 0.0156\ x^2 - 0.2089\ x + 4.653$	89.20	87.60	0.4181	0.4710

Y = Condition Rating, x = Pavement Age

Table B-4: Deterioration Models for Roughness Measurements.

Roughness (mm/m)	Severity Level	Model	R^2 (%)	R^2 (adj)	Std. Error	P-Value
$RM \leq 2.48$	Smooth	$Y = -\ 0.0011\ x^3 + 0.0589\ x^2 - 0.9720\ x + 10.140$	89.80	88.30	0.5125	0.4330
$2.49 \leq RM \leq 3.33$	Moderate	$Y = -\ 0.0050\ x^3 + 0.1431\ x^2 - 1.4710\ x + 9.065$	86.40	84.50	0.6858	0.0170
$3.34 \leq RM \leq 6.18$	Rough	$Y = -\ 0.0036\ x^3 + 0.1183\ x^2 - 1.3640\ x + 6.748$	89.80	88.30	0.5503	0.0290

Y = Condition Rating, x = Pavement Age

Table B-5: Deterioration Models for Transverse Cracking Amount.

Transverse Cracking (mm)	Severity Level	Model	R^2 (%)	R^2 (adj)	Std. Error	P-Value
cracks < 13.00	Low	$Y = 0.0025\ x^3 - 0.0327\ x^2 - 0.4324\ x + 9.651$	93.00	92.00	0.5030	0.0930
cracks ≥ 13.00	High	$Y = -\ 0.0018\ x^3 + 0.0365\ x^2 - 0.4875\ x + 5.905$	92.30	91.20	0.4492	0.1580

Y = Condition Rating, x = Pavement Age

Table B-6: Deterioration Models for rutting Amount.

Rutting (mm)	Severity Level	Model	R^2 (%)	R^2 (adj)	Std. Error	P-Value
$R \leq 9.00$	Low	$Y = 0.0045\,x^3 - 0.0895\,x^2 - 0.0077\,x + 9.162$	92.80	91.70	0.5116	0.0050
$10.00 \leq R \leq 13.00$	Moderate	$Y = 0.0028\,x^3 - 0.0577\,x^2 - 0.0707\,x + 8.023$	90.60	89.30	0.5273	0.0750
$14.00 \leq R \leq 20.00$	High	$Y = 0.0024\,x^3 - 0.0390\,x^2 - 0.3042\,x + 7.569$	85.30	83.20	0.7302	0.2550
$R > 20.00$	Critical	$Y = 0.0021\,x^3 - 0.0410\,x^2 - 0.2064\,x + 6.310$	85.10	83.00	0.7274	0.3130

Y = Condition Rating, x = Pavement Age

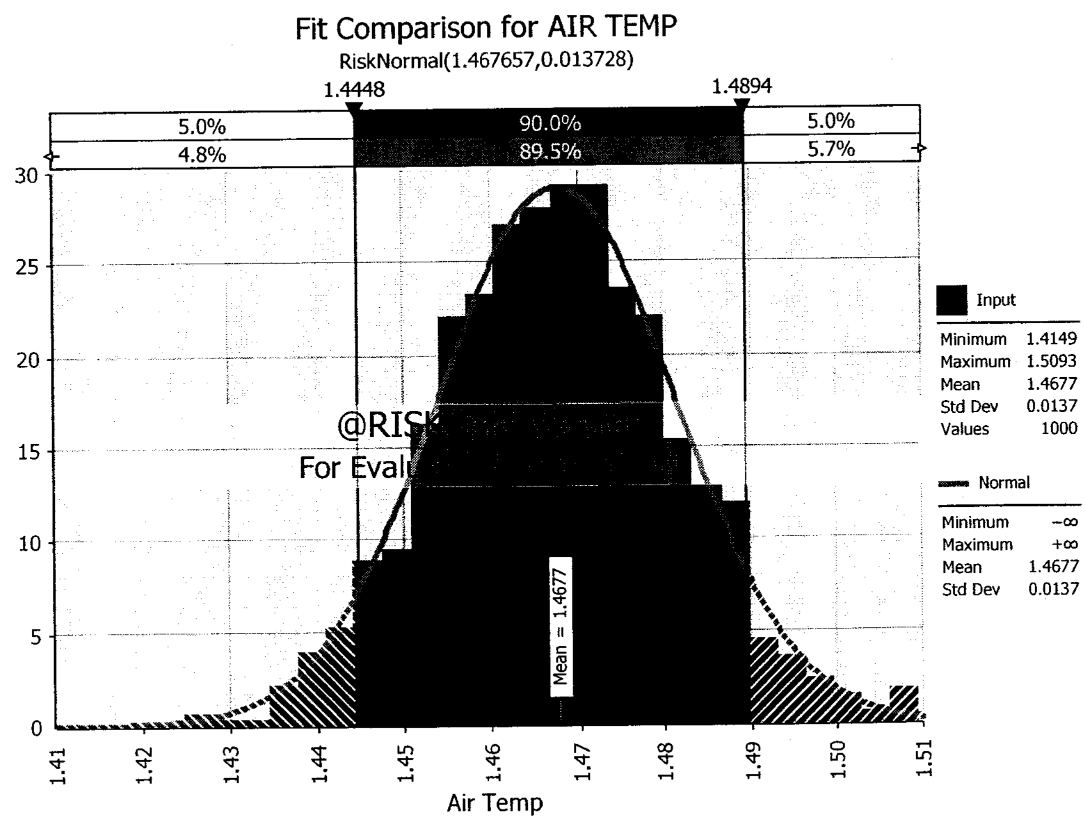
It can be noticed from the results of (R^2, adjusted R^2, standard error, and P-value) that the developed deterioration models are robust and reliable. Therefore, the deterioration curves can be used by the DOT to determine the condition rating score of an existing flexible pavement road/highway, under the same conditions of the proposed models.

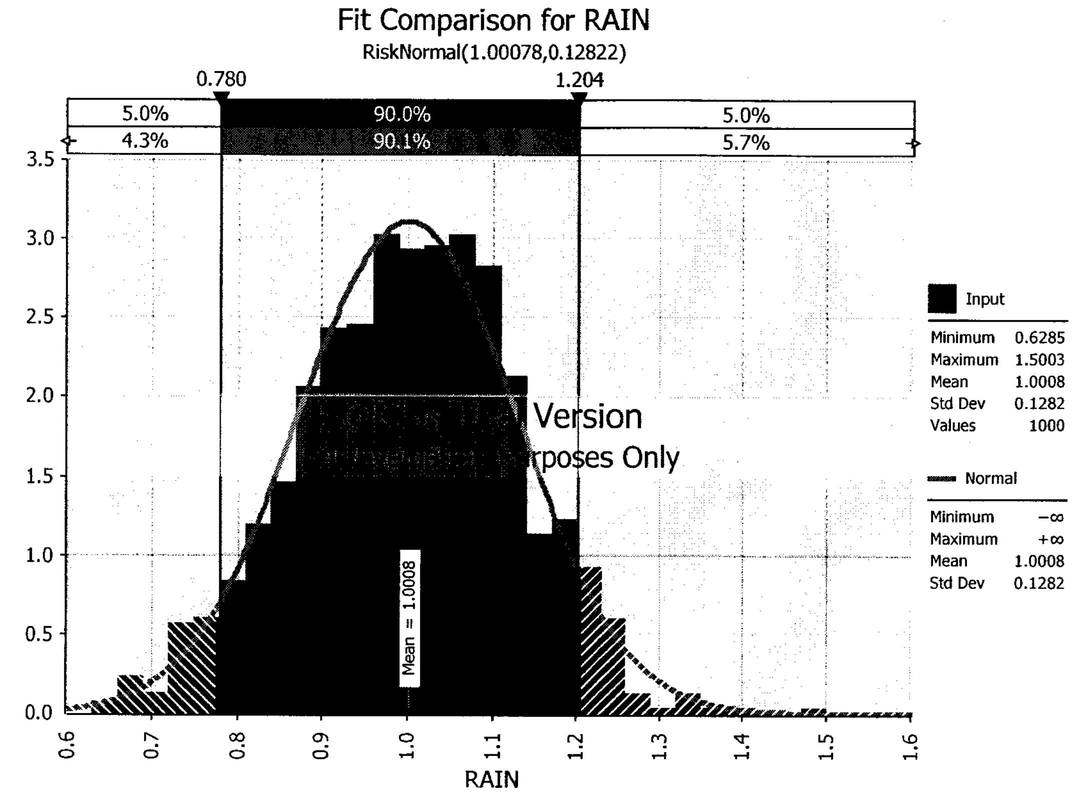
Appendix C: Results of Monte-Carlo Simulation

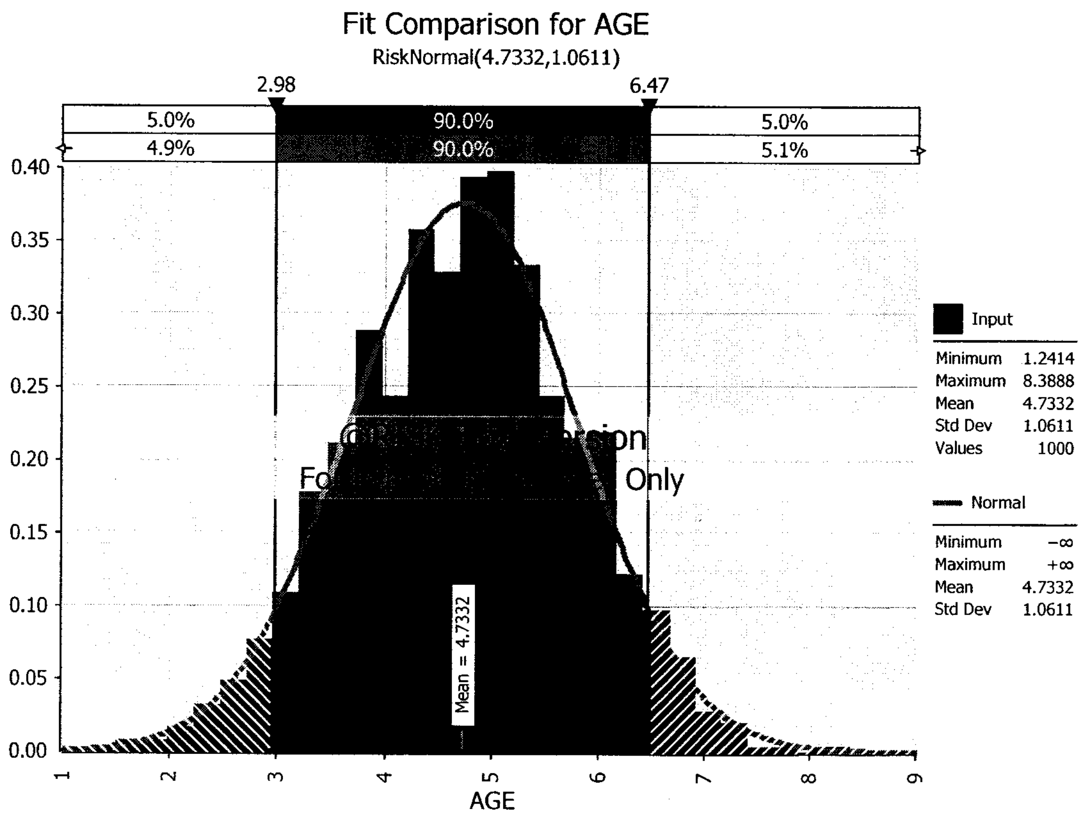
C.1 Summer Model:

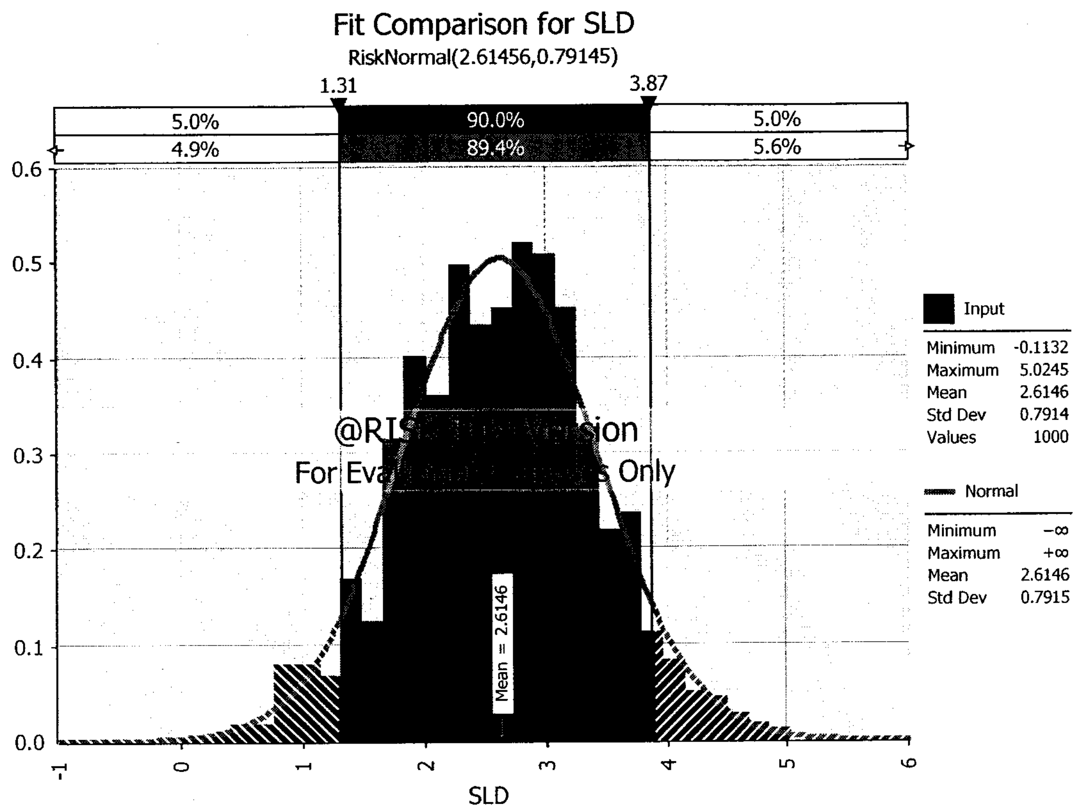
C.1.1 Defining Probability Distributions:

Based on the collected data and by using @ Risk software, probability distributions of input parameters were defined. Distributions that best fit the selected input variables are chosen as the first option and ranked along with other distributions that may fit the data as well. The ranking of the distributions is based on three statistical tests (Chi-Squared statistic, Anderson- Darling statistic, Kolmogorov-Smirnov statistic).

