2-8-2011

Sensitivity of MEPDG Using Advanced Statistical Analyses

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SENSITIVITY OF MEPDG USING ADVANCED STATISTICAL ANALYSES

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THESIS

Submitted in Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE
Civil Engineering

The University of New Mexico
Albuquerque, New Mexico

December 2010

DEDICATION

To My Parents and

My Friend Late Yi Hunag (R.I.P)

AKNOWLEDGEMENTS

I hereby acknowledge my sincere appreciation and due gratitude to my advisor Dr. Rafiqul A. Tarefder for his academic guidance, mentorship, and technical advice during the entire period of this study. This study would not have been possible without his exemplary motivation and encouragement.

Special thanks to Dr. Curtis Storlie, who is in my thesis committee, for his continued and unparalleled technical support that inevitably made this research study a success. I would like to thank Dr. John C. Stormont for his valuable inputs and time spent serving on my thesis committee.

A special word of appreciation is due to Mr. Cedric Sallaberry (Sandia National Laboratories). Through his help and valuable technical contribution, I was able to steer ahead to complete this study. This study is conducted as part of New Mexico Department of Transportation (NMDOT) Research Project NM08MSC-02 entitled "Development of a Flexible Pavement Database for Local Calibration of MEPDG". I thank NMDOT for funding this research study. Special thanks are due to Bob Meyers, Virgil N. Valdez, Robert McCoy, Parveez Anwar, and Jeffery S. Mann of NMDOT.

The success would not have been possible without the co-operation and encouragement of research group and friends. In this regard, I would like to mention Late Yi Huang (R.I.P.), my friend and research partner on this project.

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ABSTRACT

Recently, pavement design has changed from old method based on empirical relation to a new method called Mechanistic Empirical Pavement Design Guide (MEPDG). It is essential to perform a detailed sensitivity analysis of MEPDG outputs to input variables. In particular, MEPDG inputs need to be classified based on their influence on MEPDG outputs for New Mexico pavement conditions. In this study, sensitivity analyses are performed to identify a list of input variables that have significant impacts on the MEPDG outputs considering New Mexico pavement conditions. Sensitivity analyses are performed in two steps. In the first step, a preliminary sensitivity analysis is carried out by varying one input variable at a time while keeping the other inputs constant. The purpose of the preliminary sensitivity analysis is to prepare a short-list of significant input variables out of more than hundreds of variables in MEPDG. In the second step, sensitivity analyses are performed using advanced statistical approaches that consider interactions among the input variables. Parametric procedures such as tests for nonrandomness in scatterplots, linear and nonlinear regression analyses, and nonparametric procedures such as multivariate adaptive regression spline, gradient boosting machine are employed to identify and rank the significant input variables. Results show that predicted pavement performances are sensitive to traffic input variables such as Annual Average Daily Truck Traffic (AADTT) and percent of trucks in design lane. Both asphalt surface layer and total rutting are shown to be the most severe cases among all distresses for New Mexico pavements. Both AC and total rutting are highly sensitive to AADTT, percent of trucks in design lane, and bottom AC layer thickness. Outputs such as terminal IRI, longitudinal cracking, and alligator cracking are highly sensitive to bottom AC layer thickness. MEPDG outputs are also sensitive to HMA mix properties such as thickness, percent air void, binder content and PG grade. Longitudinal and transverse cracking are sensitive to base course material type, modulus and thickness. Depth of water table did not affect the MEPDG outputs at all. Transverse cracking and total rutting are sensitive to subgrade modulus, material properties, and gravimetric water content. MEPDG predicted outputs are found to be moderately sensitive to percent of trucks in design direction, traffic growth factor, and base thickness. Operational speed, depth of ground water table, and design lane width have very little to no effect to MEPDG predicted distresses. Finally, a list of significant variables is made for New Mexico pavement conditions. The list of significant inputs can be useful to pavement engineers to optimize pavement designs and analyze performances as well as for local calibration of MEPDG.

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ACRONYMS

AASTHO	American Association of State Highway and Transportation Officials
AASHO	American Association of State Highway Officials
AADTT	Annual Average Daily Truck Traffic
AC	Asphalt Cement
ACC	Asphalt Cement Content
DOT	Department of Transportation
ESAL	Equivalent Single Axle Load
FHWA	Federal Highway Administration
GPS	General Pavement Studies
GPR	Ground Penetrating Radar
GWT	Ground Water Depth
HAF	Hourly Adjustment Factor
IMS	Information Management System
IRI	International Roughness Index
JTFP	Joint Task Force on Pavements
LTPP	Long Term Pavement Performance
MAAT	Mean Annual Air Temperature
MEPDG	Mechanistic Empirical Pavement Design Guide
MAF	Monthly Adjustment Factor
NCHRP	National Cooperative Highway Research Program
NMDOT	New Mexico Department of Transportation
PCC	Portland Cement Concrete
SMP	Seasonal Monitoring Program
SA	Sensitivity Analysis
SPS	Special Pavement Studies
SHRP	Strategic Highway Research Program
SG	Subgrade
UA	Uncertainty Analysis

CHAPTER 1

INTRODUCTION

1.1 Problem Statement

Recently a Mechanistic-Empirical Pavement Design Guide (MEPDG) has been developed to design flexible pavements. The MEPDG includes a large number of input variables of different categories. Until this day, no in-depth analysis of the sensitivity of the MEPDG predicted output to these inputs has been performed. As a result, it becomes extremely challenging for a pavement designer to use MEPDG for generating alternative pavement design scenarios. If the most important inputs can be identified from the large pool of MEPDG inputs, it is possible for the pavement designers to come up with few design scenarios using only the most important inputs. This results in less time, expense and better design.

MEPDG is not only a design tool. Rather it is an analysis tool, which generates six outputs for flexible pavement that represents pavement distresses. They are mainly rutting, cracking and roughness. Literally one can work with a set of inputs to reduce the effects of only one or few outputs among those six outputs. As such, if a set of input variables can be identified, then it will be very useful for the pavement designers to deal with that particular distress. Therefore, the goal of this study is to identify a set of inputs for rutting, cracking and roughness.

Sensitivity is the quality of a model that shows how a particular scenario or predicted outputs can be affected by a set of inputs. Sensitivity is a useful tool to apportion uncertainty in the outputs of a model due to uncertainty in the model inputs (Saltelli et al., 2004). Sensitivity analysis is an important component in building mathematical, computational and simulation models. Sensitivity analysis can be performed on mathematical and computational models to determine the sensitivity of model outputs due to the uncertainty of input variables, computations, and parameter values (Campolongo et al., 1999). By conducting sensitivity analysis, the impact of input values on the model predicted outputs can be determined also.

The number of essential data elements is large (more than 100) for an appropriate design by MEPDG. Therefore, considerable understanding and effective study are required of how the change in the output of a model can be apportioned to the change in the model inputs. Several researches have performed studies regarding the MEPDG's sensitivity analysis of various input parameters for both flexible and rigid pavements. The main objective of all this research is to understand the impacts and relationships of the hundreds of input variables contained in the MEPDG. This is essential for successful implementation by state DOTs (Department of Transportation). To date, they have investigated the input variables to assess their impact on results (e.g., rutting due to changing binder type) or to ensure that the outcome makes sense. Most of the sensitivity analysis found in the literature is local or otherwise just changing one factor at a time (OAT, also known as Morris method). This is inadequate due to input dimensionality and interactions. Sensitivity of the output to a given input may depend on interactions with other inputs. However, a comprehensive analysis of each variable and its interaction with other inputs need to be fully investigated.

Sensitivity analysis can be used to explore how the impacts of the options would change in response to variations in key inputs and how they interact or to determine which variables are appropriate for a definite condition. This is what designers are trying to understand now. Based on this analysis, an importance ranking can be assigned to each input; what can significantly helps to reduce the effort and cost in obtaining the inputs that are less sensitive to the pavement performance. This analysis can also provide a better understanding of the design inputs that affect certain pavement performances the most, so that stressing the importance of careful consideration for these inputs before the design process even begins. The nominal range sensitivity analysis, log odds ratio, and automatic differentiation methods do not account for simultaneous interactions among the inputs. The regression, ANOVA, response surface method can be applied over a large domain of input space and can account for simultaneous variation of multiple inputs. There is no single method that is clearly superior to all other. To use advanced statistical approaches is the main goal for this study to account for the interactions among the key inputs and account for the nonlinearity in the outputs.

1.2 Research Objectives

The main objective of this study is to identify a set of inputs that are most sensitive to MEPDG outputs for flexible pavement design in New Mexico. To accomplish this objective, the following tasks are performed in this study:

- Collection of LTPP and NMDOT materials, traffic and climate data representing the local practice of NM and identify the range of inputs.
- Perform one to one sensitivity analysis using New Mexico pavement sections.
- Identify and ranking a set of MEPDG inputs that are significant to particular predicted distress using advanced statistical approaches.

- To quantify interactions of the sensitive inputs using advanced statistical measures.

1.3 Flow Chart of the Study

Flow chart of the study is presented in Figure 1.1. The first task of the study is to review and summarizes the recent studies performed on the sensitivity of pavement performances. Mainly it includes the sensitivity analyses done by other researchers using MEPDG in USA. It also includes review of different kind of sensitivity analysis methods. The second task of the study is data collection from LTPP and NMDOT databases. In the next task, preliminary sensitivity analysis is performed using LTPP Data by one variable at a time considering twelve LTPP sections of interstate highway I-25, one section of I-40 and one section of US 550. The next task includes preparation of a full factorial matrix of thirty variables and the corresponding MEPDG runs for the detailed sensitivity analysis. This task also deals with advanced statistical approaches to identify the interactive effects among input variables. Based on this analysis, an importance ranking is assigned to each input. This ranking provides a better understanding of the design parameters that affect certain predicted pavement performances the most. Finally, quantification of interactions of the sensitive inputs using advanced statistical measures is done for the implementation of MEPDG in New Mexico.

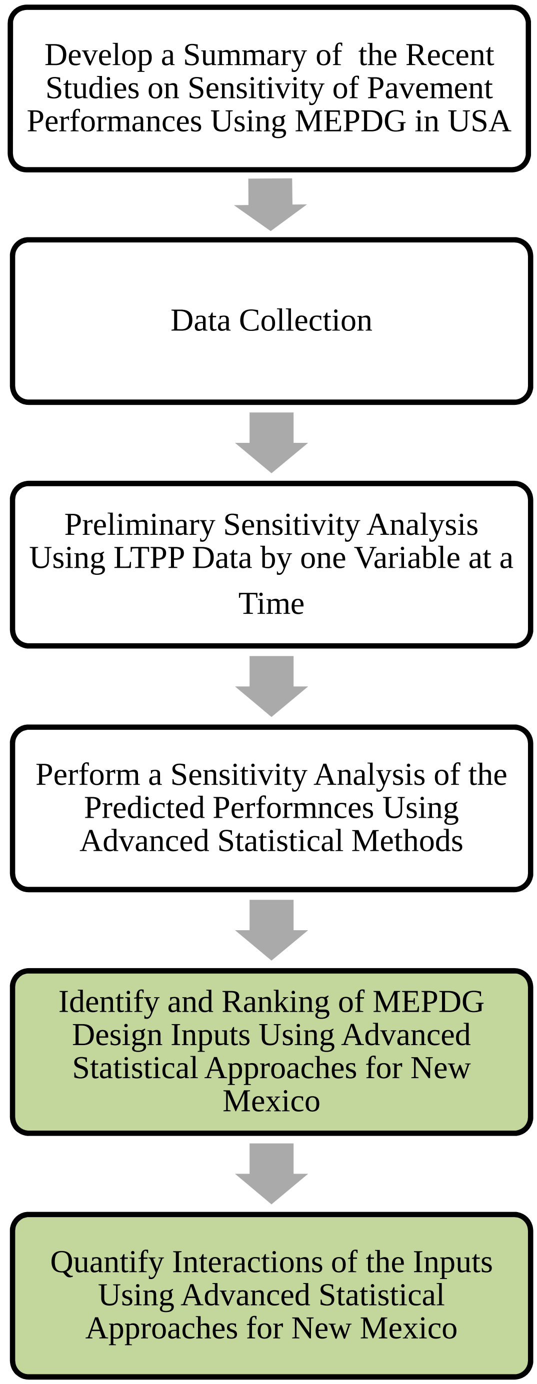


Figure 1.1: Flow Chart of the Study

CHAPTER 2

LITERATURE REVIEW

2.1 Background

Sensitivity is defined as the fractions of uncertainty in outputs due to fractions of uncertainties in inputs. Sensitivity analysis (SA) is an essential part of analyses for complex systems. It helps to determine the contribution of each individual input to the analysis results. SA helps us by providing an understanding of how the output models change due to change in inputs. Mechanistic-Empirical Pavement Design Guide (MEPDG) developed under NCHRP is a feasible tool for state-of-the-practice to evaluate and design pavement structures considering lots of design inputs, which is able to characterize materials, climatic factors and traffic loads. Figure 2.1 shows the MEPDG inputs and outputs system. The inputs are traffic, climate and pavement layer systems. The outputs include the pavement performances such as rutting, longitudinal cracking, alligator cracking, transverse cracking and international roughness index (IRI). The processing unit of the software is divided into mechanistic and empirical sections, which include pavement analysis model and load transfer functions. Several studies have been performed on the sensitivity analysis for MEPDG design inputs for performance prediction of flexible pavement (NCHRP 2004, Coree B., 2005, Li et al., 2009). Past studies determined how and which input parameters affect pavement distresses such as rutting, fatigue and smoothness. For the successful implementation of MEPDG in different geologic and climatic conditions, the load transfer functions used in MEPDG should be calibrated considering the variability associated with the pavement structures, traffic and climatic loadings. Therefore, it is important to analyze the sensitivity associated with pavement structures, climates, and traffic loading on design, construction and performance evaluation for fine-tuned calibration. One of the objectives of this chapter is to identify, review and evaluate sensitivity analysis methods applicable for this study. The other objective of this chapter is to summarize some of the recent efforts by various researchers.

2.2 Sensitivity Analysis

The term sensitivity analysis is interpreted in a variety among different problems, among different peoples. A possible definition of sensitivity analysis (SA) is the following: the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input (Saltelli et al., 2004). It shows how the given model depends upon the information fed into it. SA is a prerequisite for statistical model building. It is the measure of the effect of a given input on a given output. This is customarily obtained by computing via a direct or indirect approach, systems derivatives such as

$$S_j = \frac{\partial y}{\partial x_j} \qquad 2.1$$

where, y = output, x_j = input factor, S = sensitivity measure (Rabitz, 1989; Turanyi, 1990).

2.3 Need for Sensitivity Analysis

Sensitivity Analysis can capture the relation between the input and output of a model. It can be used to understand how the model or system changes for a change in input parameter value. There can be some uncertainty in model structures, assumptions and specifications. SA can rank the parameters in term of their importance relative to the uncertainty in the output. With this ranking of the factors, designer can pay more attention on optimization or can do more appropriate design. It helps to verify and validate the model. In addition, a set of important factors can be determined for calibration. So, SA can be employed prior to any calibration purpose for this reason. It is a powerful tool to check whether the system performs as expected.

2.4 MEPDG Calibration and Sensitivity Status of NMDOT

Some of the states Department of Transportation (DOTs) have calibrated MEPDG. These DOTs are implementing MEPDG for designing and evaluating pavement structures and characterizing design inputs. However, they are still working on fine-tuning the calibration factors of load transfer functions considering variability of the design inputs, which may allow them more reliable design representing the actual field condition and loading. Most of the DOTs are also going to walk on the same path soon. The NMDOT uses AASHTO 1972 pavement design method with department's probabilistic approach to design flexible pavement (NMDOT 2008). Recently, the NMDOT has taken a step for implementing MEPDG in state design policy and started the calibration procedures. In order to learn and gather experience on calibration procedures, the recent studies on the sensitivity of the variability of the design parameters has been reviewed.

2.5 Recent Studies on MEPDG Sensitivity Analysis

The NCHRP performed sensitivity analysis on new and rehabilitated pavement structures for permanent deformation, AC fatigue alligator cracking and AC fatigue longitudinal surface cracking (NCHRP 2004[a], NCHRP 2004[b], and NCHRP 2004[c]). The NCHRP research team investigated the effect of varying one parameter at a time, while keeping the other variables to be constant input parameters. Influence of AC mix stiffness, AC thickness, subgrade modulus, AC mix air voids, asphalt content, GWT depth, truck traffic volume, traffic speed, traffic analysis level, MAAT and bedrock depth were studied. The general input parameters (and range of variables) used in this study are described in Table 2.1. Depending on the input types, there are six different input levels were chosen for sensitivity analysis such as: very low, low, medium, medium high, high and very high. 100 to 50,000 AADTT values were considered to simulate low to very high traffic loading, respectively. Very low operating speed was considered as 2 mph for intersection and high speed was considered as 60 mph for interstate highway. MAAT's were selected to be 46.1 degree F (Minnesota), 60.7 degree F (Oklahoma) and 74.4 degree F (Phoenix) as low, medium and high, respectively. Sensitivity analysis results on pavement performances for the different parameters are presented in Table 2.2. Three types of pavement performance were taken in consideration in this sensitivity analysis: permanent deformation or rutting, fatigue alligator cracking or bottom up cracking and fatigue longitudinal cracking or top down cracking. In analysis, AC mix stiffness, AC thickness, air void, effective binder content, MAAT, base thickness, base quality, subgrade modulus, AADTT, traffic speed, traffic analysis level, traffic wander, bed rock depth and depth of groundwater table (GWT) parameters were studied to investigate the sensitivity on aforementioned pavement distresses. In case of thin AC layer, stiffness plays a minor role in rutting performance, but it has a significant role on alligator and longitudinal cracking. However, for thick layer, AC stiffness has significant role on rutting in addition to fatigue and longitudinal cracking. AC thickness has significant role on all of the aforementioned pavement distresses. An increase in air void increases pavement rutting, alligator cracking and longitudinal cracking.

Coree B. (2005) conducted a research to identify the sensitivity of the design parameters on pavement distresses such as longitudinal cracking, alligator cracking, rutting, and smoothness. He evaluated the relative sensitivity of MEPDG input parameters to AC material properties, traffic, and climatic conditions based on field data from two existing Iowa flexible pavement systems (US-020 in Buchanan County and I-80 in Cedar County). The design input parameters were divided into two groups – fixed input parameters and varied input parameters. While investigating the effect of a particular design parameter on performance, a standard value was assigned for the other design parameters. Twenty three key input parameters were studied. The results of the sensitivity analyses are summarized in Table 2.3. As shown in Table 2.3, AC thickness, aggregate nominal maximum size, PG grade, volumetric properties, unit weight of the mix, Poisson's ratio, thermal conductivity, heat capacity, AADTT, traffic tire pressure, traffic distribution, traffic velocity, traffic wander, base and sub-base properties, subgrade properties and aggregate thermal coefficient parameters were considered to investigate the sensitivity to pavement performance. The degrees of sensitivity were categorized as extreme sensitivity, very sensitive, sensitive, low sensitivity and insensitive. Longitudinal cracking was influenced by most input parameters. Table 2.3 also presented that sub-base resilient modulus and aggregate thermal coefficient are insensible to pavement rutting, cracking and smoothness. The sensitivity analysis by Iowa DOT was performed only for two pavement sections. In order to establish the result of sensitivity analysis, a number of sections should be considered with different level of traffic loading and functional classification.

Li et al. (2009) [a] developed a sensitivity chart of the design input values to predict their applicability in the State of Washington. The results of their study are summarized in Table 2.4. Table 2.4 shows that longitudinal cracking is mostly influenced by binder properties and asphalt layer thickness. Climate or temperature is the most essential input to transverse cracking as shown in Table 2.4. The hot mix asphalt (HMA) mix stiffness heavily influences the development of alligator cracking. Climate, base type and traffic loading have significant impacts on HMA rutting and roughness.

Li et al. (2009)[b] studied sensitivity of axle load spectra on MEPDG outputs for Washington State pavements. One of the significant finding is that a group of axle load spectra can present the vast majority of WSDOT axle load characteristics when the MEPDG is used. They also found out that for typical WSDOT pavement designs, the MEPDG is only moderately sensitive to the alternative axle load spectra developed from the Washington State WIM station data. However, the MEPDG used for sensitivity study was not calibrated for Washington State local condition. The un-calibrated MEPDG might have resulted in the differences of the estimated pavement performance due to various axle load spectra.

Ahn et al. (2009) studied the sensitivity of the traffic inputs on the pavement performance predicted by the MEPDG for the state of Arizona. The traffic input parameters were average daily truck traffic (ADTT), monthly adjustment factors (MAF), and axle load distribution factors. Longitudinal and alligator cracking increased nonlinearly with increases in ADTT. The use of default monthly adjustment factors (uniform throughout months) did not have significant impact on pavement performance (Ahn et. al 2009).

Aguiar-Moya et al. (2009) studied the sensitivity of the MEPDG for measured probability distributions of pavement layer thickness on performance. Long Term Pavement Performance (LTPP) SPS-1 sections located in the State of Texas were used to determine the thickness distribution associated with the hot-mix asphalt (HMA) surface layer, the HMA binder course, and the granular base layer. The layer thicknesses were considered random variables and evaluated at the mean thickness and within the range of ± 3 standard deviations from the mean. The analysis spanned a 25-year design period under Texas climatic and traffic conditions. It was found that there is a significant increase in fatigue distress at the design life as the HMA surface layer thickness decreases within the given range. Total rutting, roughness, and fatigue cracking appear to be unaffected by changes in the granular base layer thickness.

Masad and Little (2004) conducted a comprehensive sensitivity analysis of the proposed MEPDG (version 0.8) performance models to the properties of the unbound pavement layers. Their sensitivity analysis included different types of base materials, base layer thicknesses, hot mix asphalt type and thickness, environmental conditions, and subgrade materials. It was shown that the base modulus and thickness have significant influence on the international roughness index and the longitudinal cracking. The influence of base properties on alligator cracking is about half of the influence of base properties on longitudinal cracking. Their analysis results show that the base properties have almost no influence on permanent deformation (Masad and Little, 2004).

Manik et al. (2009) presented a strategy for determining optimal values for the desired design variables like asphalt layer thickness, base thickness etc. At first, they identified the variables having significant influence on performance. In that study, Manik et al. (2009) considered three of variables: asphalt layer thickness, base and subbase thickness (together), and base modulus as design variables for demonstrating the strategy. They simulated full factorial runs using MEPDG for entire range of feasible values of each of these variables with multiple levels for each of them. Response surfaces were developed using piecewise cubic spline interpolation for predicting performance for any combination of the aforementioned three design variables without running any simulation using MEPDG. The piece-wise cubic spline interpolation function fits itself to local variations in slope of the surface (Manik et al. 2009). However, it would be extremely difficult to find a suitable function to model such slope changes for such a wide range in the design input variables. That study concluded that non-linear nature of relationships between the design input variables and pavement responses, which get much more complicated because of interaction of effects of different design input variables.

Hong et al. (2008) conducted a research on the effect of different sampling schemes and performed a sensitivity analysis for evaluation of sampled WIM data accuracy. Sum of Absolute Error (SAE) was used as a criteria to address the approximation of WIM data with the mathematical fit of axle load distributions from sample to population data quantitatively. The absolute value was used to avoid offset between negative and positive errors. Mathematically, SAE can be defined as (Hong et al. 2008),

$$\boldsymbol{SAE = \sum_i \left| f_i^s - f_i^p \right|} \qquad \mathbf{2.2}$$

where, i= the ith weight interval of axle load distribution and each interval is of equal width, which is 1 kip for single axle and 2 kip for tandem axle, f_i^s : normalized frequency at the ith weight interval of axle load distribution from sampled data and f_i^p : normalized frequency at the ith weight interval of axle load distribution from the population data. From the SAE sensitivity analysis, they concluded that larger sample sizes contributed to higher data accuracy in terms of SAE and smaller variability in each group of repeated samples. Seasonal variability in sampling can also improve data accuracy (Hong et al. 2008). They performed a sensitivity analysis as second criteria on ESAL estimation error, which also suggests that with the increase in sample size error decreases and small size sample can have relatively high variability. Their third criterion was aimed to address the effect on pavement life under different load distributions from the different sampling schemes using MEPDG software. In case of vehicle classification for data input into MEPDG software, only the 18-wheeler was considered which accounted 100% for truck volume. The result indicated the similar trend between absolute error in life and different sample schemes as observed in first and second criterions.

Swan et al. (2008) conducted a sensitivity analysis of the predicted pavement performance for the traffic input parameters. Their study showed that the number and type of trucks, followed by the axle load spectra, have the significant influence on the predicted pavement performance. Hourly traffic volume adjustment factors and axle spacing have a little influence on the predicted performance (Swan et al. 2008).

Rabab'ah and Liang (2008) considered a range of different base materials, AC thickness, and subgrade soils in their study. The influences of AC thickness, moisture content, resilient modulus of base and subgrade on rutting were studied. They showed that subgrade resilient modulus influence the permanent deformation more than the base resilient modulus. The influence of unbound materials on performance as predicted by the MEPDG methodology is less pronounced than the influence of asphalt concrete layer thickness on performance.

Daniel and Chehab (2008) performed a study on reclaimed asphalt pavement (RAP) materials using MEPDG. They ran different simulations conducted for three climactic regions in which all the unbound layer properties and traffic inputs were held constant. The properties of the HMA layer were changed for the three input levels of analysis to simulate different extent of RAP in the MEPDG. Their study reveals that the Level 1 analysis is the least conservative, while Level 2 and Level 3 are more conservative for the structures and mixtures examined by them. They also showed that the difference between the Level 1 and Level 2 increases with increasing the difference between high and low temperature of asphalt PG grades. Limited simulations were conducted varying AC thickness and layer structure in their study. They found that the number of AC layers affect on the predicted performance, even though the total thickness of the AC layers is same (Daniel and Chehab 2008). Their study also reveals that the PG grade of the RAP mixtures affect performance and this effect is not significant for the Level 1 analysis while it was quite significant for the Level 2 and Level 3 analysis.

Li et al. (2007) conducted a study on truck traffic characteristics for the MEPDG including WIM data sampling, axle load distributions, number of axles, traffic input level, degree of traffic count accuracy and operational speed and effect of these parameters on pavement performance. They processed the WIM data on a monthly basis at first; and then generated the traffic inputs from specific months in five scenarios. These scenarios included one-month (May), three-month (February, April and October), six-month (January, February, March, July, September and October), nine-month (February, March, April, June, August, September, October, November, and December), and twelve-month data, respectively. Three random months data were analyzed among the collected five scenarios based on statistically soundness and satisfactory degree of accuracy. The degree of accuracy of traffic input increases as traffic data sample size increases (Hong et al. 2008, Li et al. 2007). They analyzed the sensitivity of the different pavement distresses to truck traffic inputs using MEPDG in their research. Their analysis results were summarized in Table 2.5. Their study showed that roughness, rutting and cracking are medium to highly sensitive to axle load distribution. Hourly distribution and number of axles per truck do not have any influence on roughness, rutting and cracking as shown in Table 2.5.

Tran and Hall (2007) developed state wide axle load spectra for the state of Arkansas and studied the influence of the axle load spectra on flexible pavement performance using MEPDG. They collected WIM data from the statewide 10 sites which provided good weight data among 25 selected WIM sites. From the collected data, they developed statewide axle load spectra for single (3,000 lb – 40, 000 lb at 1,000 lb interval), tandem (6,000 lb – 80, 000 lb at 2,000 lb interval) and tridem (12,000 lb – 102, 000 lb at 3,000 lb interval) axles. They did not generate quad axle load spectra as the number of quad axles in their collected data was very few. A sensitivity analysis was performed using the statewide and MEPDG default axle load spectra using MEPDG. They found significant difference in pavement performance for the developed axle load spectra and MEPDG default axle load spectra. They quantified the normalized differences for these two different axle load spectra are more than 25%, 5% and 15% associated with pavement life, rutting and cracking respectively (Tran and Hall 2007).

2.6 Summary of Background Studies

MEPDG uses a large number of inputs related to material, environment, construction and traffic. Table 2.6 shows the parameters studied by different researchers for sensitivity. However, sensitivity on the all required design parameters are not studied yet considering each of the parameters individually or simultaneous interaction as shown in Table 2.6. Using the MEPDG for designing a flexible pavement can be relatively complex and time consuming because of numerous variables and time required for each run. For getting a good result, the whole process needs to be repeated for each individual design. All these variables affect performance simultaneously though the magnitude of their affect can vary significantly. Some of the inputs have minor influence regarding pavement performance. Some of the inputs interact with each other. For example, HMA thickness and binder performance grade may affect each other. Due to this type of interaction, study of the inputs separately may not give real understanding of their affect in a real-life pavement.

2.7 Methods for Sensitivity Analysis

Several techniques have been developed to perform sensitivity analysis. They can be classified in different ways. The main three categories are Factor screening, Local SA and Global SA. Different type of sensitivity analysis strategies can be applied depending on the purpose.

For an example, a model may be contained of many parameters, but only a few of them are influential. Factor screening is the best choice to identify the most influential factor for that model among many factors. Typical screening designs are one-at-a-time (OAT) experiments in which the impact of changing the values of each factor is evaluated in turn (Daniel, 1958, 1973). The limitation of this type of SA is that it only determines the main effect of a particular input variable. The interaction among that input and others cannot be determined with this method.

Local methods can be applied on deterministic or probabilistic problems. It calculates sensitivity of the output at one location (or around neighborhood) in the input hypercube. Most of these methods calculate derivatives (i.e., Taylor series) of the function relative to one or multiple parameter. The accuracy of this analysis depends on the type of the method and the number of points used to estimate the derivative. This method is usually costly to calculate higher order derivatives, partial derivatives when it need to deal with a system consist of many inputs and outputs. Therefore, this method is applicable when input output relationship is assumed linear. It is also a good choice when the variation around the midpoint of the input factors is small.

Global methods try to apportion the entire uncertainty in the output variable to the uncertainty in each input factor. This method is the best choice when all the parameters need to be varied simultaneously and sensitivity needs to be measure over the entire range of each input parameter. Global SA typically takes a sampling approach. The range of distribution of the variables is very important in this method because the global effect of the input variable is important rather than the effect around a specific point on the hypercube.

2.8 Selection of Method

The key points of sensitivity analysis are to identify the question what model should answer and determine which of its input factors should concern the sensitivity analysis. The purpose of this study is to investigate the main and interaction effects of the design inputs for mechanistic-empirical methodology. The system is involved of many input and output variables. One of the main objectives of this study is to rank the parameters in term of their importance relative to uncertainty in the output. This study is also interested more on global effect of an input variables and its interaction with others. Factor screening and Local SA are not going to useful in this case. With factor screening, only main effects can be measured not the mutual interaction. Even local SA would not serve this purpose because of a large amount of inputs and outputs. Global SA is the best choice for this case.

As mentioned before, Global sensitivity analyses try to capture the influence of the inputs and apportion the uncertainty of the outputs among them. Several methods cover the whole range of uncertainty in inputs and output of interest. They include response surface, variance based decomposition and sampling-based methods. Depending on the problem settings of this study, sampling based method is the method of choice. Sampling based method is one of the most popular and effective approaches. For sampling based methods, the same sample set is used to perform uncertainty and sensitivity analysis. For large sample size, there is no need to rerun the code second time (Helton et al 2006).

2.9 Steps to Perform Global Sensitivity Analysis

Several approaches of Global Sensitivity Analysis Methods have been developed to perform uncertainty and sensitivity analysis. Some of them are differential analysis, response surface methodology, and Monte Carlo analysis and variance decomposition procedures. The focus of this section is on Monte Carlo (i.e., sampling-based) approaches to uncertainty and sensitivity analysis. Sampling-based approaches to uncertainty and sensitivity analysis are both effective and widely used (Helton et al 2006). Global sensitivity analysis (i.e., Monte Carlo (MC) Analysis) is based on performing multiple evaluations with randomly selected model input, and then using the results of these evaluations to determine both uncertainty in model predictions and apportioning to the input factors their contribution to this uncertainty (Saltelli et al. 2000).

Generally, for a sampling based SA, five steps are performed. These basic steps are illustrated in Figure 2.2. The process starts from the upper left corner of the figure. At the very beginning, the input variables (x_j) and output variables (y) for the analysis should be selected. Distribution or ranges of the each input variables are very important in this case. Generation of the sample (input vector/matrix) from this ranges and distribution need to be done through an appropriate design. After that, the input variables will feed through the model to create an output distribution for the response of interest. The next step is applying different kind of methods to capture the uncertainty. The result can be expressed in different ways. In this figure, the results are shown with a pie chart. The partitions of the pie chart present the variance of the input variables used in the analysis. This variance decomposition helps to identify the importance and ranking of the input variables. The details are described in the next paragraphs.

Step 1: Selection of Ranges and Distribution Function for each Input Variable

Sensitivity analysis results generally depend on the input ranges and their distributions. These distributions of the input variables determine both the uncertainty in output and the sensitivity of the elements each input variable. Sensitivity analysis results generally depend more on the selected ranges than on the assigned distributions (Saltelli et al. 2000). In the first step, in the absence of information about ranges and distributions for the input variables, a crude characterization may be adequate.

Step 2: Generation of Sample:

The second step in the Global sensitivity analysis is generation of sample. Sampling will be done from the distributions or ranges developed in the first step. Helton et al. (2002) performed a study to illustrate the sampling-based methods for uncertainty and sensitivity analysis. Conceptually, an analysis can be represented by a function of the form

$$Y = f(x) \tag{2.3}$$

where,

$$x = [x_1, x_2, \dots \dots \dots . x_{nI}] \tag{2.4}$$

is a vector of analysis inputs and

$$y = [y_1, y_1, \dots \dots \ y_{nO}] \tag{2.5}$$

is a vector of outputs which are obtained from analysis or result. Usually, for the values of the elements of x lead to uncertainty to the values for the elements of y.

In sampling based analysis (i.e., Monte Carlo method), a sample x_i is generated from the possible values for x in consistency with distributions and any associated restrictions. By following any kind of sampling method to generate a sample

$$x_k = [x_{1k}, x_{2k}, \dots \dots \dots . x_{nI,k}], \quad k = 1.2, \dots . nS, \qquad 2.6$$

where, nS is the size of the sample.

Evaluation of the analysis (Eq. 2.3) with the sample elements x_k in Eq. 2.4 creates a sequence of results of the form

$$y_k = [y_{1k}, y_{2k}, \dots \dots \dots . y_{nI,k}], \quad k = 1.2, \dots . nS, \qquad 2.7$$

where each y_k is a particular output of evaluating the model with x_k. The pairs

$$[x_k, y_k], \quad k = 1,2, \dots . nS, \qquad 2.8$$

constitute a mapping from model input x_k to model output y_k that can be explored with various sensitivity analysis techniques to determine how the individual analysis inputs contained in x (i.e., the x_i's) affect the individual analysis outcomes contained.

Several sampling strategies are available, including Random sampling, Importance sampling, and Latin hypercube sampling (Helton et. al., 2006). Latin hypercube sampling is very popular for use with computationally demanding models. It has an efficient stratification property. Therefore, large amount of uncertainty and sensitivity information can be obtained with a relatively small sample size. Details of LHS are presented in another section of this chapter.

Step 3: Evaluation of the Model

The third step is the evaluation of the model for each of the sample elements. Each of the input variables will be used in the model for analysis. It will create a sequence of result of the form of Eqn. 2.8, which will be used in the sensitivity analysis

$$y_i = f(x_i), \quad i = 1.2, \ldots .nS, \qquad 2.9$$

Step 4: Uncertainty Analysis

The fourth step is uncertainty analysis. If random sampling or LHS is used than, the expected value (E) and variance (V) for the output variable y are estimated by

$$\hat{E}(Y) = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad 2.10$$

$$\hat{V}(Y) = \frac{1}{N-1}\sum_{i=1}^{N}\left[y_i - \hat{E}(Y)\right]^2 \qquad 2.11$$

Empirical Cumulative Distribution Function (CDF) is the most common UA measure. McKay et al. (1979) showed that under various condition LHS produce more stable result than random sampling.

Step 5: Sensitivity Analysis

The final step is sensitivity analysis. To apportion the variation in the output due to the input is the main goal. Many methods are available which produce different type of sensitivity measures. Details of the methods are discussed in other sections of this chapter.

2.10 Latin Hypercube Sampling

Latin Hypercube sampling (LHS) can be considered as a stratified random procedure, provides an efficient way of sampling variables from their distributions (Saltelli et al. 2000). According to statistical concept, a square grid is called Latin square if there is only one sample in each row and each column. A Latin hypercube is the generalization of this concept to an arbitrary number of dimensions and each sample will be contained as the only one in each axis aligned hyperplane (McKay et al.1979).

Generation of sample includes the following steps. As an example, Latin hypercube sampling for an input variable $x_{k,}$

$$x_k = [x_{1k}, x_{2k}, \dots \dots, x_{nX,k}], k = 1, 2, \dots \dots \dots, nLHS \qquad 2.12$$

During generation of sample, range of each x will be divided in nLHS intervals of equal probability. Value for x_j (i.e., x_{jk}) will be randomly selected from each of the interval. To produce nLHS pairs, x_1 will be randomly paired without replacement with values for x_2. This pair will be randomly combined without replacement with values for x3 to nLHS triples. This process will be continued through all variables to produce nLHS sample elements.

McKay et al.1979, Helton et al. 2002 mentioned some comparison about sampling techniques. LHS gives unbiased estimates for means and distribution functions compare to other sampling techniques. It also provides dense stratification across range of each variable. It can be used when large samples not computationally practicable and estimation of high quantiles not required. Uncertainty/sensitivity results robust with relatively small sample sizes (e.g., nLHS = 50 to 200). Sallaberry et al (2008) conducted another study on LHS and mentioned that unlike a random sample, an LHS cannot be increased by adding one sample element at a time. Algorithm exists to increase to increase size of LHS by integer multiples of original sample size.

2.11 Sensitivity Analysis

Many techniques are being used, yielding different measures of sensitivity. Some of the techniques are reviewed for this study and used. Details of the techniques are given in the following subsections.

2.11.1 Statistical Tests for Nonrandomness

Different type of scatterplot is mainly used for the test of nonrandomness. A plot of the points (x_{ij}, y_i) for i =1, 2….nS (i.e., a scatterplot of y versus xj) can reveal nonlinear or other unexpected relationships between analysis inputs and analysis results (Helton et al. 2006). It is one of the straight forward techniques for sensitivity analysis. It can measure the importance of inputs globally. Scatterplots are model independent. They are the simplest way to observe any dependency between input and output without making any assumption (Helton 1993). This tests are usually enough to understand relationship between input and output. They are usually bi-dimensional (one output vs. one input) but can be some time tri-dimensional to show three way interactions. However, they may be impractical if hundreds of inputs and outputs are in consideration. Another disadvantage for this method is, it gives the relative importance of the input variables only. Sensitivity of a particular input variable cannot be quantified.

There are mainly three categories of test for nonrandomness. The summary of all these tests described in this section is presented in Table 2.7 and 2.8. They are:

- Tests Based on Gridding
    - Common Means (CMN)
    - Common Locations (CL)
    - Statistical Independence (SI)
- Flexible Grid-Free Tests
    - Linear and Quadratic Regression
    - Rank Correlation Coefficient Test
    - Squared Rank Differences Test (SRD)
- Combining Statistical Tests

Statistical Tests for Patterns Based On Gridding

The main objective of this type of test is Different kind of analyses based on correlation (PCC, SRC) can fail when the underlying relationships between the x_j and y are nonlinear and nonmonotonic. An alternative analysis strategy of this type is to place grids on the scatterplot for y and x_j and then perform various statistical tests to determine if the distribution of points across the grid cells appears to be nonrandom (Helton 2006). Appearance of a nonrandom pattern indicates that x_j has an effect on y. Possibilities include tests for (i) common means (CMNs), (ii) common locations (CLs), (iii) statistical independence (SI). Descriptions of these tests follow.