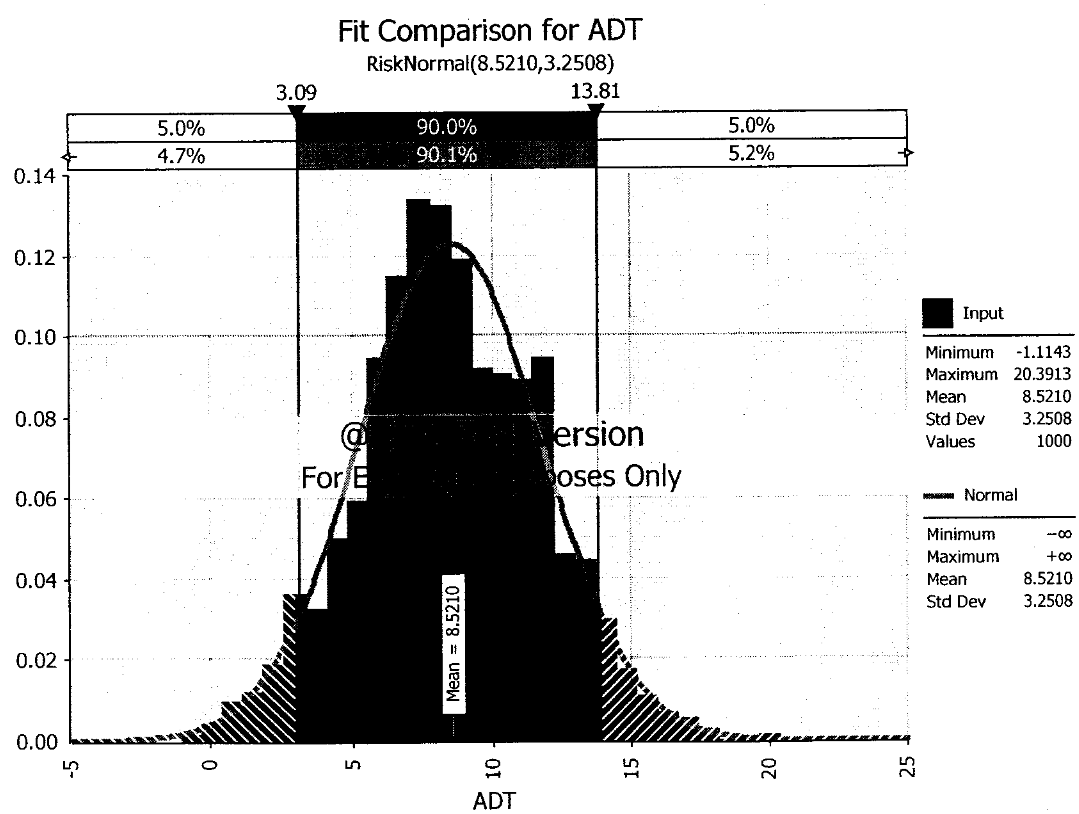



Fit Comparison for RAIN
RiskNormal(1.00078,0.12822)
0.780
1.204
5.0%
90.0%
5.0%
4.3%
90.1%
5.7%
Mean = 1.0008
RAIN
Input
Minimum 0.6285
Maximum 1.5003
Mean 1.0008
Std Dev 0.1282
Values 1000
Normal
Minimum −∞
Maximum +∞
Mean 1.0008
Std Dev 0.1282

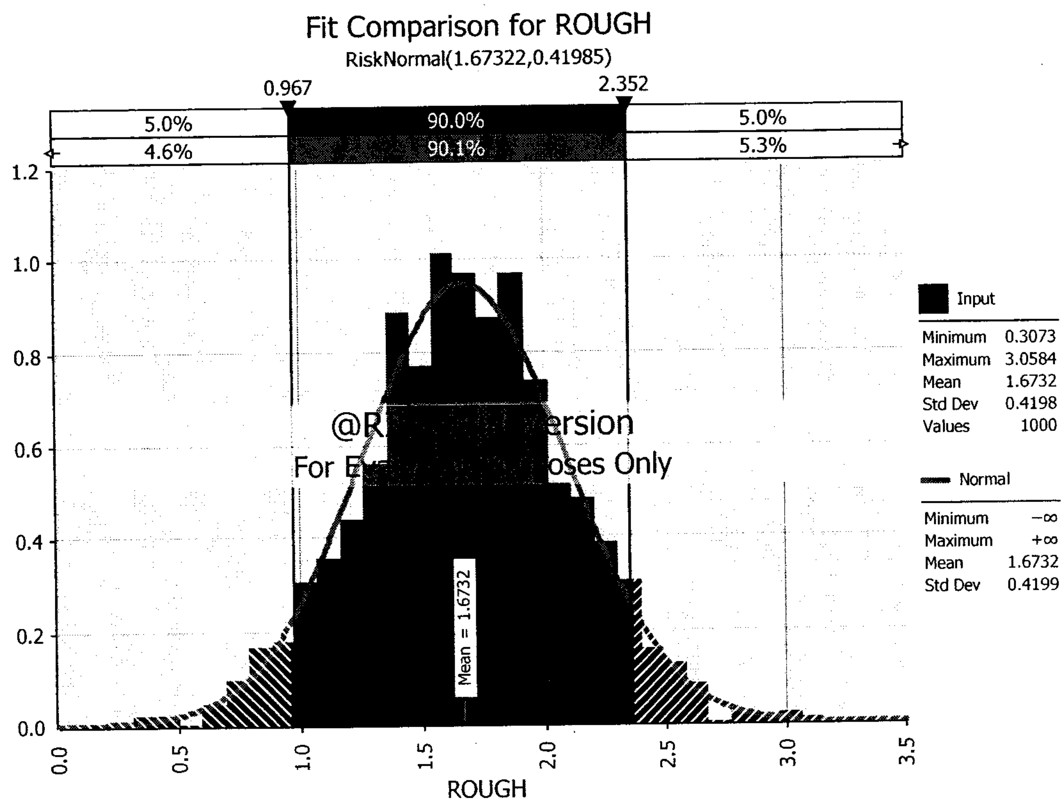

Fit Comparison for AGE
RiskNormal(4.7332,1.0611)
2.98
6.47
5.0%
90.0%
5.0%
4.9%
90.0%
5.1%
Mean = 4.7332
AGE
Input
Minimum 1.2414
Maximum 8.3888
Mean 4.7332
Std Dev 1.0611
Values 1000
Normal
Minimum −∞
Maximum +∞
Mean 4.7332
Std Dev 1.0611



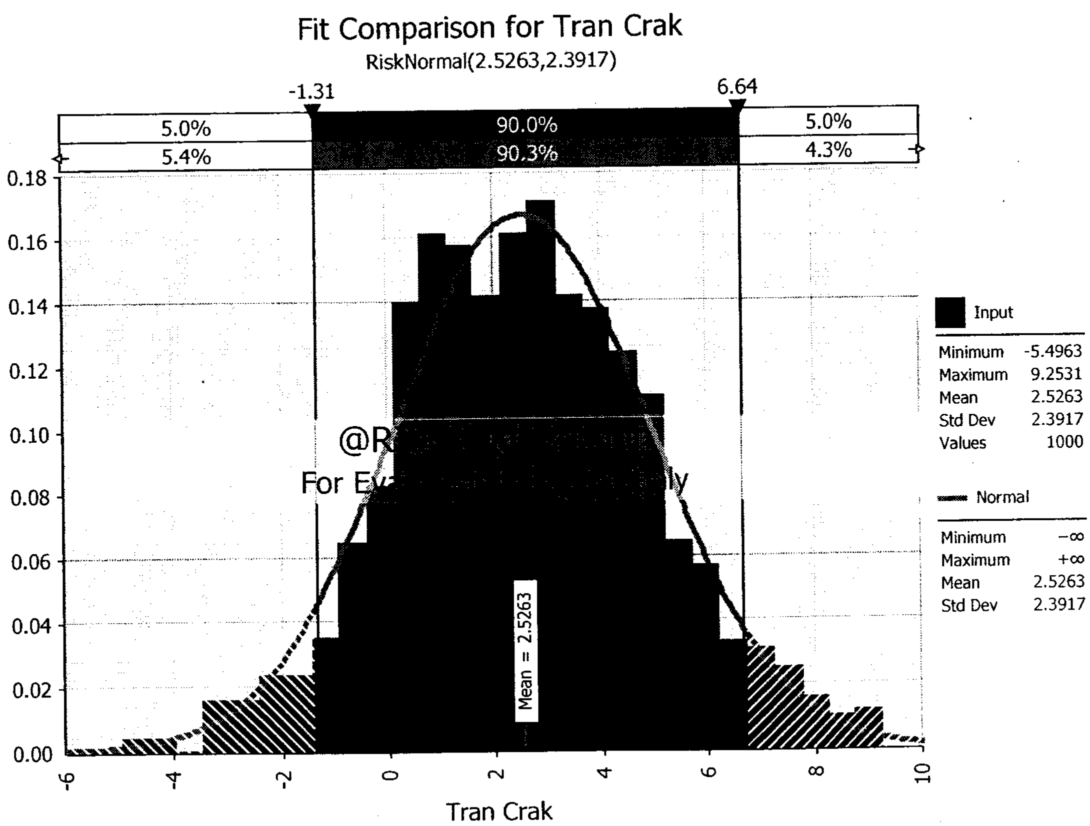
Fit Comparison for SLD
RiskNormal(2.61456,0.79145)
1.31
3.87
5.0%
90.0%
5.0%
4.9%
89.4%
5.6%
0.6
0.5
0.4
0.3
0.2
0.1
0.0
-1
0
1
2
3
4
5
6
SLD
Mean = 2.6146
@RISK Trial Version
For Evaluation Purposes Only
Input
Minimum -0.1132
Maximum 5.0245
Mean 2.6146
Std Dev 0.7914
Values 1000
Normal
Minimum −∞
Maximum +∞
Mean 2.6146
Std Dev 0.7915



Fit Comparison for ADT
RiskNormal(8.5210,3.2508)
3.09
13.81
5.0%
90.0%
5.0%
4.7%
90.1%
5.2%
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
-5
0
5
10
15
20
25
ADT
Mean = 8.5210
For Evaluation Purposes Only
Input
Minimum -1.1143
Maximum 20.3913
Mean 8.5210
Std Dev 3.2508
Values 1000
Normal
Minimum −∞
Maximum +∞
Mean 8.5210
Std Dev 3.2508



Fit Comparison for ROUGH
RiskNormal(1.67322,0.41985)
0.967
2.352
5.0%
90.0%
5.0%
4.6%
90.1%
5.3%
Mean = 1.6732
ROUGH
Input
Minimum 0.3073
Maximum 3.0584
Mean 1.6732
Std Dev 0.4198
Values 1000
Normal
Minimum −∞
Maximum +∞
Mean 1.6732
Std Dev 0.4199



Fit Comparison for Tran Crak
RiskNormal(2.5263,2.3917)
-1.31
6.64
5.0%
90.0%
5.0%
5.4%
90.3%
4.3%
Mean = 2.5263
Tran Crak
Input
Minimum -5.4963
Maximum 9.2531
Mean 2.5263
Std Dev 2.3917
Values 1000
Normal
Minimum −∞
Maximum +∞
Mean 2.5263
Std Dev 2.3917

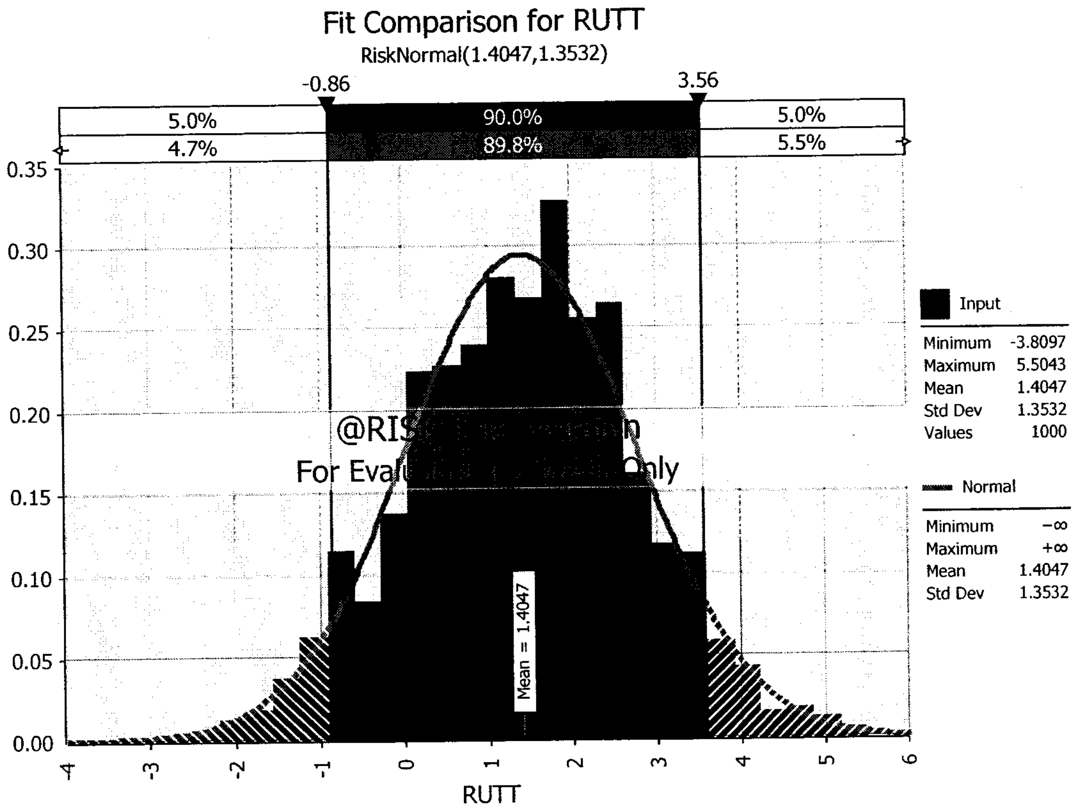
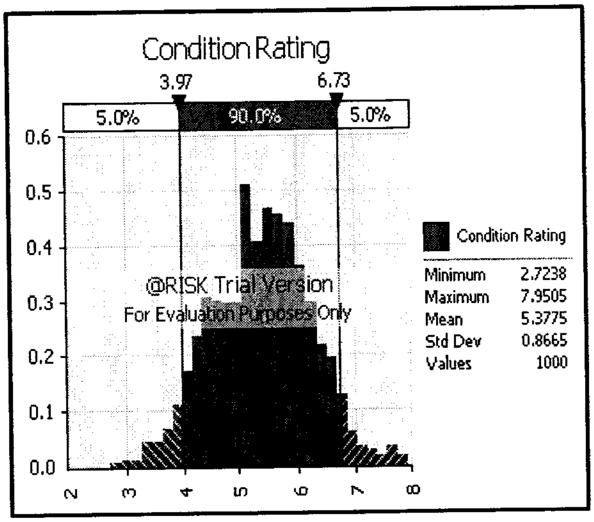
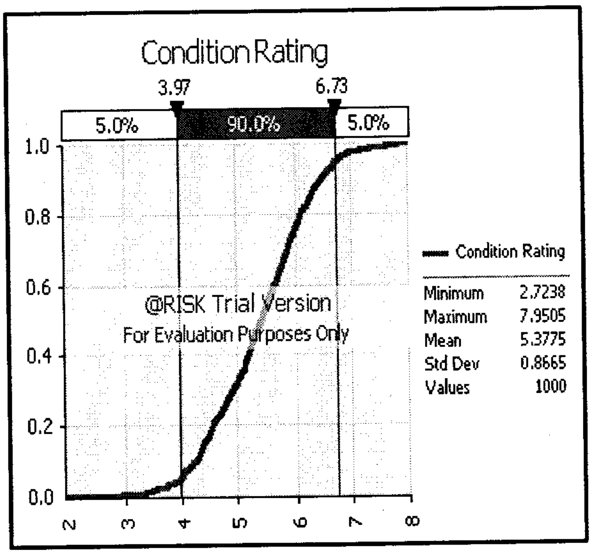


Figure C-1: @ RISK Output for Defining Distributions that Best Fit the Summer Model Sub-Factors (inputs).