- *Common Means (CMN)*

The CMNs test is based on dividing the values of xj (i.e., x_{ij}, i=1, 2 . . . nS) into nI classes and then testing to determine if y has a CMN across these classes (Helton et al. 2006; Scheffe, H. 1959). The required classes are obtained by dividing the range of x_j into a sequence of mutually exclusive and exhaustive subintervals containing equal numbers of sampled values. If x_j is discrete, individual classes are defined for each of the distinct values. Then perform an analysis of variance (ANOVA) to determine if y has a different mean across these classes. The F-test can be used to test for the equality of the mean values of y for the classes into which the values of xj have been divided.

$$F^* = \frac{\dfrac{\left[\sum_{c=1}^{M}(\bar{y}_c - \bar{y})^2\right]}{(M-1)}}{\dfrac{\left[\sum_{c=1}^{M}\sum_{i\in X_c}(y_i - \bar{y}_c)^2\right]}{(n-M)}} \qquad 2.13$$

where, (x_{ij} , y_i)=observed values of x_j and y and i=1, 2,. . , n; c = 1, 2, . . . ,M number of individual classes into which the values of x_j have been divided, X_c=the set of x_j values such that $i \in X_c$ (x_{ij} belongs to class c); M_c=number of elements contained in X_c.

Typical ANOVA assumptions are assuming y_i are independent and $y_i = N(\mu_c, \sigma^2)\ for\ i \in X_c$. The ANOVA procedure is a test of the hypothesis

$$H_0: \mu_1 = \mu_2 = \cdots = \mu_M \qquad 2.14$$

versus the alternative that H_0 is not true. If H_0 is assumed to be true, then Eqn. 2.13 will follow an F-distribution with (M − 1, n − M) degrees of freedom, where $\bar{y} = \sum_{i=1}^{n}\frac{y_i}{n}$

and $\bar{y}_c = \sum_{i\in X_c}\frac{y_i}{m_c}$.

The p-value for the test of the null hypothesis H_0 is given by

$$p = P\left[F_{M-1,n-M} > F^*\right] \qquad 2.15$$

A small p-value suggests that at least one of the μ_c is not equal to the rest. Hence, the observed pattern involving x_j and y did not arise by chance and x_j has an effect on the behavior of y. A level of significance α is specified a-priori (e.g., $\alpha = .05$). If $p < \alpha$, then it can be concluded like that x_j has an effect on the behavior of y. Relative importance of the x_j's can be assessed by ranking them according to their respective p-values (smaller the p-value, the more important).

- *Common Locations (CL)*

The CLs test employs the Kruskal–Wallis test statistic T, which is based on rank-transformed data and uses the same classes of xj values as the F-statistic in Eq. 2.13 (Helton et al. 2006, Conover, W. J. 1980). Assume that the y_i's are independent and identically distributed with median $(y_i) = \eta_c$. For $i \in X_c$, c = 1, . . . ,M. It is also assumed that the shape and scale of the distribution of the y_i's is the same across all M groups. The CL procedure is then a test of the hypothesis

$$H_0\!: \eta_1 = \eta_2 = \cdots = \eta_M \qquad 2.16$$

versus the alternative that H_0 is not true. The test statistic T* for the CL test is based on rank-transformed data. Specifically,

$$T^* = (n-1)\frac{\sum_{c=1}^{M} m_c(\bar{r}_c - \bar{r})^2}{\sum_{c=1}^{M}\sum_{i\in X_c}(r(y_i) - \bar{r}_c)^2} \qquad 2.17$$

where,
$$\bar{r}_c = \left(\frac{1}{m_c}\right)\sum_{i\in X_c} r(y_i) \qquad 2.18$$

$$\bar{r} = \left(\frac{1}{n}\right)\sum_{i\in X_c}^{n} r(y_i) \qquad 2.19$$

$r(y_i)$ denotes the rank of yi , and m_c equals the number of elements contained in X_c. If all of the y values have same distribution, then T^* approximately follows a χ^2_{M-1} distribution. The p-value of the test is

$$p = P[\chi^2_{M-1} > T^*] \qquad 2.20$$

A small p-value indicates that y has a different distribution depending on which of the groups xj is in. Since it was assumed that the shape and scale of the distribution of y across each of the M groups is the same, the difference must be between the locations (medians). Even without the shape and scale assumption though, a small p-value indicates that xj has some effect on y (location shift or otherwise).

- *Statistical Independence (SI)*

The SI test also uses the χ2 test to indicate if the pattern appearing in a scatterplot appears to be nonrandom (Helton et al. 2006). The SI test uses the same partitioning of xj values as used for the CMN, CL tests. In addition, the y values are also partitioned in a manner analogous to that used for the xj values (Helton et al. 2006). For notational convenience, r= number of individual classes into which the values of y are divided (r=1,2,.. L); Yr = set of y values, such that $i \in Y_r$ only if y_i belongs to class r; l_r= number of elements contained in Y_r . The partitioning of xj and y into M and L classes, respectively, in turn partitions (xj , y) into M × L classes. If, $O_{r,c}$ =set of value such that $i \in O_{r,c}$ only $i \in X_c$ and also $i \in Y_r$; $k_{r,c}$ = the number of elements contained in $O_{r,c}$. The SI procedure is a test of the hypothesis

$$H_0 \colon y\ is\ dependent\ of\ x_j \qquad 2.21$$

versus the alternative that H_0 is not true. Under the assumption of H0, y has the same distribution in each of the xj classes. If x_j and y are independent,

$$E_{r,c} = \frac{I_r m_c}{n} \tag{2.22}$$

is an estimate of the expected number of observations (x_j, y) that should fall in class (r, c). The test statistic

$$T^* = \sum_{c=1}^{M} \sum_{r=1}^{L} \frac{\left(k_{r,c} - E_{r,c}\right)^2}{E_{r,c}} \tag{2.23}$$

Asymptotically, T^* follows approximately follows a $\chi^2_{(M-1)(L-1)}$ distribution when x_j and y are independent.. The p-value of the test is

$$p = P\left[\chi^2_{(M-1)(L-1)} > T^*\right] \tag{2.24}$$

A small p-value indicates that xj and y are likely not independent

Flexible Grid Free Test

- *Linear & Quadratic Regression*

The regression (REG) test for nonrandomness is performed by fitting simple linear regression of the y on xj (Helton et al. 2006). The p-value for the test is obtained from the test of nonzero slope. The quadratic regression (QREG) test performs a quadratic regression of y on x_j. That is, the multiple regression models to fit the data is

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \varepsilon_i \tag{2.25}$$

The p-value is obtained by testing significance of the model. The hypothesis for these tests are $\beta_1 = \beta_2 = 0 \; versus \; \beta_1 \neq \beta_2 \neq 0$.

- *Rank Correlation Coefficient (RCC)*

The rank correlation coefficient (RCC) test is based on the rank (or Spearman) correlation coefficient (Helton et al. 2006). The equation is

$$r = \frac{\sum_{i=1}^{n}\left[r(x_{ij}) - \frac{n+1}{2}\right]\left[r(y_i) - \frac{n+1}{2}\right]}{\left\{\sum_{i=1}^{n}\left[r(x_{ij}) - \frac{n+1}{2}\right]\right\}^{1/2}\left\{\sum_{i=1}^{n}\left[r(y_i) - \frac{n+1}{2}\right]\right\}^{\frac{1}{2}}} \qquad 2.26$$

where, $r(x_{ij})$ and $r(y_i)$ are the ranks associated x_j and y for sample element i.

The null hypothesis is made as there is no monotonic relationship between xj and y. the absolute value of r is uses to accept or reject the hypothesis. The large value means the underlying rank correlation may be different from zero and there is a relationship between and x_j and y. Thus, the p value to test the null hypotheses is given by

$$p = P(|t_{n-2}| > |r|) \qquad 2.27$$

- *Squared Rank Differences (SRD)*

This test is effective at identifying linear and nonlinear patterns in analysis results (Helton et al. 2006). No grid setup is required for this test. No parametric model is considered between inputs and outputs. The SRD test is based on the statistic

$$Q = \sum_{i=1}^{n-1}\left(r_{i+1,j} - r_{i,j}\right)^2 \qquad 2.28$$

where, $r_{i,j}$=rank of y obtained with the sample element in which xj has rank i. ($r_{i,j}$=1,2,…n). Under the null hypothesis of no relationship between xj and y, the test statistic

$$S^* = \frac{Q - n\frac{(n^2-1)}{6}}{\frac{n^{5/2}}{6}} \qquad 2.29$$

approximately follows a standard normal distribution for n>40. Small values of Q (and subsequently small values of S) indicate similar ranks among y values with similar xj values. This is inconsistent with the null hypothesis of independence between xj and y. Thus, a p-value can be obtained as

$$p = P(Z < S^*) \qquad 2.30$$

where, Z is a standard normal random variable.

Combining Statistical Tests

The SRD/RCC test is the result of combining the test of RCC and SRD. This is mainly a test for nonrandomness in the relationship between an independent and a dependent variable (Helton et al. 2006; Hora, S. C, 2003). To identify linear and non-linear pattern, it is very effective. The test is used to assess the relationships between individual elements xj of x=(x_1, x_2,….x_{nx}) and a output variable y. The SRD component of the test is based on the statistic described in Eqn. 2.27 and 2.28. p value can be obtained from Eqn. 2.27. This p value gives the measure of the strength of the nonlinear relationship between xj and y.

2.11.2 Regression Analysis

More quantitative measures of sensitivity are based on regression analysis. In this study, linear and rank regression have been reviewed. Linear regression is the approach to model any relationship between two variables. It is assumed that, the variables have linear relationship. This is simple type of model because it is easier to fit than models which are non-linearly related to their parameters. The statistical properties of the resulting estimators are easier to determine. A linear regression model will take a form as mentioned below

$$y_i = b_0 + \sum_j b_j x_{ij} + \varepsilon_i \,, \qquad j = 1,2, \ldots\ldots k \qquad 2.31$$

Where, b_j=regression coefficients, ε_i= residual error. One common way to determine the coefficients b_j is to use least square methods (Draper, N. R. 1981). If bj can be calculated, they can be used to indicate the importance of individual input variables xj with respect to the uncertainty in output y (Saltelli et al. 2004). Then the regression model can be written as

$$\frac{y - \bar{y}}{\hat{s}} = \sum_j \frac{b_j \hat{s}_j}{\hat{s}} \frac{x_j - \bar{x}_j}{\bar{s}_j} \qquad 2.32$$

where,

$$\bar{y} = \sum_i \frac{y_i}{N} \;\; and \;\; \bar{x}_j = \sum_i \frac{x_{ij}}{N} \quad ;$$

$$\hat{s} = \left[\sum_i \frac{(y_i - \bar{y})^2}{N-1}\right]^{1/2} and \qquad \hat{s_j} = \left[\sum_i \frac{\left(x_{ij} - \bar{x_j}\right)^2}{N-1}\right]^{1/2}$$

The coefficients $\frac{b_j \hat{s}_j}{\hat{s}}$ are called standardized regression coefficients (SRC). This term is used for sensitivity analysis. Helton et al. 2002 reviewed in their study that, it can quantify the effect of varying input variable. When xj are independent, the absolute value of SRC can be used to provide a measure of variable importance.

Another important measure from regression analysis is partial correlation coefficient or PCC. It can be obtained by using a sequence of regression model between output and input variables. First, the following two models are constructed

$$\hat{Y} = b_0 + \sum_{h \neq 1} b_h x_h \qquad 2.33$$

$$\widehat{X_j} = c_0 + \sum_{h \neq 1} c_h x_h \qquad 2.34$$

Then the results of these two regression are used to define the new variables $Y - \hat{Y}$ and $X_j - \widehat{X_j}$. The partial correlation between Y and Xj is defined as the correlation coefficients between $Y - \hat{Y}$ and $X_j - \widehat{X_j}$ (Helton et al, 1993). It also provides the strength of the linear relationship considering the correction due to the effect of other input variables.

The model for Eqn. 2.31 can provide better results when the underlying function is approximately linear. However, the linear regression model in Eq. 2.31 can fail to appropriately identify the effects of the elements of x on y when nonlinear relations are present. Rank regression works very well to identify the strength of relationships between inputs and output in nonlinear situations as long the relationships between inputs and output are approximately monotonic (Helton et al. 2006; Iman, R. L, 1979). The procedure for rank regression involves replacing the data with their corresponding ranks.

$$y = (y_1, y_1, \ldots . y_N) \qquad 2.35$$

where, y is vector of N values is generated by repeatedly evaluating the model for a set of N sampled vector

$$(x_{11}, x_{12}, \ldots . x_{N1k}); \;\; \ldots . \quad (x_{N1}, x_{N2}, \ldots . x_{Nk})$$

The observations are then replaced by their corresponding ranks. This is followed from highest values (rank 1) to lowest values (rank N). SRC and PCC are also used in this case to measure the importance of the input variables.

2.11.3 Nonparametric Regression Analysis

In nonlinear situations, nonparametric regression methods can be used to achieve a better approximation than can be obtained with the linear regression model in Eqn. 2.31 (Storlie et al., 2009). In this study, three types of modern nonparametric regression methods have been reviewed and used. They are Quadratic Response Surface Regression (QREG), Multivariate Adaptive Regression Splines (MARS) and Gradient Boosting Machine (GBM). Details of these methods are described below.

<u>Quadratic Response Surface Regression (QREG)</u>

The procedure fits a quadratic response-surface model, which is useful in searching for factor values that optimize a response. The following features in QREFG make it preferable to other regression procedures for analyzing response surfaces:

- Automatic Generation of Quadratic Effects
- A Lack-Of-Fit Test
- Solutions For Critical Values of The Surface
- Eigen values of the Associated Quadratic Form
- A Ridge Analysis to Search For The Direction Of Optimum Response

Multivariate Adaptive Regression Splines (MARS)

MARS is a combination of spline regression, stepwise model fitting, and recursive partitioning. The process of MARS can be described as follows (Storlie et al. 2009). If observed data is (x_1, y_1), . . . , (x_n, y_n) and g_j is a generic linear spline function of the input variable x_j with knots at all the distinct values of xj , the function can be presented as Eqn 2.36. These functions can be constructed as the tensor product of two univariate spline spaces as Eqn 2.37.

$$g_j(x_j) = \sum_{l=0}^{n+1} b_{j,l}, \emptyset_{j,l}(x_j) \qquad 2.36$$

g(x) = [constant] + [main effects] + [2-way interactions] + [higher interactions] 2.37

Three way and higher order interaction models can be ignored. After specifying the order of the interaction desired for the resulting model, MARS first fits the model with only the intercept term. Then MARS fits all possible models with two basic functions:

$$\hat{f}_{2,k}(x) = d_0 + d_k \emptyset_{j,l}(x_j) \qquad 2.38$$

for j = 1, . . . , p, l = 1, . . . , n + 1 via least squares. The model that gives the smallest Sum of Square Error (SSE) is chosen to be the one that enters the model. Once this basis function is included, MARS looks for the next basis function to add and so on. Once M basis functions have been added, MARS starts to remove basis functions that will result in the smallest increase in SSE. In the end, there are 2M +1 possible models and the one with the lowest GCV score is chosen as the MARS estimate.

$$GCV_l = \frac{SSE_l}{(1-(\nu m_1+1))/_n} \qquad 2.39$$

Gradient Boosting Machine (GBM)

Boosting was originally developed for classification purposes. The underlying idea is to combine the output from many "weak" classifiers into a more powerful committee. The general idea behind boosting trees is to compute a sequence of simple regression trees, where each successive tree is built for the prediction of the residuals from the preceding tree (Storlie et al. 2009). These trees are then put together in an additive expansion to produce the final estimator. For a given GBM, each constituent regression tree is restricted to have only *J* terminal nodes (regions that allow for more complex interactions). There is also an N_t parameter corresponding to the number of trees in the expansion. This can be considered a tuning parameter in the sense that *R*2 increases as *N*t increases. The specific algorithm to fit the boosting tree is as follows (Storlie et al. 2009):

- Fit a regression tree with J nodes to the original data set
- For k = 2, . . . ,N_t , fitting a regression tree with J nodes to the data set and call this estimate ˆf k .
- The final estimate is given as

$$\hat{f}(x) = \sum_{k=1}^{N_t} \hat{f}_k(x) \qquad 2.40$$

2.12 Conclusion

In this chapter, summary of some recent efforts by various researcher are described in this chapter. Basic of Sensitivity analysis with some advanced approaches are also described in this chapter.

Table 2.1: Parameters Used in the Sensitivity Analysis (NCHRP 2004[a], NCHRP 2004[b], NCHRP 2004[c])

Parameter	Very Low	Low (L)	Medium (M)	Medium High	High (H)	Very High
Traffic Volume AADTT (Vehicle/Day)		100	1000	4000	7000	50,000
(10 years) 18 Kips ESALs		$2*10^5$	$2*10^6$	$8*10^6$	$1.5*10^7$	$1*10^8$
Facility Type (Operating Speed (mph))	Intersection (2.0)	Urban Streets (25)	State Primary (45)		Interstate (60)	
Location (MAAT)		Minnesota (46.1ºF)	Oklahoma (60.7 ºF)		Phoenix (74.4 ºF)	
GWT Depth (ft)		2	7		15	
AC thickness (in)		1	4		12	
AC Stiffness		Low Mix	Med Mix		High Mix	
AC Air Voids (During Construction for Med Mix		4	7		10	
AC Effective Binder Content		8	11		15	
SG Modulus (psi)	3,000	8,000	15,000		30,000	
Plasticity Index	45	30	15		0	

Table 2.2: Sensitivity Analysis Result (NCHRP 2004[a], NCHRP 2004[b], NCHRP 2004[c])

Factor	Permanent Deformation	Alligator Cracking	Longitudinal Surface Cracking
AC Mix Stiffness (Thin AC Layers)	For very thin AC layers, the stiffness of the AC mixture will play a minor role. However rutting in the base and subgrade layers may be very large due to lack of protection provided by a thin AC layer. The amount of rutting in the subgrade layer is nearly independent of the AC mix stiffness.	For very thin AC layers, alligator (fatigue cracking) will greatly be increased as the stiffness of the AC mix becomes larger. The rate of change in alligator cracking is small at low to medium ranges of mixture stiffness, but increases significantly as very high mix stiffness.	For very thin AC layers, the design engineer should use as low an AC mixture stiffness as possible to eliminate and / or minimize fatigue cracking. A higher probability of top down cracking appears to exist when pavements are constructed over stiff subgrade materials.
AC Mix Stiffness (Thick AC Layers)	For thick AC layers, if the mix stiffness is increased the predicted AC rut depth will decrease. Rut depths within the base and subgrade layer will also tend to decrease with increasing E*.	As the AC mix stiffness of thick AC layers increases the amount of alligator fatigue cracking decreases. The higher the subgrade modulus, the lower the alligator cracking.	As the AC mix stiffness increases the amount of longitudinal surface cracking decreases. At high levels of AC mix stiffness there is almost no longitudinal surface fatigue cracking.
AC Thickness	Maximum rutting in the AC layer generally occurs at an optimum thickness of the AC layer, near a value of 3 to 5 inches. However, increasing the AC thickness also protects the base and subgrade layers and reduces the rutting. Repetitive shear deformations, leading to permanent deformation in the unbound base and subgrade will become the most salient design consideration for thin AC pavement types due to large stress states in the unbound layers (bases, subbases and subgrades).	An optimum thickness of the AC layer, near a value of 3 to 5", will exhibit the greatest level of fatigue cracking. Cracking will be increased as the subgrade support becomes weaker. From a fatigue viewpoint, AC layers need to be either very thin or thick.	An optimum thickness of the AC layer, near a value of 6", will exhibit the greatest level of longitudinal cracking in a pavement system. Longitudinal surface cracking increases as the subgrade support becomes stiffer.

Table 2.2: Sensitivity Analysis Result (NCHRP 2004[a], NCHRP 2004[b], NCHRP 2004[c]) (Cont.)

Factor	Permanent Deformation	Alligator Cracking	Longitudinal Surface Cracking
AC Mix Air Voids	Increasing or decreasing the amount of air voids in the AC mix significantly increases the amount of rut depth.	Increasing the amount of air voids in the AC mix significantly increases the amount of alligator fatigue cracking.	Increasing the amount of air voids in the AC mix significantly increases the amount of longitudinal cracking.
Asphalt Content (Effective Bitumen Volume)	An increase in effective bitumen volume increases the amount of rutting.	The effective bitumen volume (V_{be}) parameter is approximately 2.0 to 2.2 times the numerical value of the AC content, in percentage form by weight. As the V_{be} is increased; the Voids filled with bitumen are also increased and consequently this results in a greater resistance of the mixture to fracture under fatigue damage.	An increase in the effective bitumen volume is increased in a mix; the amount of longitudinal cracking will be decreased.
MAAT	Irrespective of the AC mix stiffness, the higher the MAAT the more rutting will be expected in the AC layer.	Regardless of the thickness of the AC layer, the amount of fatigue damage and alligator cracking will increase with increasing MAAT at the design site. This is true for whatever level of AC mixture stiffness is utilized in the pavement structure.	Regardless of the thickness of the AC layer, the amount of longitudinal cracking will increase with increasing MAAT at the design site. This is true for whatever level of AC mixture stiffness is utilized in the pavement structure and thickness of the HMA layer.
Base Quality	Increasing the unbound base modulus will tend to reduce the rutting in all pavement layers.		

Table 2.2: Sensitivity Analysis Result (NCHRP 2004[a], NCHRP 2004[b], NCHRP 2004[c]) (Cont.)

Factor	Permanent Deformation	Alligator Cracking	Longitudinal Surface Cracking
Base Thickness	The impact upon rutting in the AC layer is minimal to non-existent. Rutting slightly increases in the base layer as the thickness of the base increases. This is directly due to the fact that a thicker layer of base material is being subjected to repeated load. The most significant impact of increasing the base thickness is to protect the subgrade layer from a higher stress state that will tend to cause a larger resilient strain, plastic strain and eventually rutting.		
Subgrade Modulus	Decreasing the subgrade support modulus results in an increased level of base and subgrade rut depth. The impact of subgrade support upon the asphalt layer rut depth is not significant.	Increasing the subgrade support modulus results in a decreased level of fatigue cracking.	Increasing the subgrade support modulus will result in an increased level of longitudinal cracking.
Truck Traffic Volume	Increasing the truck traffic volume (AADTT) increases the amount of rut depth in all pavement layers. AADTT or ESALs, is an extremely sensitive parameter to rutting within the AC layer.	Increasing AADTT increases the amount of alligator fatigue cracking. The rate of change of alligator cracking with AADTT is nearly linear across all ranges of truck volume. The trend becomes slightly non-linear for the very high level of truck traffic.	An increase in AADTT increases the amount of longitudinal cracking. The rate of change of longitudinal cracking with AADTT is nearly linear across all ranges of truck volume. The trend becomes slightly non-linear for the very high AADTT.

Table 2.2: Sensitivity Analysis Result (NCHRP 2004[a], NCHRP 2004[b], NCHRP 2004[c]) (Cont.)

Factor	Permanent Deformation	Alligator Cracking	Longitudinal Surface Cracking
Traffic Speed	The vehicle speed possesses a significant impact on the AC mix stiffness as the time rate of load (vehicle speed and frequency) is changed. As the speed is decreased, the time of load increases and the AC modulus which results in an increase in the AC rut depth. It may not be very significant for the base and subgrade layers.	For very thin AC layer pavement systems, the amount of fatigue damage and cracking increase as the speed of the loading system is also increased. For very thick pavements, the reverse occurs and slightly less fatigue damage may be present at higher vehicle speeds.	For very thin AC layer, the amount of fatigue damage and cracking increase as the speed of the loading system is also increased. For very thick pavements, the reverse occurs and slightly less fatigue damage may be present at higher vehicle speeds.
Traffic Analysis Level	Level 1 traffic approach, based upon the actual traffic load spectra, yields a much higher level of rutting compared to the classical use of E18KSAL's.	Level 1 traffic approach, based upon the actual traffic load spectra, yields a higher level of alligator cracking compared to the classical use of E18KSAL's.	Level 1 traffic approach, based upon the actual traffic load spectra, yields a much higher level of longitudinal cracking compared to the classical use of E18KSAL's.
Traffic Wander	As the magnitude of lateral wander is increased, the maximum predicted rut depth will decrease. The selection of an appropriate wander value dictates the width of the rut basin.		
Bedrock Depth	The closer the bedrock layer is to the surface, the less subgrade rutting.	The closer a bedrock layer comes to the subgrade surface, the less fatigue fracture occurs. The "critical bedrock depth", at which there is no more influence upon fatigue cracking will vary as a function of many properties of the cross-section.	It appears that the "effective zone of influence of the bedrock layer" must be within 6' to 7' of the pavement surface to influence the amount of longitudinal cracking.
Depth to GWT	The closer the GWT is to the surface, the more subgrade rutting. The degree of rutting and sensitivity of the GWT is greatly significant for low stiffness (modulus) subgrade materials.	Fatigue damage increases as the GWT moves closer to the surface. At depths greater than 5 feet to 7 feet, the influence of the GWT becomes very low.	Greater depths of the GWT results more longitudinal cracking due to the increased subgrade stiffness. Longitudinal cracking is almost double from a GWT depth of 2 feet to a GWT depth of 7 feet.

Table 2.3: Sensitivity Analysis for Flexible Pavements for Iowa DOT (Coree, B. 2005)

Properties	Flexible Pavements Inputs	Performance Models								
		Cracking			Rutting					Smoothness
		Longitudinal	Alligator	Transverse	ACC surface	ACC base	Sub-base	Sub-grade	Total	
ACC General Property	ACC Layer Thickness	S	I	I	I	I	I	I	I /LS	I
ACC Mix Properties	Nominal Maximum Size	S	I	I	I /LS	I	I	I	I /LS	I
	PG Grade	ES	I	ES	LS/S	I	I	I	LS/S	LS/S
	Volumetric (V_{be}/Va/ V MA)	VS	I	VS/ ES	LS	I	I	I	LS	LS/S
	Unit Weight	LS/S	I	I	I /LS	I	I	I	I /LS	I
	Poisson's Ratio	LS/S	I	I	S	I	I	I	S	I
ACC Thermal Properties	Thermal Conductive	S	I	LS	I /LS	I	I	I	I	I
	Heat Capacity	VS	I	VS	LS/S	I	I	I	LS/S	LS
Traffic	Tire Pressure	VS	I	I	LS	I	I	I	LS	I
	AADT	VS	LS/S	I	ES	S	I	S	ES	I
	Traffic Distribution	VS	I	I	LS	I	I	I	LS	I
	Traffic Velocity	VS	I	I	S/VS	I / LS	I	I	S/VS	I
	Traffic Wander	LS/S	I	I	I	I	I	I	I	I

Note: ES = Extreme Sensitivity, VS = Very Sensitive, S = Sensitive, LS = Low Sensitivity, I = Insensitive

Table 2.3: Sensitivity Analysis for Flexible Pavements for Iowa DOT (Coree, B. 2005) (Cont.)

Properties	Flexible Pavements Inputs	Performance Models: Cracking – Longitudinal	Cracking – Alligator	Cracking – Transverse	Rutting – ACC surface	Rutting – ACC base	Rutting – Sub-base	Rutting – Sub-grade	Rutting – Total	Smoothness
Climate	Climate Data From Different Stations	VS	I	ES	S	I/LS	I	I/LS	S	S
Base	Layer Thickness	S/VS	S/VS	I	VS	I/LS	I	I/LS	VS	LS
	Type of Base, Mr	LS/S	ES	I/LS	VS	LS/S	I/LS	I/LS	VS	VS/S
Sub-base	Layer Thickness	LS/S	I	I	I	I	I	I/LS	I	I
	Type of Sub-Base, Mr	I	I	I	I	I	I	I	I	I
Subgrade	Type of Subgrade, Mr	ES	LS	I	I	I	I	I/LS	I/LS	I/LS
Others	Aggregate Thermal Coefficient	I	I	I	I	I	I	I	I	I

Note: ES = Extreme Sensitivity, VS = Very Sensitive, S = Sensitive, LS = Low Sensitivity, I = Insensitive

Table 2.4: Input Sensitivity for Flexible Pavement Distress Conditions (Li et. al (2009) [a]

Input Factors	Longitudinal Cracking	Transverse Cracking	Alligator Cracking	AC Rutting	IRI
Climate	Med	High	Low	High	High
PG Binder	High	Med	Med	Med	Low
AC Thickness	High	Med	Med	High	Low
Base Type	Med	Low	Low	High	Med
AADTT	Med	Low	Low	High	Med
AC Mix Stiffness	Low	Low	Low	Low	Low
Soil Type	Med	Low	Low	Low	Low

Table 2.5: Sensitivity of the Pavement Distresses to Truck Traffic Characteristics (Li et al. 2007)

Truck Traffic Characteristics	Pavement Distress			
	Roughness (IRI)	Rutting	Longitudinal Cracking	Alligator Cracking
Class Distribution	No	Fair	High	Medium
Monthly Distribution	No	Fair	Medium	Fair
Hourly Distribution	No	No	No	No
Axle Load Distribution	Medium ~ High	Medium ~ High	High	Fair ~ High
No of Axles per Truck	No	No	No	No
Truck Count Accuracy	No	Fair	Medium	Fair
Operational Speed	No	Fair	Medium	Fair

Table 2.6: Parameters Studied for Sensitivity by Different Researchers

Researcher	Parameters studied: Significant	Parameters studied: In-significant	Considered Pavement Distress/ Pavement Life
NCHRP 2004[a], NCHRP 2004[b], and NCHRP 2004[c]	AC thickness, AC stiffness, air void, effective binder content, MAAT, base thickness, base quality, subgrade modulus, AADTT, traffic speed, traffic analysis level, traffic wander, bedrock depth and GWT depth.	Not reported	Total Rutting, Alligator and Longitudinal Cracking
Coree B., 2005	AC thickness, PG grade, binder content, nominal maximum size, Poisson's ratio, thermal conductivity, heat capacity, unit weight of AC layer, tire pressure, traffic speed, AADT, traffic distribution, climate data from 2 stations, base M_r, base thickness, sub-base thickness and subgrade M_r.	Sub-base M_r, and Aggregate Thermal Coefficient	Total Rutting, AC Rutting, Cracking (Longitudinal, Alligator and Transverse)
Li et al. , 2009 [a]	Climate, PG grade, AC thickness, base type, AADTT, AC stiffness and soil type	AC-stiffness	AC Rutting, IRI Cracking (Longitudinal, Alligator and Transverse)
Li et al., 2009[b]	Axle load spectra	Not reported	Not mentioned
Ahn et al., 2009	AADTT and axle load distribution	MAF	Longitudinal and Alligator Cracking
Aguiar-Moya et al., 2009	HMA surface thickness, HMA binder course thickness and granular base thickness	Not reported	Total Rutting, Fatigue Cracking, Roughness
Masad and Little, 2004	Type of base materials, base thickness, AC material type and thickness, environmental conditions and subgrade material type.	Not reported	IRI, Alligator and Longitudinal Cracking
Manik et al., 2009	asphalt layer thickness, base and subbase thickness (together), and base modulus	Not reported	Not mentioned
Hong et al., 2008	Axle load distribution	Not reported	Pavement Life
Swan et al., 2008	Type of trucks and axle load spectra	HAF and axle spacing	Not mentioned
Rabab'ah and Liang, 2008	AC thickness, subgrade moisture content, resilient modulus of base and subgrade	Not reported	Total rutting
Daniel and Chehab, 2008	RAP material properties: PG grade and AC thickness, input level	Not reported	Not mentioned
Li et al., 2007	Traffic class distribution, monthly distribution, axle load distribution and truck count accuracy, speed	Hourly distribution and number of axles per truck	Roughness, Total Rutting, Alligator and Longitudinal Cracking
Tran and Hall, 2007	Axle load spectra	Not reported	Pavement Life, Total Rutting, Cracking

Table 2.7: Statistical Tests Based on Gridding

Type of Test	Type of Partitioning	Test Statistic	Null Hypothesis	Criteria of Rejecting Null Hypothesis
Common Means (CMN)	Divide all of the values of xj into M equally spaced quantiles along the x-axis of scatter plot.	Conducting ANOVA or F test Eqn. 2.13	Equal mean across the classes	The small p-value concludes that xj has an effect on the behavior of y. Eqn. 2.15
Common Locations (CL)		Performing Kruskal-Wallis test Eqn. 2.17	Individual classes have same distribution. T Approximately follows a X^2 distribution.	The small p-value concludes that individual classes have different means and medians, thus xj has an effect on y. Eqn. 2.20
Statistical Independence (SI)	Partitioning in both y & x axes of scatter plot. The partitioning of xj and y into M and L classes	Based on X^2 distribution Eqn. 2.23	y has the same distribution in each of the xj classes and y is independent of xj	A small p-value indicates that xj and y are not likely to be Independent. Eqn. 2.24

Bases on (Helton et al. 2006)

Table 2.8: Flexible Grid Free Tests Statistical Tests

Type of test	**Null hypothesis**	**Criteria of Rejecting Null Hypothesis**
Linear & Quadratic Regression Tests	$\beta_1 = 0$ $\beta_1 = \beta_2 = 0$	The small p-value concludes that y has a liner or quadratic relation with xj.
Rank Correlation Coefficient Test	Rank correlation is zero, that means no relationship between xj and y	A p-value can be found using Eqn. 2.27
Squared Rank Differences (SRD) Test	xj and y are independent	A p-value can be found using Eqn. 2.30

Bases on (Helton et al. 2006)

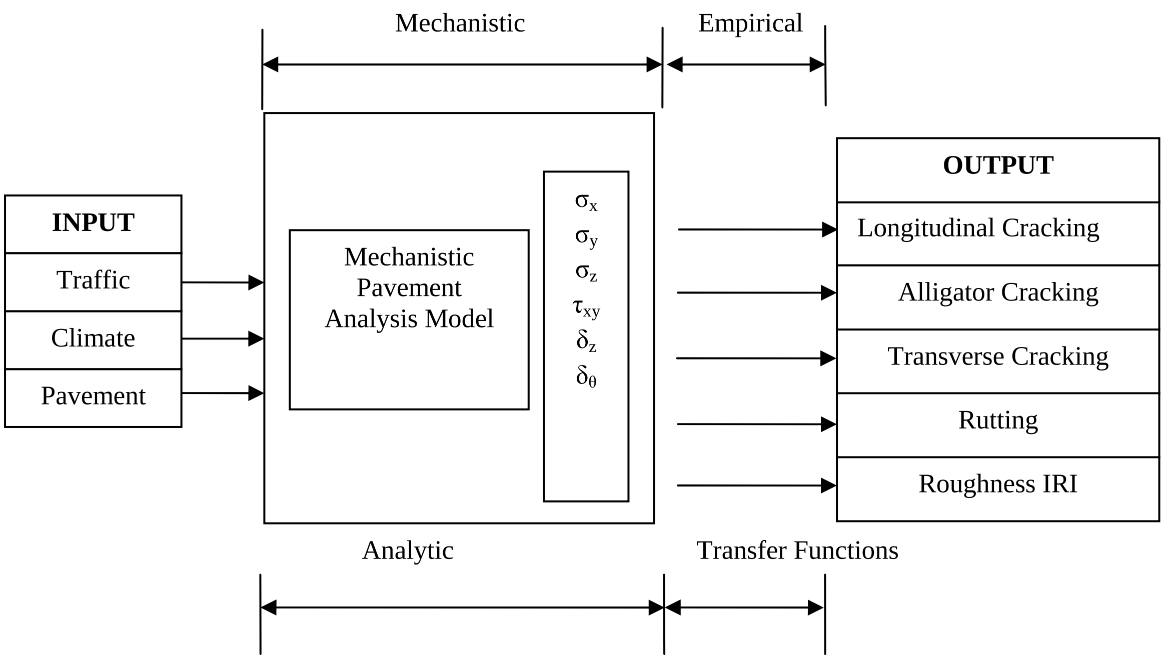


Figure 2.1: Outline of M-E Pavement Design Guide Process

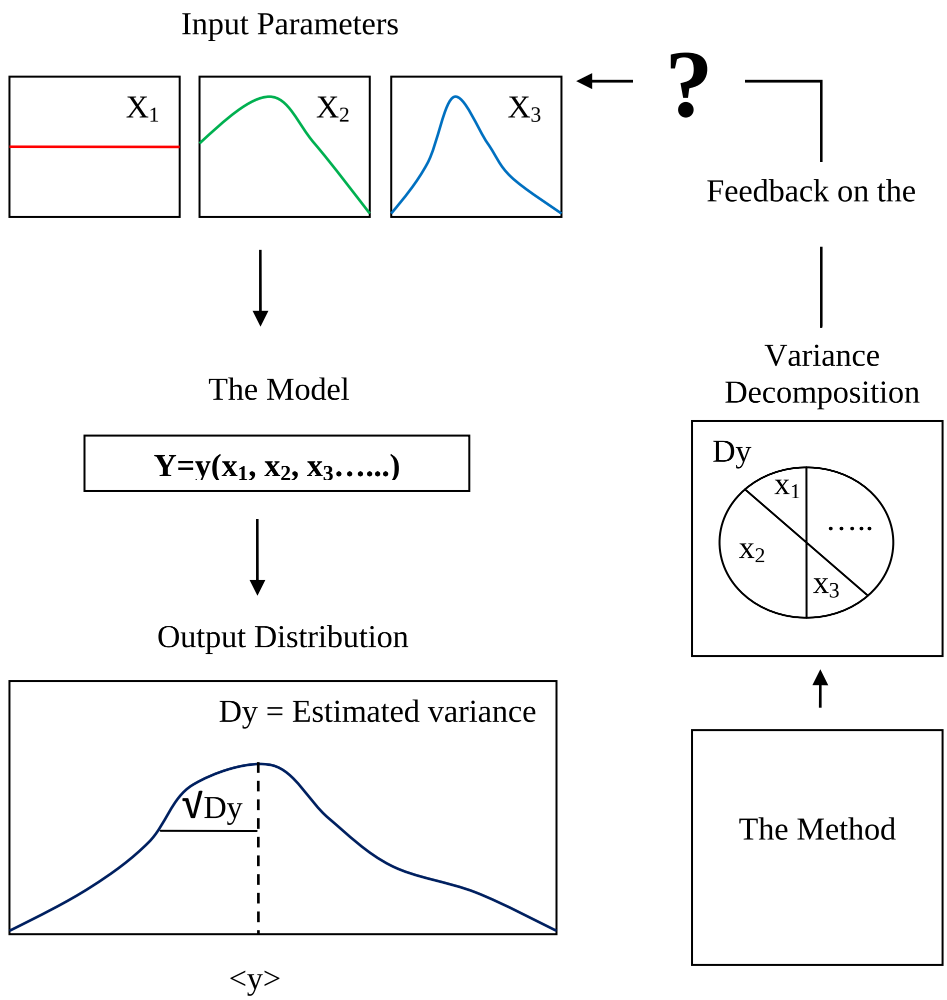


Figure 2.2: Procedure of Sampling Based Sensitivity Analysis (Saltelli et al. 2000)

CHAPTER 3

DATA COLLECTION

3.1 Introduction

Data collection and quality of the collected data play a significant role for sensitivity analysis. The first step for developing sensitivity chart of MEPDG inputs for flexible pavement design is collecting data of New Mexico pavements from different databases. Design and performance data for different road sections of New Mexico are collected from two different data sources. These data sources are Long Term Pavement Performance (LTPP) Database and New Mexico Department of Transportation (NMDOT) Databases. Both databases include structural layer, traffic, subgrade soil, and climate and distress information. The data collection process was one of the major challenges of this study due to vast amount of data, large number of data sources, quality of data and the time constraints involved. The database is still under construction by UNM research team. Part of the database used in the sensitivity analysis is listed in APPENDIX A. In the following sections, data collection procedure is explained.