C.1.2 Simulation Results:



Simulation Summary Information	
Workbook Name	Summer Model
Number of Simulations	1
Number of Iterations	1000
Number of Inputs	9
Number of Outputs	1
Sampling Type	Monte Carlo
Simulation Start Time	11/25/09 15:19:41
Simulation Duration	00:00:02
Random # Generator	Mersenne Twister
Random Seed	746157450

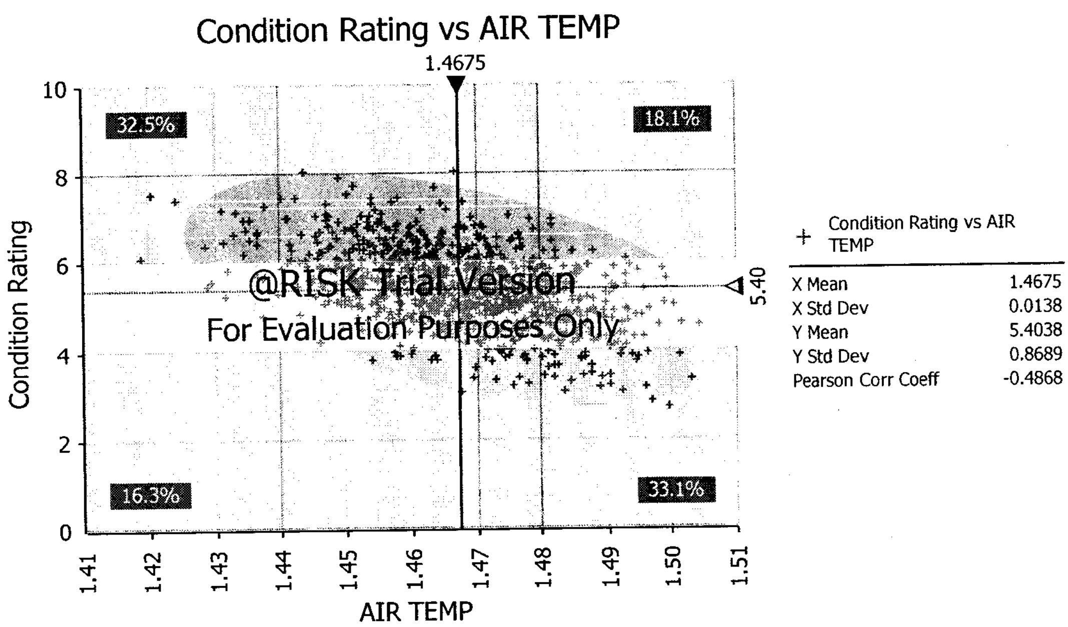


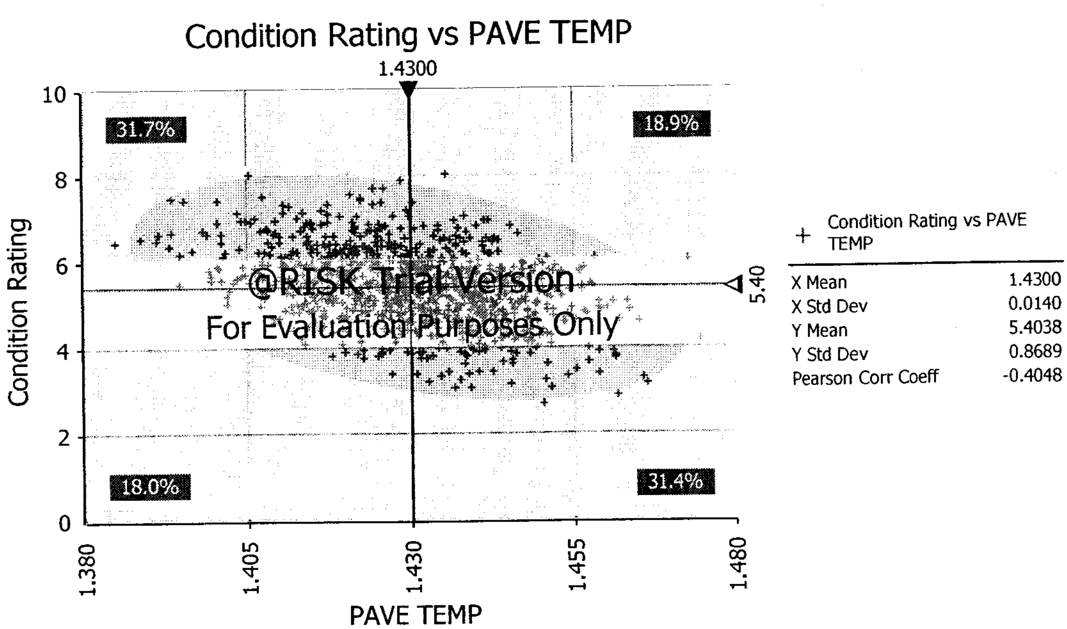
Summary Statistics for Condition Rating			
Statistics		**Percentile**	
Minimum	**2.7237**	**5%**	**3.9730**
Maximum	**7.9505**	**10%**	**4.2655**
Mean	**5.3775**	**15%**	**4.4020**
Std Dev	**0.8664**	**20%**	**4.5675**
Variance	**0.7507**	**25%**	**4.7653**
Skewness	**-0.0242**	**30%**	**4.9263**
Kurtosis	**2.8824**	**35%**	**5.0837**
Median	**5.4080**	**40%**	**5.1970**
Mode	**5.1378**	**45%**	**5.2827**
Left X	**3.9730**	**50%**	**5.4080**
Left P	**5%**	**55%**	**5.5122**
Right X	**6.7327**	**60%**	**5.6327**
Right P	**95%**	**65%**	**5.7547**
Diff X	**2.7597**	**70%**	**5.8613**
Diff P	**90%**	**75%**	**5.9644**
#Errors	**0**	**80%**	**6.0764**
Filter Min	**Off**	**85%**	**6.2564**
Filter Max	**Off**	**90%**	**6.4595**
#Filtered	**0**	**95%**	**6.7327**

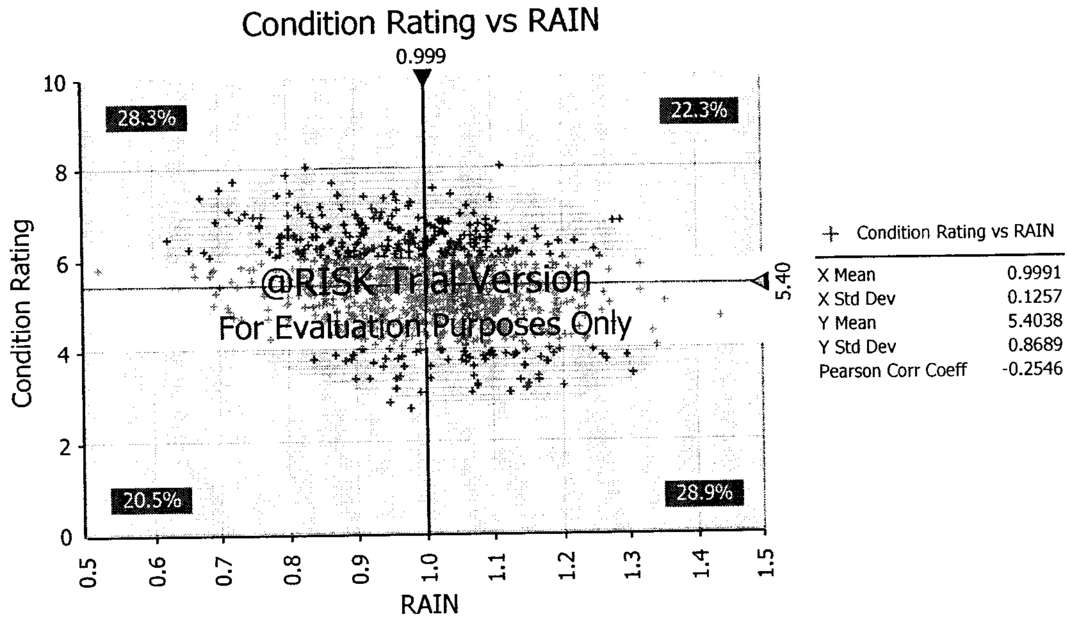
Figure C-2: @ RISK Output for Simulation Results of Summer Model.

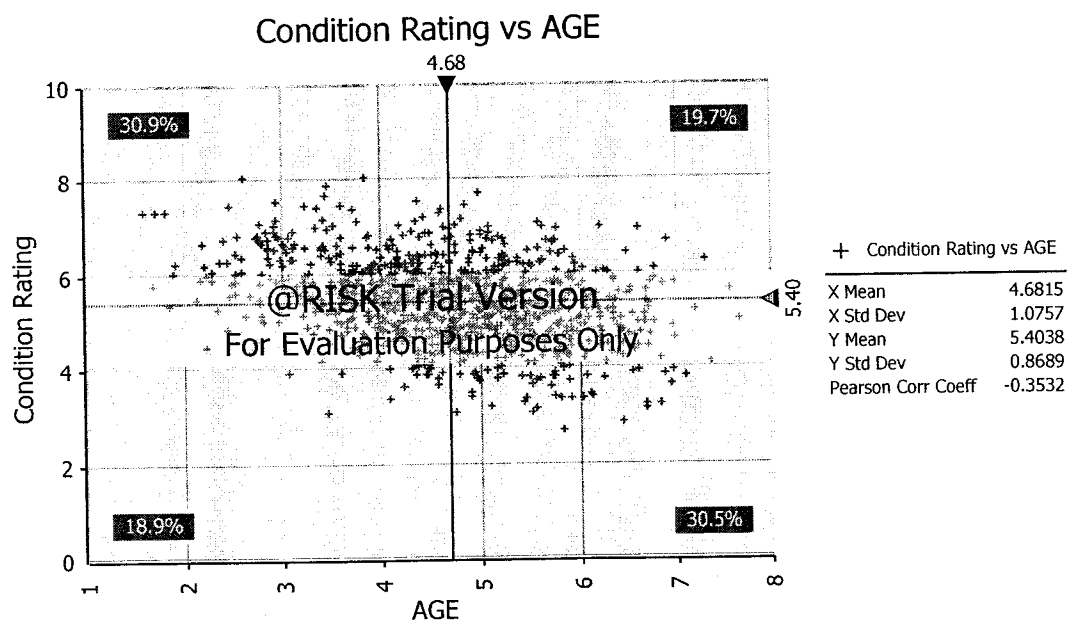
C.1.3 Analysis of Results:

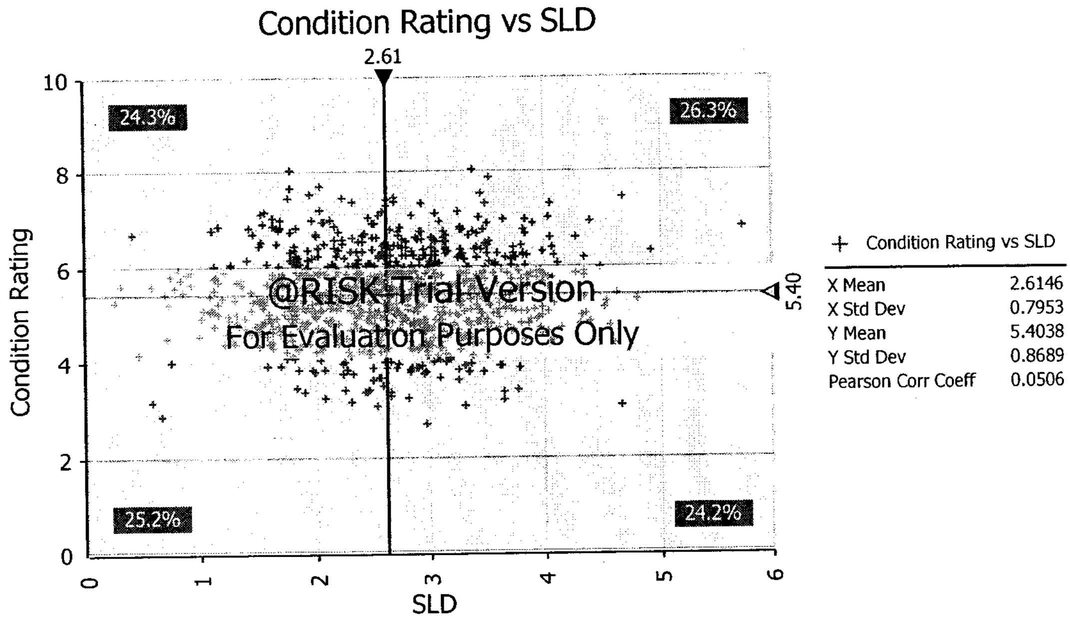
II. Scatter Plots:

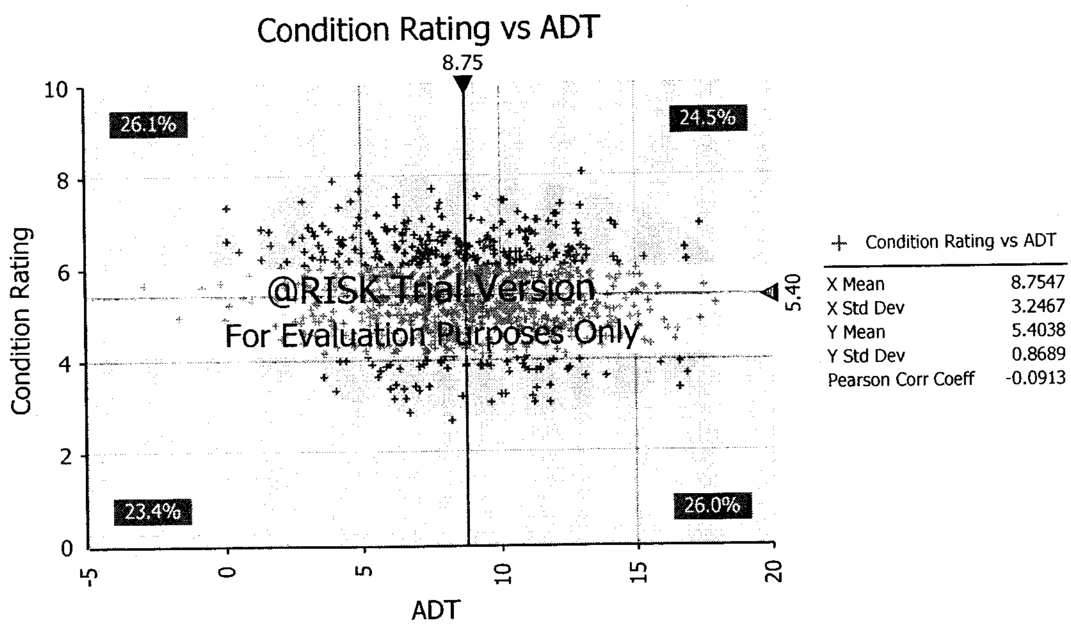


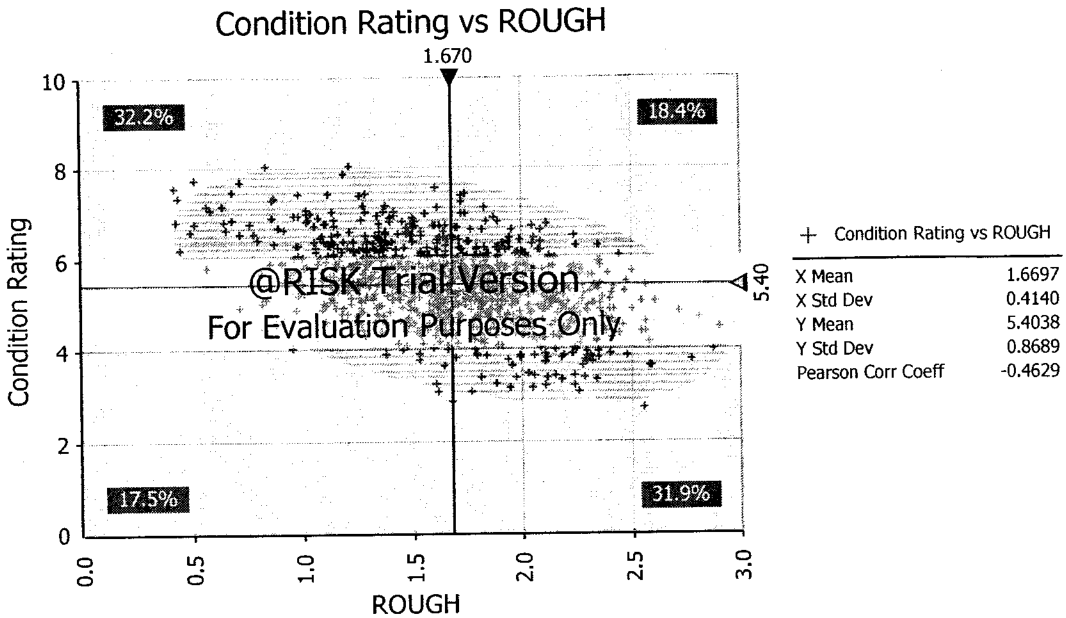



Condition Rating vs RAIN
0.999
28.3%
22.3%
20.5%
28.9%
@RISK Trial Version
For Evaluation Purposes Only
Condition Rating
RAIN
5.40
Condition Rating vs RAIN
X Mean 0.9991
X Std Dev 0.1257
Y Mean 5.4038
Y Std Dev 0.8689
Pearson Corr Coeff -0.2546