3.2 LTPP Database

3.2.1 Background

Long Term Pavement Performance (LTPP) is an information management system and world's largest pavement performance database. LTPP study is conducted under the sponsorship of Federal Highway Administration (FHWA) to satisfy pavement information needs. United States is investing a lot of money every year to build, maintain and repair the highway infrastructure to have one of the best transportation systems in the world. To address the issues of how best to use and protect this recurring investment, the highway community initiated the LTPP program in 1987, a comprehensive 20-year study of in-service pavements. The LTPP database was developed by FHWA and with the cooperation of the American Association of State Highway and Transportation Officials (AASHTO) under Strategic Highway Research Program (SHRP). The main goal of LTPP program was to gain technical knowledge as well as to seek models that help for better explanation of the pavement performance. It was also used to study the effects of materials, loading, environmental, specific design features on the performance of the pavement (SHRP, 1986).

The LTPP database was first published in 1986 and it has been being modified day-by-day (FHWA, 2008). LTPP collects information on pavement performance and the elements that may influence pavement performance for both flexible and rigid pavements. Pavement performance information includes roughness, different type of pavement distress, deflection testing and skid information. Materials, climate, traffic, maintenance and construction activities data are also available in this database (FHWA, 2007). The LTPP program monitors more than 2400 asphalt and Portland Cement Concrete pavement (PCC) test sections throughout the U.S. and Canada. General Pavement Studies (GPS) includes 792 of the LTPP test sections, which are common types of pavement in use in the U.S. To study special engineering factors in pavement design Specific Pavement Studies (SPS) are performed contains specially constructed 1250 test sections. Different types of data are regularly collected at each GPS and SPS test sections. Selected sites within the GPS and SPS experiments are continuously monitored for temperature and moisture as part of the Seasonal Monitoring Program (SMP) study.

3.2.2 Data Extraction for New Mexico

The LTPP database contains data since 1989 of more than 2400 test sections located across North America. Currently, the LTPP IMS consists of 16 general data modules with 430 tables containing more than 8,000 unique data elements (FHWA, 2004). There are 39 LTPP sections with 12 GPS and 27 SPS test sections located in New Mexico (FHWA, 2004). Table 3.1 represents the total list of LTPP test sections of New Mexico. The LTPP database has been examined in order to extract data relevant to New Mexico.

The first step to extract data from the database is to select the LTPP test sections of interest. Selecting the region or state code is the way to this procedure (New Mexico, state code is 35). Total six digits are used to express the identification of each test section. The first two digits are State ID and rest of the digits is SHRP ID for the test section. For example, 35-0101-1 (State Code_SHRP ID) represents Section No. 01 of the SPS-1 pavement in New Mexico.

3.2.3 Collecting MEPDG Data

The LTPP database is sub grouped into different modules such as climate, general, inventory, monitoring, maintenance, test sections, SPS sections, and traffic. All the data relevant to the MEPDG have been extracted for all the GPS/SPS sections in New Mexico (FHWA, 2007). The data available for New Mexico in the LTPP database are not complete. Many type of data are still missing, such as thermal conductivity, heat capacity, unit weight, etc. When data are not available, MEPDG recommendations are followed (NCHRP, 2004.a). Three main routes are selected from the LTPP database to perform the preliminary sensitivity analysis. The routes are I-25, I-40 and US 550 (former NM-44). All of these pavement sections are of standard length of 500 ft. Details of these sections are described in Table 3.2 and these sections are used for preliminary sensitivity analysis.

3.3 NMDOT Database

According to this task, NMDOT database related to flexible pavement structure has preliminarily reviewed first. Currently there are 30 Oracle databases with 22 programs and 22 owners available at NMDOT (Project report: 3rd quarter). Some of the databases include some external databases, such as OSE, NOA, Morlin Group. Review of selected databases is not a simple task due to the complexity of database structures, documentation and platform. From the review of the data, it is understood that not all the required MEPDG inputs are available in NMDOT database, too. Due to lack of reliable data, only certain types of data are taken from this database. These data type are: AC mix properties, base layer properties and subgrade soil data.

3.4 Data Used for Sensitivity Analysis

In this task, most of the essential data elements required for sensitivity analysis are identified based on collected data from LTPP and NMDOT databases. The collected data are organized into three fundamental types of inputs. They are traffic inputs, climate inputs and structural inputs. The relevant information of these inputs is presented, along with a discussion.

3.4.1 Traffic Inputs

This is one of the main categories of inputs. Traffic data (number and weight of trucks) is a key data element for the design and analysis of pavement structures. Traffic inputs can be provided depending upon the extent of traffic information available for a given project. The full axle-load spectrum data for single, tandem and tridem axles is needed for MEPDG for both new pavement and rehabilitation design procedures. It is required for estimating the loads that are applied to a pavement's design life. The traffic data measured at the site includes counting and classifying the number of vehicles traveling over the roadway, along with the breakdown by lane and direction, and measuring the axle loads for each vehicle class over a sufficient period to reliably determine the design traffic. On-site data is considered the most accurate because it uses the actual axle weights and vehicle class spectrum measured over or near the project site. Table 3.3 gives a schematic of the traffic inputs required for MEPDG.

Mainly all traffic data was collected from LTPP Traffic Module. AADTT data is collected for the sites mentioned in Table 3.2. Number of lanes, percent of trucks and vehicle class distribution are also collected from LTPP database. The details of the collected data are presented in Appendix A. Operational Speed data is collected from NMDOT database for all the routes located in NM. Rest of the categories are kept as default values of MEPDG.

3.4.2 Climate Inputs

Environmental conditions have a significant effect on the performance of both flexible and rigid pavements. Some external factors such as precipitation, temperature, freeze-thaw cycles and depth to water table affect the load-carrying capacity of the pavement. Without these, there are some internal factors, which also play a significant role for this issue, such as drain ability of paving layers, infiltration potential of pavement, susceptibility of pavement materials to moisture and freeze thaw damage.

Changing temperature and profiles in the pavement structure and subgrade over the design life of a pavement are fully considered in MEPDG through a sophisticated climatic modeling tool called Integrated Climatic Model (ICM) (MEPDG Documentation). This model contains climatic data from over 800 locations in North America, which allow user to easily select a given station or to generate virtual weather stations. There are total 13 weather stations in New Mexico included in the ICM. These stations are shown in Figure 3.1.

The weather of NM is not to extreme. To get the proper impact of climate in sensitivity analysis, NM is divided in five zones according to the locations to create 5 virtual weather stations. They are zone 1 to zone 5. Details of these zones are presented in Figure 3.2 and Table 3.4. To achieve the real climatic behavior, some weather stations also taken from New Mexico border. These stations are also shown in Figure 3.2. These stations are located in Colorado, Arizona and Texas. Ground water table (GWT) depth values are provided by NMDOT and LTPP database.

3.4.3 Material Inputs

Many combinations of material types and quality are used in flexible pavement design. Pavement design files obtained from NMDOT contain structural information, i.e., layer thickness, HMA mix type, gradation of subgrade materials. Through the years, NMDOT has developed its own major material classifications. Due to lack of data, stiffness property of asphalt materials is not possible to include in this study. NMDOT uses three common super pave mixes, which are also collected from these design files. These mixes are SP-II, SP-III and SP-IV. Details of these gradations are presented in Table 3.5. Asphalt mix properties data mainly contains percent air void, pg grade and effective binder content. The gradation for subgrade materials are presented in Table 3.6.

3.5 Summary

This chapter describes the data collection effort expended in obtaining the data from the LTPP and NMDOT databases. The required data for the LTPP sections are obtained from the LTPP database. Data from the Materials unit, Construction Unit, Traffic Unit and the Geotechnical Unit (subgrade and ground water table depth data) of the NMDOT are also collected. Among all these data, fourteen LTPP pavements sections are separated to use in the preliminary sensitivity analysis. The next chapter describes the sensitivity analysis study to identify the inputs that are sensitive to the New Mexico conditions using LTPP database.

Table 3.1: List of LTPP Test Sections in New Mexico

Experiment No	Section ID Number	Type
SPS 1	35-0101, 35-0102, 35-0103, 35-0104, 35-0105, 35-0106, 35-0107, 35-0108, 35-0109, 35-0110, 35-0111, 35-0112	Strategic Study of Structural Factors for Flexible Pavements
SPS 2	35-0501, 35-0502, 35-0503, 35-0504, 35-0505, 35-0506, 35-0507, 35-0508, 35-0509	Rehabilitation of Asphalt Concrete Pavements
SPS 8	35-0801, 35-0802	Study of Environmental Effects in the Absence of Heavy Loads
SPS 9	35-0901, 35-0902, 35-0903, 35-0959	Validation of SHRP Asphalt Specification and Mix Design (Superpave)
GPS 1	35-1003, 35-1005, 35-1022, 35-1112	Asphalt Concrete (AC) on Granular Base
GPS 2	35-2006, 35-2118	AC on Bound Base
GPS 3	35-3010	Jointed Plain Concrete Pavement (JPCP)
GPS 6	35-1002, 35-6033, 35-6035, 35-6401, 35-2007	AC Overlay of AC Pavement

Table 3.2: List of LTPP Test Sections in New Mexico used for Preliminary Sensitivity Analysis

SHRP ID	Functional Class	Route Number	County	Location Info	Mile Point	Elevation (Ft)
35-0101, 35-0102, 35-0103, 35-0104, 35-0105, 35-0106, 35-0107, 35-0108, 35-0109, 35-0110, 35-0111, 35-0112	Rural Principal Arterial - Interstate	25	Dona Ana	These projects are located to the North of Rincon Interchange	37	4117
35-2006	Rural Principal Arterial - Other	44	Sandoval	This project is located approximately 4.1 miles North of the Junction of SR-537.	89.5	6742
35-6035	Rural Principal Arterial - Interstate	40	Cibola	Approx 0.1 Mile East of McCarty's overpass.	96.7	6200

Table 3.3: Traffic Inputs Required for MEPDG

Input Name	Type	
AADTT	Initial two-way AADTT	
Number of Lanes in Design Direction		
Percent of Trucks in Design Direction		
Percent of Trucks in Design Lane		
Operational Speed		
Traffic Volume Adjustment Factors	Monthly Adjustment	
	Vehicle Class Distribution	
	Hourly Distribution	
	Traffic Growth factors	
Axle Load Distribution Factors	Axle Load Distribution	
	Axle Type	Single Axle
		Tandem Axle
		Tridem Axle
		Quad Axle
Axle Load Distribution Factors	Distribution Type	Normal Distribution
		Cumulative Distribution
	Lateral traffic Wander	Mean Wheel Location
		Traffic wander standard deviation
		Design lane width
General Traffic Inputs	Number axles/Truck	
	Axle Configuration	Average axle width
		Dual tire spacing
		Tire pressure
	Axle spacing	Tandem Axle
		Tridem Axle
		Quad Axle
	Average axle spacing	Short
		Medium
		Long
	Percent of trucks	Short
		Medium
		Long

Table 3.4: List of Climatic Zones for Detailed Sensitivity Analysis

Serial No	Name	Region	No of Weather Stations	Latitude	Longitude
1	Zone 1	SouthEast	4	33.19	-104.32
				31.5	-104.49
				31.47	-103.12
				32.2	-104.16
2	Zone 2	SouthWest	4	34.31	-109.23
				32.51	-109.38
				33.14	-107.16
				32.16	-107.43
3	Zone 3	NorthWest	3	37.18	-108.38
				36.44	-108.14
				37.08	-107.46
4	Zone 4	NorthEast	3	37.16	-104.2
				36.44	-104.3
				36.27	-103.09
5	Zone 5	Central	4	35.37	-106.05
				35.39	-105.08
				35.02	-106.37
				35	-105.4

Table 3.5: NMDOT HMA Mix Gradations

Mix Design	Cumulative % Retained 3/4 inch sieve	Cumulative % Retained 3/8 inch sieve	Cumulative % Retained #4 sieve	% Passing #200 sieve
SP-II	15	45	67	4
SP-III	3	35	59	5
SP-IV	0	25	55	5.5

Table 3.6: Sieve Analysis Data for Subgrade Soil

No	Type	% Passing #200	% Passing #80	% Passing #40	% Passing # 10	% Passing #4	% Passing #3/8	% Passing #3/4
1	CL	80	85	90	94	96	98	100
2	A-4	60	75	85	90	92	94	96
3	ML	52	55	60	75	85	90	95
4	SM	30	35	40	70	80	85	92
5	SP	8	10	12	45	75	80	90

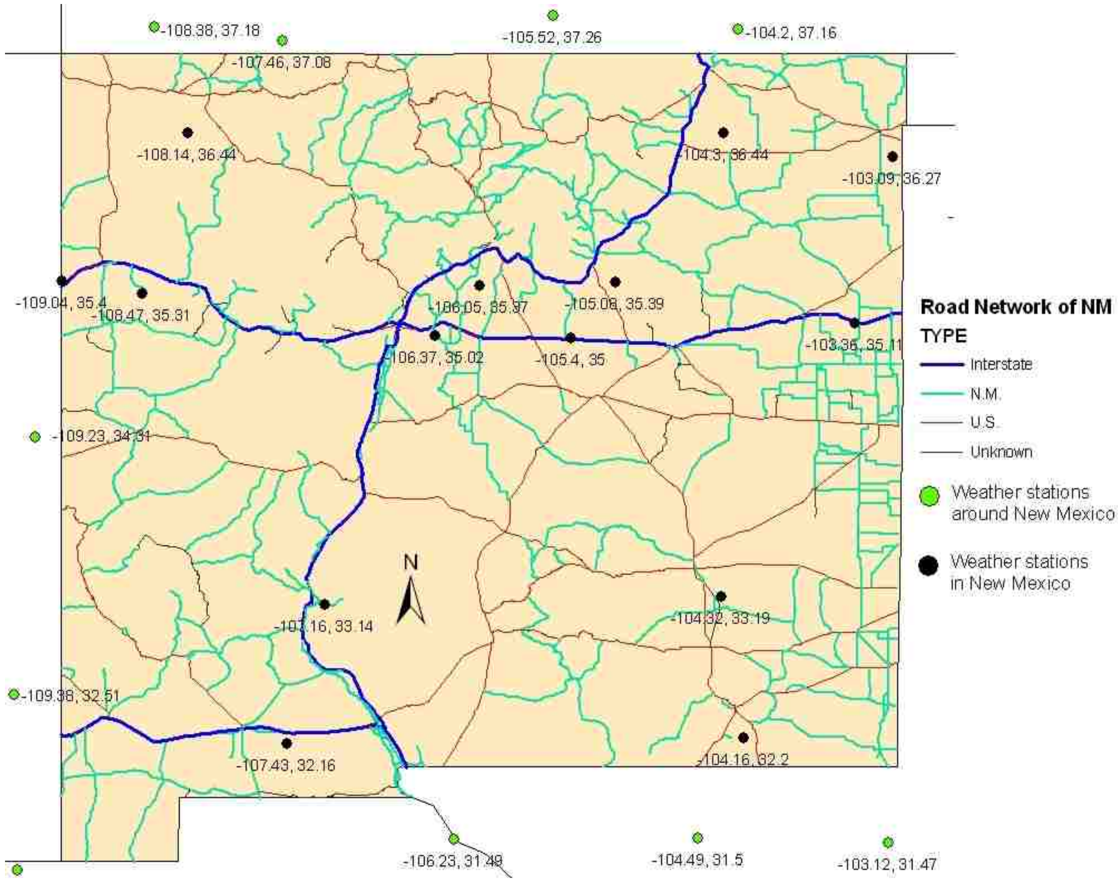


Figure 3.1: Location of Weather Station

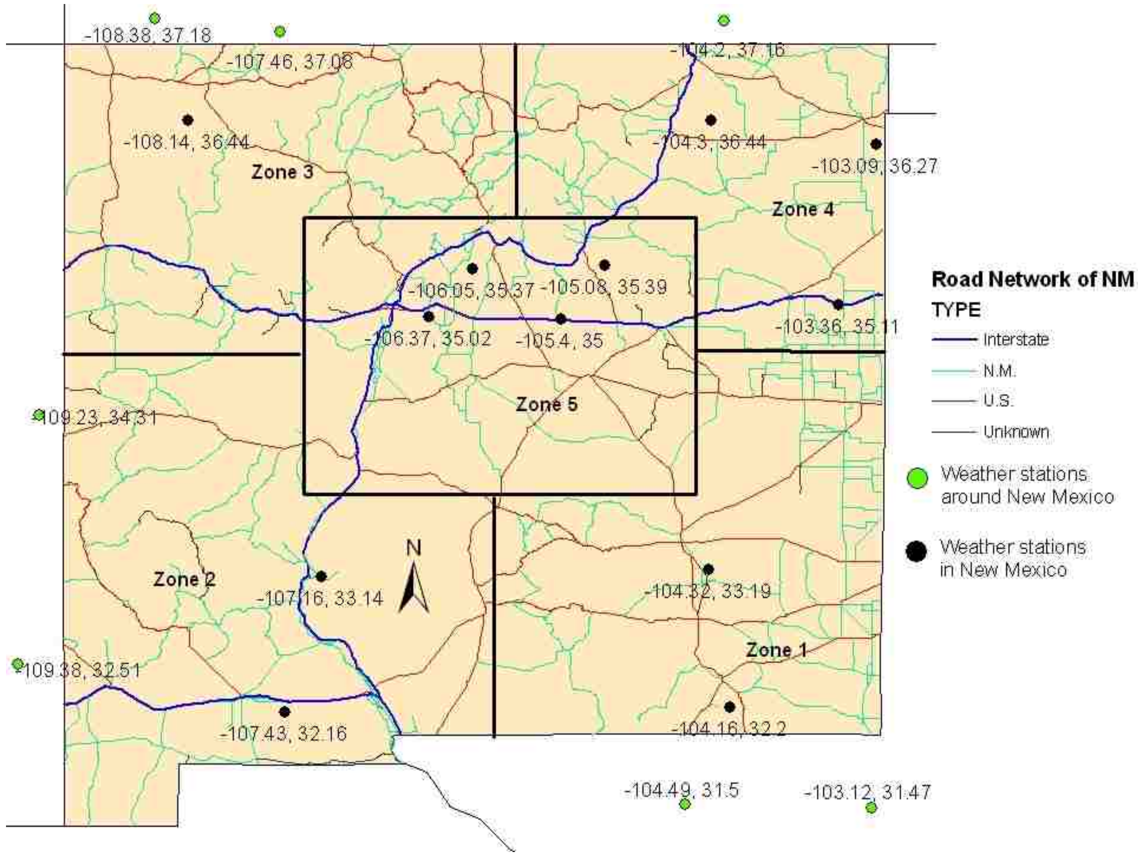


Figure 3.2: Location of Climatic Zones Used for Sensitivity Analysis

CHAPTER 4

PRELIMINARY SENSITIVITY ANALYSIS

4.1 Introduction

For design of flexible pavement, the AASHTO 1993 Design Guide requires very limited design inputs. Unlike the AASHTO 1993, the new Mechanistic Empirical Pavement Design Guide (MEPDG) is heavily dependent on a large number of inputs such as asphalt mixture variables, properties of pavement layer materials, subgrade soil conditions, climate, traffic, etc. Therefore, it is important for pavement designers and engineers to have sufficient knowledge of how a particular input parameter affects the MEPDG output or pavement performance during the service life. In addition to this, it is very important to know the extent at which different input variables would affect pavement performance would differ. Therefore, the user should have the knowledge on the relative sensitivity of predicted pavement performance to different input variables. A sensitivity chart may be a helpful tool for the designer to facilitate efficient design through an educated selection of input. In order to determine the effects of input variables on predicted pavement performance as well the interaction among all variables, all the input variables should be studied together. This advance sensitivity would require either a full factorial set of experiments using experiment design methods or at least a partial factorial analysis which is discussed in Chapter 2. Therefore as a first step, one-at-a-time (OAT) sensitivity analysis is performed. This chapter presents the results of preliminary sensitivity analysis.

4.2 Methodology

In one-at-a-time (OAT) sensitivity analysis, the value of one variable is varied at a time to determine if that input variable has significant impact on predicted performance. As a result, a smaller number of input variables are chosen from the full set of input variables for carrying out detailed sensitivity analysis. The methodology of one-at-a-time (OAT) sensitivity analysis includes the following steps:

Step 1: Preparation of Initial Sensitivity Test Matrix and fixing the Input Variable Ranges

An initial test matrix was formed with variable design parameters to perform OAT sensitivity analysis. The lower and upper boundary of the design parameters are fixed in order to count the robustness on the pavement distresses. The ranges of the different parameters are set reviewing previous researches on sensitivity analysis (Chapter 2). Table 4.1 presents the test matrix for OAT sensitivity analysis. The following parameters are considered: air void, binder content, percent fines in superpave mix, thickness of asphalt concrete, depth of groundwater table, operational speed, average annual daily truck traffic (AADTT), base course thickness, resilient modulus of base course materials and performance grade of the superpave mix. Appendix B gives the summary of all the inputs for total 14 test sections. The simulations are performed considering 12 sections of interstate highway I-25, one section of I-40 and one section of US 550. The other design inputs in addition to the above mentioned matrix, are collected from LTPP database (LTPP Database 2009). Therefore, the subgrade strength parameters are kept fixed in these simulations for OAT sensitivity analysis. However, sensitivity of the subgrade strength parameters is evaluated in the next chapter.

Step 2: MEPDG analysis

In this step, the MEPDG software was run to develop the performance curves for the different distress. MEPDG software, version 1.1 was used for OAT sensitivity analysis (MEPDG Documentation 2009). In OAT sensitivity analysis, the simulations are performed considering a design life of 20 years. Climatic inputs are simulated by interpolating the information from the adjacent LTPP weather stations. In these analyses, the target distresses are set for AC rutting = 6.35 mm (0.25 inch), total rutting = 19.05 mm (0.75 inch), IRI = 2715 mm/kilometer (172 inch/mile), fatigue cracking (bottom-up) = 100%, and top-down cracking (longitudinal) = 189.43 meter/kilometer (1000 feet/mile) with a reliability value of 90% (MEPDG Documentation 2009).

MEPDG simulations are performed more than 1000 times for all 10 input parameters to obtain performance curves for all test sections. For each run, only one variable was varied at a time. Lower value for one particular input or variable was used while keeping all other variable constant. Then the upper value was used also following the same manner. Some values are taken in this range and used for MEPDG runs. This process is repeated for each variable.

Step 3: Identification of Variables Significant for Pavement Performance

Effects of variables on pavement distresses are identified from the simulation results. The effects are identified based on predicted distresses. To identify the effects, first the results corresponding to the simulations for each variable are plotted on the same graph. Result and Discussion section of this chapter presents the sensitivity of the design variables from OAT sensitivity analysis. The detail result of OAT sensitivity analysis for one particular pavement section (35-4035) is presented in Appendix B.

4.3 Result and Discussion

MEPDG simulation results are analyzed based on the predicted distresses of total rutting, asphalt concrete (AC) rutting, longitudinal cracking, fatigue cracking and international roughness index (IRI) for the considered test matrix (Table 4.1).

4.3.1 Sensitivity of Pavement Performances to Air Void

The amount of air void in hot mix asphalt (HMA) is an important criterion in mix design. Sensitivity of pavement performance to air void is discussed in this section. Figure 4.1(a) represents the sensitivity of total rutting to air void. Vertical axis of this plot shows the amount of total rutting and the horizontal axis shows the variable air void. The amount of air void varied within the range between 2% and 10%. The amount of total rutting depth increases with increase in the amount of air voids. The pattern of the curves follows the similar trends for most of the curves. However, for the LTPP sections 35-0102, 35-2006 and 35-6035, the amount total rut was found higher than that of the other sections. This criterion indicates that some other variables are also contributing significantly in total rutting which are active in these three sections. Therefore, an advance multivariate sensitivity analysis is required.

Figure 4.1(b) shows the sensitivity of AC rutting for air void. AC rut increases with the increases in air void. All of the sections follow the similar increasing trend for AC rut. Sensitivity of international roughness index (IRI) to air void is presented in Figure 4.1(c). IRI slightly increased with increase in air void with the assumed range. There are no significant sharp changes observed in IRI pattern due to variable air void. However, IRI for LTPP section 35-2006, was higher sensitive than that of other sections for the assumed air void range.

Figure 4.1(d) represents the sensitivity of longitudinal cracking to air void. The amount of longitudinal cracking is shown in vertical axis and horizontal axis indicates the amount of air void. In section 35-6035 and 35-2006, a sharp change was observed starting from air void 4% to 10% and a mild change was observed for section 35-0101 and 35-0102 starting from 8% to 10%. The rest of the sections are remained unchanged with variable air voids. Therefore, an advanced multivariate sensitivity analysis might be an appropriate approach to predict the sensitivity of longitudinal cracking.

Sensitivity of alligator or bottom up cracking to air void is plotted in Figure 4.1(e). This plot indicates that alligator cracking remain unchanged for 11 sections out of 14 sections. Section 35-0102, 35-0101 and 35-2006 showed a sharp change within the considered range of air voids. This implies that although air void is not a significant factor for increasing alligator cracking in majority of the sections, however for three sections a very small increase in air voids can increase the alligator cracking significantly.

4.3.2 Sensitivity of Pavement Performances to Binder Content

Binder content in HMA mix design is one of the most important parameters for hot mix asphalt (HMA) design. However, it is important to determine the optimum binder content for a mix to obtain the best performance. Sensitivity of pavement performance to binder content is discussed in this section. In order to analyze the sensitivity to binder content, a range of volumetric binder content is considered between 8% and 15%.

Figure 4.2(a) represents the sensitivity total rutting depth to binder content. This plot indicates that total rutting depth increases with the increase in binder content. The increase in total rutting depth show the similar pattern for all the LTPP sections considered in analysis. However, the LTPP section 35-6035, 35-2006 and 35-0102 show higher total rutting depth than that of other sections. An advanced multivariate sensitivity analysis will be able to find the contributions for pavement distresses.

The sensitivity of asphalt concrete (AC) layer rut depth to binder content on is shown in Figure 4.2(b). AC rut depth increases with the increase in binder content. All of the assumed LTPP sections show the similar pattern for increasing AC rut depth with the increase in binder content in the HMA mix design. However, the increasing rate of AC rut depth with binder is observed to be high at LTPP section 35-6035, 35-2006 and 35-0102 compared to other sections.

Figure 4.2(c) represents the sensitivity of international roughness index (IRI) to asphalt binder content in mix design. IRI is slightly to low sensitive to binder content within the assumed range for all the LTPP sections with an exception for 35-2006. In LTPP section 35-2006, IRI increase with increase in binder content. Figure 4.2(d) represents the sensitivity of longitudinal cracking distress for asphalt binder content in the HMA mix design. This figure indicates that the effect of binder content on longitudinal cracking distress is very low for all of the assumed LTPP sections in New Mexico with the exception in section 35-6035 and 35-2006. In 35-6035 and 35-2006, sensitivity of longitudinal cracking for binder content on is observed to be very high. In these two sections, amount of longitudinal cracking decreases substantially with increase in binder content in the HMA mix design.

The sensitivity of alligator cracking for asphalt binder in the HMA mix design is presented in Figure 4.2(e). This plot indicates that alligator cracking is very low sensitive to binder content all of the assumed LTPP sections in New Mexico with an exception for 35-2006. In section 35-2006, alligator cracking decreases with an increase in binder content.

4.3.3 Sensitivity of Pavement Performances to Asphalt Performance Grade

Asphalt performance grade (PG) indicates the stiffness of the asphalt binder, which is also known as PG grade. PG grade is an important HMA design parameter for its contribution in stability of the mix. In order to assess the sensitivity of pavement performances the following PG grades are assumed based on the existing design of the sections and NMDOT specifications (NMDOT 2008): i. PG58-28, ii. PG64-28, iii. PG70-22, iv. PG76-22, v. PG82-22 and vi. AC 20.

Figure 4.3(a) represents the sensitivity of total rutting depth for asphalt performance grade (PG). This plot indicates that total rutting depth is sensitive to asphalt PG grade for all the LTPP sections in New Mexico used in this analysis. The maximum total rutting depth is observed for PG grade PG58-28 and the minimum total rutting depth is observed for PG grade 82-22. The total rutting depth in section 35-6035, 35-2006 and 35-0102 is observed to be very high compared to other sections assumed in the analysis. Figure 4.3(b) shows the sensitivity of Ac rut depth on asphalt PG grade. AC rut is also sensitive to PG grade following the similar pattern to total rut depth (Figure 4.3(a)). Figure 4.3(c) show that IRI follows the trend of rutting curve. Because IRI is a composite distress index, which is a function of surface roughness as well as rutting distress. However, IRI is not very sensitive to PG compared to that of rutting

The sensitivity of longitudinal cracking to asphalt performance grade is presented in Figure 4.3(d). This figure indicates that longitudinal cracking is low sensitive to asphalt PG grade with an exception at section 35-6035. At section 35-6035, longitudinal cracking decreases with an increase in stiffness of asphalt PG grade for PG 58-28 to PG 82-22. Figure 4.3(e) represents the sensitivity of alligator cracking to asphalt performance grade. It indicates that alligator cracking is low to non-sensitive to asphalt performance grade. The fact is the bottom up or alligator cracking is related to the strain induced at the bottom of the asphalt layer due to repeated traffic loading. Usually, softer binder (e.g., unmodified PG 58-22) will be more flexible and they have show less fatigue cracking compared to a stiff binder (e.g. PG 82-22). However, such behavior is not reflected in Figure 4.3(e).

4.3.4 Sensitivity of Pavement Performance to Fineness Content

The amount of material passing # 200 sieve is known as fineness content. The optimum amount of fines is an important criterion for HMA mix design. Figure 4.4(a) represents the sensitivity of total rutting to percent fines. It should be noted that total rutting depths change with a concave pattern with increase in percent fines in HMA mix for all of the assumed LTPP sections. However, 35-6035, 35-2006 and 35-0102 sections show a higher total rut value compared to others sections. Sensitivity of AC rutting to fine content is shown in Figure 4.4(b). This plot indicates that the AC rutting depths change with a similar pattern to total rutting depth with increase in fine content in HMA mix.

Figure 4.4(c) shows the sensitivity of international roughness index (IRI) to fine content in HMA mix design. This sensitivity study shows that IRI is moderate sensitive to fine content. However in LTPP section 35-6035, 35-2006 and 35-0102, IRI changes substantially with increases in fine content from 2% to 12% following a concave pattern. Therefore, it is important to determine an optimum fine content for each mix design to obtain a better performance.

Figure 4.4(d) represents the sensitivity of longitudinal cracking to fine content in HMA mix design. In this sensitivity analysis, a range of fine content was varied from 2% to 12%. All of the sections show that longitudinal cracking is low sensitive to fine content in HMA mix design with an exception in 35-6035 and 35-2006. In section 35-6035 and 35-2006, longitudinal cracking change significantly following a concave pattern with increasing fine content in HMA mix design. The sensitivity of alligator cracking to fine content is shown in Figure 4.4(e). The analysis indicates that alligator cracking is low to moderate sensitive to fine content in HMA mix design.

4.3.5 Sensitivity of Pavement Performances to Asphalt Thickness

The thickness of asphalt concrete (AC) layer may contribute a large portion in cost of the pavement construction and rehabilitation projects. Therefore, AC thickness is one the most important inputs for structural design of pavements. Figure 4.5(a) represents the sensitivity of total rutting depth to AC thickness. In this sensitivity analysis, AC thickness was varied with a range between 3 inches and 10 inches. The analysis indicates that total rutting depth is highly sensitive on AC thickness. Figure 4.5(a) shows that total rutting depth decreases significantly with increases in AC thickness. The sensitivity of AC rutting depth to AC thickness is analyzed and shown in Figure 4.5(b). AC rutting depth also change in a similar fashion compared to total rutting depth with increasing AC layer thickness from 3 inches to 10 inches.

Figure 4.5(c) represents the sensitivity of international roughness index (IRI) to AC layer thickness. The analysis shows that the overall sensitivity of IRI to AC layer thickness is moderate with an exception in LTPP section 35-6035. In section 35-6035, IRI is highly sensitive to AC layer thickness. Figure 4.5(d) represents the sensitivity of longitudinal cracking to AC layer thickness. This analysis indicates that longitudinal cracking is low sensitive to AC layer thickness at all the assumed section except section 35-6035, 35-2006 and 35-0101. In LTPP section 35-6035, 35-2006 and 35-0101, longitudinal cracking is highly sensitive to AC thickness within a range between 3 inches and 8 inches. However, the sensitivity of longitudinal cracking becomes low from 8 inches to 10 inches AC thickness for all the assumed LTPP sections in analysis.

Sensitivity of alligator cracking to AC layer thickness is presented in Figure 4.5(e). The analysis shows that overall sensitivity of alligator cracking to AC thickness is moderate (AC thickness= 3-6 inches) to low (AC thickness= 6-10 inches) with an exception in section 35-6035. In section 35-6035, AC layer thickness is highly sensitive on alligator cracking.

4.3.6 Sensitivity of Pavement Performances to GWT Depth

Depth of groundwater table may affect subgrade strength if a shallow groundwater table is observed. Therefore, a sensitivity study was conducted varying groundwater table depth from 2 feet to 25 feet on 14 LTPP sections in New Mexico. Figure 4.6(a) represents the sensitivity of total rutting depth to depth of groundwater table depth. Analysis shows that total rutting is low sensitive to ground water table depth from 5 feet to 25 feet. However, total rutting depth decreases substantially for increasing water table depth from 2 feet to 5 feet. Sensitivity of AC rut to the depth of groundwater table is shown in Figure 4.6(b). The analysis results suggest that AC rut is low to no sensitive to depth of groundwater table. Figure 4.6(c) shows the sensitivity of international roughness index (IRI) to the depth of groundwater table. The overall sensitivity of IRI to depth of groundwater table is very low to no from 2 feet to 25 feet for all the assumed sections except 35-2006 and 35-6035. In section 35-2006 and 35-6035, IRI decreases with increasing the depth of groundwater table from 2 feet to 5 feet and it becomes very low to not sensitive from 5 feet to 25 feet.

Figure 4.6(d) represents the sensitivity of longitudinal cracking to depth of groundwater table. The plot indicates that longitudinal cracking is low to no sensitive to groundwater table depth for all of the assumed LTPP sections except 35-2006 and 35-6035. In section 35-2006, longitudinal cracking increases with increasing the depth of groundwater table from 2 feet to 25 feet. In section 35-6035, longitudinal cracking increases with increasing the depth of groundwater table from 2 feet to 5 feet and it becomes very low to no sensitive from 5 feet to 25 feet groundwater table depth. The sensitivity of alligator cracking to depth of groundwater table is shown in Figure 4.6(e). The analysis indicates that the alligator cracking is low to no sensitive to GWT depth from 2 feet to 25 feet for all assumed sections with an exception in 35-2006. In section 35-2006, alligator-cracking decreases with increasing the depth of groundwater table from 2 feet to 5 feet and it shows low to no sensitivity from 5 feet to 25 feet GWT depth.

4.3.7 Sensitivity of Pavement Performances to Operational Speed

Operational speed of a vehicle determines the duration for acting the axle load at a certain over the pavement. Therefore, a sensitivity study for operational speed on pavement performance is performed. In this analysis, a speed limit range of 15 mile per hour (mph) for schooling zone to 90 mph for highway speeding is considered. Figure 4.7(a) represents the sensitivity of total rut to operational speed. The results of the analysis represent that the depth of total rut decreases with increasing speed limit for all the assumed sections following the similar pattern. In section 35-6035, 35-2006 and 35-0102, the total rutting depths are high compared to other section. Figure 4.7(b) shows the sensitivity of AC rut to operational speed. The depth of AC rutting also decreases with increasing operational speed.

Figure 4.7(c) represents the sensitivity of IRI to operational speed limit. Terminal IRI at the end of design life decreases with the increasing operational speed limit. The analysis indicates that the sensitivity of IRI to operational speed limit is very low to low for all of the assumed sections with an exception in section 35-6035. In section 35-6035, operational speed limit shows moderate sensitivity on IRI.

Figure 4.7(d) represents the sensitivity of longitudinal cracking to operational speed. The analysis results indicate that longitudinal cracking is very low to no sensitive to operational speed limit for all of the assumed section with exception in section 35-6035 and 35-2006. In section 35-2006, longitudinal cracking is moderately sensitive to operational speed. In section, 35-6035, the sensitivity longitudinal cracking is high due to of operational speed.

The sensitivity of alligator cracking to operational speed is presented in Figure 4.7(e). The analysis indicates that the sensitivity of alligator cracking to operational speed limit is very low to low for all the assumed LTPP sections with an exception observed in 35-2006. In section 35-2006, operational speed limit shows moderate sensitivity on alligator cracking.

4.3.8 Sensitivity of Pavement Performances to AADTT

Traffic loading is the most important factor of traffic input section in pavement design. A sensitivity analysis is performed varying traffic loads in terms of annual average daily truck traffic (AADTT). A range of AADTT from 800 to 2000 is considered in analysis. Figure 4.8(a) represents the sensitivity of total rut to AADTT. The analysis shows that the sensitivity of total rut to AADTT is high for all of the assumed LTPP sections. In section, 35-2006, the observed total rutting depth is more than twice compared to other sections for AADDT 800 to 2000. Figure 4.8(b) represents the sensitivity of AC rut to AADTT. AC rut depth is also increased with increasing AADTT with a similar pattern for all of the assumed LTPP sections.

The sensitivity of IRI to AADTT is shown in Figure 4.8(c). The study indicates that IRI is low to moderately sensitive to AADTT for all assumed LTPP sections except 35-0102, 35-2006 and 35-6035. In section 35-0102 and 35-6035, IRI is sensitive to AADTT with the assumed range. IRI is highly sensitive on AADTT in section 35-2006.

The sensitivity of longitudinal cracking to AADTT is presented in Figure 4.8(d). Analysis results indicate that longitudinal cracking is low sensitive to AADTT for all LTPP sections with the assumed range except 35-2006. In section 35-2006, longitudinal cracking is highly sensitive to AADTT within the assumed range. For increasing AADTT value from 800 to 2000, longitudinal cracking increases more than three times in LTPP section 35-2006.

Figure 4.8(e) represents the sensitivity of alligator cracking to AADTT. The analysis with assumed AADTT range shows that the overall sensitivity of alligator cracking is low for all sections except 35-2006 and 35-6035. In section 35-2006 and 35-6035, alligator cracking is very sensitive to AADTT. Alligator cracking increases to double for increasing AADTT from 800 to 2000 in section 35-2006 and 35-6035.

4.3.9 Sensitivity of Pavement Performances to Base Thickness

Thickness of the base course material controls pavements designs in many cases. Sometimes it also considered as a compensation of asphalt concrete thickness. A sensitivity analysis is performed on base course thickness. In this sensitivity analysis, base course range is assumed between 4 inches and 18 inches. Figure 4.9(a) represents the sensitivity of total rut to base course thickness. The amount of total rutting depth decreases with increasing base course thickness from 4 inches to 18 inches. The change in total rutting depth is prominent from the base course thickness 4 inches to 10 inches. However in some sections, total rut shows very low to no sensitive to base thickness. Figure 4.9(b) shows the sensitivity of AC rut to base course thickness. The analysis indicates that AC rut is very low to no sensitive to base course thickness.

The sensitivity of IRI to thickness of the base course material is shown in Figure 4.9(c). The analysis result shows that IRI is very low to no sensitive to base thickness for all of the assumed LTPP sections with an exception in 35-6035. In section 35-6035, a moderate sensitivity was observed with decreasing IRI for increasing the thickness of the base course material within the assumed range.

The sensitivity of longitudinal cracking to base course thickness is presented in Figure 4.9(d). The study indicates that the sensitivity of longitudinal cracking to base course thickness is very low to non-sensitive for all of the assumed LTPP sections except 35-2006 and 35-6035. In section 35-2006, longitudinal cracking is highly sensitive to base course thickness. An increase in base course thickness from 4 inches to 10 inches, longitudinal cracking drops down to 3 times in section 35-2006. In section 35-6035, a moderate sensitivity was observed increasing base course thickness.

Figure 4.9(e) shows the sensitivity of alligator cracking to base course. The analysis shows that alligator cracking is very low to no sensitive to the thickness of base course material for all of the assumed LTPP sections except 35-2006 and 35-0102 within the considered range. In section 35-2006 and 35-0102, alligator cracking is moderately sensitive to the thickness of the base course material.

4.3.10 Sensitivity of Pavement Performances to Base Resilient Modulus

The strength of the base course material is considered as an compensation for the strength of asphalt layer and subgrade layer. In case of high traffic volume, increasing base course resilient modulus may turned into a reliable design in terms of economy and performance. Therefore, a sensitivity of base course resilient modulus is performed considering a range between 15,000 pound per square inch (psi) and 45,000 psi. Figure 4.10(a) represents the sensitivity of total rut to base course resilient modulus. The study shows that the sensitivity of total rut to base course resilient modulus is low except 35-

0102 and 35-2006. In section 35-0102 and 35-2006, total rut is moderately sensitive to base course resilient modulus. Figure 4.10(b) shows the sensitivity of AC rut to base course resilient modulus. The analysis indicates that AC rut is very low to no sensitive to resilient modulus of the base course material.

The sensitivity of IRI to resilient modulus of the base course material is shown in Figure 4.10(c). A very low to no sensitivity of IRI is observed for increasing the resilient modulus of the base course material with the assumed range for all considered section with an exception in 35-6035. In section 35-6035, the sensitivity of IRI to resilient modulus of the base course material is observed to be high.

The sensitivity of longitudinal cracking to resilient modulus of the base course materials is shown in Figure 4.10(d). The analysis indicates that the sensitivity of longitudinal cracking is very low except 35-2006 and 35-6035. In section 35-2006 and 35-6035, longitudinal cracking is highly sensitive to the resilient modulus of the base course material. Longitudinal cracking decreases approximately 3 times for increasing base course resilient modulus from 15,000 psi to 45,000 psi in section 35-2006 and 35-6035.

Figure 4.10(e) represents the sensitivity of alligator cracking to resilient modulus of the base course material. The sensitivity of alligator cracking to resilient modulus of the base course material is low to very low except 35-0102 and 35-2006. In section 35-0102 and 35-2006, the sensitivity of alligator cracking to resilient modulus of the base course material is observed to be high compared to other assumed LTPP sections in New Mexico.

4.4 Conclusions

A one-at-a-time (OAT) sensitivity analysis is performed varying the design parameters in 14 LTPP sections in New Mexico. The sensitivity of ten design parameters is analyzed for five different distresses in this chapter. Total summary is presented in Table 4.2. The analysis indicates that none of distresses sensitivity curves yield to a similar pattern for all of the assumed LTPP sections in New Mexico. The contribution of all of the design parameters should be considered in sensitivity analysis in order to assess their importance in design. Therefore, a multi variant sensitivity analysis is performed considering a full factorial set of design inputs in next chapter.

The results from the preliminary sensitivity analysis

- Binder PG has significant impact on AC rut performance of the pavements analyzed. AC binder content and AC air voids also significantly affect on rutting performance, though to a lesser degree than the asphalt PG.
- The LTPP test sections used for this analysis did not show extensive longitudinal cracking in almost all cases. Air void has maximum impact on longitudinal cracking performance on the test sections.
- Effective binder content and air void of the top AC layer have significant effects on fatigue performance of the pavement. As expected pavement with higher effective binder content has less fatigue cracking. Lower air voids turns the pavement as densely packed. As a result, it provides a greater fatigue resistance.
- The mix variable such as asphalt content, air voids, and binder grade have little to no effect on the pavement IRI performances.

Table 4.1 Test Matrix for Sensitivity Analysis

No	Variable	Range Value
1	Air Void (%)	2 to 10
2	Binder Content	8 to 15
3	% Passing #200 Sieve	2 to 12
4	AC thickness (in)	3 to 10
5	Depth to GWT (ft)	2 to 25
6	Operational Speed (mph)	15 to 90
7	AADTT	800 to 2000
8	Base Thickness (inch)	4 to 18
9	Base Resilient Modulus (psi)	15000 to 45000
10	Performance Grade	PG 58-28
		PG 64-28
		PG 70-22
		PG 76-22
		PG 82-22
		AC 20

Table 4.2: Results from Preliminary Sensitivity Analysis

No	Variable	Total Rut	AC Rut	Terminal IRI	Longitudinal Cracking	Alligator Cracking
1	Air Void (%)	S	S	*S*	S	S
2	Binder Content	S	S	*LS*	*S*	S
3	% Passing #200 Sieve	S	S	*LS*	*S*	LS
4	AC thickness (in)	S	S	*S*	*S*	S
5	Depth to GWT (ft)	LS	LS	*LS*	LS	LS
6	Operational Speed (mph)	S	S	*LS*	LS	LS
7	AADTT	S	S	*S*	*S*	S
8	Base Thickness (inch)	LS	LS	*LS*	*S*	S
9	Base Resilient Modulus (psi)	LS	LS	*LS*	*S*	S
10	Performance Grade	S	S	*LS*	LS	S

Note: S=Sensitive, LS=Low Sensitive

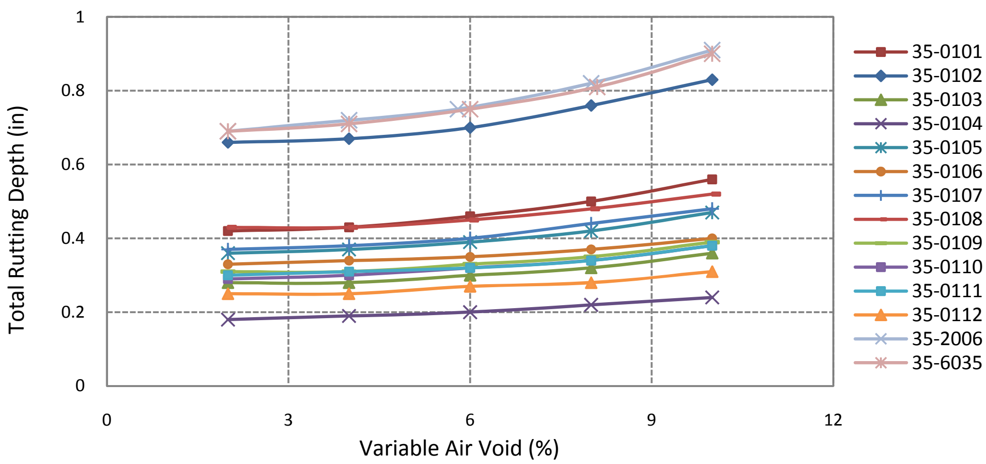


Figure 4.1 (a): Sensitivity of Total Rut Depth to Air Void

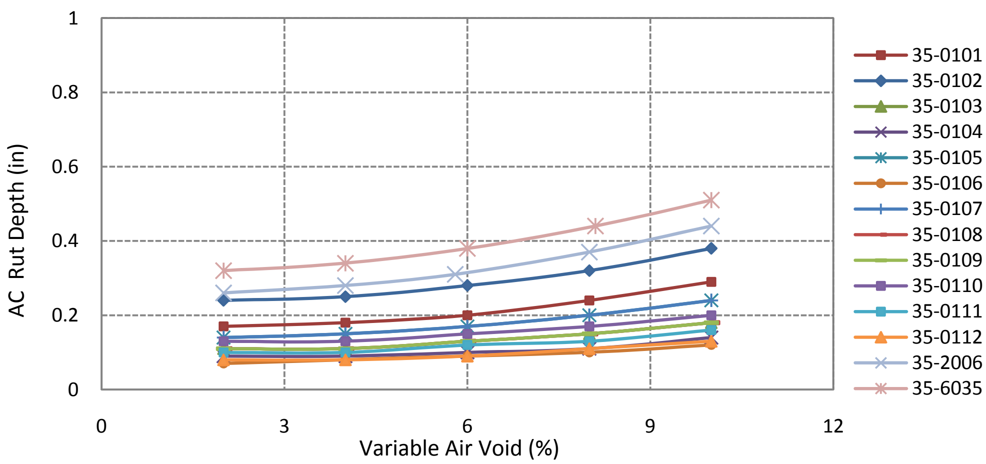


Figure 4.1 (b): Sensitivity of AC Rut Depth to Air Void

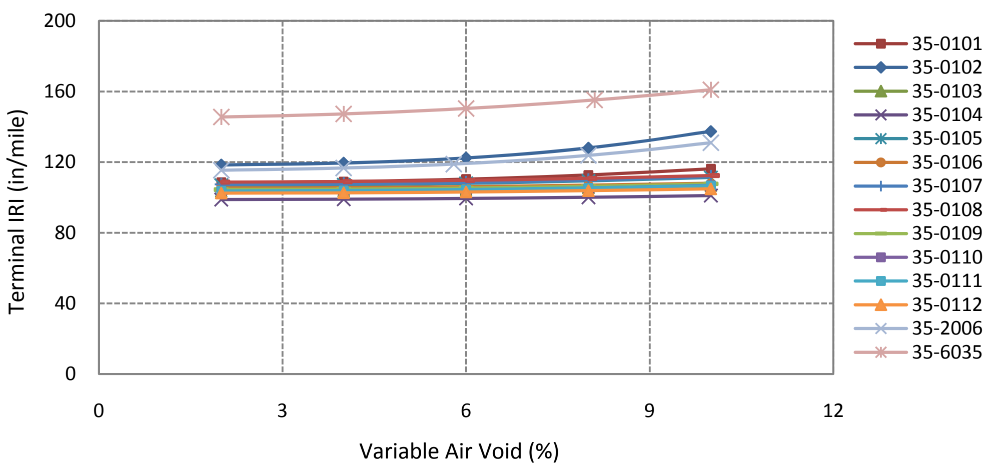


Figure 4.1 (c): Sensitivity of Terminal IRI to Air Void

Figure 4.1: Sensitivity of Pavement Performances to Air Void

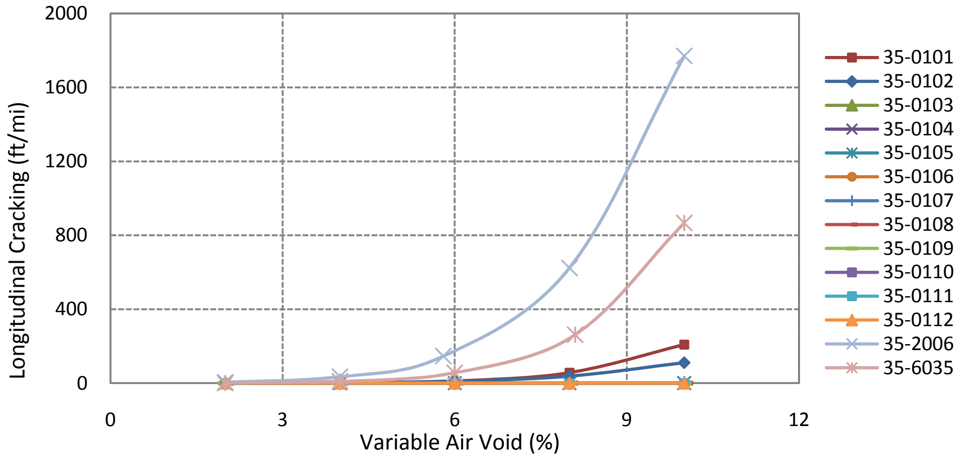


Figure 4.1 (d): Sensitivity of Longitudinal Cracking to Air Void

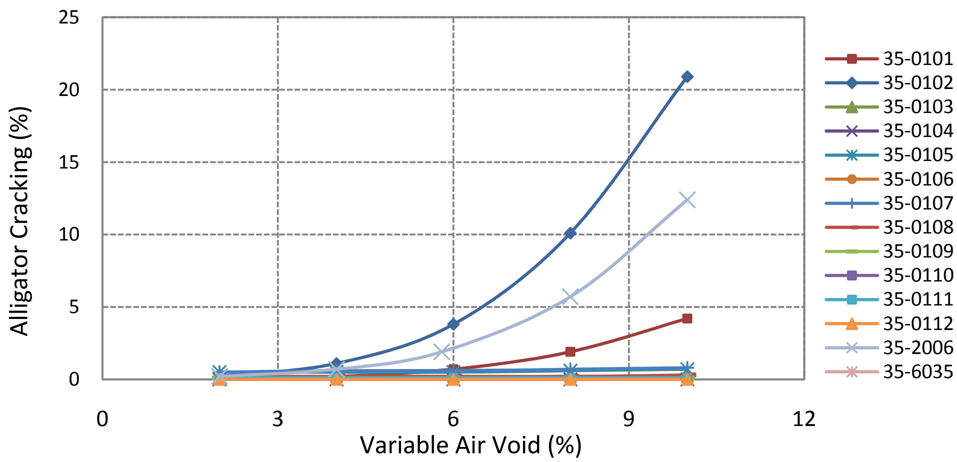


Figure 4.1 (e): Sensitivity of Alligator Cracking to Air Void

Figure 4.1: Sensitivity of Pavement Performances to Air Void (Cont.)

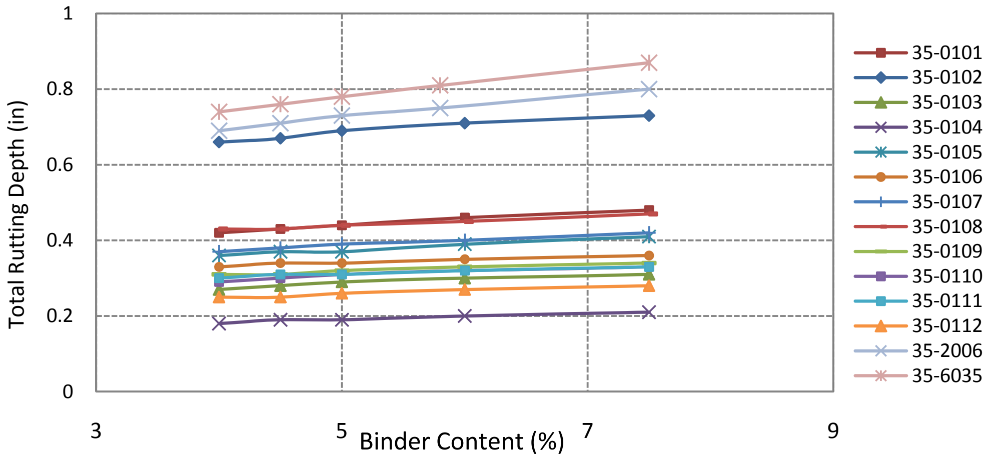


Figure 4.2 (a): Sensitivity of Total Rut Depth to Binder Content

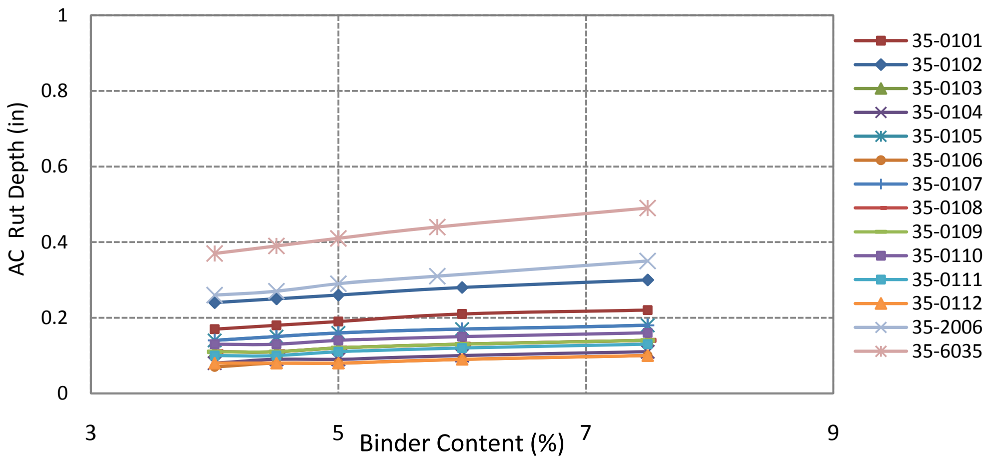


Figure 4.2 (b): Sensitivity of AC Rut Depth to Binder Content

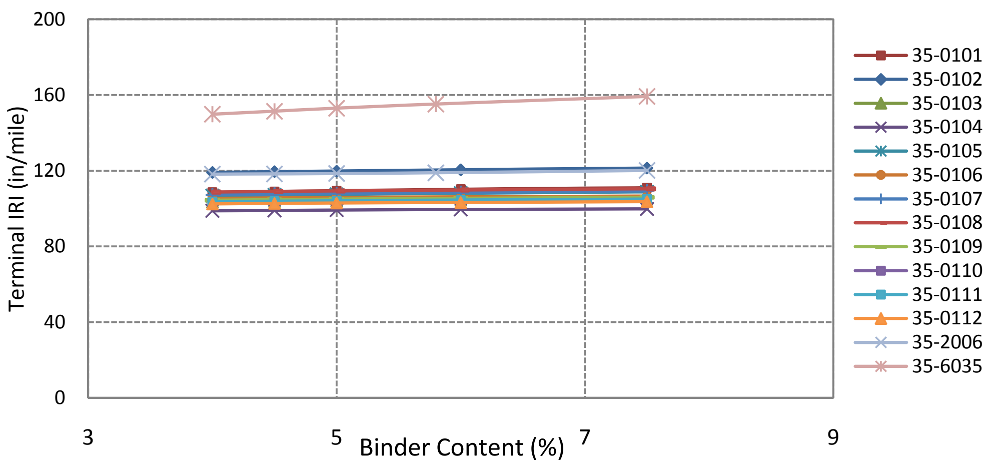


Figure 4.2 (c): Sensitivity of Terminal IRI to Binder Content

Figure 4.2: Sensitivity of Pavement Performances to Binder Content

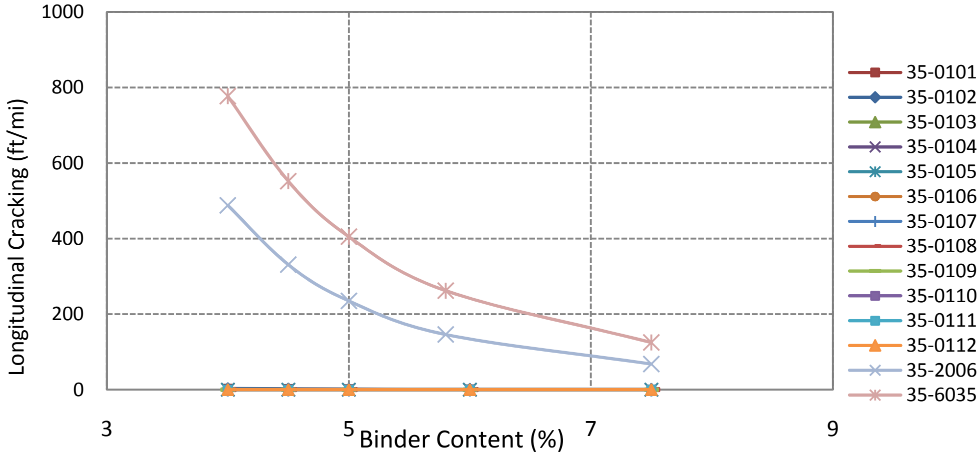


Figure 4.2 (d): Sensitivity of Longitudinal Cracking to Binder Content

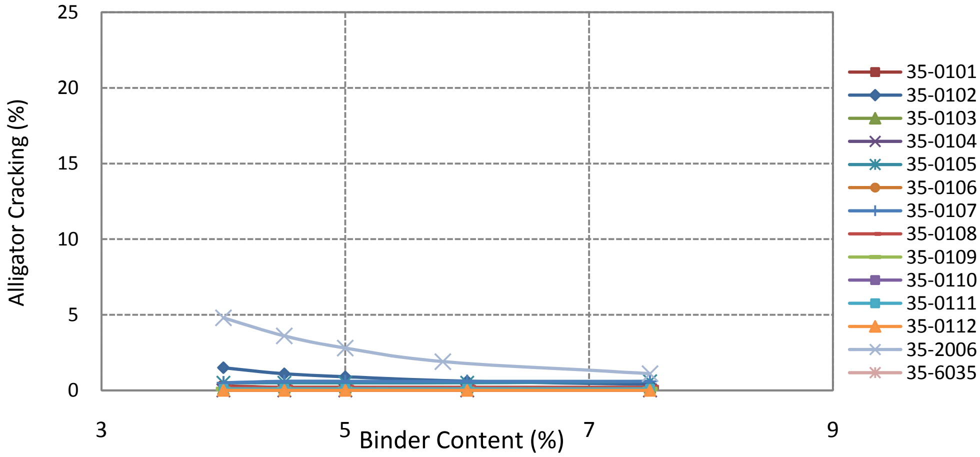


Figure 4.2 (e): Sensitivity of Binder Content on Alligator Cracking

Figure 4.2: Sensitivity of Pavement Performances to Binder Content (Cont.)

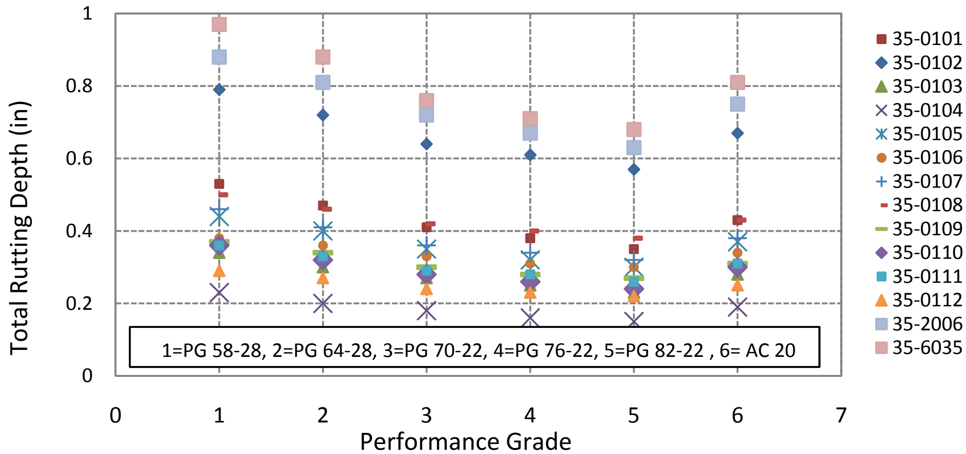


Figure 4.3 (a): Sensitivity of Total Rut Depth to Performance Grade (PG)

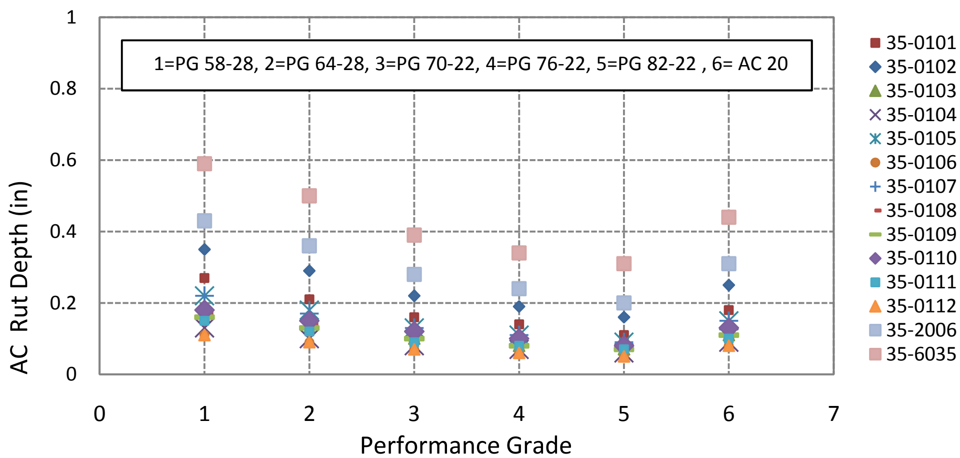


Figure 4.3 (b): Sensitivity of AC Rut Depth to Performance Grade (PG)

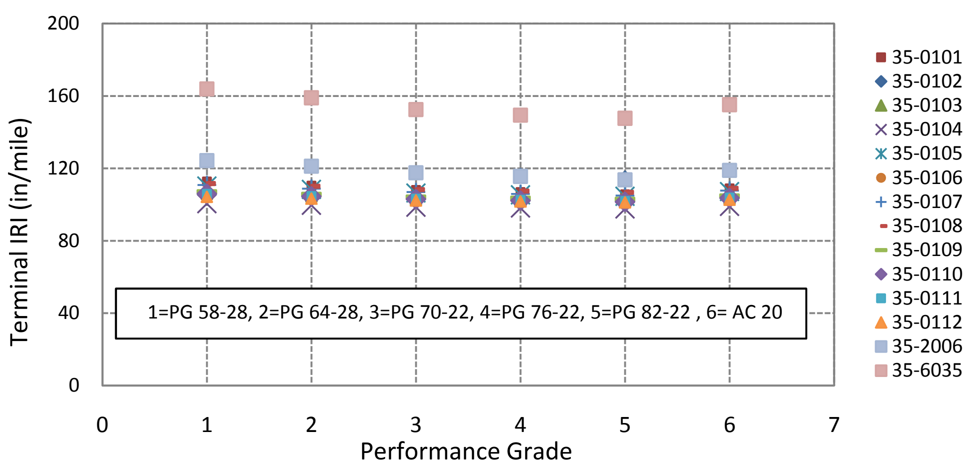


Figure 4.3 (c): Sensitivity of Terminal IRI to Performance Grade (PG)

Figure 4.3: Sensitivity of Pavement Performances to Performance Grade (PG)

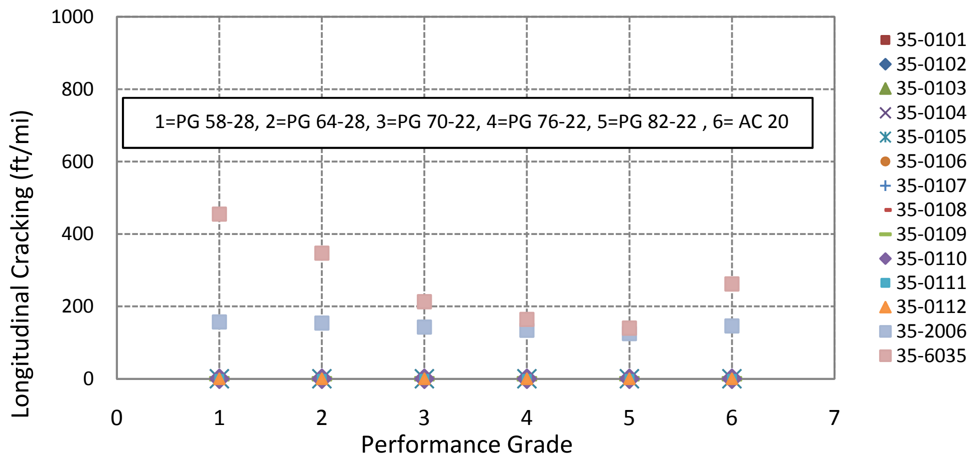


Figure 4.3 (d): Sensitivity of Longitudinal Cracking to Performance Grade (PG)

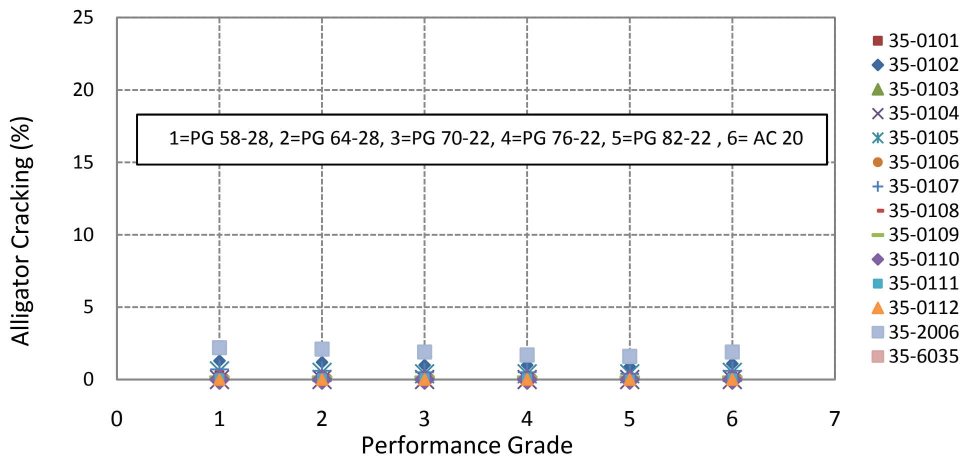


Figure 4.3 (e): Sensitivity of Alligator Cracking to Performance Grade (PG)

Figure 4.3: Sensitivity of Pavement Performances to Performance Grade (PG) (Cont.)

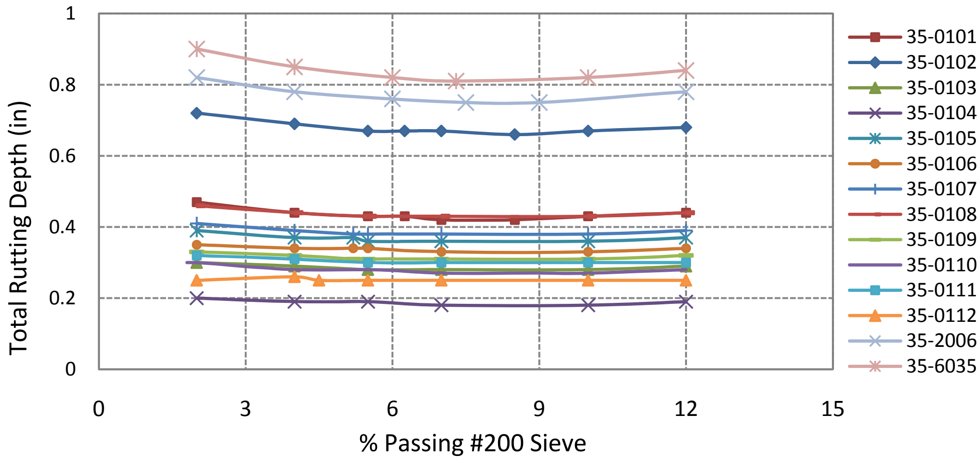


Figure 4.4 (a): Sensitivity of Total Rut Depth to Fineness Content

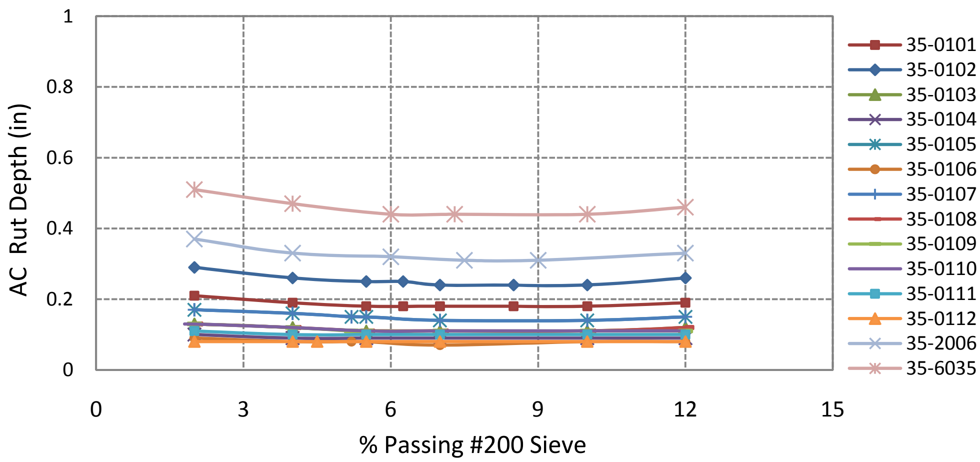


Figure 4.4 (b): Sensitivity of AC Rut Depth to Fineness Content

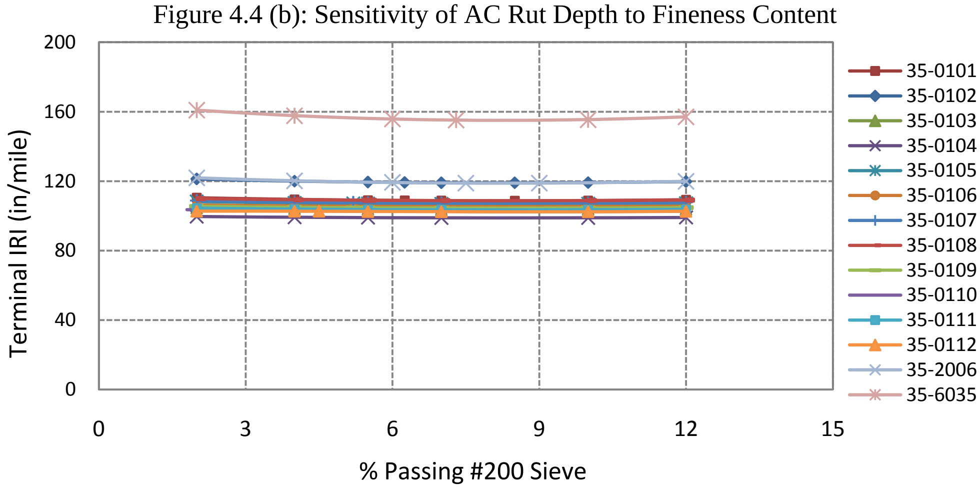


Figure 4.4 (c): Sensitivity of Terminal IRI to Fineness Content

Figure 4.4: Sensitivity of Pavement Performances to Fineness Content

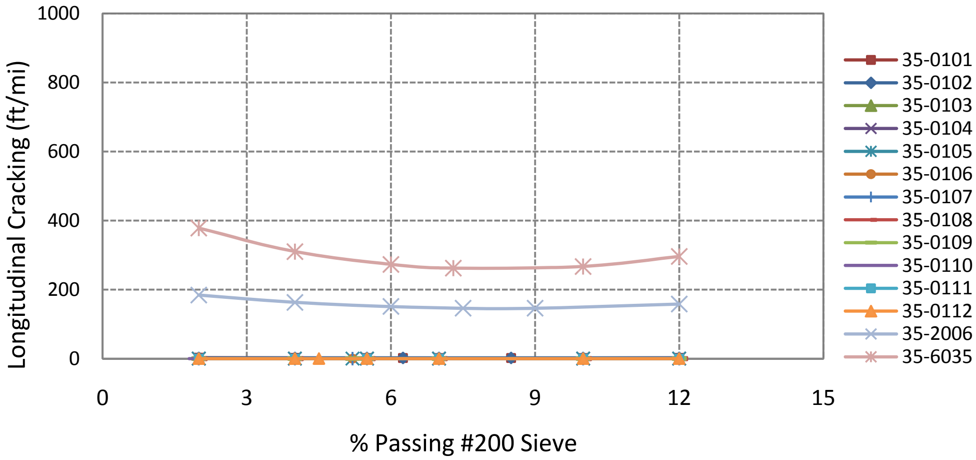


Figure 4.4 (d): Sensitivity of Longitudinal Cracking to Fineness Content

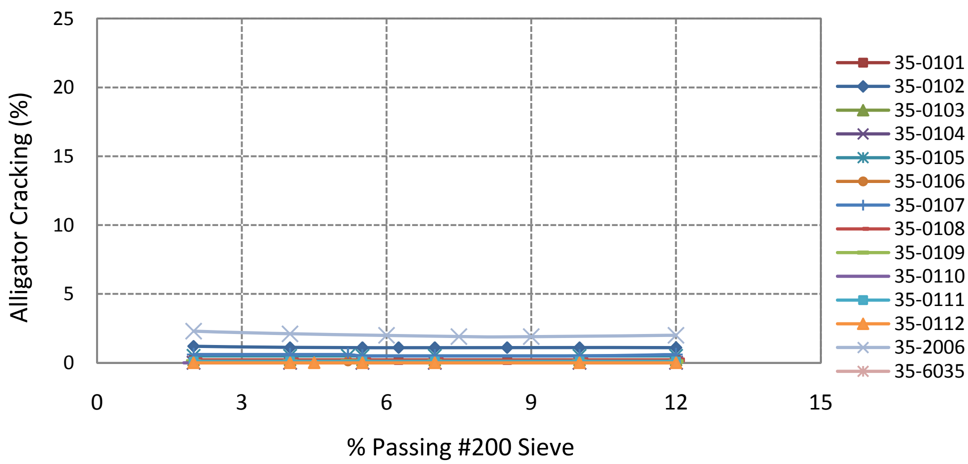


Figure 4.4 (e): Sensitivity of Alligator Cracking to Fineness Content

Figure 4.4: Sensitivity of Pavement Performances to Fineness Content (Cont.)