Condition Rating vs AGE
4.68
30.9%
19.7%
18.9%
30.5%
@RISK Trial Version
For Evaluation Purposes Only
Condition Rating
AGE
5.40
Condition Rating vs AGE
X Mean 4.6815
X Std Dev 1.0757
Y Mean 5.4038
Y Std Dev 0.8689
Pearson Corr Coeff -0.3532


Condition Rating vs SLD
2.61
24.3%
26.3%
25.2%
24.2%
5.40
@RISK Trial Version
For Evaluation Purposes Only
Condition Rating
SLD
0
2
4
6
8
10
0
1
2
3
4
5
6
Condition Rating vs SLD
X Mean 2.6146
X Std Dev 0.7953
Y Mean 5.4038
Y Std Dev 0.8689
Pearson Corr Coeff 0.0506


Condition Rating vs ADT
8.75
26.1%
24.5%
23.4%
26.0%
5.40
@RISK Trial Version
For Evaluation Purposes Only
Condition Rating
ADT
0
2
4
6
8
10
-5
0
5
10
15
20
Condition Rating vs ADT
X Mean 8.7547
X Std Dev 3.2467
Y Mean 5.4038
Y Std Dev 0.8689
Pearson Corr Coeff -0.0913



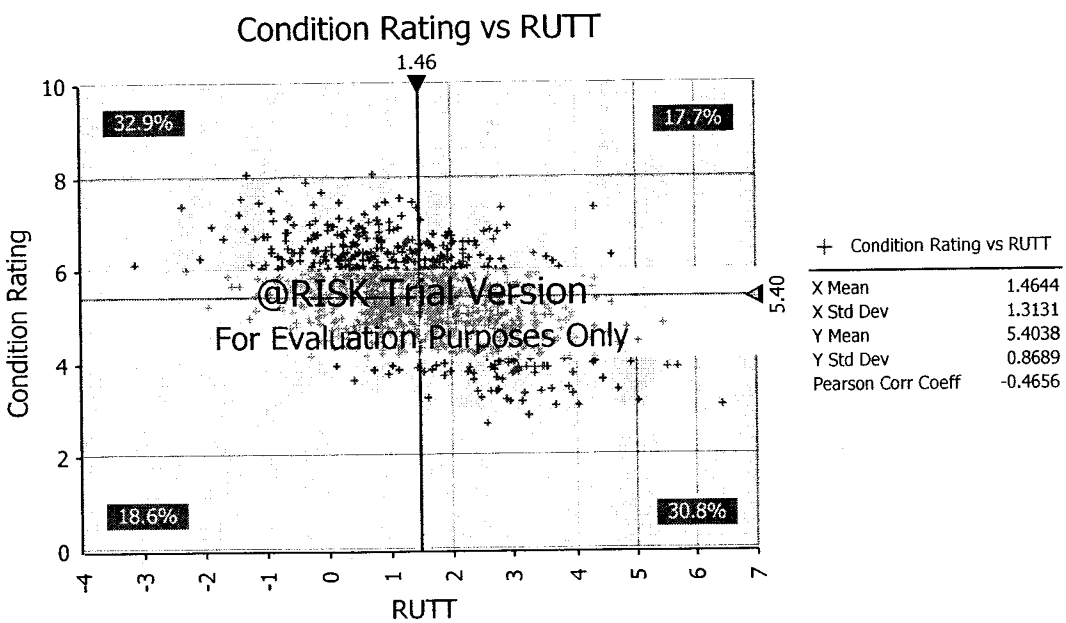


Figure C-3: @ RISK Output of Scatter Plots for Summer Model Sub-Factors.

III. Sensitivity Analysis:

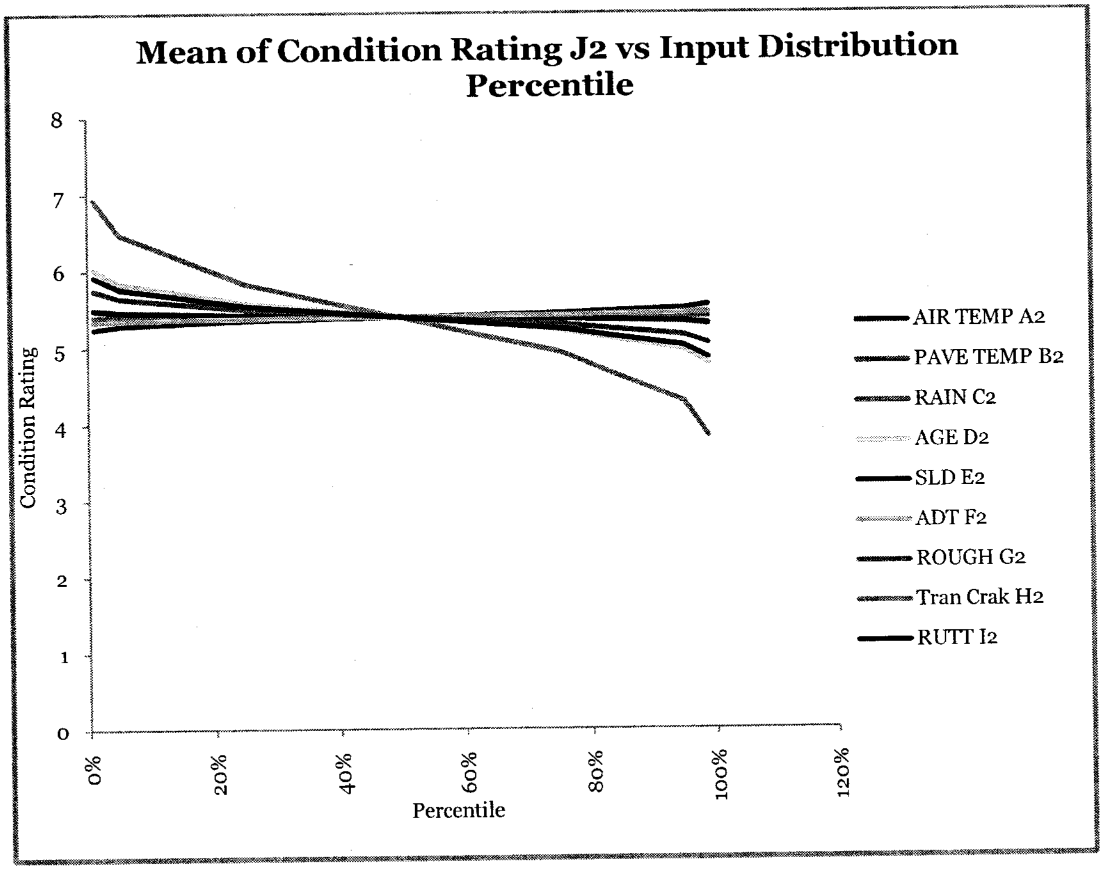


Figure C-4: Advanced Sensitivity Analysis Percentile Graph.

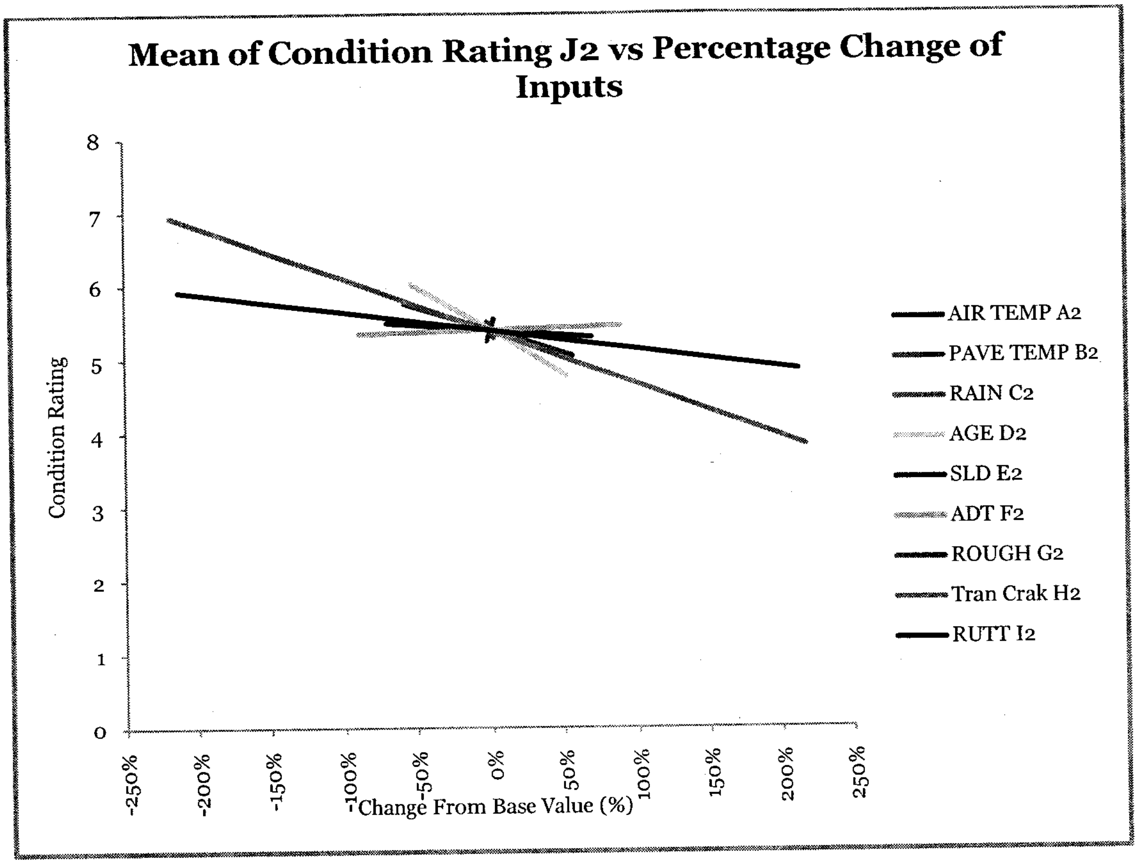
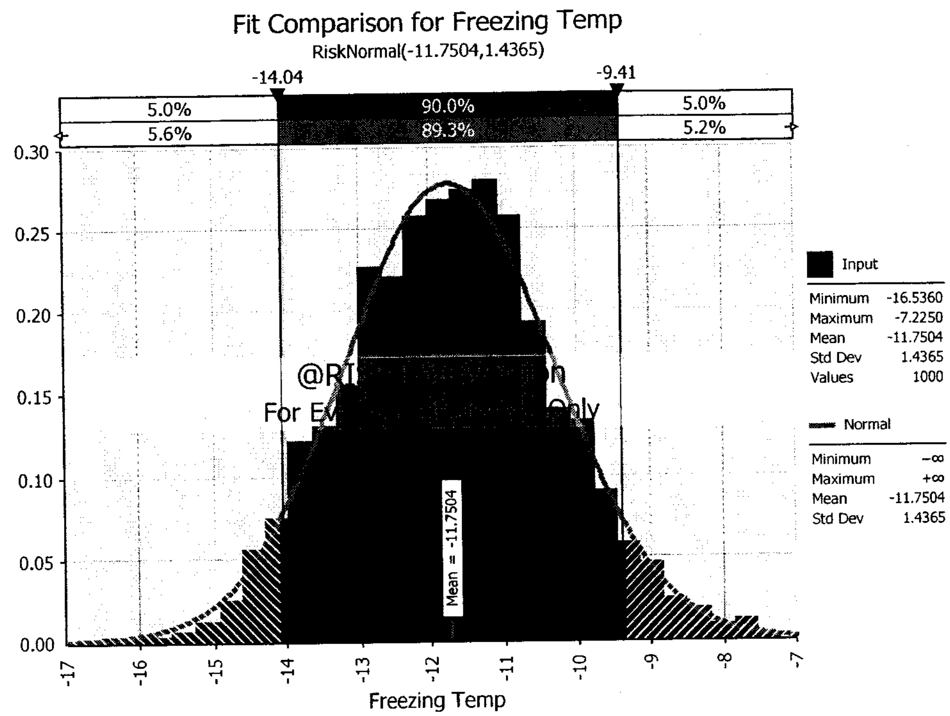


Figure C-5: Advanced Sensitivity Percent Change Graph.

C.2 Winter Model:

C.2.1 Defining Probability Distributions:

The following graphs are only for sub-factors (Freezing Temperature and winter-Pavement Temperature). The rest sub factors were presented earlier in (Section C.1.1, Figure C-1).



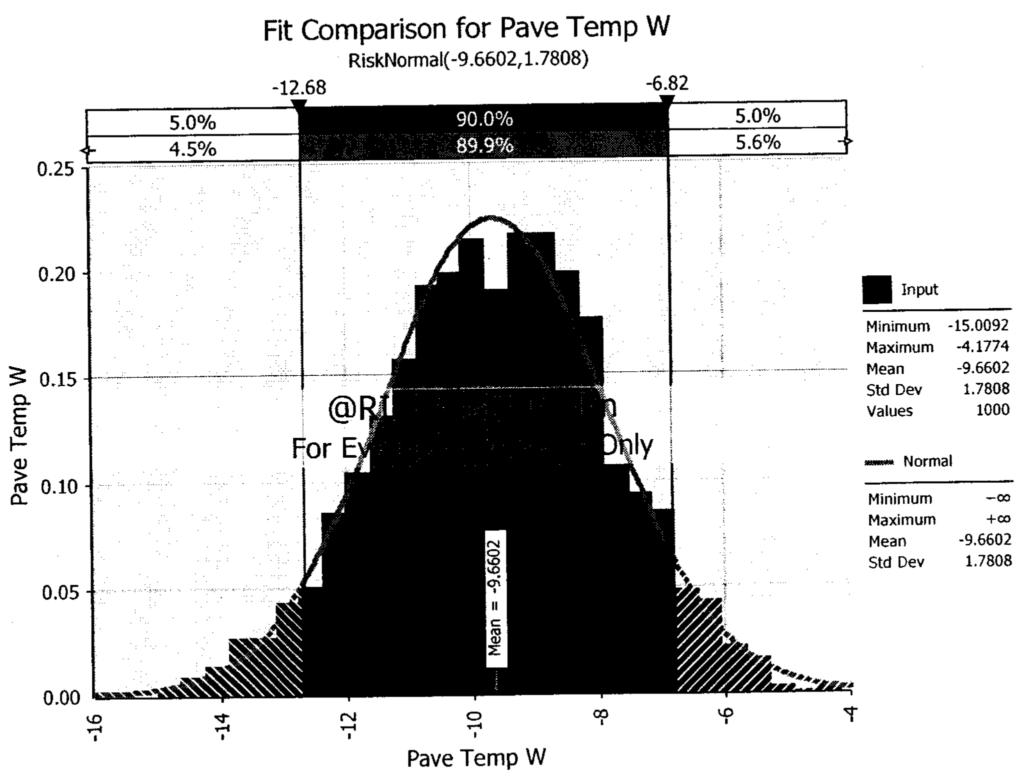
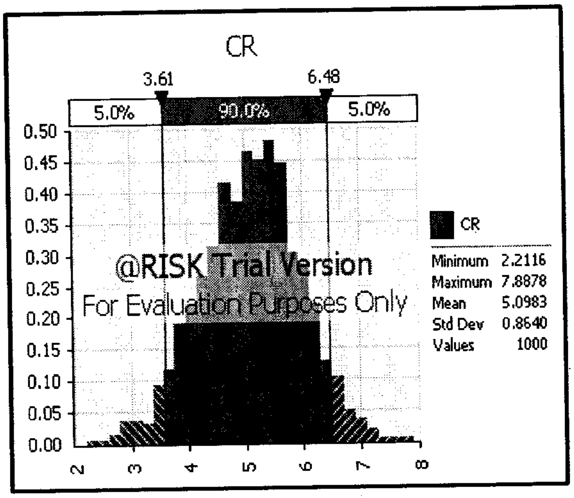
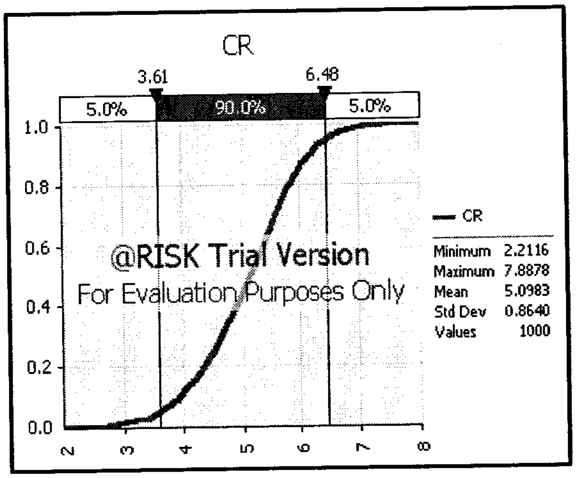


Figure C-6: @ RISK Output for Defining Distributions that Best Fit the Winter Model Sub-Factors (Freezing and Pavement Temperature).