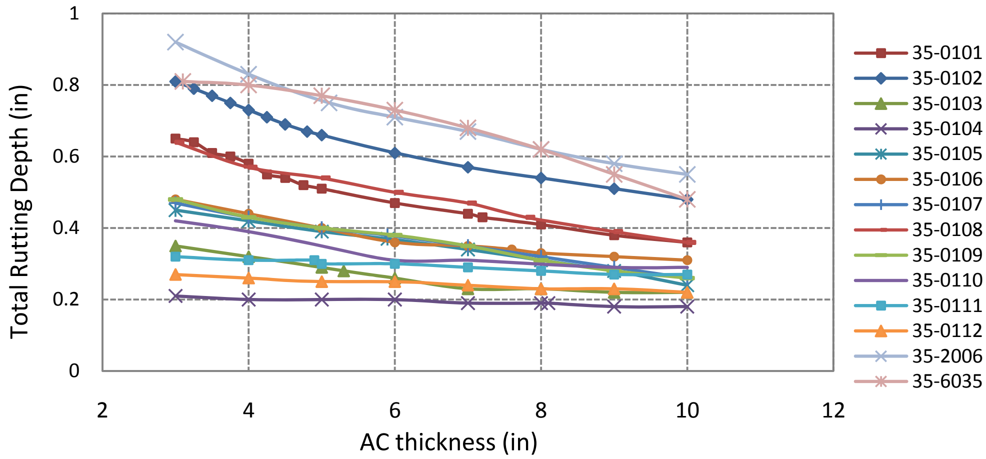


Figure 4.5 (a): Sensitivity of Total Rut Depth to Asphalt Layer Thickness

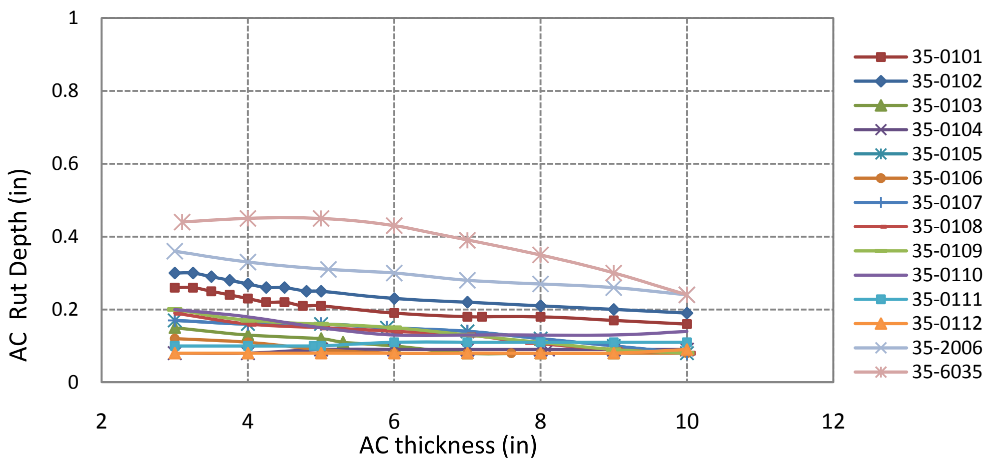


Figure 4.5 (b): Sensitivity of AC Rut Depth to Asphalt Layer Thickness

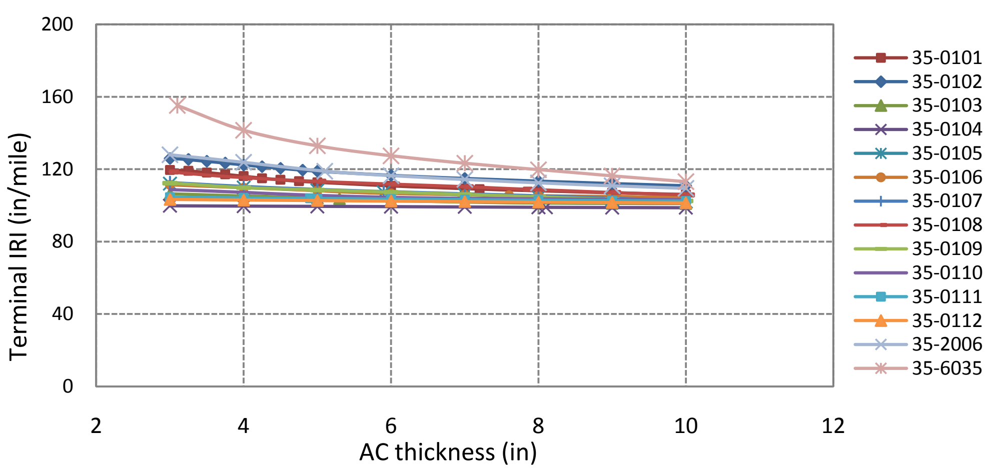


Figure 4.5 (c): Sensitivity of Terminal IRI to Asphalt Layer Thickness

Figure 4.5: Sensitivity of Pavement Performances to Asphalt Layer Thickness

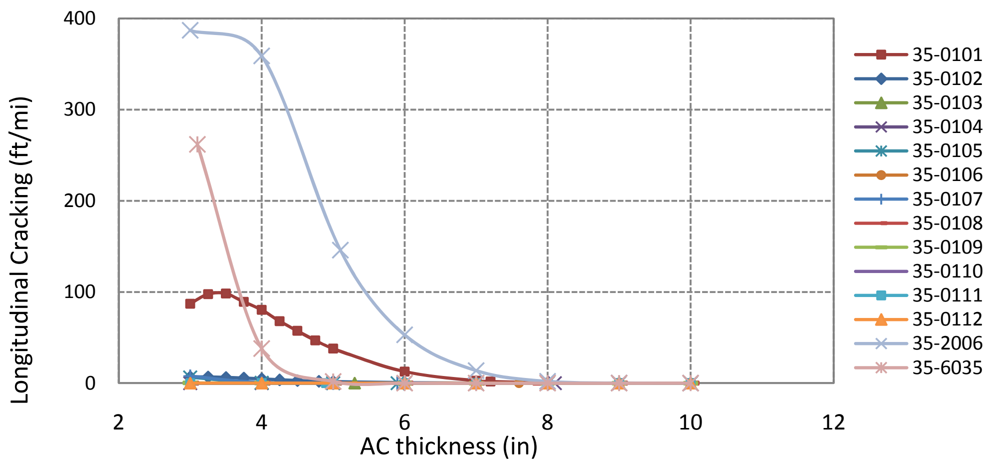


Figure 4.5 (d): Sensitivity of Longitudinal Cracking to Asphalt Layer Thickness

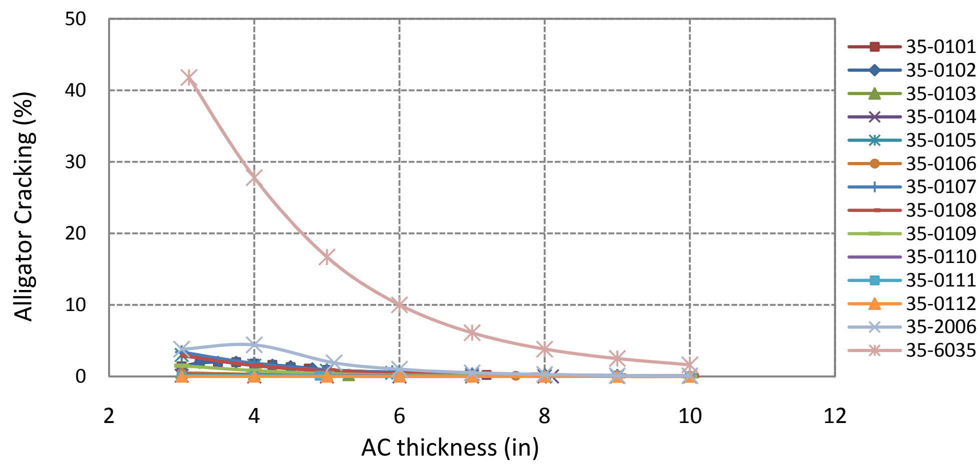


Figure 4.5 (e): Sensitivity of Alligator Cracking to Asphalt Layer Thickness

Figure 4.5: Sensitivity of Pavement Performances to Asphalt Layer Thickness (Cont.)

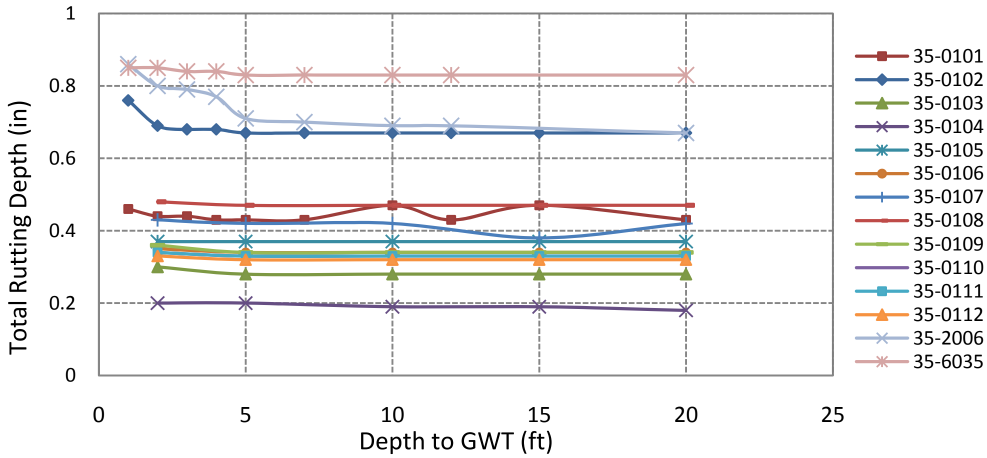


Figure 4.6 (a): Sensitivity of Total Rut Depth to Ground Water Table Depth

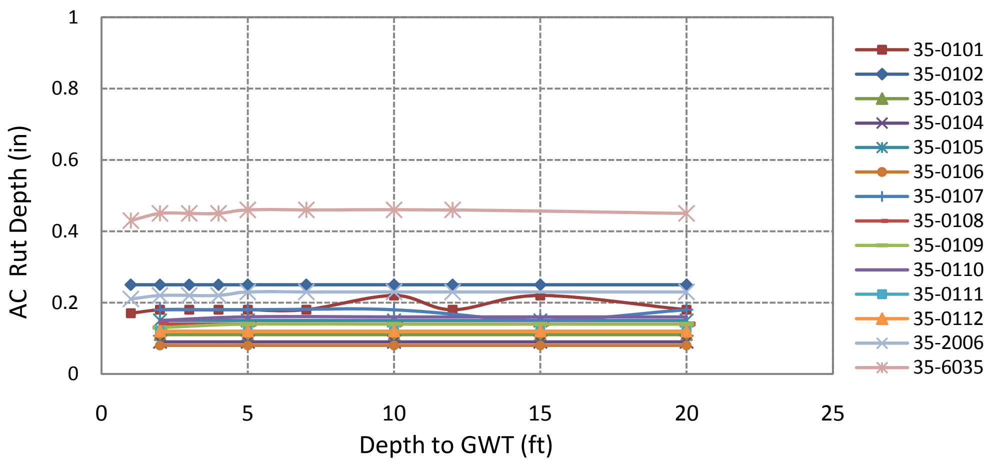


Figure 4.6 (b): Sensitivity of AC Rut Depth to Ground Water Table Depth

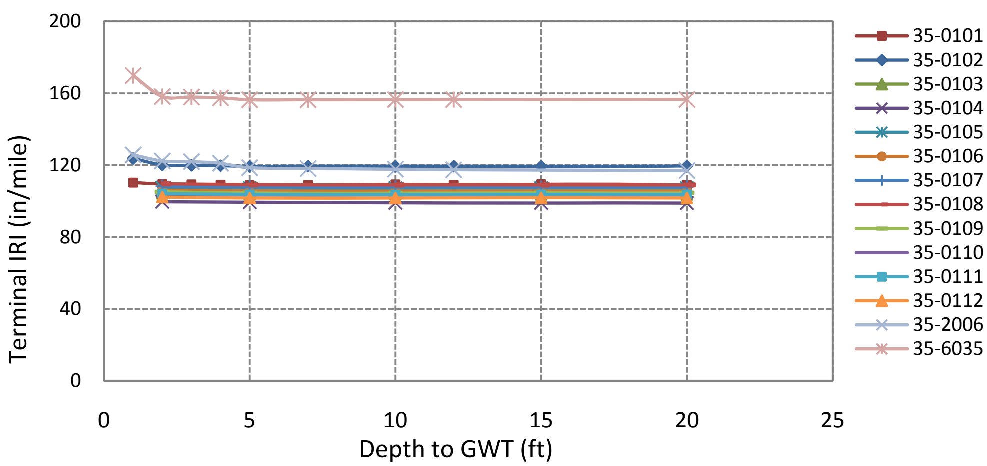


Figure 4.6 (c): Sensitivity of Terminal IRI to Ground Water Table Depth

Figure 4.6: Sensitivity of Pavement Performances to Ground Water Table Depth

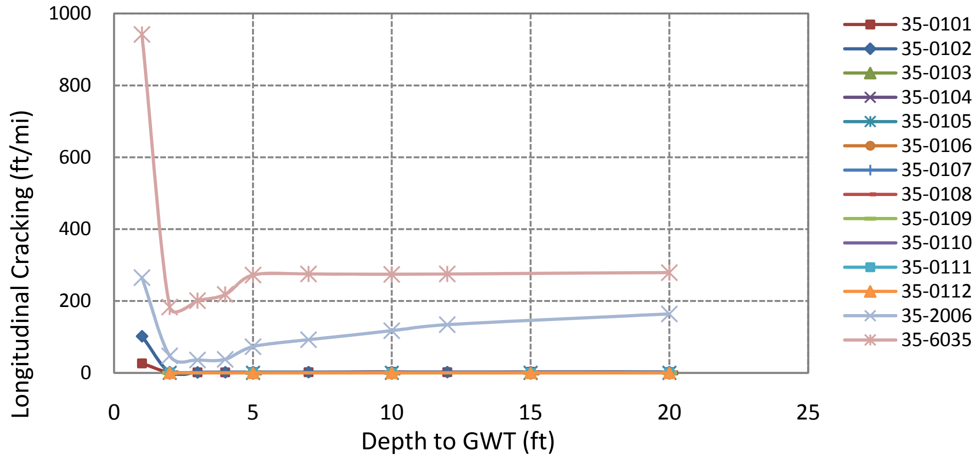


Figure 4.6 (d): Sensitivity of Longitudinal Cracking to Ground Water Table Depth

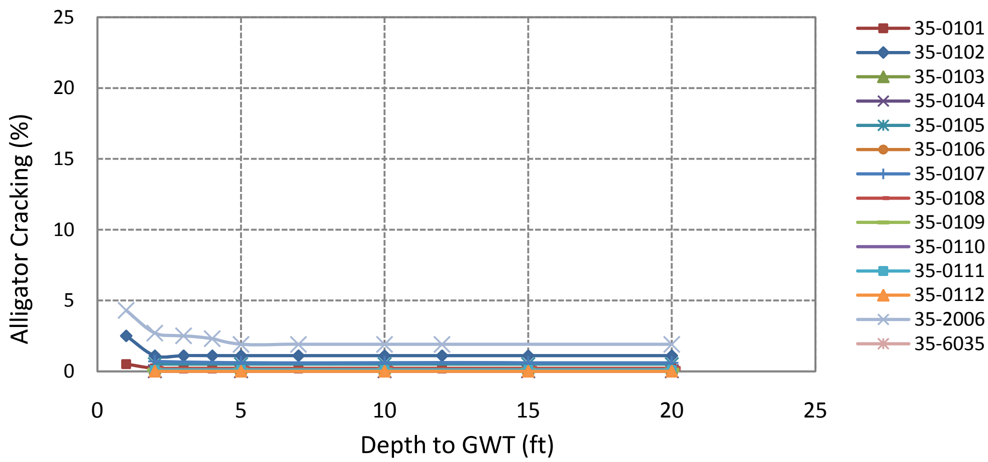


Figure 4.6 (e): Sensitivity of Alligator Cracking to Ground Water Table Depth

Figure 4.6: Sensitivity of Pavement Performances to Ground Water Table Depth (Cont.)

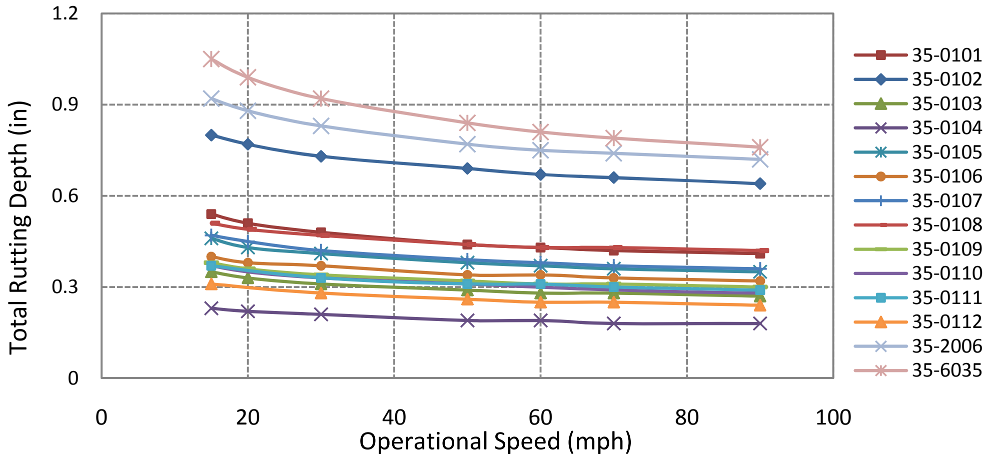


Figure 4.7 (a): Sensitivity of Total Rut Depth to Operational Speed

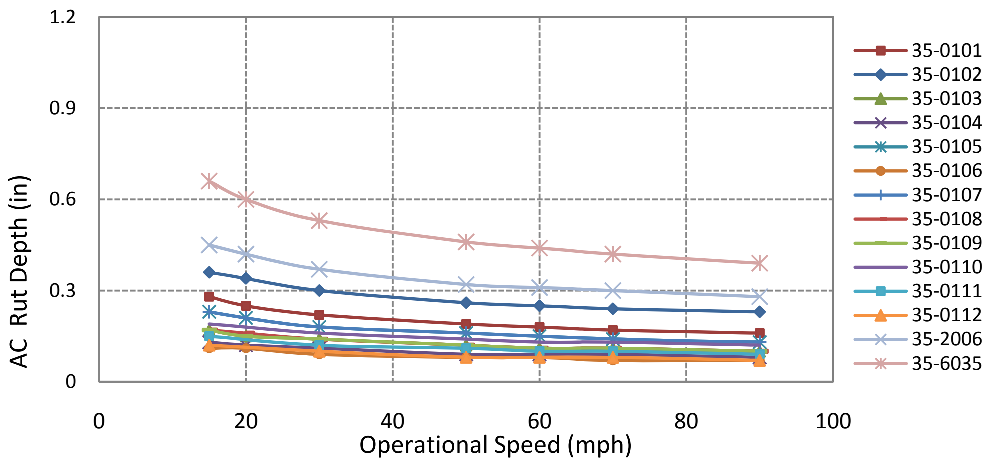


Figure 4.7 (b): Sensitivity of AC Rut Depth to Operational Speed

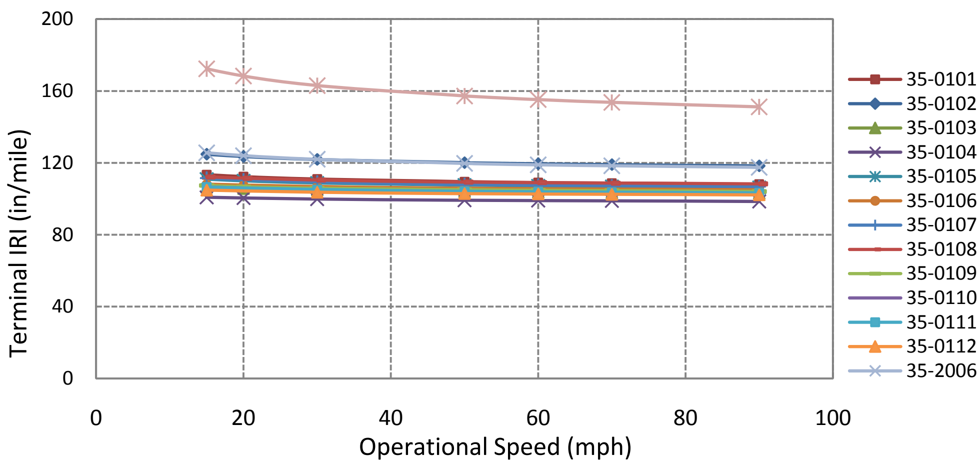


Figure 4.7 (c): Sensitivity of Terminal IRI to Operational Speed

Figure 4.7: Sensitivity of Pavement Performances to Operational Speed

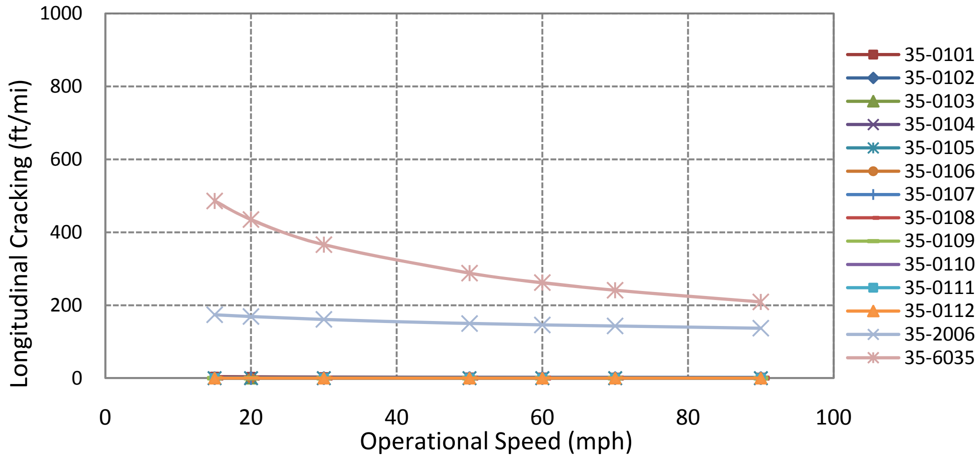


Figure 4.7 (d): Sensitivity of Longitudinal Cracking to Operational Speed

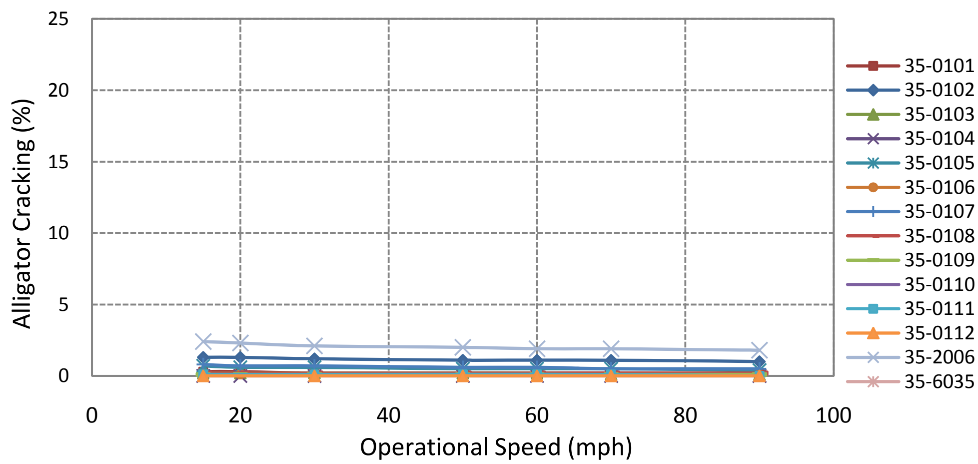


Figure 4.7 (e): Sensitivity of Alligator Cracking to Operational Speed

Figure 4.7: Sensitivity of Pavement Performances to Operational Speed (Cont.)

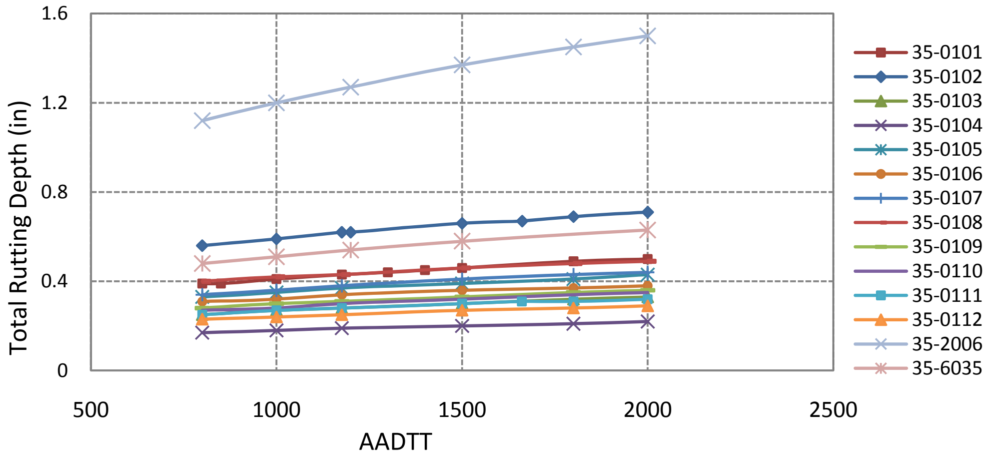


Figure 4.8 (a): Sensitivity of Total Rut Depth to AADTT

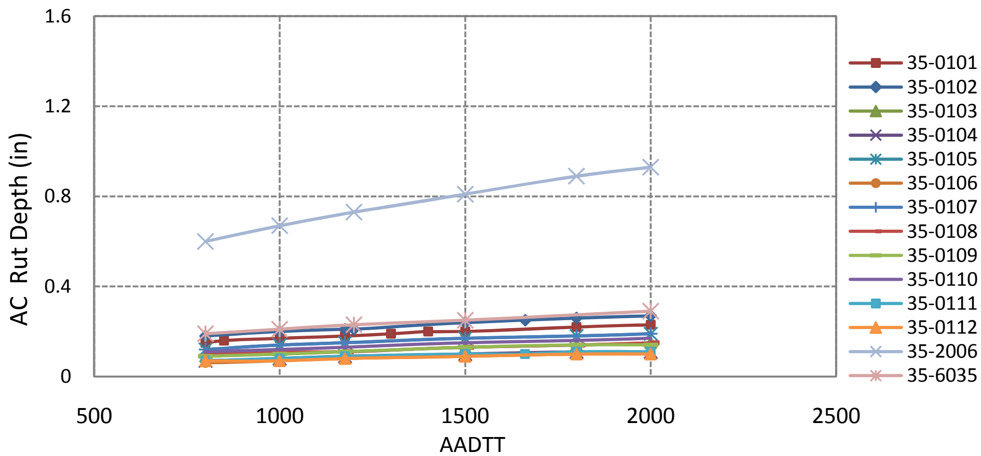


Figure 4.8 (b): Sensitivity of AC Rut Depth to AADTT

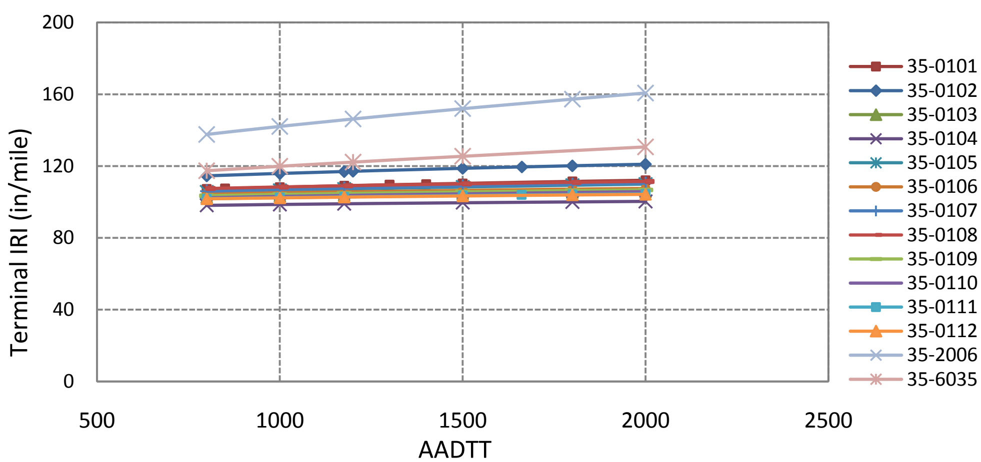


Figure 4.8 (c): Sensitivity of Terminal IRI to AADTT

Figure 4.8: Sensitivity of Pavement Performances to AADTT

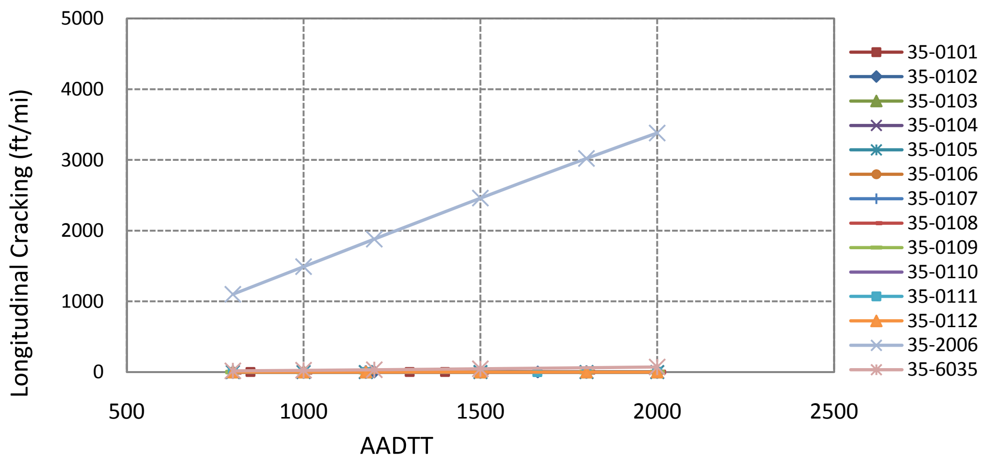


Figure 4.8 (d): Sensitivity of Longitudinal Cracking to AADTT

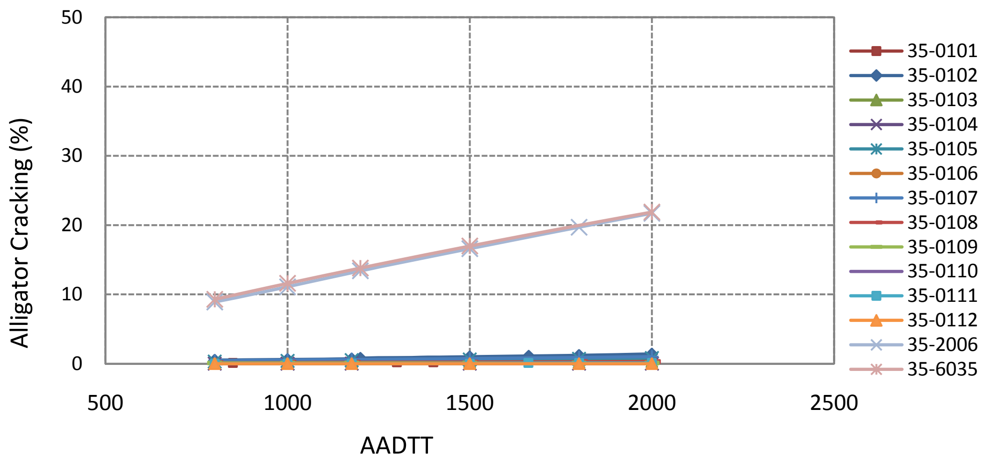


Figure 4.8 (e): Sensitivity of Alligator Cracking to AADTT

Figure 4.8: Sensitivity of Pavement Performances to AADTT (Cont.)

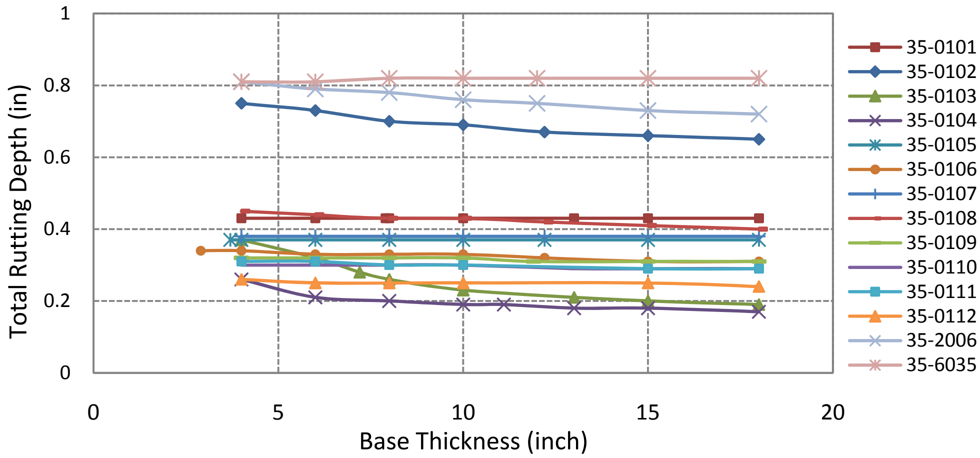


Figure 4.9 (a): Sensitivity of Total Rut Depth to Base Thickness

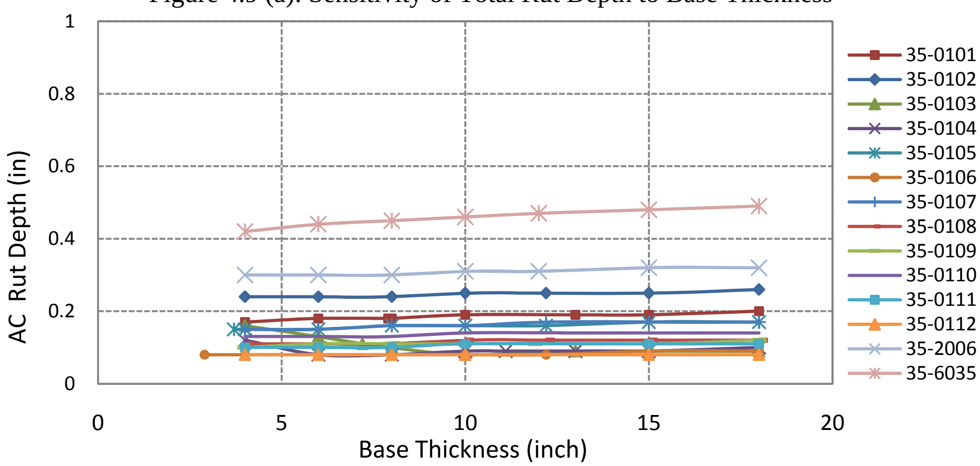


Figure 4.9 (b): Sensitivity of AC Rut Depth to Base Thickness

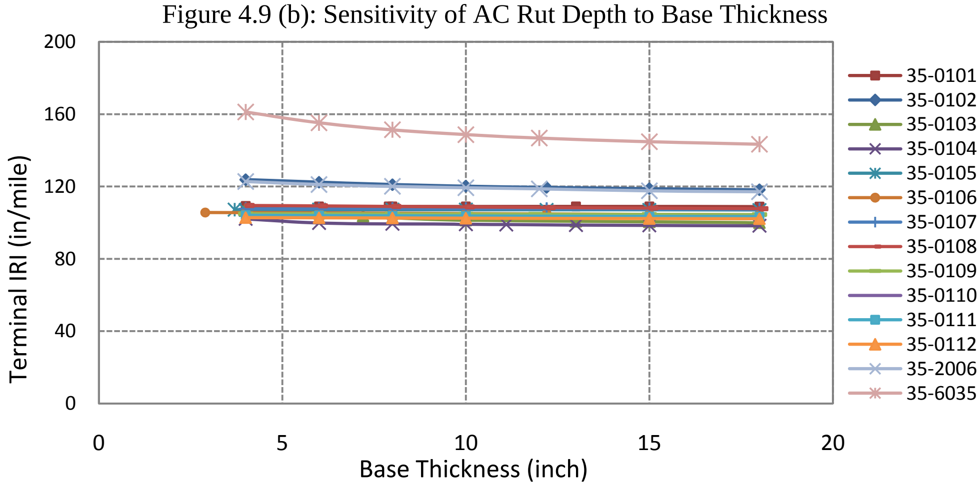


Figure 4.9 (c): Sensitivity of Terminal IRI to Base Thickness

Figure 4.9: Sensitivity of Pavement Performances to Base Thickness

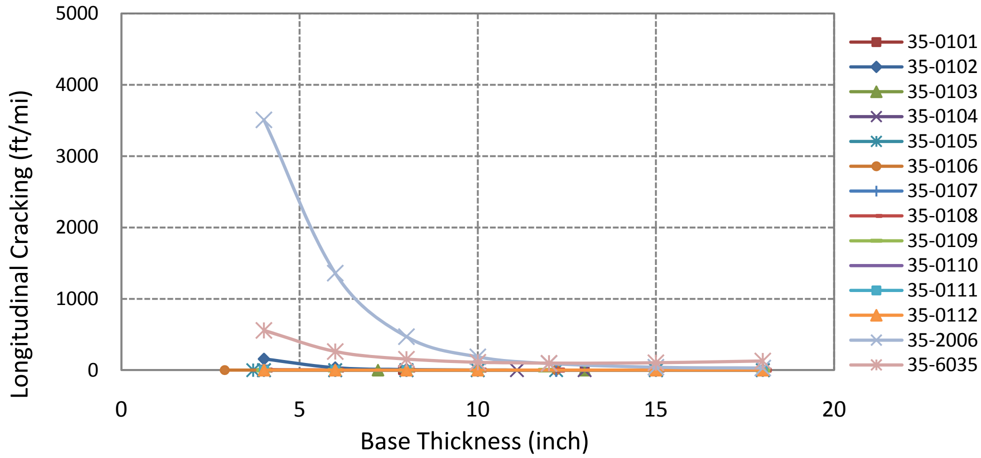


Figure 4.9 (d): Sensitivity of Longitudinal Cracking to Base Thickness

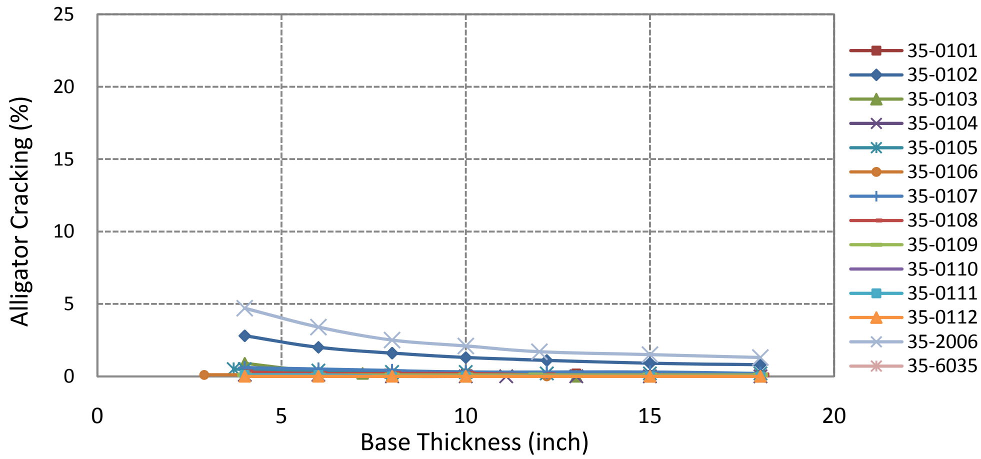


Figure 4.9 (e): Sensitivity of Alligator Cracking to Base Thickness

Figure 4.9: Sensitivity of Pavement Performances to Base Thickness (Cont.)