C.2.2 Simulation Results:





Simulation Summary Information	
Workbook Name	Winter Model
Number of Simulations	1
Number of Iterations	1000
Number of Inputs	8
Number of Outputs	1
Sampling Type	Monte Carlo
Simulation Start Time	12/6/09 14:53:19
Simulation Duration	00:00:01
Random # Generator	Mersenne Twister
Random Seed	26642263

Summary Statistics for CR

Statistics		**Percentile**	
Minimum	2.21161754	**5%**	3.6124
Maximum	7.887773844	**10%**	3.9466
Mean	5.098263076	**15%**	4.1997
Std Dev	0.864009363	**20%**	4.3679
Variance	0.74651218	**25%**	4.5359
Skewness	- 0.145851288	**30%**	4.6489
Kurtosis	2.984317436	**35%**	4.7768
Median	5.126552324	**40%**	4.9065
Mode	5.102357107	**45%**	5.0145
Left X	3.612430179	**50%**	5.1265
Left P	5%	**55%**	5.2588
Right X	6.475848852	**60%**	5.3560
Right P	95%	**65%**	5.4667
Diff X	2.863418673	**70%**	5.5657
Diff P	90%	**75%**	5.6699
#Errors	0	**80%**	5.8139
Filter Min	Off	**85%**	5.9764
Filter Max	Off	**90%**	6.2036
#Filtered	0	**95%**	6.4758

Figure C-7: @ RISK Output for Simulation Results of Summer Model.

C.2.3 Analysis of Results:

I. Tornado Graphs :

Tornado Graphs are used to display the most important probability distribution of inputs in the proposed model. Figure C-8 shows the sub-factor (input) distributions ranked by their impact on the condition rating-CR (output), in which the Transverse Cracking amount (Tran Crak) variable has the highest impact with a value of (0.75); then the Pavement Age (AGE) variable with an impact of (0.29); on the other hand, the Pavement Temperature (Pave Temp) variable almost has no impact on the model output with a value close to (0.01).

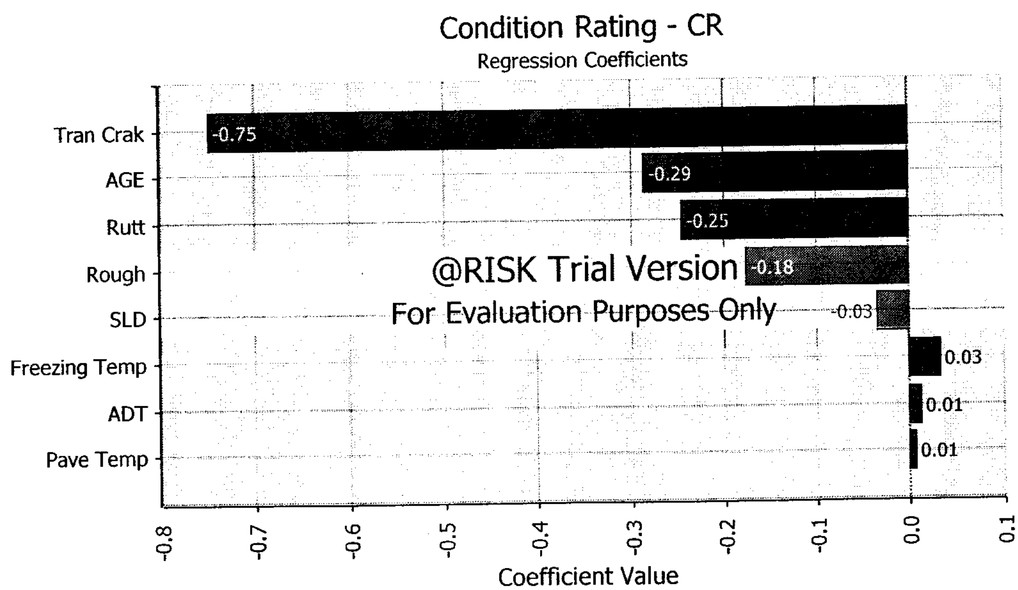
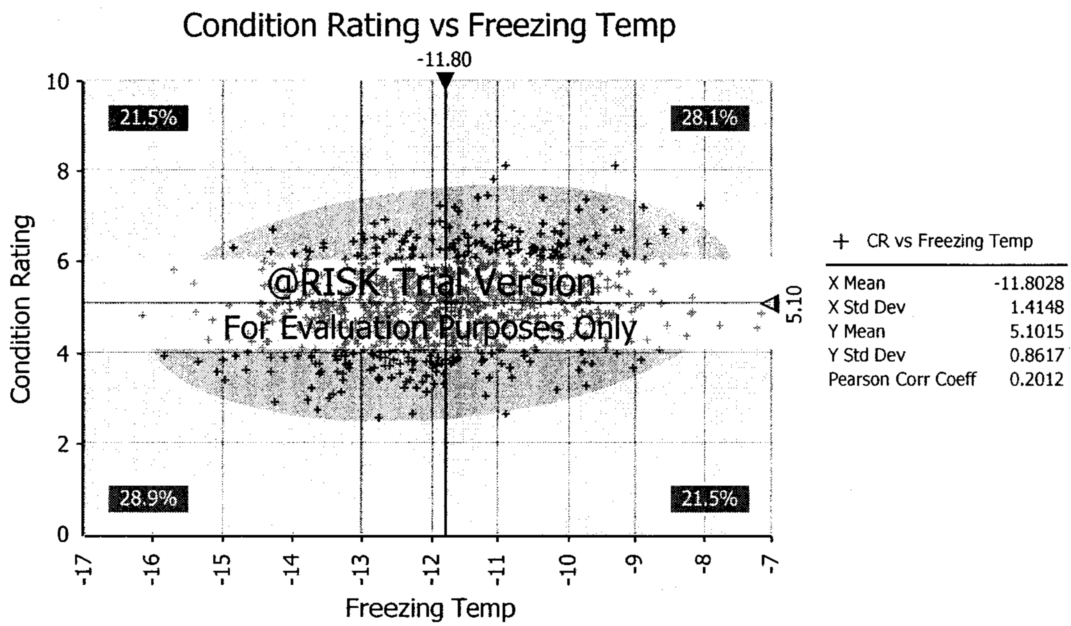
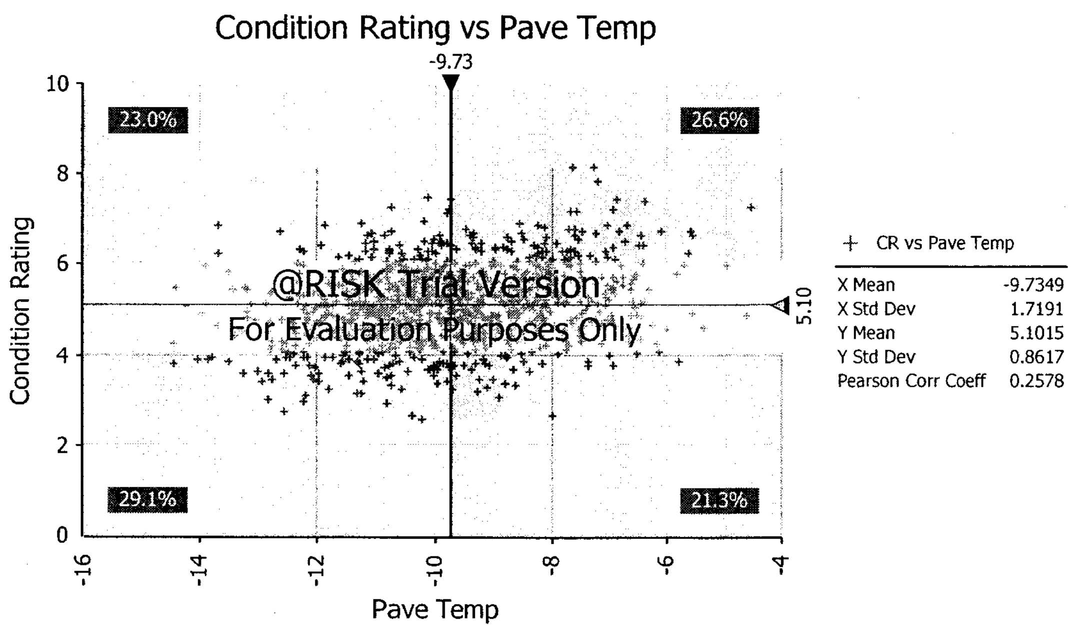
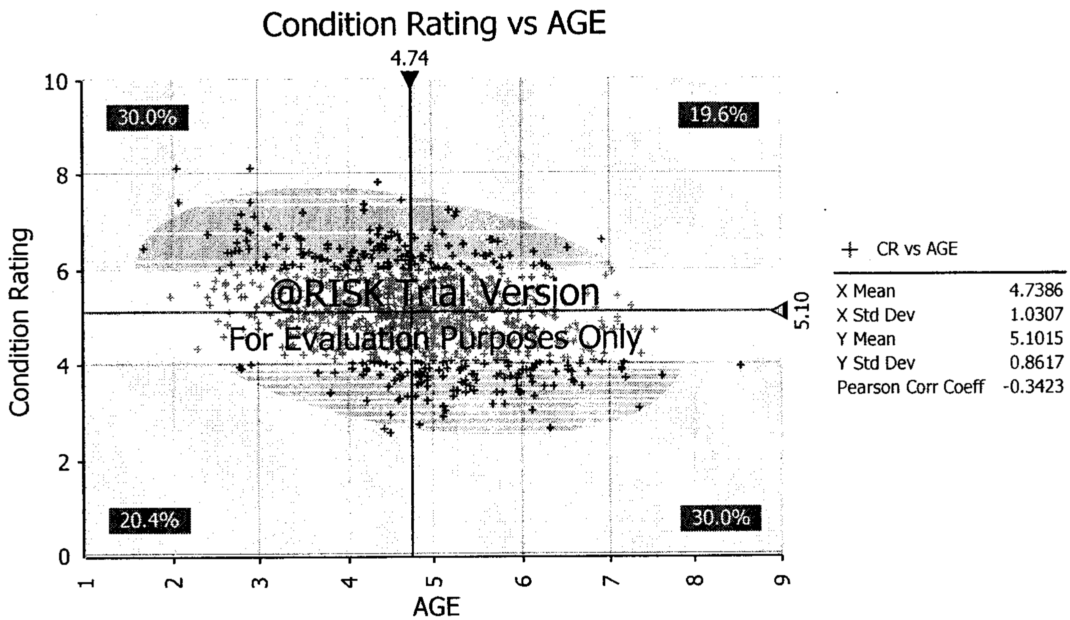


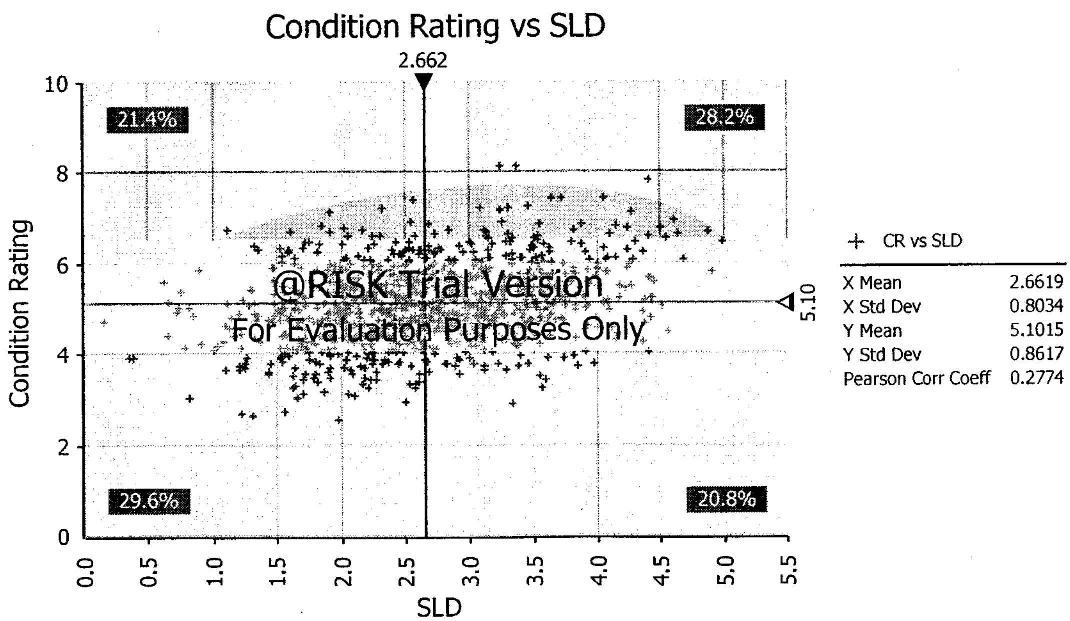
Figure C-8: @ RISK Output of Tornado Graphs for Winter Model.

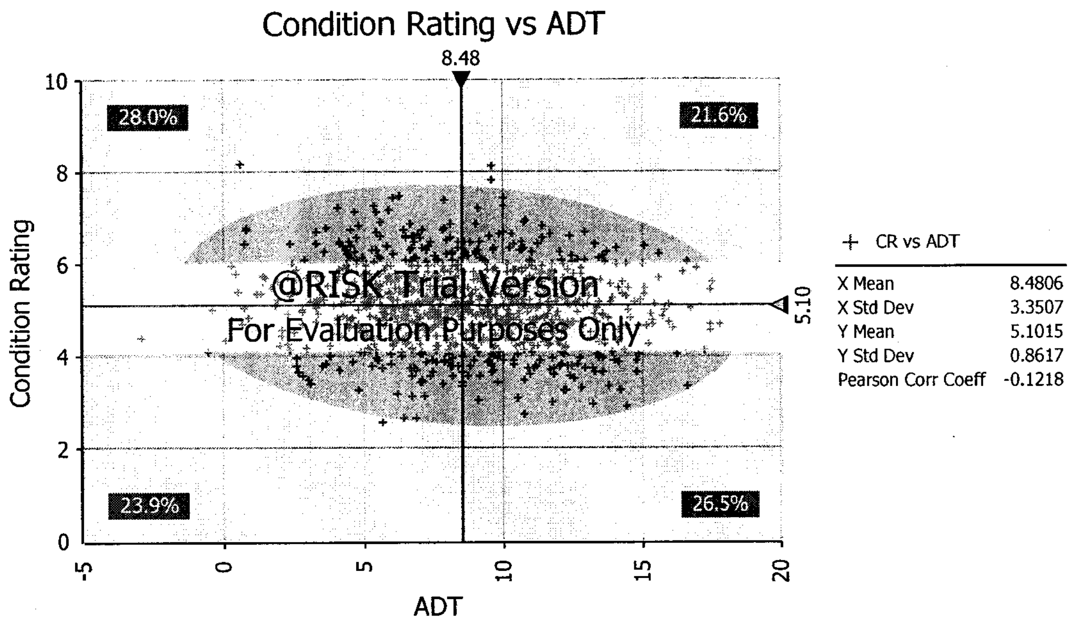
II. Scatter Plots:

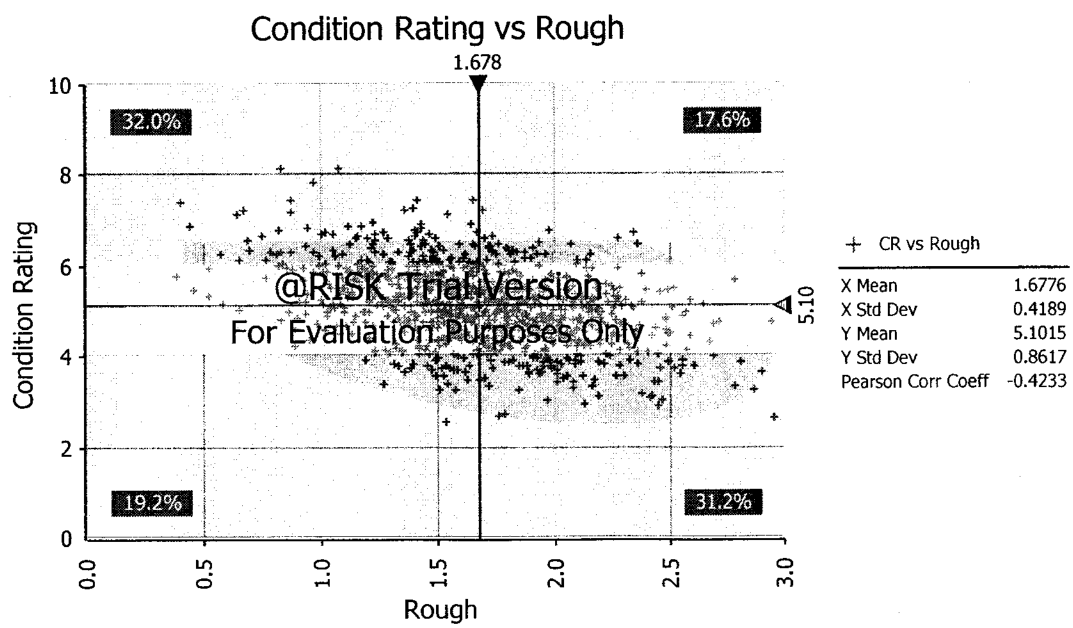


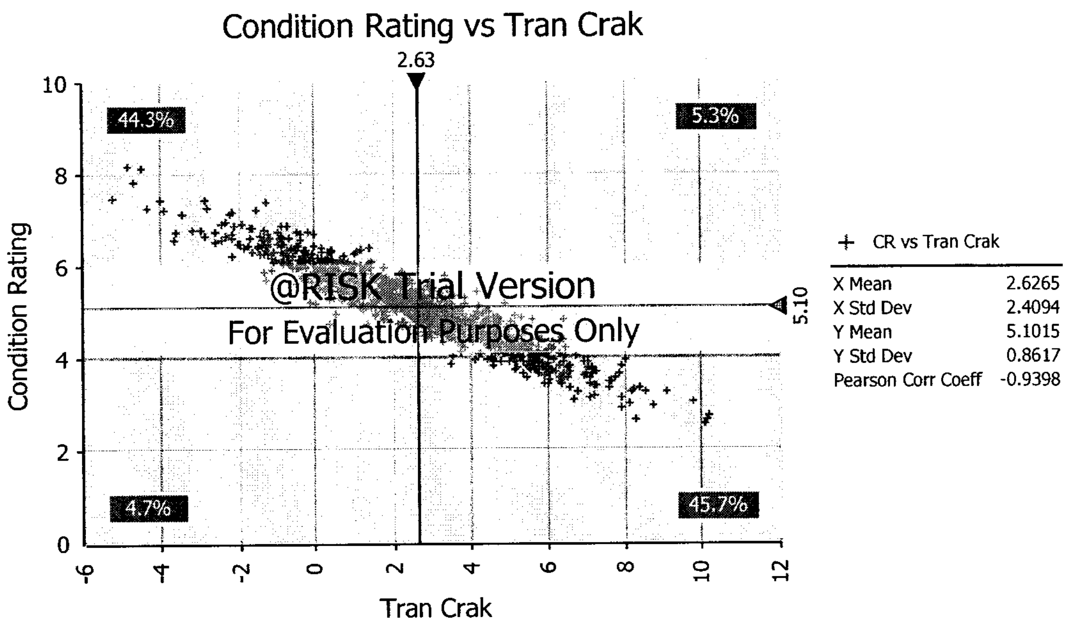



Condition Rating vs AGE
4.74
30.0%
19.6%
20.4%
30.0%
5.10
@RISK Trial Version
For Evaluation Purposes Only
Condition Rating
AGE
+ CR vs AGE
X Mean 4.7386
X Std Dev 1.0307
Y Mean 5.1015
Y Std Dev 0.8617
Pearson Corr Coeff -0.3423


Condition Rating vs SLD
2.662
21.4%
28.2%
29.6%
20.8%
5.10
@RISK Trial Version
For Evaluation Purposes Only
Condition Rating
SLD
+ CR vs SLD
X Mean 2.6619
X Std Dev 0.8034
Y Mean 5.1015
Y Std Dev 0.8617
Pearson Corr Coeff 0.2774


Condition Rating vs ADT
8.48
5.10
28.0%
21.6%
23.9%
26.5%
@RISK Trial Version
For Evaluation Purposes Only
Condition Rating
ADT
CR vs ADT
X Mean 8.4806
X Std Dev 3.3507
Y Mean 5.1015
Y Std Dev 0.8617
Pearson Corr Coeff -0.1218


Condition Rating vs Rough
1.678
5.10
32.0%
17.6%
19.2%
31.2%
@RISK Trial Version
For Evaluation Purposes Only
Condition Rating
Rough
CR vs Rough
X Mean 1.6776
X Std Dev 0.4189
Y Mean 5.1015
Y Std Dev 0.8617
Pearson Corr Coeff -0.4233



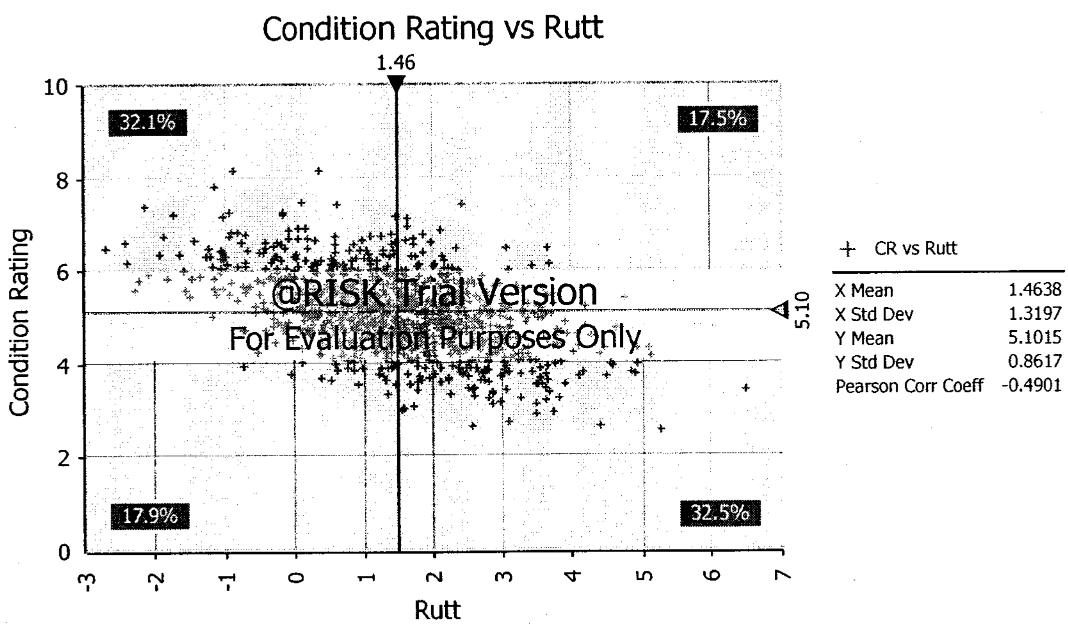
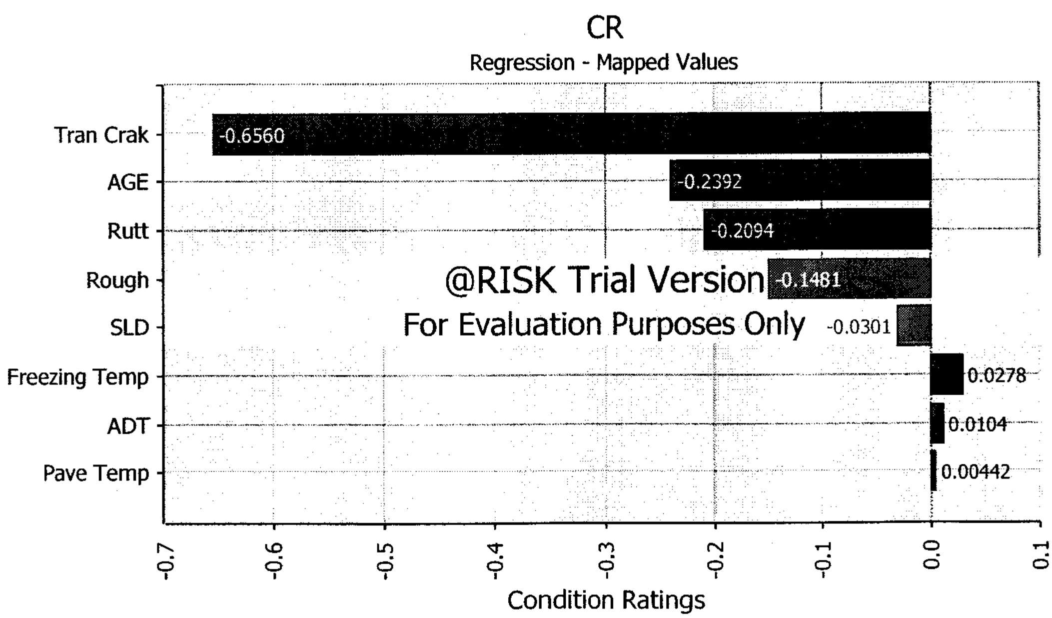


Figure C-9: @ RISK Output of Scatter Plots for Winter Model Sub-Factors.

C.2.4 Sensitivity Analysis:

Figure C-10 represents a Regression-Mapped values graph that shows the actual change in condition ratings (output) for ± 1 standard deviation change in each sub-factor value (input).

It can be noticed that the Transverse Cracking amount (Tran Crak) variable is indeed the most important factor affecting the condition rating output of this model; and when this variable changes by one standard deviation, the amount of change in the CR score from the x-axis will be equal to (-0.6560). This value (-0.6560) is shown in the bar corresponding to the (Tran Crak) variable. Similarly, all CR change values corresponding to each input variable are shown in Figure C-10.



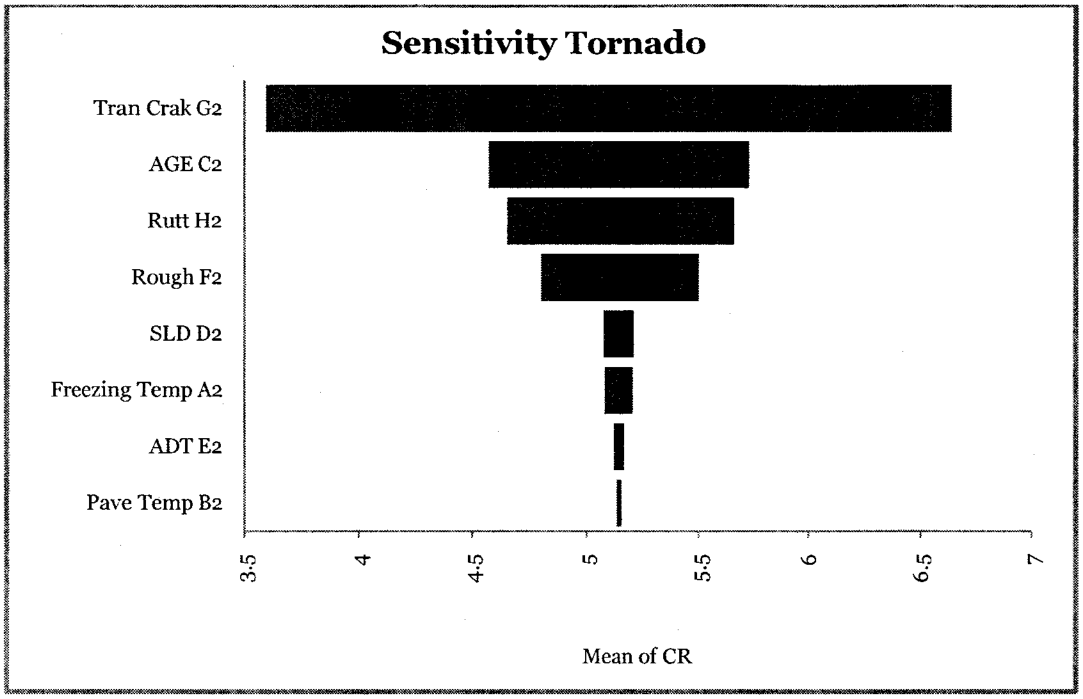


Figure C-10: @ RISK Output of (Mapped Values + Sensitivity Tornado) for Winterer Model.

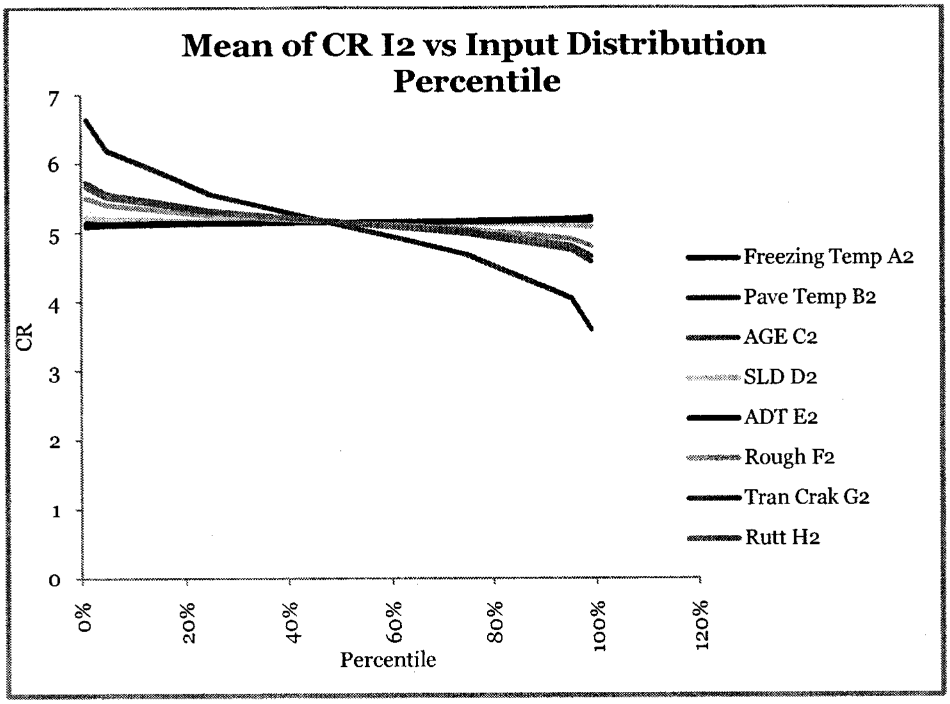


Figure C-11: Advanced Sensitivity Analysis Percentile Graph.