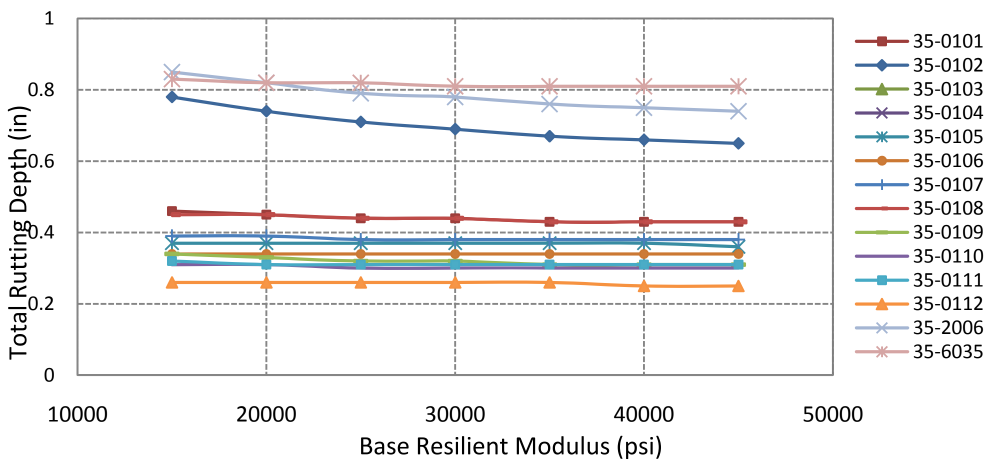


Figure 4.10 (a): Sensitivity of Total Rut Depth to Base Resilient Modulus (M_r)

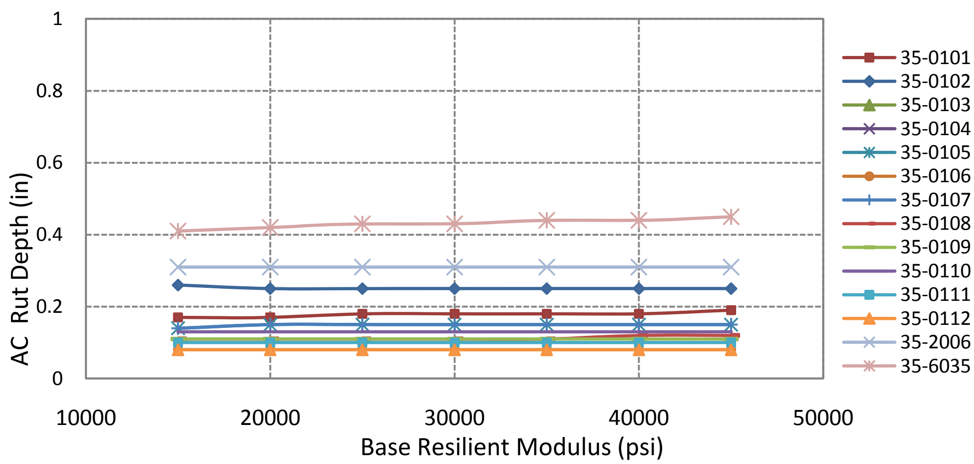


Figure 4.10 (b): Sensitivity of AC Rut Depth to Base Resilient Modulus (M_r)

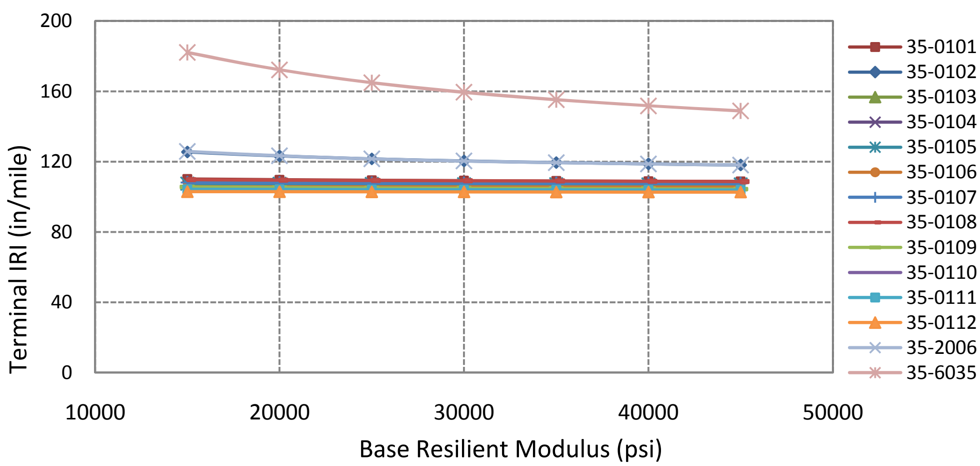


Figure 4.10 (c): Sensitivity of Terminal IRI to Base Resilient Modulus (M_r)

Figure 4.10: Sensitivity of Pavement Performances to Base Resilient Modulus (M_r)

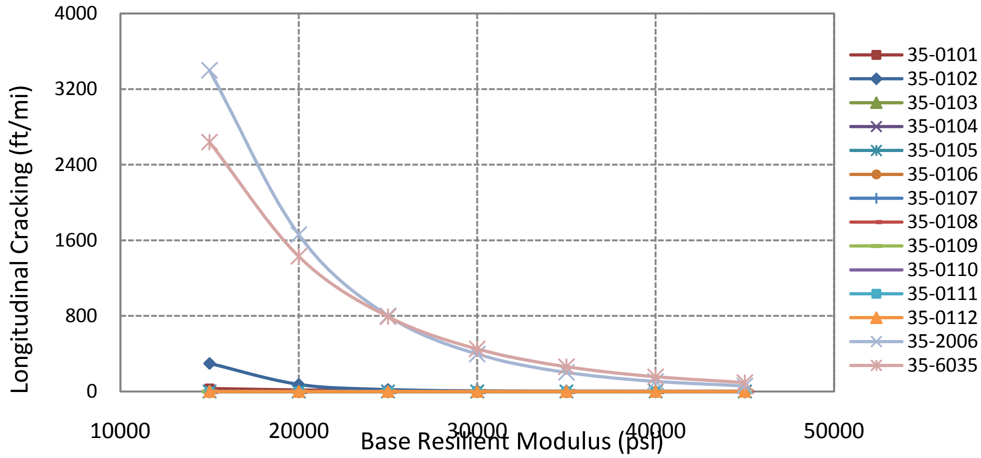


Figure 4.10 (d): Sensitivity of Longitudinal Cracking to Base Resilient Modulus (M_r)

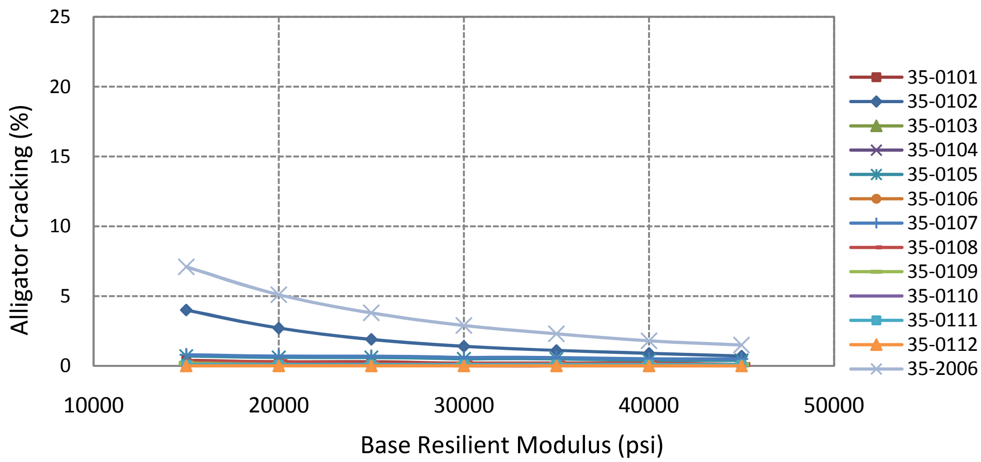


Figure 4.10 (e): Sensitivity of Alligator Cracking to Base Resilient Modulus (M_r)

Figure 4.10: Sensitivity of Pavement Performances to Base Resilient Modulus (M_r) (Cont.)

CHAPTER 5

A PARAMETRIC APPROACH TO SENSITIVITY ANALYSIS

5.1 Introduction

Procedures for identifying sensitive variables using scatterplots and regression methods are described in this chapter. Sensitivity analyses performed in Chapter 4 are inadequate when the output is a function of several input variables. Sensitivity of output to a given set of inputs depends on interactions of inputs with each other. To understand the impacts and relationships of the hundreds of input variables contained in the MEPDG, a comprehensive analysis of each variable and its interaction with other inputs need to be fully investigated. Therefore, sampling based sensitivity analyses have performed in this chapter. To identify the most sensitive variables several parametric approaches are used, such as test of nonrandomness in scatterplots (such as Common Means test, Common Location test, Statistical Independence test), regression (linear and rank) methods.

5.2 Development of Sensitivity Matrix

5.2.1 Defining Inputs and Outputs

It is necessary to effectively manage and organize all variables for detailed sensitivity analysis. Too many or too few data fields are risky for building models. Too many data fields can lead low performance models. Too few data fields can result models that are not well correlated. To define data fields, variables that effect pavement performances significantly, are selected from chapter 2 and 4. The data field is organized into three fundamental types of inputs for flexible pavement design based on MEPDG (NCHRP

2004). The inputs are traffic, climate/environment, and structure/material inputs. To conduct a detailed sensitivity analysis, a flexible pavement structure has been selected as shown in Figure 5.1. The pavement structure is consists of four layers. The top layer is thin AC layer with thickness varies from 1.5 to 3 inch. The second layer is a thick AC layer with thickness varies from 2 to 8 inches. Rests of the layers are base (6 to 10 inch) and subgrade.

The variables selected for the sensitivity study are shown in Table 5.1. To the extent possible, the variables and their limit values are chosen to represent the practices adopted by NMDOT. Data are collected from LTPP and NMDOT Database. Total 30 variables are selected (X1 to X30) and presented in Table 5.1. First 10 variables (X1 to X10) are related to traffic. Variables X11 and X12 represent climatic inputs. Rest of the variables is related to structural properties. Interaction of these inputs is quantified in terms of six MEPDG outputs shown in Table 5.2. These output variables are identified as Y1 to Y6.

5.2.2 Generation of Input Sample

Due to lack of data, the nature and distribution of all input variable are unknown. Therefore, random LHS method is followed to generate sample data for the variables of Table 5.1 (nS=750). Total number of column is 30 in the resultant test matrix (750X30). Each column is for each variable (X1 to X30). Total number of row is 750, which is the sample size. Due to space limitation, a part of the test matrix is shown in Table 5.3. In this table, the highlighted part presents a segment of the test matrix (20x10). The columns represent one type of input variable(X1 to X10). Each row represents one data set, generated by LHS method.

Figure 5.2 presents the distribution of sample size. Figure 5.2(a) describes the sample for AADTT which is integer type. AADTT varies from 300 to 6000 based on LTPP database. Unlike random sampling, this method ensures a full coverage of the range of input space. Figure 5.2(b) shows the sample distribution of climatic zones that is a discrete number. It is clear from the plot that each sample is the only one in each axis-aligned hyper plane containing it.

5.2.3 MEPDG Simulation

MEPDG software has used to develop the output variables for the different distress measures. MEPDG version 1.00 (MEPDG 2010) is used in this study. Total number of simulation is 750. Considering the fact that one run takes about 50 minutes, 750 run took 37500 minutes or 26 days of nonstop computation. Each row of the test matrix shows the value of the variables for particular one run.

5.2.4 MEPDG Outputs

Six distress measures are taken as output variables for sensitivity study. They are IRI, rut (total and AC) and cracking (longitudinal, transverse and alligator). Measurement of these distresses is based on pavement life predictions. Pavement life is assumed 20 years in these simulations. In MEPDGs, the target distresses are set for AC rutting = 6.35 mm or 0.25 inch, total rutting = 19.05 mm or 0.75 inch, IRI = 2715 mm/kilometer or 172 inch/mile, fatigue cracking (bottom-up) = 25%, and top-down cracking (longitudinal) = 378.87 meter/kilometer (2000 feet/mile), transverse cracking = 189.44 meter/kilometer (1000 feet/mile) with a reliability value of 90% (MEPDG Documentation 2010).

Summary of MEPDG simulation results are plotted in graphical format and presented in Figure 5.3. Figure 5.3(a) presents the result of Terminal IRI. Two horizontal lines are plotted through initial IRI set at 63 and allowable IRI set at 172. It is evident that most of the IRI result falls within the range from 93 to 140. Few cases, pavement section failed due to IRI. Figure 5.3(b) shows summary of longitudinal cracking. The lowest value for longitudinal cracking is zero and the highest predicted longitudinal cracking is 10400 ft/mile, which is almost 52 times of the target value. Figure 5.3(c) represents alligator cracking for the pavement test sections. The number of pavement sections with no alligator cracking is 26 and total 47 sections are failed. The highest value predicted for alligator cracking is 88%, which is 3.52 times of target value. Figure 5.3(d) presents transverse cracking result for the test sections. Only one pavement section is failed due to transverse cracking. The highest predicted value for this failed section is 1891.2 ft/mile, which is almost two times of target value. For AC rut case, almost test sections are failed which is clear from the Figure 5.3(e). About two hundred of the pavement section fall within the target range and rest of the sections are not. The highest value is 1.09 inch, which is almost 5 times of the target distress value. The same type of result is found in case of total rut, which is shown in Figure 5.3(f). Total sixty percent of the pavement sections pass in this case. The highest value for total rut is 1.84 inch, which is 2.5 times of the target distress.

Table 5.4 presents the number of the simulations that pass or fail. Pavement section can be considered as fail in case of predicted distress or predicted reliability. The most severe cases are obtained for AC rut and total rut. For AC rut, almost 75% test sections are failed. For total rut, 40% of total pavement sections are failed. Longitudinal cracking is the third most severe distress among the all six distress. 24% of test sections are failed in case of long crack. Total no of failed section in case of alligator crack is 47, which is 6% of total test sections. For terminal IRI, 22 test sections are failed among all 750-test sections. Only one case is found for transverse cracking which is failed. In case of reliability, failure proportion is higher compare to distress value failure case. From this table, it is clear that for New Mexico climatic condition and present design method, pavement engineers should be more careful about permanent deformations and then longitudinal cracking.

5.2.5 Development of Full Test Matrix

To conduct the advanced sensitivity analysis of the input variables, it is essential to develop the full factorial test matrix. After required number of MEPDG simulation, results for the output variables (Y1 to Y6) are summarized and full factorial test matrix is developed (750x36). This result matrix is used in the next steps for advanced statistical analysis to determine the sensitivity of various pavement performances.

5.2.6 R statistical computing environment

All statistical analyses in this study are carried out within the R statistical computing environment. R is a language and environment for statistical computing and graphics (R 2010). R provides a wide variety of statistical (linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering etc) and graphical techniques, and is highly extensible.

5.3 Correlation and Dependence

Correlation Coefficients: Correlation is one of the simple procedures to calculate the sensitivity. It can predict relationship between two or more random variables. There are several correlation coefficients. The most common of these is the Pearson Correlation Coefficient, which is used in this study. This test answers three questions. It indicates if there is any relationship exists or not between input and output variables. It also indicates the direction (negative or positive) and power (strong or weak) of the relationship. The Pearson correlation coefficient, c (x_j, y) between x_j and y is defined by (Saltelli et al. 2000)

$$c(x_j, y) = \frac{\sum_{i=1}^{nS}(x_{ij}-\overline{x_j})(y_i-\bar{y})}{\left[\sum_{i=1}^{nS}(x_{ij}-\overline{x_j})^2\right]^{\frac{1}{2}}\left[\sum_{i=1}^{nS}(y_i-\bar{y})\right]^{\frac{1}{2}}} \quad 5.1$$

where, $$\overline{x_j} = \sum_{i=1}^{nS}\frac{x_{ij}}{nS} \quad 5.2$$

and $$\bar{y} = \sum_{i=1}^{nS}\frac{y_i}{nS} \quad 5.3$$

The CC c(xj, y) will have a value between -1 (negative one) to 1 (positive one). If the obtained value is positive, than it indicates that x_j has positive relationship with y. If the value of x_j increases, then y value will increase too. The value of y will decrease if value of x_j decreases. A negative value indicates that x_j and y have negative relationship among them. If the value of x_j increases, then y value will decrease and vice versa. Absolute value of c(xj, y) between 0 and 1 correspond to a trend from no linear relationship to an exact linear relationship between x_j and y. Correlation of zero value only indicates that absence of linear relationship between xj and y. it means that, there is a probability of nonlinear relationship between xj and y.

Test of Correlation: Test of correlation is performed to have idea about the linear relationship among the input and output variables and presented in Table 5.5. Pearson product-moment correlation coefficient was performed for each input with each output. In the table all correlation coefficients values are between -1.00 and +1.00 which indicates that there is no data error in the test matrix. Table 5.5 also shows a good amount of correlation coefficient of 0.00 means that there is no linear relationship between two variables. To interpret the correlation values, the entire range of correlation is divided in four parts (Cohen 1988), which is mention as note in the table.

From Table 5.5, it is seen that terminal IRI (output variable Y1) has medium strength relationship with three input variables (X1, X4 and X18). These inputs are AADTT, percentage of trucks and asphalt layer thickness. Among them, first two has positive and the third one has negative relation with IRI. This result seems logical because distress increases with increasing AADTT and distress decreased with increasing asphalt layer thickness. Longitudinal cracking (output variable Y2) has strong negative relationship with asphalt layer thickness (X18). No medium relationship is found for longitudinal cracking. Similar result is obtained for alligator cracking (output variable Y3). None of the input variables used for analysis has influence for transverse cracking (output variable Y4) in correlation test. For AC rut (output variable Y5) total two input variable has strong positive relation. They are AADTT (X1) and truck percentage (X4). AADTT (X1) also has positive strong relationship with total rut (output variable Y6). However, truck percentage (X4) and asphalt layer thickness (X18) have medium strength relationship with total rut but direction of the relationships is reverse. Total rut increases with increasing truck percentage and decreases with increasing asphalt layer thickness.

After performing, the Pearson product-moment correlation coefficient test, three major input variables has been identified which have some relationship of different strength and direction. These relationships are presented in graphical format in Figure 5.4 to Figure 5.6. Figure 5.4 presents the effect of AADTT on pavement performance. AADTT has positive relationship with IRI, AC rut and total rut. The relationship is stronger for AC rut and total rut compare to terminal IRI. Figure 5.5 presents effects of percentage of truck in design direction in pavement performance. IRI increases with increasing truck percentage. For AC rut and total rut, increasing rate is higher compare to IRI. Figure 5.6 presents that with increasing asphalt layer thickness, pavement distress can be minimized. Total four types of distresses have relationship with asphalt layer thickness. They are terminal IRI, longitudinal and alligator crack and total rut. For both type of cracking relationship is stronger than IRI and total rut.

5.4 Statistical Analyses to Identify Important Factors

In this study, several approaches are used to perform sensitivity analysis. There is no particular method that can said as superior to others. Different approaches yield different measures of sensitivity. That is why several approaches are used to cover wide range of assumption. In this section statistical tests bases on gridding, grid free tests, linear and nonlinear regression analysis are performed to cover the wide range of assumption.

5.4.1 Tests Based on Gridding

In this step, scatter plot test is performed with placing grids for particular output variable (Y1, Y2….Y6) and all input variables (X1 to X30). Common means (CMNs), Common distributions or locations (CLs) and Statistical independence (SI) tests are performed to determine if the distribution of points across the grid cells appears to be nonrandom. Appearance of a nonrandom pattern indicates that x_j has an effect on y. While performing CMN and CL test, the values of x_j are divided into M=5 disjoint class. In Figure 5.7(a), one example is shown. In this figure, horizontal axis represents the value range of input variable X18 (asphalt layer thickness, value range: 2 to 8 inch). This axis is divided into 5 equal parts which are spaced at 1.2 inch interval. For discrete x_j, classes are defined for each of the distinct values. In the vertical axis, output variable Y6 is presented. No portioning is done for this axis. Figure 5.7(b) represents the partitioning used for SI test for the same input and output variable (X18 and Y6). The horizontal axis partitioning is same as CL and CMN test. In addition, the y values are also partitioned in a manner analogous to that used for the x_j values.

The result obtained from these tests is presented in Table 5.6(a) to Table 5.6(f) for each output variable (Y1 to Y6). These tests results are all based on p-values that derived from the assumptions that are made during performing each test. A level of significance α was specified before running the codes ($\alpha = 0.05$). if $p < \alpha$, then it is proved that all hypothesis made at the beginning are rejected and it is confirmed that x_j has an effect on the behavior of y. Relative importance of the x_j's, are measured and ranked according to their respective p-values. The smaller the p-value, the more important is that input variable.

Table 5.6(a) presents the test result for output Y1 (terminal IRI). For CMN test, total twelve inputs have significant p-value among all the thirty. From CL test and SI, total eleven input variables showed effect on this output. For all three tests, four input variable has lowest p value (zero). Among them, three inputs are common for all tests. They are: asphalt layer thickness for second layer (X18), AADTT (X1) and percent of trucks in design direction (X4). In CMN test, top AC layer thickness (X13) also has zero p value which is almost similar to CL and SI result (0.0002 and 0.0003). Almost similar result is obtained for X26 (Subgrade Material type) which has zero p-values for CL and SI test and 0.0001 for CMN test. Results are almost similar for CL and SI test and a very small difference with CMN test. The rest of the inputs has almost same ranking in all three tests but has different p-values with a very negligible difference. Similar results are also observed for other output variables which are presented in Table 5.6 (b) to Table 5.6 (f). It is noticeable that no result is obtained for output Y4 (transverse cracking) in CMN test. Only two input variable are obtained in CL result. They are X16 (PG grade for top AC layer) and X12 (Climatic Zones). But for SI test total eight input variable have obtained with significant p value. Maximum number (14) of input variable has obtained for output variable Y6 (Total rut) in CMN test result which is shown in Table 5.6 (f).

5.4.2 Regression Analysis

Regression analysis provides an algebraic representation of the relationships between y and one or more of the x_j's. In this step Regression (REG) and Quadratic Regression (QREG) test have been performed. REG test is performed by fitting simple linear regression of the y on x_j. The methodology is described in Chapter 2. P value is obtained from this test for all input variables and ranked according to the corresponding p-value same as previous section. The QREG test is done by performing a quadratic regression of y on x_j's by creating multiple regression models. P value is also obtained by testing the null model for significance. Detailed result for both of these test are shown in Table 5.7(a) to Table 5.7(e). In Table 5.7(a), results are obtained for the output variable Y1 (terminal IRI). In this table, for both REG and QREG ranking among the input variables are almost same for first nine. Rest of the inputs is almost similar with little bit difference in p-value. For output variable Y2 (Longitudinal cracking), both test provided the same result for top six input variable in the ranking list which is shown in Table 5.7(b). Similar pattern is also observed for output variable Y3 (Alligator cracking). In Table 5.7 (d), for Y4 (Transverse cracking) REG test has not return any result with significant p-value. For QREG test, only one input (X28, plastic limit) is obtained with p-value 0.0301. The same input variable ranked top in REG result with p-value 0.0927. In this case, both tests give the same ranking list but p-value is different in both tests for same input variable. Table 5.7(e) presents the ranking list for AC rut. For both of the test provided the same ranking list for top ranked inputs. Same result is also observed for output variable Y6 (total rut) which is presented in Table 5.7 (f).

5.4.3 Flexible Grid Free Tests

For detailed sensitivity analysis, flexible grid free tests are performed in this step. These tests are Rank Correlation Coefficient test (RCC Test) and Squared Rank Differences Test (SRD). Details of these test methodology are described in Chapter 2. The rank correlation coefficient (RCC) test is based on the rank (or Spearman) correlation coefficient. The Squared Rank Differences (SRD) Test is effective at identifying linear and very general nonlinear patterns in analysis results. Both of these tests do not involve the specification of a grid. In addition to these two tests, combined statistical test (SRD/RCC) is performed in this step which can perform better than either test alone. P value also obtained by testing the null model for significance and ranked according to corresponding p-values as mentioned in the previous sections. Summary of these three test results are given in Table 5.8(a) to Table 5.8 (f).

It is noticeable that for every output variable, RCC test gives the largest set of important input variables compare to SRD and SRD/RCC test. For all three tests provide almost the same input ranking for each output variable. These test results also has similarity with the other test done in the previous sections. For output variable Y4 (Transverse Cracking), combined statistical test SRD/RCC did not provide any result which is shown in Table 5.8 (d). Results of SRD/RCC tests are more reliable because this test is able to identify nonlinear effect during the analysis, which is not possible with regression tests.

5.4.4 Summary

Table 5.8 (g) represents the total summary of all scatter plot test. In this table, the most important factors (zero p-value) are listed for all output variables (Y1, Y2…Y6).

For model Y1 (terminal IRI), X1 (AADTT) and X4 (Percent of Trucks in Design Lane) is common for all test. So, it can be said that these two variables are most important factor for Y1 without any doubt. X13 (top AC layer thickness), X18 (bottom AC layer Thickness), X26 (subgrade modulus) are obtained in most of the tests, except one or two. X27 or subgrade modulus is obtained only in two tests.

For Y2 (longitudinal Cracking) X18 is found in all test result. X1 and X4 are also obtained except one test result each. Among all 8 test, X25 (base modulus) is obtained in 6 test result. Both X27(subgrade modulus) and X17 (percent air void of top AC layer) are obtained in four test result. X24 (type of base material) and X13 (top AC layer thickness) are obtained but not very common like other variables obtained for Y2.

For Y3 or alligator cracking two input variables are common for all test result. They are X18 and X4 which can be said as vary important factor for alligator cracking. X1 is also common for all test except SRD test. X22 (percent air void of bottom AC layer) and X13 (top AC layer thickness) are common for six test result except SI and SRD test. X1, X22 and X13 are also important for Y3. Without these, another variable is obtained for Y3 which is X25 (Base modulus) which is captured by two test results. For Y4 or transverse cracking no variable is obtained with zero p values except SI test. For SI test, total five input variables are found with zero p values. Among them, two are X14 and X19 (aggregate gradation of top and bottom AC layer). Superpave binder grade of both layers (X16 and x21) are also captured in this test. So, an idea can be made on this test that mix properties are important for transverse cracking. The remaining variable is X2 or number of lanes in design direction is obtained in this test result with zero p-value.

For Y5 or AC rut, excellent result is obtained from scatter plot test result. X1 (AADTT) and X4 (Percent of Trucks in Design Lane) can be categorized as most important factor as they are attained in all test result. X10 (tire pressure), X18 (bottom AC layer thickness) and X8 (traffic growth factor) are important because they are captured in almost of the cases. In case of model Y6 or total rut, the results are common for all test. Like AC rut, most important factors are X1 and X4 as they are obtained for all tests. X18, X27 and X10 can be categorized as important as they are not common for all cases but almost every of them. X26 (material type of subgrade) and X13 (top Ac layer thickness) should be part of attention as they are also captured in one test result individually for total rut.

5.5 Ranking of Inputs based on Sensitivity Indices

In this section, calculation of sensitivity is performed using Stepwise Linear and Rank regression methods. To avoid the problem of nonlinearity, these two tests are chosen.

Standardized Regression Coefficient (SRC) and Partial Correlation Coefficient (PCC) of the variables are used here to measure sensitivity of these models. It is difficult to fit a nonparametric regression model with a large number of input variables. To solve this issue, stepwise variable selection is used for this regression models. An example is showed in Appendix B and C for both type of regression calculation. P value provides the criterion for assessing the importance of input variables. Number of bootstrap is 1000 for each model.

5.5.1 Ranking of Inputs by Linear Regression

In this method, the relationship of an output variable and one or more input variables are determined. Results of the statistical analysis of the regression models are presented in Table 5.9 (a) to Table 5.9 (f). The corresponding R^2 value of each model is also presented as a note to each of the table. This value indicates the proportion of uncertainty of model is accounted. An R^2 value close to zero indicates that the regression model is not very successful to account all the uncertainties in the model. Conversely, an R^2 value tends to one means, almost of the uncertainties is considered in the model.

<u>Output Y1 (Terminal IRI)</u>

Table 5.9 (a) presents the model summary of output variable Y1. The R^2 of this model is 0.61. This is a not a very good model because only 60 percent uncertainties are captured in this model. Among 30 input variables, this model is summarized with 16 input variables by following stepwise addition/deletion. Total model summary is given as note of the table. R^2, SRC, PCC and p value is determined for all these 16 input variables, which are described in this table. For all variables in each row, R^2 value for regression

model is calculated and shown in the third column in cumulative terms. In the next column to this, increment of R^2 is presented which the individual R^2 value for each input variable is. The highest value is obtained for X18 (second AC layer thickness) is 0.164. It means that 16.4% of the variance is explained by this input only. The next R^2 value (0.326) tells that 32.6 % of the variance is explained by both X18 and X1 (AADTT). X1 itself explains 16% uncertainties of the model. Then X4 (percent of trucks in design lane) explains 12% of the uncertainties. Both X13 (top AC layer thickness) and X26 (Subgrade Material Type) has captured 3% of uncertainties individually. Rest of the input variables has increment R^2 value either 2% or 0%. Therefore, it can be said that first three parameters are very important as they have explained at least 10% of the variance and altogether accounted almost half of the variance. The next five parameters (X13, X26, X27, X30 and X27) are somewhat important as they explained at least 2% of the variance and altogether 10% of the variance. Rest of the parameters is not very important because they explain 1% or less of the variance individually. In addition to this, they altogether explained less that 5% of the variance.

SRC provides the measure of importance of the variables. The SRC sign represent whether the parameter has a positive or negative influence on the output. The highest SRC value obtained for X18 and X1, which are -0.392 and 0.397 respectively. This means that, model Y1 will increase if X1 increases and vice versa. The negative sign means that if X18 increases then Y1 will decrease and vice versa. Another variable X4 (percent of trucks in design lane) has SRC value 0.336 which is almost close to X18 and X1. It has also the same positive effect like X1. The impact of X1 is approximately 18% larger than the impact of X4 (i.e., (0.397-0.336)/0.336=0.182). In this table, the lowest positive SRC value is obtained for X21 (Superpave Binder grade of AC 2nd Layer) and the value is 0.054. The impact of X1 is 600% larger then X21.

PCC^2 value is also provided in this table in a separate column. Usually PCC works out the same as SRC. The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y1. The confidence interval column given here, helps testing the stability of the result. So for X18, the estimated value for PCC^2 is 0.277, but 95% of the time, the true value of PCC^2 would be between 0.222 and 0.332. However, for X1, calculated PCC^2 is 0.384 but 95% of the time, the true value of PCC^2 would be between 0.0183 to 0.413.

In the last column of this table, p value is provided for all these 16 input variables. These p values provide an indication of the relationship between the input and output variable in which the underlying assumption is satisfied. If the p-value is zero then this risk is unlikely and it can be ignored. In this model, first seven input variables have almost zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on Y1. For instance, the relation between the output and X3 has 1.2% of chance of being spurious, which seems small. Usually 5% or more than 5% is considered high enough to screen out a parameter. Therefore, X24, X29 and X21 should take care in this model.

<u>Output Y2 (Longitudinal Cracking)</u>

Table 5.9 (b) presents the model summary of output variable Y2. In this model, the total R2 is about 0.6, which means that only 60% of the variance is explained, which is not a lot: other methods may be more appropriate. Among 30 input variables, this model is

summarized with 11 input variables by following stepwise addition/deletion. The highest value is obtained for X18 (second AC layer thickness) is 0.311. It means that 31% of the variance is explained by this input only. The next R^2 value (0.383) tells that 39 % of the variance is explained by both X18 and X4 (AADTT). X4 itself explains 7% uncertainties of the model. X1 (AADTT) has almost same R^2 (6%). Next X24 (Base Material type), X17 (percent air void of top AC layer) and X25 (Base modulus) has captured 3% or more of uncertainties individually. Rest of the input variables has increment R^2 value either 2% or 0%. Therefore, it can be said that first parameter is very important as itself explained they have explained more than half of the variance. The next two parameters are important as they have explained at least 5% of the variance and altogether accounted 13% of the variance. The next three parameters (X24, X17 and X25) are somewhat important as they explained at least 2% of the variance and altogether 10% of the variance. Rest of the parameters is not very important because they explain 1% or less of the variance individually. In addition to this, they altogether explained less that 5% of the variance.

The highest SRC value obtained for X18 that is -0.547. This means that, X18 has a negative influence on model Y2. Y2 will increase if X18 decreases and vice versa. X4 and X1 has positive influence on Y2. It means that if the value of these input variable increases, then Y2 value will increase also. X24 (base material type) has also positive influence on Y2 which means that for some particular base material longitudinal cracking can occur. The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y2.

For X18, the estimated value for PCC^2 is 0.424, but 95% of the time; the true value of PCC^2 would be between 0.382 and 0.487. However, for X4, calculated PCC^2 is 0.134 but 95% of the time, the true value of PCC^2 would be between 0.097 to 0.188. In the last column of this table, p value is provided for all these 11 input variables. In this model, first eight input variables have almost zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on Y2 without any doubt. For instance, the relation between the output and X15 or the output and X23 has 2% of chance of being false, which seems very small. X3 should be taken care in this model.

Output Variable Y3 (Alligator Cracking)

Table 5.9 (c) presents the model summary of output variable Y3 (Alligator Cracking). The R^2 of this model is 51%, which represents that it is not a good model to capture the uncertainties. Other methods may be more appropriate in this case. Among 30 input variables, this model is summarized with 15 input variables by following stepwise addition/deletion. Total model summary is given as note of the table. R^2, SRC, PCC and p value is determined for all these 15 input variables, which are described in this table. For all variables in each row, R^2 value for regression model is calculated and shown in the third column in cumulative terms. The highest value is obtained for X18 (second AC layer thickness) is 0.262. It means that 26% of the variance is explained by this input only. The next R^2 value (0.330) tells that 33 % of the variance is explained by both X18 and X1 (AADTT). X1 itself explains 7% uncertainties of the model. X4 (percent of trucks in design lane) explains 5% of the uncertainties. X22 (percent air void of 2nd AC layer) captured 4% of uncertainties. X13 (top AC layer thickness) has captured 3% of uncertainties. Rest of the input variables has increment R^2 value either 2% or 0%.

The first parameter, X18 (second AC layer thickness) is very important as it has explained 26% of the variance and altogether accounted almost half of the variance. The next four parameters (X1, X4, X13 and X22) are important as they explained around 20% of the variance altogether. These five parameters (X25 X24, X12, X27 and X3) are somewhat important as they explained altogether 6% of the variance. Rest of the parameters is not important because they altogether explained 0% of the variance.

The highest SRC value obtained for X18 which is -0.491. This means that, model Y3 will increase if X18 decreases. X1 and X4 have almost the same SRC value of same type. Model Y3 will increase if any of these increases and vice versa. X22 and X13 have the same SRC value but the influence types are opposite. It means that if X22 increase then Y3 will increase. The same magnitude of Y3 will decrease if X13 increases. The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y3. The confidence interval column given here, helps testing the stability of the result. So for X18, the estimated value for PCC^2 is 0.326, but 95% of the time, the true value of PCC^2 would be between 0.271 and 0.415. However, for X1, calculated PCC^2 is 0.121 but 95% of the time, the true value of PCC^2 would be between 0.080 to 0.180.

In the last column of this table, p value is provided for all these input variables. In this model, first five input variables have almost zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on

Y3. The relation between the output and X24 has 2% of chance of being spurious, which seems small. In this model, total eight input variables have p value greater than 5%, which is high enough. Therefore, this method is not good enough for Y3.

Output Y4 (Transverse Cracking)

Table 5.9 (d) represents the model summary of Y4 (transverse cracking). In this model, the total R^2 is about 0.005, which means that only 0.5% of the variance is explained, which is very small. It indicates that, regression method is not applicable for this method. Other methods may be more appropriate. Only one input variable is identified in this model, which is X24 (base material type). Total 0.3% uncertainties is explained. The SRC value for this input variable is 0.052. it means that base material type has a positive influence on transverse cracking. The p value is 0.164 that also indicates that this model should be done by any other method.

Output Y5 (AC Rut)

Table 5.9 (e) presents the model summary of output variable Y5. The R^2 of this model is 0.86. This is a very good model because almost 90 percent uncertainties are captured in this model. Among 30 input variables, this model is summarized with 18 input variables by following stepwise addition/deletion. Total model summary is given as note of the table. R^2, SRC, PCC and p value is determined for all these 18 input variables, which are described in this table.

The highest value is obtained for X1 (AADTT) is 0.364. It means that 36.4% of the variance is explained by this input only. The next R^2 value (0.611) tells that 61.1 % of the variance is explained by both X1 and X4 (percent of trucks in design lane). X4 itself explains 25% uncertainties of the model. Then X10 (tire pressure) explains 9% of the uncertainties. These three input variables altogether explain 70% of the variance. Both X18 (second AC layer thickness) and X8 (traffic growth factor) has captured 4% and 3% of uncertainties respectively. Rest of the input variables has increment R^2 value either 2% or 0%. Therefore, it can be said that first two parameters are very important as they have explained at least 25% of the variance and altogether accounted almost 70% of the variance. Then X10 is important as itself explained around 10 % of the variance. The other parameters (X18, X8, X12 and x13) are somewhat important as they explained at least 2% of the variance and altogether 11% of the variance. Rest of the parameters is not very important because they explain 1% or less of the variance individually. In addition to this, they altogether explained around 5% of the variance.

SRC provides the measure of importance of the variables. The highest SRC value obtained for X1 and the value is 0.552. This positive value means that if X1 increases then tY5 will increase also. If X1 decreases, then Y5 will show less value. X4 has almost same value and influence on Y5. That means Y5 will increase as X4 increases and vice versa. X10 has also the same positive effect like X1 and X4, which is in third place among the list. The impact of X1 is approximately 10% larger than the impact of X4 (i.e., (0.552-0.502)/0.502=0.182). The impact of X1 is 86% larger then X10.

The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs working in this model Y5. For X1, the estimated value for PCC^2 is 0.683, but 95% of the time; the true value of PCC^2 would be between 0.649 and 0.726. However, for X4, calculated PCC^2 is 0.637 but 95% of the time, the true value of PCC^2 would be between 0.602 to 0.690.

In the last column of this table, p value is provided for all these input variables. These p values provide an indication of the relationship between the input and output variable. In this model, first thirteen input variables have almost zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on Y5. The relation between the output and X20 has 1.3% of chance of being spurious, which seems small. No parameter is showing more than 2% of p value. So, overall this is a very good model for output variable Y5.

Output Y6 (Total Rut)

Model Y6 is represented in Table 5.9 (f). The R^2 of this model is 0.847. This is a very good model because 85 percent uncertainties are captured in this model. Among 30 input variables, this model is summarized with 12 input variables by following stepwise addition/deletion. Total model summary is given as note of the table. R^2, SRC, PCC and p value is determined for all these 12 input variables, which are described in this table. The highest value is obtained for X1 (AADTT) is 0.302. It means that 30% of the variance is explained by this input only. The next R^2 value is obtained by X4(percent of trucks in design lane). X4 explains 23% uncertainties of the model. The R^2 value 0.527 tells that around 53 % of the variance is explained by both X1 and X4. Then X18 (second AC layer thickness) explains 10% of the uncertainties. These three input variable altogether explain 62.4% of the variance. The next three parameters X27 (Subgrade Modulus), X10 (Tire pressure) and X30 (Optimum gravimetric water content (%)) have the same the same R^2 value (4% each). These three altogether explain 12% of the variance. Rest of the input variables has increment R2 value either 2% or 0%.

Therefore, it can be said that first two parameters are very important as they have explained at least 10% of the variance and altogether accounted 60% of the variance. The next parameter X18 is important as it explains more than 10% of the variance. The next three parameters (X27, X10 and X30) are important as they explained at least 4% of the variance and altogether 12% of the variance. Rest of the parameters is not very important because they explain 2% or less of the variance individually. In addition to this, they altogether explained less than 10% of the variance.

The highest SRC value obtained for X1. This value is positive 0.524. This means that, model Y6 will increase if X1 increases and vice versa. Another variable X4 (percent of trucks in design lane) has SRC value 0.462 which is almost close to X1. It has also the same positive effect like X1. The impact of X1 is approximately 13% larger than the impact of X4 (i.e., (0.524-0.462)/0.462). In this table, the lowest positive SRC value is obtained for X22 (percent air void of AC 2nd Layer) and the value is 0.048. The impact of X1 is 1000% larger then X22.

The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y6. The confidence interval column given here, helps testing the stability of the result. So for X1, the estimated value for PCC^2 is 0.630, but 95% of the time, the true value of PCC^2 would be between 0.557 and 0.694. However, for X4, calculated PCC^2 is 0.568 but 95% of the time, the true value of PCC^2 would be between 0.488 to 0.643.

In the last column of this table, p value is provided for all these 12 input variables. If the p-value is zero then this risk is unlikely and it can be ignored. In this model, first thirteen input variables have almost zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on Y6. For instance, the relation between the output and X3 has 1.2% of chance of being spurious, which seems small. Usually 5% or more than 5% is considered high enough to screen out a parameter. Therefore, X22, and X16 should be taken care in this model.