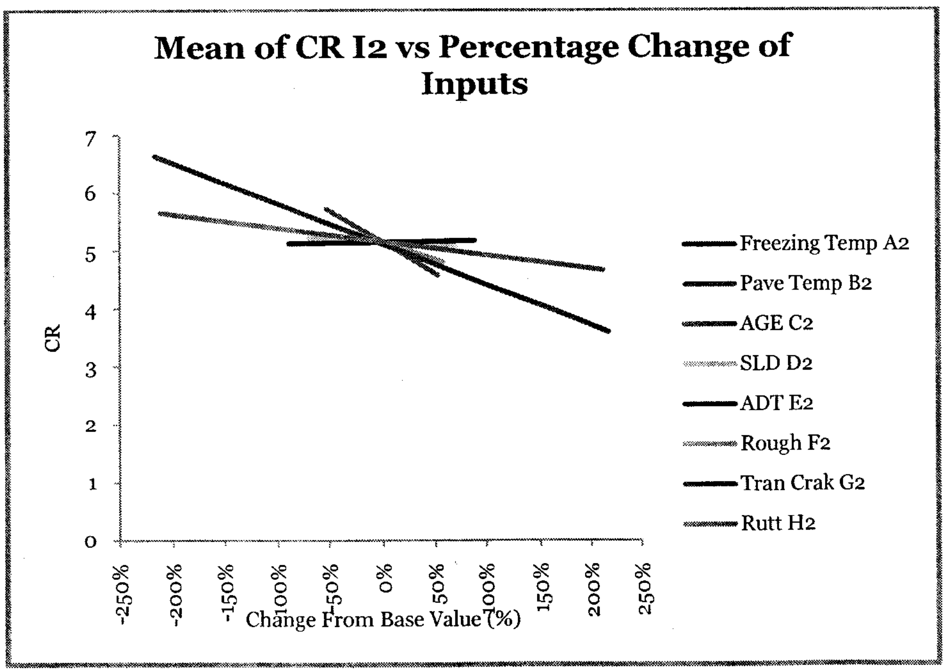


Figure C-12: Advanced Sensitivity Percent Change Graph.

Appendix D: SAMPLE QUESTIONAIRE

Urban road deterioration is a complex function of several factors that have a significant time- dependent effect on the surface condition of the pavements. In this research these factors have been classified into three main categories: (Climate conditions, Physical properties, and Operational Factors). The identification of effect and weight of these factors on pavement deterioration is vital and will be used as a base for rating the existing condition of pavement. It, accordingly, helps engineers in choosing the suitable maintenance and rehabilitation techniques for their existing roads and highways.

By filing this questionnaire, we will use your valuable judgment and expertise in building the proposed model. The questionnaire is divided into four main sections.

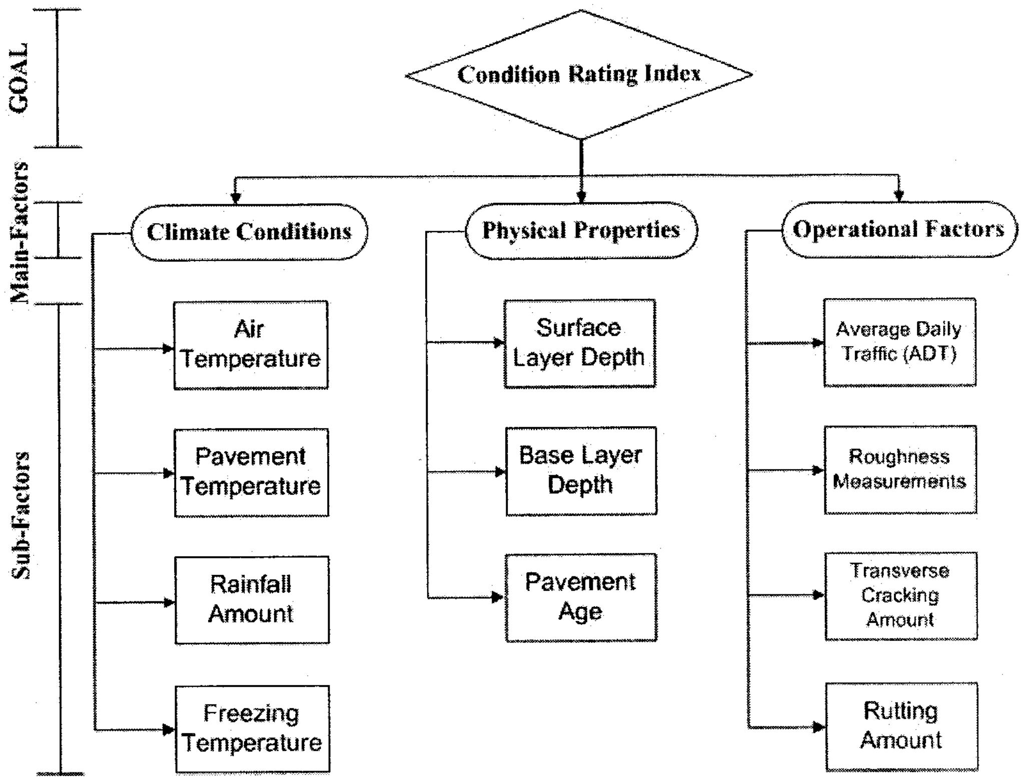
1- Section One: Company information in which there are some questions to be answered by the respondent and we guarantee that this information is confidential and not for public use.

Name	
Position	
Type of company partnership	
Years of experience	

2- Section Two: is a Pair-wise comparison matrix between factors and sub-factors that affect Condition of Flexible Pavement.

2.a **Main factors pair-wise comparison matrix:**

Main Factors	Climate Conditions	Physical Properties	Operational Factors
Climate Conditions	1		



2.b **Climate Conditions' sub-factors pair-wise comparison matrix:**

Sub-Factors	Air Temperature	Pavement Temperature	Rainfall Amount	Freezing Temperature
Air Temperature	1			

2.c **Physical Properties' sub-factors pair-wise comparison matrix:**

Sub-Factors	Surface Layer Depth	Base Layer Depth	Pavement Age
Surface Layer Depth	1		

2.d **Operational Factors' sub-factors pair-wise comparison matrix:**

Sub-Factors	Average Daily Traffic (ADT)	Roughness Measurements	Transverse Cracking Amount	Rutting Amount
Average Daily Traffic (ADT)	1			

3- Section Three: the following table collects the impacts of the factors on pavement condition, by answering this question **[How do you rate the effect of factor (x) on the pavement condition].** You just have to choose a number on a scale of 0 to 10; as shown below.

0	2	3	4	5	6	7	8	10
Extremely Neg	**Very Neg**	**Moderately Neg**	**Neg**	**Even Impact**	**Pos**	**Moderately Pos**	**Very Pos**	**Extremely Pos**

Neg: Negative impact on flexible pavement condition.
Pos: Positive impact on flexible pavement condition.
Even: Neither Negative nor Positive impact on flexible pavement condition.

Main Factors	**Sub-Factors**	**Attributes**	**0**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**10**
Climate Conditions	Air Temperature	$0\ °C \leq T_a < 10\ °C$									
		$10\ °C \leq Ta < 22\ °C$									
		$Ta \geq 22\ °C$									
	Rainfall Amount	$R_f < 0.5$ mm/hr									
		$0.5 \leq R_f < 3$ mm/hr									
		$R_f \geq 3$ mm/hr									
	Pavement Temperature	$T_P \geq \|-22\ °C\|$									
		$\|-22\ °C\| > T_P \geq \|-10\|$									
		$\|-10\ °C\| > T_P > \|\ 0\ °C\|$									
		$0\ °C \leq T_P < 10\ °C$									
		$10\ °C \leq T_P < 22\ °C$									
		$T_P \geq 22\ °C$									
	Freezing Temperature	$T_F \geq \|-22\ °C\|$									
		$\|-22\ °C\| > T_F \geq \|-10\|$									
		$\|-10\ °C\| > T_F > \|\ 0\ °C\|$									
Physical Properties	Surface Layer Depth	SDL < 2 in									
		SDL ≥ 2 in									
	Base Layer Depth	BDL < 4 in									
		BDL ≥ 4 in									
	Pavement Age	Less than 5 yrs									
		5 yrs ≤ Age < 9									
		9 yrs ≤ Age < 12									
		12 yrs ≤ Age < 14									
		Equal to 15									
		16 yrs ≤ Age < 19									
		19 yrs ≤ Age < 22									
		22 yrs ≤ Age < 26									

		26 yrs ≤ Age < 30									
		More than 30 yrs									
Operational Factors	Average Daily Traffic (ADT)	(ADT < 20 vch/day)									
		(20 ≤ ADT ≤ 100)									
		(ADT > 100)									
	Roughness Measurements	($R_M \leq 2.48$ mm/m)									
		($2.49 \leq R_M \leq 3.33$)									
		($3.34 \leq R_M \leq 6.18$)									
	Transverse Cracking	(Crk < 13 mm)									
		(Crk ≥ 13 mm)									
	Rutting Amount	(Rut ≤ 9 mm)									
		(10 mm ≤ Rut ≤ 13 mm)									
		(14 mm ≤ Rut ≤ 20 mm)									
		(Rut > 20 mm)									

4- Section Four: the following table contains a list of Maintenance and Rehabilitation Strategies suggested by us to be used. If you have any other strategies that you would like to add or cancel, please feel free to add them in the available blank spaces.

Distress Type	**Severity Level**	Chip Seals	Thin HMA Overlays	Hot In-Place Recycling	Full Depth Reclamation	Slurry seal	
Transverse Cracking Amount	Low severity cracks < 1/2 inch wide						
	High severity cracks ≥ 1/2 inch wide						

Distress Type	**Severity Level**	Doing Nothing	Micro-surfacing	Milling off and replacement	
Rutting Amount	Slight ruts < 1/3 inch deep				
	Sever ruts ≥ 1/3 inch deep				

Your cooperation with us to advance the knowledge of Flexible-Pavement infrastructure is highly appreciated.

Supervisor,

Tarek Zayed, Ph.D., P.E.

Associate Professor Department of Building, Civil & Environmental Engineering

EV 6.401, 1515 Ste. Catherine St., Montreal, Canada H3G 1M8

Tel.: (514) 848-2424 ext. 8779

Fax: (514) 848-7965

Email: zayed@bcee.concordia.ca

Information Return: Please, return this questionnaire to ***Wael Tabara*** Research Assistant, Department of Building, Civil & Environmental Engineering, Concordia University	Tel: (514) 848-2424 ext. 7091 E-mail: **w_tabr@encs.concordia.ca**

Appendix E: Utility Functions of Sub-Factors Attributes

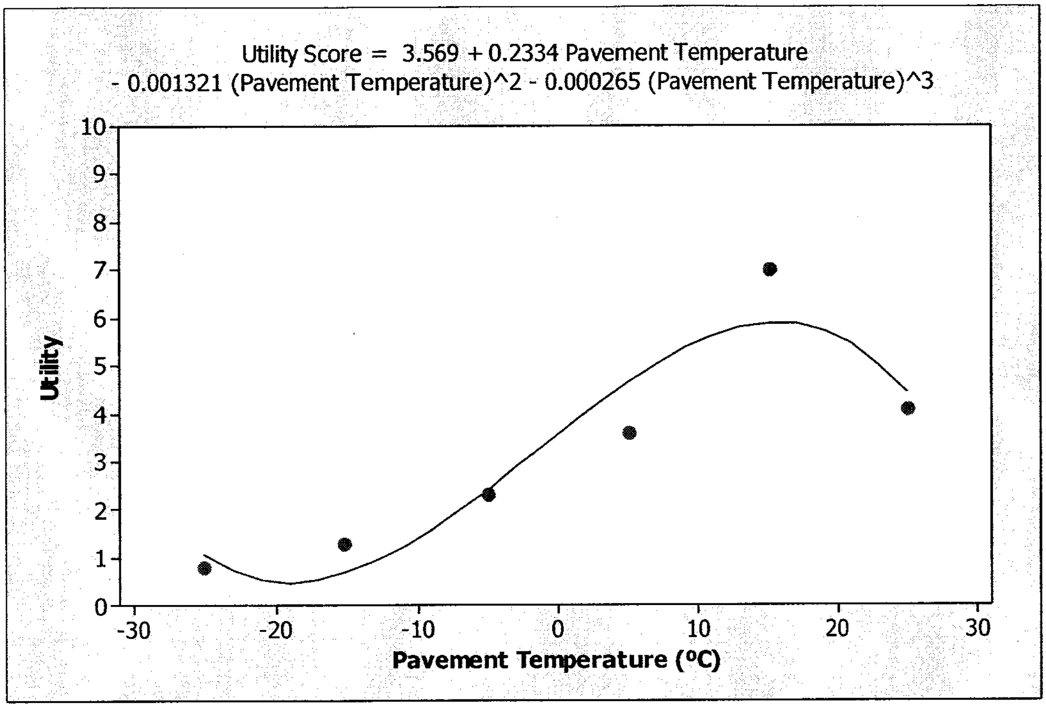


Figure E-1: Utility Function of the Sub-Factor (Pavement Temperature) Attributes.

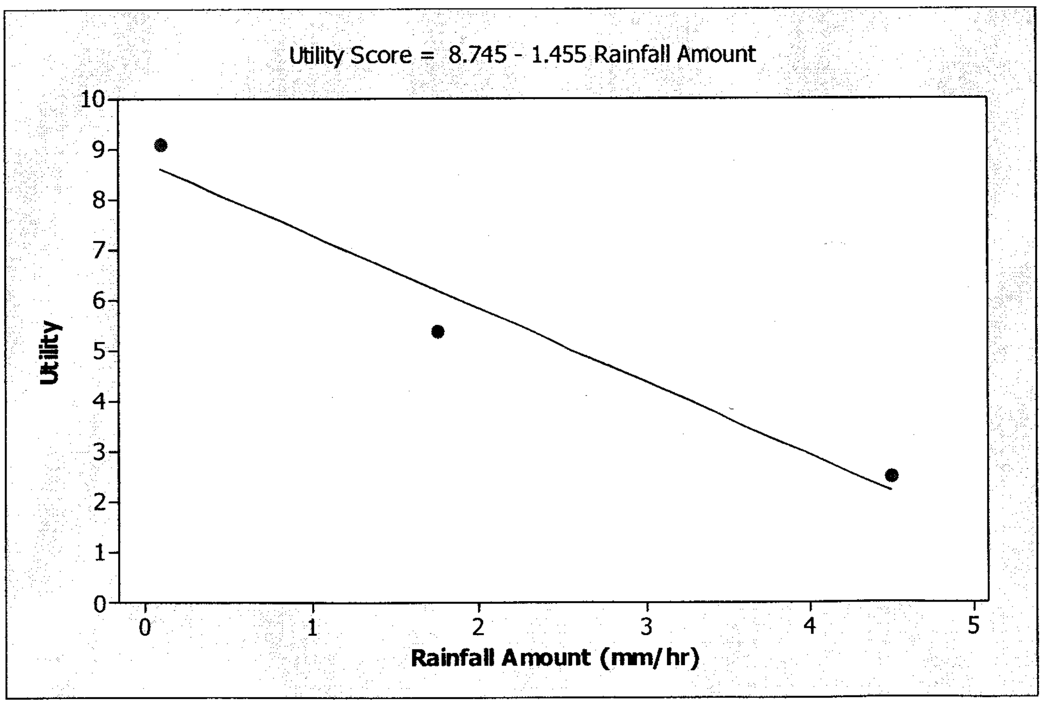


Figure E-2: Utility Function of the Sub-Factor (Rainfall Amount) Attributes.