5.5.2 Ranking of Inputs by Rank Regression

Results of the statistical analysis of the rank regression method are presented in Table 5.10 (a) to Table 5.10 (f). The corresponding R^2 value of each model is given as a note to each of the table. This value indicates the proportion of uncertainty of model is accounted. Rank regression method provides a good R^2 value for all models compare to linear regression method.

Output Y1 (Terminal IRI)

Table 5.10 (a) presents the model summary of output variable Y1 (Terminal IRI). The R^2 of this model is 0.854. This is a very good model because about 90 percent uncertainties are captured in this model. Among 30 input variables, this model is summarized with 20 input variables by following stepwise addition/deletion. Total model summary is given as note of the table. R^2, SRC, PCC, CI and p value are determined as summary result of rank regression method, which are described in this table. In the first and second column of the table, the input variables and their explanation are given. R^2 value for regression model is calculated and shown in the third column in cumulative terms. In the next column to this, increment of R^2 is presented which the individual R^2 value for each input variable.

For rank regression, R^2 value is very informative. The highest R^2value is obtained for input variable X1 (AADTT) and the value is 0.267. It means that 26.7% of the variance is explained by this input only. The second highest R^2 value is obtained by X4 (percent of trucks in design lane) and the value is 0.226. about 23% of the variance captured by X4. The R^2 value (0.493) tells that 49% of the variance is explained by both X1 and X4. Input variable X18 (2nd AC layer thickness) has captured 14% uncertainties by itself. These three input variable mentioned above have captured 63.5% of uncertainties altogether among all the input variables used in these model. Then X26 (type of subgrade material) explains 5% of the uncertainties. Both X27 (subgrade modulus), X10 (tire pressure) and X30 (optimum gravimetric water content) has captured 3% of uncertainties individually. Rest of the input variables has increment R^2 value either 2% or 0%.

From the R^2 value discussed above, it can be said that first two parameters (X1 and X4) are very important as they have explained at least 20% of the variance and altogether accounted almost half of the variance. Next parameter X18 is important as itself explained at least 10% of the variance. The next parameters (X26, X27, X10 and X30) are somewhat important as they explained at least 2% of the variance and altogether 14% of the variance. Rest of the parameters is not very important because they explain less than 10% of the variance altogether.

According to SRC value, importance of the variables can be measured. The SRC sign represent whether the parameter has a positive or negative influence on the output. The highest SRC value obtained for X1 and X4, which are 0.503 and 0.465 respectively. This means that, model Y1 will increase if X1 increases and vice versa. X4 has also positive influence like X1 on model Y1. X18 has negative SRC value which is -0.373. The negative sign means that if X18 increases then Y1 will decrease and vice versa. Another variable X26 has SRC value 0.201, which has also the same positive effect like X1 and X4. X27, X10 and X30 has the same R2 value individually but they have different SRC value with different sign. Among these three, X27 and X30 has negative influence on Y1. That means if any of these two variable increase then y1 will decrease. X10 has positive influence that means Y1 will increase or decrease if X10 increase or decreases.

The impact of X1 is approximately 8% larger than the impact of X4 (i.e., (0.503-0.465)/0.465=0.082). In this table, the lowest positive SRC value is obtained for X24 (base material type) and the value is 0.059. The impact of X1 is 750% larger then X24.

PCC^2 value is also provided in this table in a separate column. The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y1. The confidence interval column given here, helps testing the stability of the result. So for X1, the estimated value for PCC^2 is 0.604, but 95% of the time, the true value of PCC^2 would be between 0.551 and 0.653. However, for X4, calculated PCC^2 is 0.565 but 95% of the time, the true value of PCC^2 would be between 0.505 to 0.617.

In the last column of this table, p value is provided for all these input variables used in this regression model. If the p-value is zero then this risk is unlikely and it can be ignored. In this model, first ten input variables have almost zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on Y1. For instance, the relation between the output and X22 has 1.1% of chance of being spurious, which seems small. Usually 5% or more than 5% is considered high enough to screen out a parameter. Therefore, X12 and X24 need to be taken care in this model.

Output Y2 (Longitudinal Cracking)

Rank Regression analysis has done for Model Y2 (Longitudinal Cracking) and presented in Table 5.10 (b). This is a very good model because the R^2 value of this model is 0.843. About 90 percent uncertainties are captured in this model so this method is appropriate for this model. Among 30 input variables, this model is summarized with 18 input variables by following stepwise addition/deletion. Total model summary is given as note of the table. R^2, SRC, PCC, CI and p value are determined as summary result of rank regression method, which are described in this table. In the first and second column of the table, the input variables and their explanation are given. R^2 value for all input variables used in this model Y2 is calculated and shown in the third column in cumulative terms. In the next column to this, increment of R^2 is presented which the individual R^2 value for each input variable.

The highest R^2 value is obtained for X18 (second AC layer thickness) is 0.485. It means that 49% of the variance is explained by this input only. From this R^2 value, it can be said this parameter (X18) is very important as itself explained almost half of the variance. SRC value for this input variable is obtained 0.680, which is negative. It means that, if X18 decreases then model Y2 will increase. If Y2 need to be decrease then X18 needs to be increased. The PCC value obtained for this variable is 0.727. this is the highest value among all other input variables. Therefore, it is decided that this is the most important factor for this model. However, the calculated PCC value for this input is 0.727, but 95% of the time this value will be within 0.680 to 0.770.

In this table, three input variables can be categorized as slightly less important. These are X1 (AADTT), X4 ((percent of trucks in design lane) and X27(subgrade modulus). R^2 value obtained for these three input variables are almost close to each other (7%, 6% and 6% respectively). these three input variables explain at least 5% of the variance individually and altogether around 20%. SRC values of these variables are also close to each other. From SRC value, it can be said that these all three have positive influence on model Y2.Y2 will increase if any of these value increases and vice versa.

Total four input variables can be categorized as somewhat important for model Y2. They explain at least 2% of the variance and altogether 13% of the variance). They are X24, X25, X13 and X17. Among these, X24 and X25 represent base material type and base modulus. X24 (base material type) has positive influence on Y2 but X25 (base modulus) has negative effect. X13 and X17 indicate top AC layer properties, which are thickness and percent air void. X13 and X17 have same SRC value but of opposite sign. If AC layer thickness or X13 increases then Y2 or long crack will be reduced. Again, Y2 will increase if percent air void or X17 increases. Rest of the parameters mentioned in the model is not important because they explain less than 10% of the variance altogether.

The impact of X18 (thickness of 2nd AC layer) is approximately 280% larger than the impact of X13 (thickness of top AC layer) (i.e., (0.680-0.175)/0.175=2.8) which seems interesting in this result. The impact of X27 (subgrade modulus) and the impact of X25 (base modulus) are opposite which is also remarkable.

PCC^2 value is also provided in this table in a separate column. The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y2. The confidence interval column given here, helps testing the stability of the result. So for the most important parameter X18, the estimated value for PCC^2 is 0.727, but 95% of the time, the true value of PCC^2 would be between 0.680 and 0.770.

In the last column of this table, p value is provided for all these input variables used in this regression model. In this model, first twelve input variables have almost zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on Y2. Usually 5% or more than 5% is considered high enough to screen out a parameter. Therefore, X16, X19 and X11 need to be screen out from this model.

Output Y3 (Alligator Cracking)

Table 5.10 (c) presents the model summary of output variable Y3 (alligator cracking). This can be said as an excellent model because the R^2 of this model is 0.883. About 90 percent uncertainties are captured in this model. this method is appropriate for modeling alligator crack. This model is summarized with 16 input variables by following stepwise addition/deletion among 30 input variables. Total model summary is given as note of the table. R^2, SRC, PCC and p value is determined for all these 16 input variables, which are described in this table. For all variables in each row, R^2 value for regression model is calculated and shown in the third column in cumulative terms. In the next column to this, increment of R^2 is presented which is the individual R^2 value for each input variable.

The highest value is obtained for X18 (second AC layer thickness) is 0.466. It means that 47% of the variance is explained by this input only. The next R^2 value (0.610) tells that 61 % of the variance is explained by both X18 and X4 (percent of trucks in design lane). The R^2 value (0.736) tells that 74 % of the variance is explained by both X18, X4 and X1 (AADTT). X4 itself explains 14% uncertainties of the model. Then X1 explains 13% of the uncertainties. Both X22 (percent air void of second AC layer) and X13 (top AC layer thickness) has captured 5% and 3% of uncertainties individually. Rest of the input variables has increment R^2 value either 1% or 0%. Therefore, the most important factor for model Y3 is X18. The SRC value for this parameter is -0.660, which helps to understand the influence type of this factor. X18 has negative effect on Y3. It means that if Y3 value needs to be minimized, than at first X18 value needs to be increase and vice versa. X18 also has highest PCC value among this table, which also helps to categorize this input as most important. For X18, the estimated value for PCC^2 is 0.779, but 95% of the time; the true value of PCC^2 would be between 0.732 and 0.821.

Both X4 and X1 can be considered as important factor for the model Y3 because they explain at least 10% of the variance. These two parameters have also same type of effect with same SRC value. This means that Y3 will increase if any of these parameter value increases. The next two parameters (X22 and X13) are somewhat important as they explained at least 2% of the variance and altogether 8% of the variance. X22 has negative effect on Y3 with SRC value 0.291. X13 has positive effect on Y3 with SRC value 0.187. Rest of the parameters is not very important because they explain 1% or less of the variance individually. In addition to this, they altogether explained less that 10% of the variance. The impact of X18 (second AC layer thickness) is approximately 300% larger than the impact of X13 (top AC layer thickness) (i.e., (0.660-0.168)/0.168=2.92). PCC^2 value is also provided in this table in a separate column. The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y3.

In the last column of this table, p value is provided for all these input variables. In this model, input variables have almost zero p value except X26 and X12. Therefore, it can be said that all the inputs without these two have significant influence (nonzero regression coefficients) on the output model Y3. For instance, the relation between the output and X26 has 2.6% of chance of being spurious, which seems small. Usually 5% or more than 5% is considered high enough to screen out a parameter. Therefore, X12 should be screen out from this model.

<u>Output Y4 (Transverse Cracking)</u>

Table 5.10 (d) presents the model summary of output variable Y4 (transverse cracking). The R^2 of this model is 0.067. This is a not a very good model because only 7 percent uncertainties are captured in this model. Therefore, any other method may be appropriate for this model. Among 30 input variables, this model is summarized with 9 input variables by following stepwise addition/deletion. Total model summary is given as note of the table. R^2, SRC, PCC and p value is determined for all these input variables, which are described in this table.

For all variables in each row, R^2 value for regression model is calculated and shown in the third column in cumulative terms. In the next column to this, increment of R^2 is presented which the individual R^2 value for each input variable is. The highest value is obtained for X26 (Superpave binder grade of top AC layer) is 0.015. It means that 2% of the variance is explained by this input only. The next R^2 value (0.021) tells that 2.1 % of the variance is explained by both X16 and X12 (Climatic zones). X12 itself explains 1% uncertainties of the model. Then X24 (base material type) explains 1% of the uncertainties. Rest of the parameters is not very important because they explain 1% or less of the variance individually. In addition to this, they altogether explained less that 5% of the variance.

SRC provides the measure of importance of the variables. The highest SRC value obtained for X16 which is 0.027. This means that, model Y4 will increase if X16 increases and vice versa. The next SRC value obtained for X12 and the value is -0.016. The negative sign means that X12 has negative effect on model Y3. Another variable X24 (base material type) has SRC value 0.015 which has also the same positive effect like X16. The impact of X16 is approximately 80% larger than the impact of X24 (i.e., (0.027-0.015)/0.015=0.8).

The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y4. The confidence interval column given here, helps testing the stability of the result. So for X16, the estimated value for PCC^2 is 0.015, but 95% of the time, the true value of PCC^2 would be between 0.000 and 0.035. However, for X12, calculated PCC^2 is 0.006 but 95% of the time, the true value of PCC^2 would be between 0 to 0.027. In the last column of this table, p value is provided for all input variables. If the p-value is zero then risk is unlikely and it can be ignored. Usually 5% or more than 5% is considered high enough to screen out a parameter. In this model, all input variable has p value more than 5% which means other methods may be more appropriate.

Output Y5 (AC Rut)

Table 5.10 (e) presents the model summary of output variable Y5 (AC rut). The R^2 of this model is 0.88, which means almost 90% of uncertainties are captured in this model. Therefore, this is a very good model and this method is appropriate for this model, too. Among 30 input variables, this model is summarized with 20 input variables by following stepwise addition/deletion. Total model summary is given as note of the table. R^2, SRC, PCC and p value is determined for all these input variables, which are described in this table. In the first two column of this table, name and explanation of these input variables are given. R^2 value for this regression model is calculated and shown in the third column in cumulative terms. In the next column to this, increment of R^2 is given which is the individual R^2 value for each input variable. In this model the first two input variable can be categorized as most important factor because they explain at least 10% of the variance and altogether more than half of the variance. Among them, one is X1 (AADTT). The highest R^2 value in this model is obtained for X1 and the value is 0.389. It means that 39% of the variance is explained by this input only. Another most important factor for this model is X4 (percent of trucks in design lane). X4 explains 26% of the total uncertainties. The R^2 value (0.645) tells that 65 % of the variance is explained by both X1 and X4. Then X10 (tire pressure) explains 8% of the uncertainties. Therefore it can be categorized as slightly less important as less than 10% of the variance are captured by this input. Both X18 (second AC layer thickness) and X8 (traffic growth factor) has captured 4% and 3% of uncertainties individually. These two parameters are somewhat important as they explained at least 2% of the variance and altogether 7% of the variance. Rest of the input variables has increment R^2 value either 2% or less. They are not very important because they explain 2% or less of the variance individually. In addition to this, they altogether explained less that 10% of the variance.

The SRC number and sign gives the importance and influence type on the output. The highest SRC value obtained for X1 which is 0.573. This means that, model Y5 will increase if X1 increases and vice versa. X4 has also SRC value 0.516 which is almost close to X1. It has the same positive effect like X1. X10 has SRC value 0.29 and has the same positive effect like X1 and X4.X18 has negative SRC value of 0.188. The negative sign means that if X18 increases then Y5 will decrease and vice versa. The impact of X1 is approximately 11% larger than the impact of X4 (i.e., (0.573-0.516)/0.516=0.11). In this table, the lowest positive SRC value is obtained for X22 (percent air void of AC 2nd Layer) and the value is 0.059. The impact of X1 is 870% larger then X22.

Usually PCC works out the same as SRC. The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y5. The confidence interval column given here, helps testing the stability of the result. So for X1, the estimated value for PCC2 is 0.724, but 95% of the time, the true value of PCC2 would be between 0.687 and 0.757. However, for X4, calculated PCC2 is 0.678 but 95% of the time, the true value of PCC2 would be between 0.626 to 0.719. In the last column of this table, p value is provided for all these input variables. These p values provide an indication of the relationship between the input and output variable. If the p-value is zero then this risk is unlikely and it can be ignored. In this model, first eleven input variables have zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on Y1. For instance, the relation between the output and X6, X27 and X22 have p value within 0.007 to 0.02. Usually 5% or more than 5% is considered high enough to screen out a parameter. Therefore, the model is overall ok and this regression method is appropriate for this model.

<u>Output Y6 (Total Rut)</u>

Table 5.10 (f) presents the model summary of output variable Y6 for total rut. The R^2 of this model is 0.857. This is a very good model because almost 90 percent uncertainties are captured in this model. Among 30 input variables, this model is summarized with 20 input variables by following stepwise addition/deletion which is given as a note of the table. R^2, SRC, PCC and p value is determined for all these input variables, which are described in this table. For all variables in each row, R^2 value for regression model is calculated and shown in the third column in cumulative terms. In the next column to this, increment of R^2 is presented which the individual R^2 value for each input variable is.

The highest value is obtained for X1 (AADTT) is 0.317. It means that 32% of the variance is explained by this input only. The next R^2 value (0.554) tells that 55.5 % of the variance is explained by both X1 and X4 (percent of trucks in design lane).X4 itself explains 24% uncertainties of the model. Then X18 (AC layer thickness of 2nd layer) explains 8% of the uncertainties. The next three parameters X10 (tire pressure), X27 (subgrade modulus) and X30 (optimum gravimetric water content) captured 4% of uncertainties individually. Rest of the input variables has increment R^2 value either 3% or less. Therefore, it can be said that first two parameters are very important as they have explained at least 10% of the variance and altogether accounted almost half of the variance. The next parameters (X18) is important as it explained 8% of the variance. The next three parameters are somewhat important (they explain at least 4% of the variance and altogether 12% of the variance). Rest of the parameters is not very important because they explain 2% or less of the variance individually. In addition to this, they altogether explained 10% of the variance.

SRC provides the measure of importance of the variables and type of the influence on the output. The highest SRC value obtained for X1 and X4, which are 0.537 and 0.480 respectively. This means that, model Y6 will increase if X1 increases and vice versa. The same condition also applies for X4. Another variable X18 has SRC value -0.288 which has opposite effect of X1 and X4. The impact of X1 is approximately 12% larger than the impact of X4 (i.e., (0.537-0.480)/0.4800=0.12). In this table, the lowest positive SRC value is obtained for X15 (effective binder content of top AC layer) and the value is 0.052. The impact of X1 is 900% larger then X15.

PCC^2 value is also provided in this table in a separate column. The ranking of importance between SRC and PCC is the same here, which means that there is no strong correlation between the inputs is working in this model Y6. The confidence interval column given here, helps testing the stability of the result. So for X1, the estimated value for PCC^2 is 0.654, but 95% of the time, the true value of PCC^2 would be between 0.600 and 0.698. However, for X4, calculated PCC^2 is 0.600 but 95% of the time, the true value of PCC^2 would be between 0.546 to 0.651. In the last column of this table, p value is provided for all these input variables. If the p-value is zero then this risk is unlikely and it can be ignored. In this model, almost all variables have zero p value. Therefore, it can be said that these inputs have significant influence (nonzero regression coefficients) on the output on Y6. Usually 5% or more than 5% is considered high enough to screen out a parameter. Therefore, X16, X21 and X15 need to be screened out from this model. Overall, this regression model is appropriate for output variable Y6.

5.5.3 Summary Result of Regression Methods

Linear and Rank regression method both have been performed for sensitivity analysis. Based on these analyses, results are summarized and presented in Table 5.11. In this table, R^2 of the models are given for both of these methods. If the total R^2 is about 0.6, which means that only 60% of the variance is explained which is not a lot. Other sensitivity analysis methods may be more appropriate for those models. If the total R^2 is about 0.8, which means that 80% of the variance is explained which means the model is very good.

For model Y1 (terminal IRI), Y2 (longitudinal cracking) and Y3 (alligator cracking) linear regression has not provide good R2 value (0.5 to 0.6). For these models, good R^2 value is obtained from rank regression method (more than 0.8). In case of model Y4 (Transverse cracking) both method failed to provide any reasonable R^2 value. Any other method needs to be applying for this model Y4. Both type of regression methods provide very good result for Y5 (permanent deformation of AC layer) and Y6 (permanent deformation of total pavement). The input ranking is almost same for both of them. It indicates that, these two models are perfect to get an idea about the input variables which have significant effect on flexible pavement performance.

The variables have been categorized in four groups based on their individual R^2 value. It is more a rule of thumb statisticians are using based on passed analysis. In order to classify the input variables in groups of importance (high importance, medium importance, low importance or not important) it is easier to determine some cut off values in the incremental R^2 reported. Usually, R^2 increment of more than 10% will be visible on a scatterplot. Between 2% and 10% they may be visible (they may sometimes require log transform values). Below, it will look like randomness. Based on this, the following discretization which seems reasonable and appropriate in the context of the analysis will be used for the remaining sections in this study.

a. If the variance in an input parameter explains at least 10% of the variance of the output of interest, then it is considered of high importance (Group A)
b. If the variance in a input parameter explains between 6% and 9% of the variance of the output of interest, then is it considered of importance (Group B)
c. If the variance in a input parameter explains between 3% and 5% of the variance of the output of interest, then is it considered of medium importance (Group C)
d. Finally if the variance of an input parameter explains less than 2% of the variance of the output of interest or if the parameter is not selected by the stepwise algorithm, it is considered of small importance (Group D)

For both of the methods, variables of group A and B has almost same variable list. But there are some difference for C and D. it can be concluded like this that, both type of regression method is able to capture the most important factor for pavement performances.

5.6 Conclusions

Sensitivity analysis are performed using different type of advanced statistical approaches. Parametric regression procedures are mainly used to measure the strength of the relationship between input and output variables. These tests are scatterplot test, linear regression, rank regression analysis. Based on these analysis results, input variables are ranked according to their significance and influence on outputs. The highly sensitive variables are listed below:

Terminal IRI:

1. Bottom AC layer Thickness
2. AADTT
3. Percent of trucks in Design Lane
4. Type of Subgrade Material
5. Top AC layer Thickness

Longitudinal Cracking

1. Bottom AC layer Thickness
2. AADTT
3. Percent of trucks in Design Lane
4. Modulus of Base Layer
5. Percent Air void of Top AC Layer

Alligator Cracking

1. Bottom AC layer Thickness
2. Percent of trucks in Design Lane
3. AADTT
4. Percent Air void of Bottom AC Layer
5. Top AC layer Thickness

Transverse Cracking

1. PG grade of Top AC layer
2. Type of Base Material
3. Aggregate gradation of Top AC layer
4. Aggregate gradation of Bottom AC layer
5. PG grade of Bottom AC layer

AC Rut

1. AADTT
2. Percent of trucks in Design Lane
3. Tire Pressure
4. Bottom AC layer Thickness
5. Traffic Growth Factor

Total Rut

1. AADTT
2. Percent of trucks in Design Lane
3. Bottom AC layer Thickness
4. Modulus of Subgrade
5. Tire Pressure

Table 5.1: Variables Identified for Detailed Sensitivity Analysis

Serial No	Category	Input Name	Variable No	Range of Inputs	Numeric Values Assigned for Input	Variable Type	Data Source
1	**TRAFFIC**	Initial two-way AADTT	**X1**	300 to 6000		Integer	LTPP
2		Number of Lanes in Design Direction	**X2**	1 to 3		Integer	LTPP
3		Percent of Trucks in Design Direction (%)	**X3**	40 to 60		Non Integer	Design Guide
4		Percent of Trucks in Design Lane (%)	**X4**	6 to 94		Non Integer	Huang, 2004
5		Operational Speed (mph)	**X5**	35 to 75		Non Integer	NMDOT
6		AADTT Distribution by Vehicle Class 9 (%)	**X6**	2 to 85		Non Integer	LTPP
7		AADTT Distribution by Vehicle Class 11 (%)	**X7**	0.1 to 7		Non Integer	LTPP
8		Traffic Growth Factor	**X8**	3 to 9		Non Integer	LTPP
9		Design Lane Width (ft)	**X9**	10 to 12		Non Integer	LTPP
10		Tire Pressure (psi)	**X10**	90 to 150		Non Integer	Design Guide
11	**CLIMATE**	Depth of Water Table (ft)	**X11**	5 to 20		Non Integer	NMDOT
12		Climatic Zones	**X12**	1 to 5	1=SouthEast 2=SouthWest 3=NorthWest 4=NorthEast 5=Central	Discrete	Design Guide

Table 5.1: Variables Identified for Detailed Sensitivity Analysis (Continued)

Serial No	Category		Input Name	Variable No	Range of Inputs	Numeric Values Assigned for Input	Variable Type	Data Source
13	STRUCTURE	Asphalt Mix 1	Layer Thickness (in)	**X13**	1.5 to 3		Non Integer	NMDOT
14			Aggregate Gradation	**X14**	1 to 2	1=SP-III 2=SP-IV	Discrete	NMDOT
15			Effective Binder Content (%)	**X15**	9 to 12		Non Integer	NMDOT
16			Superpave Binder Grade	**X16**	1 to 3	1=PG 64-22 2=PG 70-28 3=PG 76-28	Discrete	NMDOT
17			Air Voids (%)	**X17**	4 to 7		Non Integer	LTPP
18		Asphalt Mix 2	Layer Thickness (in)	**X18**	2 to 8		Non Integer	NMDOT
19			Aggregate Gradation	**X19**	1 to 3	1=SP-II 2=SP-III 3=SP-IV	Discrete	NMDOT
20			Effective Binder Content (%)	**X20**	9 to 12		Non Integer	NMDOT
21			Superpave Binder Grade	**X21**	1 to 3	1=PG 64-22 2=PG 70-28 3=PG 76-28	Discrete	NMDOT
22			Air Voids (%)	**X22**	4 to 7		Non Integer	LTPP
23		Base	Layer Thickness (in)	**X23**	6 to 10			NMDOT
24			Material Type	**X24**	1 to 5	1=Crushed Gravel 2=A-1-b 3=A-2-6 4=A-3 5=A-2-4	Discrete	LTPP
25			Modulus (psi)	**X25**	20,000 to 40, 000		Non integer	NMDOT
26		Subgrade	Material Type	**X26**	1 to 5	1=CL 2=CL-ML 3=ML 4=SM 5=SP	Discrete	LTPP
27			Modulus (psi)	**X27**	5000 to 20,000		Non integer	LTPP
28			Plastic Limit (PL)	**X28**	10 to 24		Non integer	NMDOT
29			Liquid Limit (LL)	**X29**	25 to 90		Non integer	NMDOT
30			Optimum Gravimetric Water Content (%)	**X30**	12 to 60		Non integer	NMDOT

Table 5.2: List of Outputs Variables for Detailed Sensitivity Analysis

Serial No	Output Name	Variable No
1	Terminal IRI (inch/mile)	Y1
2	Longitudinal Cracking (ft/mile)	Y2
3	Alligator Cracking (%)	Y3
4	Transverse Cracking (ft/mile)	Y4
5	Permanent Deformation (AC Only) (in)	Y5
6	Permanent Deformation (Total Pavement) (in)	Y6

Table 5.3: Example of Test Matrix of LHS Sampling for Traffic Inputs

Input Name	Initial two-way AADTT	Number of Lanes in Design Direction	Percent of Trucks in Design Direction (%)	Percent of Trucks in Design Lane (%)	Operational Speed (mph)	AADTT Distribution by Vehicle Class 9 (%)	AADTT Distribution by Vehicle Class 11 (%)	Traffic Growth Factor	Design Lane Width (ft)	Tire Pressure (psi)
Variable	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*X8*	*X9*	*X10*
Lower Limit	*300*	*1*	*40*	*6*	*35*	*2*	*0.1*	*3*	*10*	*90*
Upper Limit	*6000*	*3*	*60*	*94*	*75*	*85*	*7*	*9*	*12*	*150*
1	312	3	43.43	58.62	70.31	50.93	3.483	3.491	11.34	106.6
2	5354	1	55.4	75.22	59.56	73.87	4.504	6.295	11.67	128
3	5796	1	46.43	86.31	63.03	75.88	5.041	5.68	11.45	119.3
4	2025	2	59.86	88.66	58.05	58.33	6.813	8.913	10.19	128.5
5	2665	2	48.34	51.8	42.25	80.7	4.653	4.216	10.36	124.2
6	2389	1	42.33	39.6	50.92	74.42	3.819	7.786	10.77	92.6
7	4273	2	50.61	10.46	55.79	22.72	1.652	8.276	11.97	104.1
8	5454	1	53.11	25.71	55.42	57.57	0.99	7.805	10.68	130
9	662	2	52.59	25.22	44.13	52.64	4.967	7.941	11.47	125.6
10	330	1	56.25	30.48	65.15	39.52	6.115	4.263	10.24	146.5
11	1003	1	55.66	21.41	43.1	50.42	0.231	4.489	10.24	98.47
12	5974	1	41.13	46.24	51.5	53.37	0.168	3.148	10.76	101.5
13	512	1	44.24	57.72	49.34	42.47	2.733	5.091	10.52	133.3
14	1885	2	40.15	23.66	73.26	62.83	3.944	5.504	11.92	118.2
15	3830	3	45.34	11.96	44.33	17.34	3.064	5.272	10.66	133.1
16	1264	2	51.9	66.84	68.98	10.95	5.377	5.307	11.10	136.2
17	3857	3	45.89	13.54	60.19	46.3	0.8	7.665	10.25	132.9
18	5408	1	47.17	7.218	41.64	38.11	5.434	4.194	10.32	112.5
19	5510	3	59.52	23.15	36.99	61.78	0.471	6.405	10.13	149.3
20	3426	1	51.31	63.53	63.36	40.78	5.829	7.071	10.88	142

Note: Test Matrix is represented by the highlighted rectangular part.

Table 5.4: Summary Result of MEPDG Simulations

Variable No	Output Name	In case of Distress Value		In case of Reliability (90%)	
		Pass	Fail	Pass	Fail
Y1	Terminal IRI (inch/mile)	728	22	547	203
Y2	Longitudinal Cracking (ft/mile)	570	180	325	425
Y3	Alligator Cracking (%)	703	47	595	155
Y4	Transverse Cracking (ft/mile)	749	1	749	1
Y5	Permanent Deformation (AC Only) (in)	199	551	100	650
Y6	Permanent Deformation (Total Pavement) (in)	450	300	303	447

Table 5.5: Measurement of Correlation of Coefficient

Output/ Input	Terminal IRI (inch/mile)			Longitudinal Cracking (ft/mile)			Alligator Cracking (%)		
	Value	Type	Sign	Value	Type	Sign	Value	Type	Sign
X1	0.4037	M	+	0.2465	S	+	0.2603	S	+
X2	0.0164	N	+	0.0329	N	+	0.0243	N	+
X3	0.1209	S	+	0.0789	N	+	0.0702	N	+
X4	0.3633	M	+	0.2817	S	+	0.2473	S	+
X5	-0.0718	N	-	-0.0874	N	-	-0.0518	N	-
X6	0.0338	N	+	-0.0193	N	-	0.0085	N	+
X7	-0.0017	N	-	0.0132	N	+	0.0357	N	+
X8	0.1050	S	+	0.0335	N	+	0.0672	N	+
X9	-0.0410	N	-	0.0200	N	+	-0.0315	N	-
X10	0.1059	S	+	0.0318	N	+	0.0242	N	+
X11	0.0593	N	+	0.0848	N	+	0.0638	N	+
X12	-0.0024	N	-	0.0020	N	+	0.0292	N	+
X13	-0.1902	S	-	-0.1601	S	-	-0.1949	S	-
X14	-0.0018	N	-	0.0187	N	+	-0.0054	N	-
X15	-0.0222	N	-	-0.0999	N	-	-0.0103	N	-
X16	-0.0349	N	-	-0.0507	N	-	-0.0155	N	-
X17	0.0847	N	+	0.1910	S	+	0.0416	N	+
X18	-0.4049	M	-	-0.5581	L	-	-0.5124	L	-
X19	-0.0567	N	-	-0.0379	N	-	-0.0310	N	-
X20	0.0669	N	+	0.0289	N	+	-0.0046	N	-
X21	-0.0567	N	-	0.0545	N	+	-0.0222	N	-
X22	0.1439	S	+	-0.0013	N	-	0.2095	S	+
X23	0.0227	N	+	-0.0689	N	-	-0.0346	N	-
X24	0.0466	N	+	0.0663	N	+	0.0647	N	+
X25	-0.1531	S	-	-0.2019	S	-	-0.1861	S	-
X26	-0.1616	S	-	0.0233	N	+	-0.0615	N	-
X27	-0.1633	S	-	0.0959	N	+	-0.1064	S	-
X28	0.0083	N	+	-0.0198	N	-	0.0010	N	+
X29	0.0380	N	+	-0.0348	N	-	-0.0199	N	-
X30	-0.0797	N	-	-0.0043	N	-	-0.0008	N	-

Note:

1. *N= None, S=Small, M=Medium, L=Large, (+)=Positive, (-)=Negative*
2. *None=(0.0 to 0.09 or (-0.09 to 0.0), Small=(0.1 to 0.3) or (-0.3 to -0.1), Medium=(0.3 to 0.5) or (-0.5 to -0.03), Large=(0.5 to 1.0) or (-1.0.5 to-0.5)*

Table 5.5: Measurement of Correlation of Coefficient (Continued)

Output/ Input	Transverse Cracking (ft/mile)			Permanent Deformation (AC Only) (in)			Permanent Deformation (Total Pavement) (in)		
	Value	Type	Sign	Value	Type	Sign	Value	Type	Sign
X1	-0.0072	N	-	0.6037	L	+	0.5500	L	+
X2	0.0000	N	+	0.0216	N	+	0.0325	N	+
X3	0.0134	N	+	0.0979	N	+	0.1379	S	+
X4	0.0594	N	+	0.5094	L	+	0.4859	M	+
X5	0.0022	N	+	-0.1080	S	-	-0.1172	S	-
X6	0.0302	N	+	0.1015	S	+	0.0455	N	+
X7	-0.0532	N	-	-0.0338	N	-	-0.0426	N	-
X8	-0.0100	N	-	0.1815	S	+	0.1555	S	+
X9	0.0066	N	+	-0.0049	N	-	-0.0261	N	-
X10	0.0203	N	+	0.2977	S	+	0.1873	S	+
X11	0.0447	N	+	0.0427	N	+	0.0800	N	+
X12	0.0257	N	+	-0.1188	S	-	-0.0903	N	-
X13	0.0257	N	+	-0.1565	S	-	-0.1660	S	-
X14	0.0366	N	+	0.0409	N	+	0.0169	N	+
X15	-0.0036	N	-	0.0061	N	+	-0.0104	N	-
X16	0.0002	N	+	-0.1206	S	-	-0.0615	N	-
X17	0.0236	N	+	0.1264	S	+	0.1185	S	+
X18	0.0099	N	+	-0.2047	S	-	-0.3253	M	-
X19	0.0000	N	+	-0.0618	N	-	-0.0579	N	-
X20	-0.0438	N	-	0.1086	S	+	0.1109	S	+
X21	0.0448	N	+	-0.0963	N	-	-0.0844	N	-
X22	0.0508	N	+	0.0809	N	+	0.0784	N	+
X23	-0.0279	N	-	0.0467	N	+	0.0544	N	+
X24	0.0259	N	+	0.0187	N	+	0.0345	N	+
X25	0.0001	N	+	-0.0034	N	-	-0.0944	N	-
X26	0.0516	N	+	-0.0277	N	-	-0.1346	S	-
X27	0.0332	N	+	0.0556	N	+	-0.2207	S	-
X28	0.0614	N	+	0.0254	N	+	0.0210	N	+
X29	0.0518	N	+	-0.0177	N	-	0.0079	N	+
X30	0.0009	N	+	0.1173	S	+	-0.1421	S	-

Note:

1. *N= None, S=Small, M=Medium, L=Large, (+)=Positive, (-)=Negative*
2. *None=(0.0 to 0.09 or (-0.09 to 0.0), Small=(0.1 to 0.3) or (-0.3 to -0.1), Medium=(0.3 to 0.5) or (-0.5 to -0.03), Large=(0.5 to 1.0) or (-1.0.5 to-0.5)*

Table 5.6(a): Comparison of Statistical Tests Based on Gridding for Output Y1 (Terminal IRI)

Rank	CMN Results		CL Results		SI Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AC Layer Thickness (2nd Layer)	0.0000	AADTT	0.0000	AADTT	0.0000
2	AADTT	0.0000	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	Percent of Trucks in Design Lane (%)	0.0000	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
4	AC Layer Thickness (Top Layer)	0.0000	Subgrade Material Type	0.0000	Subgrade Material Type	0.0000
5	Subgrade Material Type	0.0001	Subgrade Modulus	0.0000	AC Layer Thickness (Top Layer)	0.0003
6	Subgrade Modulus	0.0001	AC Layer Thickness (Top Layer)	0.0002	Tire Pressure (psi)	0.0005
7	Base Modulus	0.0003	Tire Pressure (psi)	0.0005	Subgrade Modulus	0.0033
8	Air Void (%)(2nd Layer)	0.0031	Percent of Trucks in Design Direction (%)	0.0020	Traffic Growth Factor	0.0089
9	Percent of Trucks in Design Direction (%)	0.0056	Operational Speed (mph)	0.0031	Air Void (%) (Top Layer)	0.0400
10	Traffic Growth Factor	0.0234	Traffic Growth Factor	0.0032	Operational Speed (mph)	0.0400
11	Tire Pressure (psi)	0.0368	Optimum gravimetric water content (%)	0.0166	Liquid Limit	0.0495
12	Design Lane Width (ft)	0.0479				

Table 5.6(b): Comparison of Statistical Tests Based on Gridding for Output Y2 (Longitudinal Cracking)

Rank	CMN Results		CL Results		SI Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	AADTT	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	AADTT	0.0000	Percent of Trucks in Design Lane (%)	0.0000	AADTT	0.0000
4	Base Material Type	0.0000	Subgrade Modulus	0.0000	Subgrade Modulus	0.0000
5	Base Modulus	0.0000	Base Material Type	0.0000	AC Layer Thickness (Top Layer)	0.0002
6	Air Void (%)(Top Layer)	0.0000	Base Modulus	0.0000	Base Material Type	0.0002
7	AC Layer Thickness (Top Layer)	0.0005	AC Layer Thickness (Top Layer)	0.0000	Base Modulus	0.0006
8	Design Lane Width (ft)	0.0011	Air Void (%) (1st Layer)	0.0001	Design Lane Width (ft)	0.0020
9	Percent of Trucks in Design Direction (%)	0.0152	Design Lane Width (ft)	0.0094	Air Void (%)(Top Layer)	0.0080
10	Effective binder content (%) (Top AC layer)	0.0217	Operational Speed (mph)	0.0301	Traffic Growth Factor	0.0453
11			Traffic Growth Factor	0.0373	Effective binder content (%) (2nd AC Layer)	0.0462
12			Percent of Trucks in Design Direction (%)	0.0449		

Table 5.6(c): Comparison of Statistical Tests Based on Gridding for Output Y3 (Alligator Cracking)

Rank	CMN Results		CL Results		SI Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
2	AADTT	0.0000	Percent of Trucks in Design Lane (%)	0.0000	AADTT	0.0000
3	Percent of Trucks in Design Lane (%)	0.0000	AADTT	0.0000	Percent of Trucks in Design Lane (%)	0.0000
4	Air Void (%) (2nd Layer)	0.0000	Air Void (%)(2nd Layer)	0.0000	Air Void (%) (2nd Layer)	0.0000
5	AC Layer Thickness (Top Layer)	0.0000	AC Layer Thickness (Top Layer)	0.0000	Base Modulus	0.0007
6	Base Modulus	0.0000	Base Modulus	0.0002	AC Layer Thickness (Top Layer)	0.0023
7	Design Lane Width (ft)	0.0186	Base Material Type	0.0037	Tire Pressure (psi)	0.0075
8	Optimum gravimetric water content (%)	0.0209	Optimum gravimetric water content (%)	0.0066	Base Material Type	0.0198
9	Base Material Type	0.0458	Percent of Trucks in Design Direction (%)	0.0074	Percent of Trucks in Design Direction (%)	0.0214
10	Subgrade Modulus	0.0488	Traffic Growth Factor	0.0135		
11			Tire Pressure (psi)	0.0279		

Table 5.6(d): Comparison of Statistical Tests Based on Gridding for Output Y4 (Transverse Cracking)

Rank	CMN Results		CL Results		SI Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	N/A		Superpave Binder Grade (Top AC Layer)	0.0010	Aggregate Gradation (Top AC Layer)	0.0000
2			Climatic Zones	0.0127	Aggregate Gradation (2nd AC Layer)	0.0000
3					Superpave Binder Grade (2nd AC Layer)	0.0000
4					Superpave Binder Grade (Top AC Layer)	0.0000
5					Number of Lanes in Design Direction	0.0000
6					Base Material Type	0.0003
7					Design Lane Width	0.0029
8					Tire Pressure (psi)	0.0278