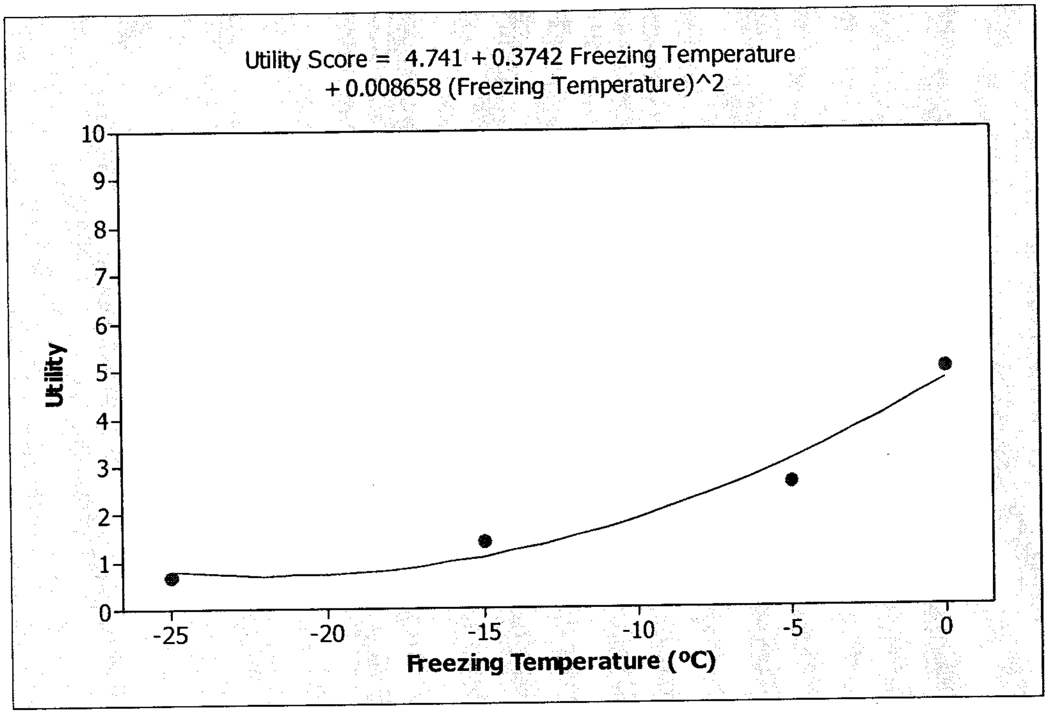


Figure E-3: Utility Function of the Sub-Factor (Freezing Temperature) Attributes.

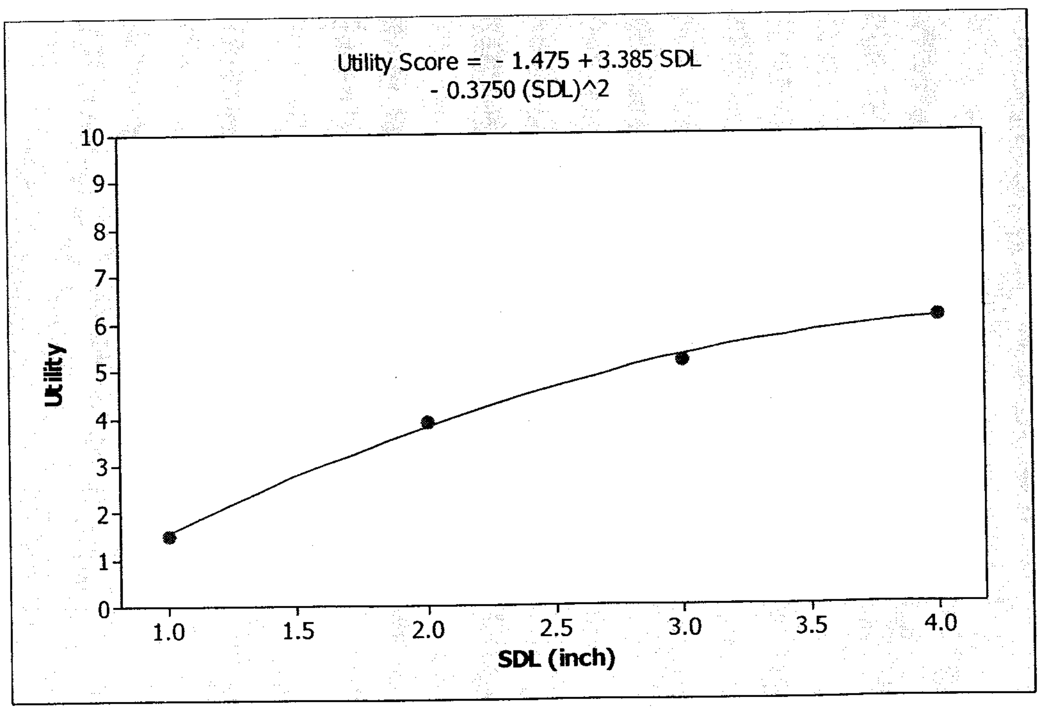


Figure E-4: Utility Function of the Sub-Factor (Surface Layer Depth) Attributes.

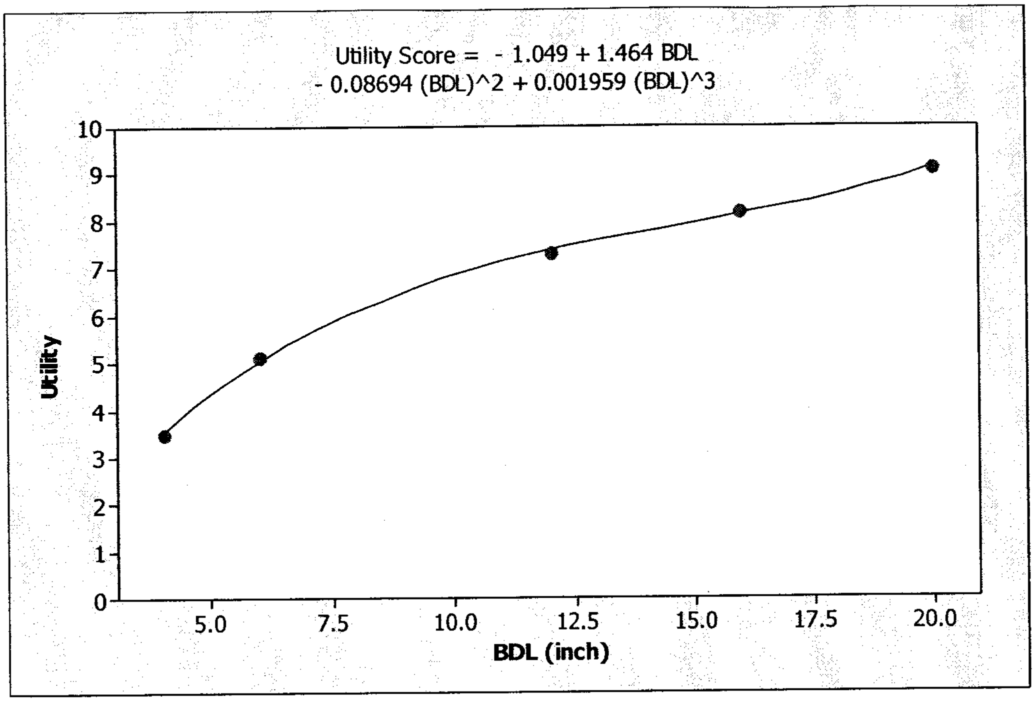


Figure E-5: Utility Function of the Sub-Factor (Base Layer Depth) Attributes.

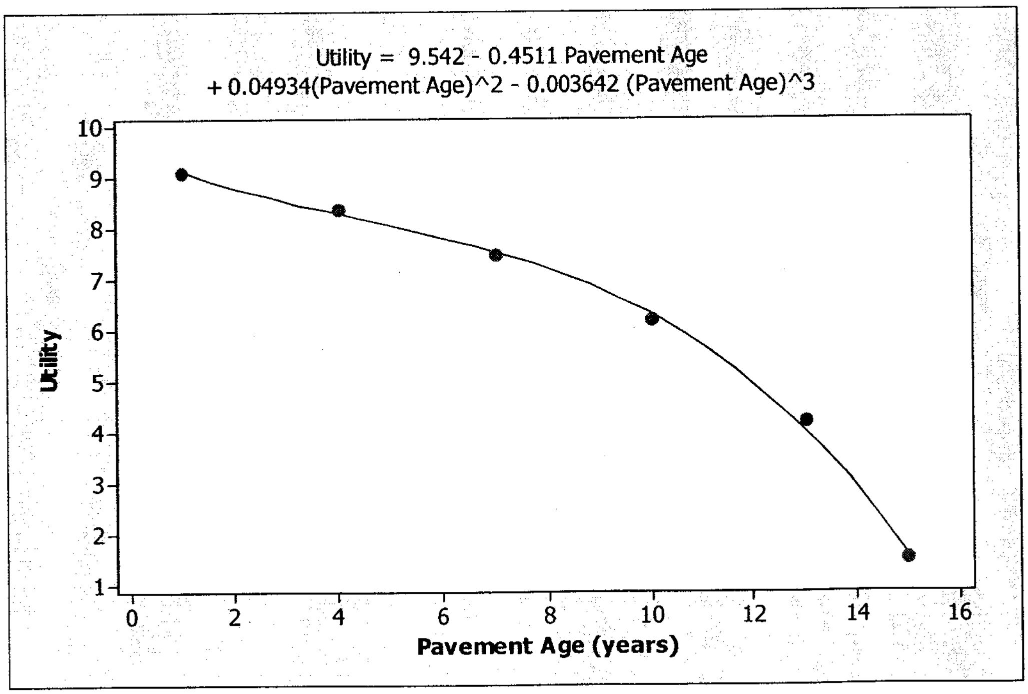


Figure E-6: Utility Function of the Sub-Factor (Pavement Age) Attributes.

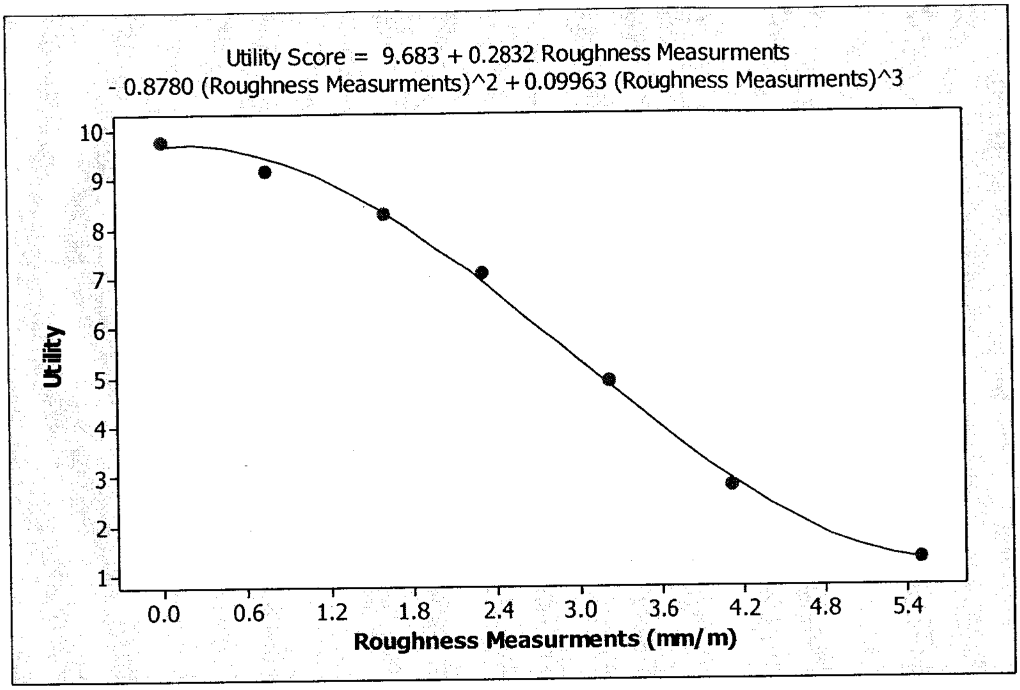


Figure E-7: Utility Function of the Sub-Factor (Roughness Measurements) Attributes.

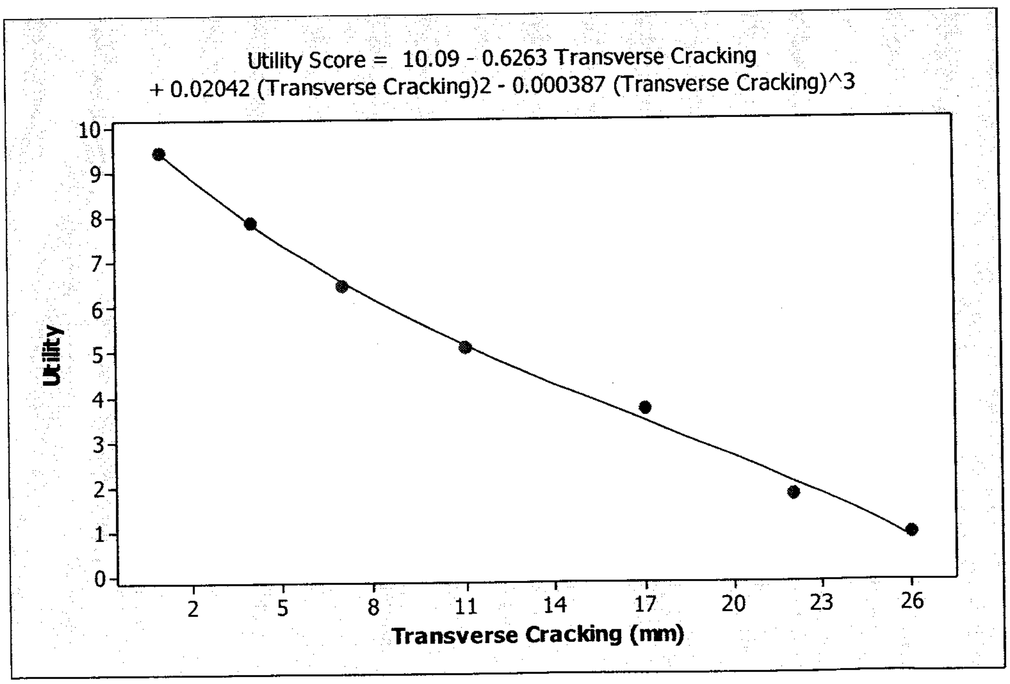


Figure E-8: Utility Function of the Sub-Factor (Transverse Cracking) Attributes.

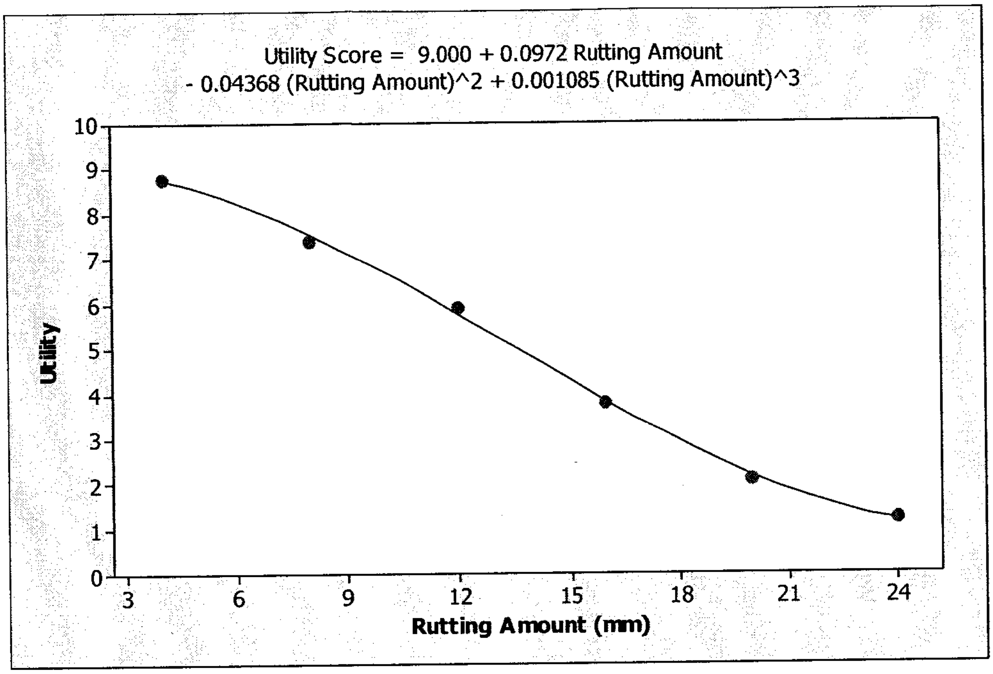


Figure E-9: Utility Function of the Sub-Factor (Rutting Amount) Attributes.