Note: N/A= No variables found with significant p-value

Table 5.6(e): Comparison of Statistical Tests Based on Gridding for Output Y5 (Permanent Deformation (AC Only))

Rank	CMN Results		CL Results		SI Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AADTT	0.0000	AADTT	0.0000	AADTT	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	Tire Pressure (psi)	0.0000	Tire Pressure (psi)	0.0000	Tire Pressure (psi)	0.0000
4	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0001
5	Traffic Growth Factor	0.0000	Traffic Growth Factor	0.0000	Climatic Zones	0.0014
6	Climatic Zones	0.0002	Climatic Zones	0.0001	Traffic Growth Factor	0.0034
7	AC Layer Thickness (Top Layer)	0.0008	AC Layer Thickness (Top Layer)	0.0027	AC Layer Thickness (Top Layer)	0.0132
8	Optimum gravimetric water content (%)	0.0092	Operational Speed (mph)	0.0060		
9	Operational Speed (mph)	0.0141	Optimum gravimetric water content (%)	0.0244		
10	Percent of Trucks in Design Direction (%)	0.0251	Percent of Trucks in Design Direction (%)	0.0295		
11	Effective binder content (%) (2nd Layer)	0.0281	Effective binder content (%) (2nd Layer)	0.0398		
12	Air Voids (%) (Top AC Layer)	0.0378	Superpave Binder Grade (Top AC Layer)	0.0428		
13	Superpave Binder Grade (Top AC Layer)	0.0495				

Table 5.6(f): Comparison of Statistical Tests Based on Gridding for Output Y6 (Permanent Deformation (Total Pavement))

Rank	CMN Results		CL Results		SI Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AADTT	0.0000	AADTT	0.0000	AADTT	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
4	Subgrade Modulus	0.0000	Subgrade Modulus	0.0000	Subgrade Material Type	0.0000
5	Tire Pressure (psi)	0.0000	Tire Pressure (psi)	0.0000	Subgrade Modulus	0.0000
6	Traffic Growth Factor	0.0002	Traffic Growth Factor	0.0001	Tire Pressure (psi)	0.0007
7	AC Layer Thickness (Top Layer)	0.0002	Subgrade Material Type	0.0003	AC Layer Thickness (Top Layer)	0.0012
8	Percent of Trucks in Design Direction (%)	0.0015	AC Layer Thickness (Top Layer)	0.0006	Optimum gravimetric water content (%)	0.0015
9	Subgrade Material Type	0.0023	Optimum gravimetric water content (%)	0.0012	Climatic Zones	0.0039
10	Optimum gravimetric water content (%)	0.0026	Percent of Trucks in Design Direction (%)	0.0013	Traffic Growth Factor	0.0140
11	Operational Speed	0.0063	Operational Speed	0.0024	Operational Speed	0.0346
12	Effective binder content (%) (2nd Layer)	0.0137	Climatic Zones	0.0026		
13	Climatic Zones	0.0234	Effective binder content (%) (2nd Layer)	0.0181		
14	Base Modulus	0.0258				

Table 5.7(a): Comparison of Linear and Quadratic Regression Tests for Output Y1 (Terminal IRI)

Rank	REG Results		QREG Results	
	Input	p-Value	Input	p-Value
1	AC Layer Thickness (2nd Layer)	0.0000	AADTT	0.0000
2	AADTT	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	Percent of Trucks in Design Lane (%)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
4	AC Layer Thickness (Top Layer)	0.0000	AC Layer Thickness (Top Layer)	0.0000
5	Subgrade Modulus	0.0000	Subgrade Material Type	0.0000
6	Subgrade Material Type	0.0000	Subgrade Modulus	0.0000
7	Base Modulus	0.0000	Base Modulus	0.0001
8	Air Voids (%) (2nd AC Layer)	0.0001	Air Voids (%) (2nd AC Layer)	0.0003
9	Percent of Trucks in Design Direction (%)	0.0009	Percent of Trucks in Design Direction (%)	0.0033
10	Tire Pressure (psi)	0.0037	Operational Speed (mph)	0.0039
11	Traffic Growth Factor	0.0040	Traffic Growth Factor	0.0076
12	Air Voids (%) (Top AC Layer)	0.0203	Tire Pressure (psi)	0.0114
13	Optimum gravimetric water content (%)	0.0292	Optimum gravimetric water content (%)	0.0182
14	Operational Speed (mph)	0.0492	Design Lane Width (ft)	0.0272
15			Air Voids (%) (Top AC Layer)	0.0445

Table 5.7(b): Comparison of Linear and Quadratic Regression Tests for Output Y2 (Longitudinal Cracking)

Rank	REG Results		QREG Results	
	Input	p-Value	Input	p-Value
1	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	AADTT	0.0000	AADTT	0.0000
4	Base Modulus	0.0000	Base Modulus	0.0000
5	Air Voids (%) (Top AC Layer)	0.0000	Air Voids (%) (Top AC Layer)	0.0000
6	AC Layer Thickness (Top Layer)	0.0000	AC Layer Thickness (Top Layer)	0.0001
7	Effective Binder Content (%) (Top AC Layer)	0.0062	Base Material Type	0.0002
8	Subgrade Modulus	0.0086	Design Lane Width (ft)	0.0024
9	Operational Speed (mph)	0.0167	Effective Binder Content (%) (Top AC Layer)	0.0092
10	Depth of Water Table (ft)	0.0202	Subgrade Modulus	0.0148
11	Percent of Trucks in Design Direction (%)	0.0307	Percent of Trucks in Design Direction (%)	0.0320
12			Effective Binder Content (%) (2nd AC Layer)	0.0366
13			Operational Speed (mph)	0.0369

Table 5.7(c): Comparison of Linear and Quadratic Regression Tests for Output Y3 (Alligator Cracking)

Rank	REG Results		QREG Results	
	Input	p-Value	Input	p-Value
1	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
2	AADTT	0.0000	AADTT	0.0000
3	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
4	Air Voids (%) (2nd AC Layer)	0.0000	Air Voids (%) (2nd AC Layer)	0.0000
5	AC Layer Thickness (Top Layer)	0.0000	AC Layer Thickness (Top Layer)	0.0000
6	Base Modulus	0.0000	Base Modulus	0.0000
7	Subgrade Modulus	0.0035	Optimum gravimetric water content (%)	0.0093
8			Subgrade Modulus	0.0114
9			Design Lane Width (ft)	0.0163
10			Operational Speed (mph)	0.0412

Table 5.7(d): Comparison of Linear and Quadratic Regression Tests for Output Y4 (Transverse Cracking)

Rank	REG Results		QREG Results	
	Input	p-Value	Input	p-Value
1	N/A		Plastic Limit	0.0301

Note: N/A= No variables found with significant p-value

Table 5.7(e): Comparison of Linear and Quadratic Regression Tests for Output Y5 (Permanent Deformation (AC Only))

Rank	REG Results		QREG Results	
	Input	p-Value	Input	p-Value
1	AADTT	0.0000	AADTT	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	Tire Pressure (psi)	0.0000	Tire Pressure (psi)	0.0000
4	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
5	Traffic Growth Factor	0.0000	Traffic Growth Factor	0.0000
6	AC Layer Thickness (Top Layer)	0.0000	AC Layer Thickness (Top Layer)	0.0001
7	Air Voids (%) (Top AC Layer)	0.0005	Air Voids (%) (Top AC Layer)	0.0007
8	Superpave Binder Grade (Top AC Layer)	0.0009	Operational Speed (mph)	0.0015
9	Climatic Zones	0.0011	Superpave Binder Grade (Top AC Layer)	0.0028
10	Optimum gravimetric water content (%)	0.0013	Climatic Zones	0.0043
11	Effective Binder Content (%) (2nd AC Layer)	0.0029	Optimum gravimetric water content (%)	0.0048
12	Operational Speed (mph)	0.0031	Effective Binder Content (%) (2nd AC Layer)	0.0057
13	AADTT Distribution by Vehicle Class 9 (%)	0.0054	AADTT Distribution by Vehicle Class 9 (%)	0.0208
14	Percent of Trucks in Design Direction (%)	0.0073	Percent of Trucks in Design Direction (%)	0.0246
15	Superpave Binder Grade (2nd AC Layer)	0.0083	Superpave Binder Grade (2nd AC Layer)	0.0301
16	Air Voids (%) (2nd AC Layer)	0.0267		

Table 5.7(f): Comparison of Linear and Quadratic Regression Tests for Output Y6 (Permanent Deformation (Total Pavement))

Rank	REG Results		QREG Results	
	Input	p-Value	Input	p-Value
1	AADTT	0.0000	AADTT	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
4	Subgrade Modulus	0.0000	Subgrade Modulus	0.0000
5	Tire Pressure (psi)	0.0000	Tire Pressure (psi)	0.0000
6	AC Layer Thickness (Top Layer)	0.0000	AC Layer Thickness (Top Layer)	0.0000
7	Traffic Growth Factor	0.0000	Traffic Growth Factor	0.0000
8	Optimum gravimetric water content (%)	0.0001	Operational Speed (mph)	0.0003
9	Percent of Trucks in Design Direction (%)	0.0002	Optimum gravimetric water content (%)	0.0004
10	Subgrade Material Type	0.0002	Subgrade Material Type	0.0004
11	Air Voids (%) (Top AC Layer)	0.0012	Percent of Trucks in Design Direction (%)	0.0007
12	Operational Speed (mph)	0.0013	Air Voids (%) (Top AC Layer)	0.0024
13	Effective Binder Content (%) (2nd AC Layer)	0.0024	Effective Binder Content (%) (2nd AC Layer)	0.0049
14	Base Modulus	0.0097	Base Modulus	0.0257
15	Climatic Zones	0.0134	Depth of Water table (ft)	0.0332
16	Superpave Binder Grade (2nd AC Layer)	0.0208	Climatic Zones	0.0458
17	Depth of Water table (ft)	0.0285		
18	Air Voids (%) (2nd AC Layer)	0.0319		

Table 5.8(a): Comparison of Statistical Grid-Free Tests for Output Y1 (Terminal IRI)

Rank	RCC Results		SRD Results		SRD/RCC Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AADTT	**0.0000**	Percent of Trucks in Design Lane (%)	**0.0000**	AADTT	**0.0000**
2	Percent of Trucks in Design Lane (%)	**0.0000**	AADTT	**0.0000**	Percent of Trucks in Design Lane (%)	**0.0000**
3	AC Layer Thickness (2^{nd} Layer)	**0.0000**	AC Layer Thickness (2^{nd} Layer)	0.0001	AC Layer Thickness (2^{nd} Layer)	**0.0000**
4	Subgrade Material Type	**0.0000**			Subgrade Material Type	**0.0000**
5	Subgrade Modulus	**0.0000**			Subgrade Modulus	**0.0000**
6	AC Layer Thickness (Top Layer)	**0.0000**			AC Layer Thickness (Top Layer)	**0.0000**
7	Tire Pressure (psi)	**0.0000**			Tire Pressure (psi)	**0.0000**
8	Traffic Growth Factor	0.0003			Operational Speed (mph)	0.0008
9	Percent of Trucks in Design Direction (%)	0.0009			Traffic Growth Factor	0.0010
10	Operational Speed (mph)	0.0013			Percent of Trucks in Design Direction (%)	0.0045
11	Optimum Gravimetric Water Content (%)	0.0033			Optimum Gravimetric Water Content (%)	0.0048
12	Air Voids (%) (Top AC Layer)	0.0083			Air Voids (%) (Top AC Layer)	0.0226
13	Air Voids (%) (2nd AC Layer)	0.0120			Base Modulus	0.0320
14	Climatic Zones	0.0126			Climatic Zones	0.0399
15	Base Modulus	0.0232			Depth of Water Table (ft)	0.0444
16	Depth of Water Table (ft)	0.0242				

Table 5.8(b): Comparison of Statistical Grid-Free Tests for Output Y2 (Longitudinal Cracking)

Rank	RCC Results		SRD Results		SRD/RCC Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	AADTT	0.0007	AADTT	0.0000
3	AADTT	0.0000	Effective Binder Content (%) (Top AC Layer)	0.0070	Percent of Trucks in Design Lane (%)	0.0000
4	Subgrade Modulus	0.0000	Base Material Type	0.0136	Subgrade Modulus	0.0000
5	Base Modulus	0.0000	Aggregate Gradation (2nd AC Layer)	0.0176	Base Modulus	0.0000
6	AC Layer Thickness (Top Layer)	0.0000	Base Modulus	0.0454	AC Layer Thickness (Top Layer)	0.0000
7	Air Voids (%) (Top AC Layer)	0.0000			Air Voids (%) (Top AC Layer)	0.0000
8	Operational Speed (mph)	0.0068			Base Material Type	0.0051
9	Depth of Water Table (ft)	0.0146			Effective Binder Content (%) (Top AC Layer)	0.0061
10	Superpave Binder Grade (Top AC Layer)	0.0257			Depth of Water Table (ft)	0.0157
11	Traffic Growth Factor	0.0389			Operational Speed (mph)	0.0238
12	Base Material Type	0.0444			Climatic Zones	0.0443

Table 5.8(c): Comparison of Statistical Grid-Free Tests for Output Y3 (Alligator Cracking)

Rank	RCC Results		SRD Results		SRD/RCC Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AC Layer Thickness (2^{nd} Layer)	0.0000	AC Layer Thickness (2^{nd} Layer)	0.0000	AADTT	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	AADTT	0.0000	AADTT	0.0000	AC Layer Thickness (2^{nd} Layer)	0.0000
4	Air Voids (%) (2nd AC Layer)	0.0000	AADTT Distribution by Vehicle Class 9 (%)	0.0247	Air Voids (%) (2^{nd} AC Layer)	0.0000
5	AC Layer Thickness (Top Layer)	0.0000	Aggregate Gradation (2^{nd} AC Layer)	0.0354	AC Layer Thickness (Top Layer)	0.0000
6	Base Modulus	0.0000			Base Modulus	0.0000
7	Traffic Growth Factor	0.0024			Traffic Growth Factor	0.0108
8	Subgrade Modulus	0.0027			Subgrade Modulus	0.0142
9	Depth of Water Table (ft)	0.0132			Operational Speed (mph)	0.0159
10	Operational Speed (mph)	0.0172			Depth of Water Table (ft)	0.0163
11	Climatic Zones	0.0408			AADTT Distribution by Vehicle Class 9 (%)	0.0316
12					Climatic Zones	0.0357

Table 5.8(d): Comparison of Statistical Grid-Free Tests for Output Y4 (Transverse Cracking)

Rank	RCC Results		SRD Results		SRD/RCC Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	Superpave Binder Grade (Top AC Layer)	0.0029	Effective binder content (%) (2nd AC Layer)	0.0000	N/A	
2			Plastic Limit	0.0000		
3			Subgrade Material Type	0.0000		
4			Aggregate Gradation (Top AC Layer)	0.0000		
5			Superpave Binder Grade (Top AC Layer)	0.0000		
6			Superpave Binder Grade (2nd AC Layer)	0.0000		

Note: N/A= No variables found with significant p-value

Table 5.8(e): Comparison of Statistical Grid-Free Tests for Output Y5 (Permanent Deformation (AC Only))

Rank	RCC Results		SRD Results		SRD/RCC Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AADTT	0.0000	AADTT	0.0000	AADTT	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	Tire Pressure (psi)	0.0000	Traffic Growth Factor	0.0094	Tire Pressure (psi)	0.0000
4	AC Layer Thickness (2^{nd} Layer)	0.0000	AC Layer Thickness (2^{nd} Layer)	0.0156	AC Layer Thickness (2^{nd} Layer)	0.0000
5	Traffic Growth Factor	0.0000	Base Modulus	0.0203	Traffic Growth Factor	0.0000
6	AC Layer Thickness (Top Layer)	0.0001	Tire Pressure (psi)	0.0488	Climatic Zones	0.0003
7	Climatic Zones	0.0003			AC Layer Thickness (Top Layer)	0.0004
8	Superpave Binder Grade (Top AC Layer)	0.0007			Superpave Binder Grade (Top AC Layer)	0.0007
9	Operational Speed (mph)	0.0014			Optimum Gravimetric Water Content (%)	0.0029
10	Optimum Gravimetric Water Content (%)	0.0016			Operational Speed (mph)	0.0033
11	Air Voids (%) (Top AC Layer)	0.0028			Air Voids (%) (Top AC Layer)	0.0159
12	Effective binder content (%) (2nd AC Layer)	0.0046			Effective binder content (%) (2^{nd} AC Layer)	0.0212
13	Superpave Binder Grade (2^{nd} AC Layer)	0.0095			Superpave Binder Grade (2^{nd} AC Layer)	0.0229
14	Percent of Trucks in Design Direction (%)	0.0151				
15	Air Voids (%) (2^{nd} AC Layer)	0.0177				
16	AADTT Distribution by Vehicle Class 9 (%)	0.0390				

Table 5.8(f): Comparison of Statistical Grid-Free Tests for Output Y6 (Permanent Deformation (Total Pavement))

Rank	RCC Results		SRD Results		SRD/RCC Results	
	Input	p-Value	Input	p-Value	Input	p-Value
1	AADTT	0.0000	AADTT	0.0000	AADTT	0.0000
2	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000	Percent of Trucks in Design Lane (%)	0.0000
3	AC Layer Thickness (2nd Layer)	0.0000	AC Layer Thickness (2nd Layer)	0.0240	AC Layer Thickness (2nd Layer)	0.0000
4	Subgrade Modulus	0.0000	Traffic Growth Factor	0.0283	Subgrade Modulus	0.0000
5	Tire Pressure (psi)	0.0000			Tire Pressure (psi)	0.0000
6	AC Layer Thickness (Top Layer)	0.0000			Traffic Growth Factor	0.0000
7	Traffic Growth Factor	0.0000			AC Layer Thickness (Top Layer)	0.0001
8	SUBGRADE MATERIAL TYPE	0.0000			SUBGRADE MATERIAL TYPE	0.0001
9	Optimum gravimetric water content (%)	0.0001			Optimum gravimetric water content (%)	0.0001
10	Percent of Trucks in Design Direction (%)	0.0002			Percent of Trucks in Design Direction (%)	0.0012
11	Operational Speed (mph)	0.0010			Operational Speed (mph)	0.0014
12	Climatic Zones	0.0021			Climatic Zones	0.0033
13	Air Voids (%) (Top AC Layer)	0.0034			Air Voids (%) (Top AC Layer)	0.0099
14	Effective binder content (%) (2nd AC Layer)	0.0038			Effective binder content (%) (2nd AC Layer)	0.0130
15	Depth of Water Table (ft)	0.0262			Depth of Water Table (ft)	0.0362

Table 5.8(g): Summary of Scatter plot test Result

Name of Test	Model Y1	Model Y2	Model Y3	Model Y4	Model Y5	Model Y6
CMN	X18 X1 X4 X13	X18 X4 X1 X24 X25	X18 X1 X4 X22 X13	N/A	X1 X4 X10 X18 X8	X1 X4 X18 X27
CL	X1 X4 X18 X26	X18 X1 X4 X27 X24 X25 X13	X18 X4 X1 X22 X13	N/A	X1 X4 X10 X18	X1 X4 X18 X27
SI	X1 X4 X18 X26	X18 X4 X1 X27	X18 X1 X4	X14 X19 X21 X16 X2	X1 X4 X10	X1 X4 X18 X26
REG	X18 X1 X4 X13	X18 X4 X1 X25 X17	X18 X1 X4 X22 X13 X25	N/A	X1 X4 X10 X18 X8	X1 X4 X18 X27 X10 X13
QREG	X1 X4 X18 X13	X18 X4 X1 X25 X17	X18 X1 X4 X22 X13 X25	N/A	X1 X4 X10 X18 X8	X1 X4 X18 X27 X10
RCC	X1 X4 X18 X26 X27	X18 X4 X1 X27 X25 X13 X17	X18 X4 X1 X22 X13	N/A	X1 X4 X10 X18 X8	X1 X4 X18 X27 X10
SRD	X1 X4	X18	X18 X4	N/A	X1 X4	X1 X4
SRD/RCC	X1 X4 X18 X26 X27	X18 X1 X4 X27 X25 X13 X17	X1 X4 X18 X22 X13	N/A	X1 X4 X10 X18 X8	X1 X4 X18 X27 X10

Note: N/A= No variables found with zero p-value

Table 5.9 (a): Result of Regression Analysis Result for Output Y1 (Terminal IRI)

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X18	AC Layer Thickness (2nd AC Layer)	0.164	16	-0.392	0.277	(0.186, 0.421)	0.000
X1	AADTT	0.326	16	0.397	0.284	(0.183, 0.413)	0.000
X4	Percent of Trucks in Design Lane (%)	0.445	12	0.336	0.219	(0.127, 0.351)	0.000
X13	AC Layer Thickness (Top Layer)	0.475	3	-0.174	0.070	(0.032, 0.134)	0.000
X26	Subgrade Material Type	0.502	3	0.145	0.050	(0.019, 0.101)	0.000
X27	Subgrade Modulus	0.521	2	-0.135	0.044	(0.018, 0.096)	0.000
X30	Optimum gravimetric water content (%)	0.536	2	-0.116	0.032	(0.011, 0.073)	0.001
X22	Air Void (%) (AC 2nd Layer)	0.551	2	0.110	0.029	(0.010, 0.072)	0.003
X10	Tire Pressure	0.564	1	0.105	0.027	(0.006, 0.059)	0.010
X25	Base Modulus	0.575	1	-0.096	0.023	(0.006, 0.057)	0.015
X8	Traffic Growth Factor	0.584	1	0.102	0.025	(0.007, 0.062)	0.004
X3	Percent of Trucks in Design Direction (%)	0.593	1	0.094	0.021	(0.006, 0.053)	0.012
X24	Base Material Type	0.596	0	0.067	0.011	(0.000, 0.029)	0.156
X29	Liquid Limit	0.600	0	0.060	0.009	(0.000, 0.031)	0.185
X21	Superpave Binder Grade (2nd AC Layer)	0.603	0	0.054	0.007	(0.000, 0.023)	0.282

Note:

Estimated Model Summary:

1. *Y1 = f(X18, X1, X4, X13, X26, X27, X30, X22, X10, X25, X8, X3, X24, X29, X21, X6)*
2. R^2*=0.610531*

Table 5.9 (b): Result of Regression Analysis Result for Output Y2 (Longitudinal Cracking)

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X18	AC Layer Thickness (2nd AC Layer)	0.311	31	-0.547	0.424	(0.382, 0.487)	0.000
X4	Percent of Trucks in Design Lane (%)	0.383	7	0.251	0.134	(0.097, 0.188)	0.000
X1	AADTT	0.440	6	0.239	0.124	(0.081, 0.171)	0.000
X24	Base Material Type	0.484	4	0.197	0.087	(0.055, 0.134)	0.000
X17	Air Void (%) (Top AC Layer)	0.518	3	0.178	0.072	(0.042, 0.112)	0.000
X25	Base Modulus	0.543	3	-0.154	0.055	(0.026, 0.089)	0.000
X13	AC Layer Thickness (Top Layer)	0.562	2	-0.139	0.046	(0.023, 0.085)	0.000
X27	Subgrade Modulus	0.576	1	0.124	0.036	(0.013, 0.068)	0.000
X15	Effective binder content (%) (Top AC Layer)	0.586	1	-0.094	0.021	(0.004, 0.046)	0.021
X23	Base Thickness	0.594	1	-0.088	0.019	(0.000, 0.041)	0.027
X3	Percent of Trucks in Design Direction (%)	0.597	0	0.057	0.008	(0.000, 0.029)	0.195

Note:

Estimated Model Summary:

1. *Model: Y2 = f(X18, X4, X1, X24, X17, X25, X13, X27, X15, X23, X3)*
2. $R^2 = 0.6050822$

Table 5.9 (c): Result of Regression Analysis Result for Output Y3 (Alligator Cracking)

Input	**Name**	**R^2**	**Increment R^2 (%)**	**SRC**	**PCC^2**	**95% PCC^2 CI**	**p-Value**
X18	AC Layer Thickness (2nd Layer)	0.262	26	-0.491	0.326	(0.271, 0.415)	0.000
X1	AADTT	0.330	7	0.262	0.121	(0.080, 0.180)	0.000
X4	Percent of Trucks in Design Lane (%)	0.382	5	0.216	0.085	(0.050, 0.136)	0.000
X22	Air Void (%) (AC 2nd Layer)	0.419	4	0.176	0.058	(0.031, 0.102)	0.000
X13	AC Layer Thickness (Top Layer)	0.448	3	-0.176	0.059	(0.031, 0.099)	0.000
X25	Base Modulus	0.469	2	-0.127	0.031	(0.012, 0.064)	0.002
X24	Base Material Type	0.477	1	0.098	0.019	(0.004, 0.047)	0.013
X12	Climatic Zones	0.483	1	0.073	0.011	(0.000, 0.031)	0.073
X27	Subgrade Modulus	0.489	1	-0.074	0.011	(0.000, 0.033)	0.093
X3	Percent of Trucks in Design Direction (%)	0.494	1	0.065	0.008	(0.000, 0.026)	0.209
X8	Traffic Growth Factor	0.497	0	0.059	0.007	(0.000, 0.024)	0.210
X26	Subgrade Material Type	0.499	0	0.045	0.004	(0.000, 0.018)	0.207
X23	Base Thickness	0.502	0	-0.054	0.006	(0.000, 0.023)	0.261
X20	Effective binder content (%) (2nd AC Layer)	0.505	0	-0.062	0.008	(0.000, 0.026)	0.243
X30	Optimum gravimetric water content (%)	0.507	0	-0.046	0.004	(0.000, 0.019)	0.373

Note:

Estimated Model Summary:

1. *Model: Y3 = f(X18, X1, X4, X22, X13, X25, X24, X12, X27, X3, X8, X26, X23, X20, X30)*
2. *R^2 = 0.5124539*

Table 5.9 (d): Result of Regression Analysis Result for Output Y4 (Transverse Cracking)

Input	Name	R^2	SRC	PCC^2	95% PCC^2 CI	P value
X24	Base Material Type	0.003	0.052	0.003	(0.000, 0.296)	0.164

Note:

Estimated Model Summary:

1. *Model: Y4 = f(X24)*
2. $R^2 = 0.005351839$

Table 5.9 (e): Result of Regression Analysis Result for Output Y5 (Permanent Deformation (AC Only))

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X1	AADTT	0.364	36	0.552	0.683	(0.649, 0.726)	0.000
X4	Percent of Trucks in Design Lane (%)	0.611	25	0.502	0.637	(0.602, 0.690)	0.000
X10	Tire Pressure	0.701	9	0.296	0.377	(0.333, 0.445)	0.000
X18	AC Layer Thickness (2nd Layer)	0.740	4	-0.195	0.212	(0.168, 0.277)	0.000
X8	Traffic Growth Factor	0.772	3	0.176	0.179	(0.138, 0.233)	0.000
X12	Climatic Zones	0.790	2	0.116	0.087	(0.057, 0.140)	0.000
X13	AC Layer Thickness (Top Layer)	0.807	2	-0.129	0.106	(0.068, 0.156)	0.000
X6	AADTT Distribution by Vehicle Class 9 (%)	0.816	1	0.093	0.057	(0.026, 0.093)	0.000
X16	Superpave Binder Grade (Top AC Layer)	0.825	1	0.090	0.054	(0.027, 0.092)	0.000
X3	Percent of Trucks in Design Direction (%)	0.832	1	0.097	0.061	(0.035, 0.103)	0.000
X30	Optimum gravimetric water content (%)	0.840	1	0.089	0.052	(0.026, 0.090)	0.000
X5	Operational Speed	0.846	1	-0.085	0.047	(0.026, 0.086)	0.000
X21	Superpave Binder Grade (2nd AC Layer)	0.850	0	0.068	0.031	(0.014, 0.068)	0.000
X20	Effective binder content (%) (2nd AC Layer)	0.853	0	0.056	0.021	(0.006, 0.049)	0.013
X27	Subgrade Modulus	0.856	0	0.057	0.023	(0.006, 0.049)	0.015

Note:

Estimated Model Summary:

1. *Model: Y5 = f(X1, X4, X10, X18, X8, X12, X13, X6, X16, X3, X30, X5, X21, X20, X27, X22, X17, X19)*
2. *R^2 = 0.8633162*

Table 5.9 (f): Result of Regression Analysis Result for Output Y6 (Permanent Deformation (Total Pavement))

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X1	AADTT	0.302	30	0.524	0.630	(0.557, 0.694)	0.000
X4	Percent of Trucks in Design Lane (%)	0.527	23	0.462	0.568	(0.488, 0.643)	0.000
X18	AC Layer Thickness (2nd Layer)	0.624	10	-0.315	0.380	(0.302, 0.461)	0.000
X27	Subgrade Modulus	0.666	4	-0.200	0.199	(0.144, 0.270)	0.000
X10	Tire Pressure	0.706	4	0.201	0.197	(0.137, 0.268)	0.000
X30	Optimum gravimetric water content (%)	0.741	4	-0.177	0.160	(0.123, 0.233)	0.000
X8	Traffic Growth Factor	0.765	2	0.147	0.119	(0.079, 0.183)	0.000
X13	AC Layer Thickness (Top Layer)	0.784	2	-0.141	0.110	(0.070, 0.167)	0.000
X26	Subgrade Material Type	0.800	2	0.117	0.079	(0.043, 0.129)	0.000
X12	Climatic Zones	0.809	1	0.082	0.040	(0.016, 0.077)	0.001
X3	Percent of Trucks in Design Direction (%)	0.819	1	0.098	0.055	(0.027, 0.102)	0.000
X5	Operational Speed	0.827	1	-0.086	0.043	(0.017, 0.076)	0.000
X21	Superpave Binder Grade (2nd AC Layer)	0.831	0	0.066	0.027	(0.010, 0.059)	0.003
X22	Air Void (%) (AC 2nd Layer)	0.834	0	0.048	0.014	(0.000, 0.036)	0.095
X16	Superpave Binder Grade (Top AC Layer)	0.834	0	0.000	0.000	(0.000, 0.007)	0.085

Note:

Estimated Model Summary:

1. *Model Y6 = f(X1, X4, X18, X27, X10, X30, X8, X13, X26, X12, X3, X5, X21, X22, X16, X17, X25, X6, X15, X20)*
2. $R^2 = 0.847782$

Table 5.10 (a): Result of Rank Regression Analysis Result for Output Y1 (Terminal IRI)

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X1	AADTT	0.267	27	0.503	0.604	(0.551, 0.653)	0.000
X4	Percent of Trucks in Design Lane (%)	0.493	23	0.465	0.565	(0.505, 0.617)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.635	14	-0.373	0.457	(0.397, 0.512)	0.000
X26	Subgrade Material Type	0.684	5	0.209	0.201	(0.145, 0.263)	0.000
X27	Subgrade Modulus	0.712	3	-0.173	0.153	(0.100, 0.208)	0.000
X10	Tire Pressure	0.739	3	0.168	0.143	(0.098, 0.197)	0.000
X30	Optimum gravimetric water content (%)	0.764	3	-0.158	0.129	(0.084, 0.177)	0.000
X13	AC Layer Thickness (Top Layer)	0.786	2	-0.147	0.116	(0.075, 0.172)	0.000
X8	Traffic Growth Factor	0.801	2	0.140	0.106	(0.065, 0.151)	0.000
X3	Percent of Trucks in Design Direction (%)	0.809	1	0.091	0.047	(0.019, 0.079)	0.000
X29	Liquid Limit (LL)	0.816	1	0.086	0.042	(0.018, 0.076)	0.001
X5	Operational Speed (mph)	0.824	1	-0.090	0.046	(0.022, 0.082)	0.000
X22	Air Void (%) (AC 2nd Layer)	0.828	0	0.061	0.021	(0.004, 0.046)	0.011
X12	Climatic Zones	0.828	0	-0.006	0.000	(0.000, 0.008)	0.039
X24	Base Material Type	0.832	0	0.059	0.020	(0.000, 0.042)	0.083

Note:

Estimated Model Summary:

1. *Y1 = f(X1, X4, X18, X26, X27, X10, X30, X13, X8, X3, X29, X5, X22, X12, X24, X16, X15, X21, X28, X14)*
2. *R^2=0.8547123*

Table 5.10 (b): Result of Rank Regression Analysis Result for Output Y2 (Longitudinal Cracking)

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X18	AC Layer Thickness (2nd AC Layer)	0.485	49	-0.680	0.727	(0.680, 0.770)	0.000
X1	AADTT	0.555	7	0.249	0.262	(0.200, 0.321)	0.000
X4	Percent of Trucks in Design Lane (%)	0.615	6	0.236	0.241	(0.175, 0.312)	0.000
X27	Subgrade Modulus	0.676	6	0.253	0.269	(0.214, 0.327)	0.000
X24	Base Material Type	0.712	4	0.196	0.174	(0.121, 0.234)	0.000
X13	AC Layer Thickness (Top Layer)	0.746	3	-0.175	0.150	(0.104, 0.210)	0.000
X17	Percent Air Void (Top AC Layer)	0.777	3	0.175	0.150	(0.101, 0.202)	0.000
X25	Base Modulus	0.805	3	-0.159	0.126	(0.087, 0.178)	0.000
X26	Subgrade Material Type	0.812	1	0.077	0.032	(0.012, 0.060)	0.000
X15	Effective binder content (%) (Top AC layer)	0.816	0	-0.063	0.022	(0.005, 0.051)	0.006
X8	Traffic Growth Factor	0.821	1	0.073	0.029	(0.008, 0.063)	0.006
X23	Base Thickness	0.824	0	-0.062	0.021	(0.003, 0.048)	0.015
X16	Superpave Binder Grade (Top AC Layer)	0.825	0	0.030	0.005	(0.000, 0.021)	0.143
X19	Aggregate Gradation (2nd AC Layer)	0.825	0	0.006	0.000	(0.000, 0.007)	0.162
X11	Depth of Water Table	0.826	0	0.032	0.006	(0.000, 0.022)	0.247

Note:

Estimated Model Summary:

1. *Model: Y2 = f(X18, X1, X4, X27, X24, X13, X17, X25, X26, X15, X8, X23, X16, X19, X11, X14, X3, X5)*
2. $R^2 = 0.8430639$

Table 5.10 (c): Result of Rank Regression Analysis Result for Output Y3 (Alligator Cracking)

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X18	AC Layer Thickness (2nd AC Layer)	0.466	47	-0.660	0.779	(0.732, 0.821)	0.000
X4	Percent of Trucks in Design Lane (%)	0.610	14	0.362	0.514	(0.427, 0.592)	0.000
X1	AADTT	0.736	13	0.363	0.518	(0.455, 0.586)	0.000
X22	Air Void (%) (AC 2nd Layer)	0.790	5	0.227	0.291	(0.213, 0.363)	0.000
X13	AC Layer Thickness (Top Layer)	0.818	3	-0.168	0.187	(0.138, 0.255)	0.000
X20	Effective binder content (%) (2nd AC layer)	0.831	1	-0.117	0.099	(0.060, 0.149)	0.000
X24	Base Material Type	0.841	1	0.105	0.078	(0.041, 0.126)	0.000
X8	Traffic Growth Factor	0.852	1	0.108	0.087	(0.045, 0.139)	0.000
X25	Base Modulus	0.861	1	-0.086	0.056	(0.028, 0.092)	0.000
X27	Subgrade Modulus	0.867	1	-0.076	0.045	(0.018, 0.084)	0.000
X3	Percent of Trucks in Design Direction (%)	0.872	1	0.062	0.029	(0.010, 0.059)	0.001
X30	Optimum gravimetric water content (%)	0.874	0	-0.048	0.018	(0.006, 0.044)	0.006
X26	Subgrade Material Type	0.875	0	0.023	0.004	(0.000, 0.017)	0.026
X23	Base Thickness	0.877	0	-0.049	0.019	(0.004, 0.047)	0.013
X12	Climatic Zones	0.877	0	0.000	0.000	(0.000, 0.008)	0.108

Note:

Estimated Model Summary:

1. *Model: Y3 = f(X18, X4, X1, X22, X13, X20, X24, X8, X25, X27, X3, X30, X26, X23, X12, X5)*
2. *R^2= 0.8833345*

Table 5.10 (d): Result of Regression Analysis Result for Output Y4 (Transverse Cracking)

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X16	Superpave Binder Grade (Top AC Layer)	0.015	2	0.027	0.015	(0.000, 0.035)	0.051
X12	Climatic Zones	0.021	1	-0.016	0.006	(0.000, 0.027)	0.167
X24	Base Material Type	0.027	1	0.015	0.005	(0.000, 0.017)	0.183
X4	Percent of Trucks in Design Lane (%)	0.031	0	0.014	0.005	(0.000, 0.018)	0.424
X2	Number of Lanes in Design Direction	0.035	0	0.015	0.005	(0.000, 0.018)	0.348
X5	Operational Speed	0.039	0	-0.014	0.005	(0.000, 0.019)	0.368
X10	Tire Pressure	0.043	0	0.014	0.005	(0.000, 0.017)	0.511
X15	Effective binder content (%) (Top AC Layer)	0.046	0	0.012	0.003	(0.000, 0.012)	0.582
X29	Liquid Limit (LL)	0.050	0	-0.012	0.003	(0.000, 0.015)	0.630

Note:

Estimated Model Summary:

1. *Model: Y4 = f(X16, X12, X24, X4, X2, X5, X10, X15, X29)*
2. *R2 = 0.0671173*

Table 5.10 (e): Result of Rank Regression Analysis Result for Output Y5 (Permanent Deformation (AC Only))

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X1	AADTT	0.389	39	0.573	0.724	(0.687, 0.757)	0.000
X4	Percent of Trucks in Design Lane (%)	0.645	26	0.516	0.678	(0.626, 0.719)	0.000
X10	Tire Pressure	0.728	8	0.290	0.399	(0.339, 0.459)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.765	4	-0.188	0.219	(0.170, 0.277)	0.000
X8	Traffic Growth Factor	0.793	3	0.166	0.180	(0.130, 0.236)	0.000
X12	Climatic Zones	0.813	2	0.130	0.113	(0.069, 0.163)	0.000
X13	AC Layer Thickness (Top Layer)	0.827	1	-0.119	0.102	(0.057, 0.148)	0.000
X5	Operational Speed	0.836	1	-0.094	0.065	(0.036, 0.104)	0.000
X16	Superpave Binder Grade (Top AC Layer)	0.844	1	0.097	0.063	(0.030, 0.101)	0.000
X3	Percent of Trucks in Ddesign Direction (%)	0.850	1	0.093	0.064	(0.032, 0.099)	0.000
X30	Optimum gravimetric water content (%)	0.856	1	0.079	0.047	(0.020, 0.083)	0.000
X21	Superpave Binder Grade (2nd AC Layer)	0.860	0	0.070	0.033	(0.012, 0.063)	0.002
X6	AADTT Distribution by Vehicle Class 9 (%)	0.865	1	0.068	0.035	(0.014, 0.065)	0.007
X27	Subgrade Modulus	0.869	0	0.061	0.029	(0.010, 0.062)	0.011
X22	Air Void (%) (AC 2nd Layer)	0.872	0	0.059	0.027	(0.007, 0.053)	0.020

Note:

Estimated Model Summary:

1. *Model: Y5 = f(X1, X4, X10, X18, X8, X12, X13, X5, X16, X3, X30, X21, X6, X27, X22, X20, X19, X15, X25, X14)*
2. $R^2 = 0.8795673$

Table 5.10 (f): Result of Rank Regression Analysis Result for Output Y6 (Permanent Deformation (Total Pavement))

Input	Name	R^2	Increment R^2 (%)	SRC	PCC^2	95% PCC^2 CI	p-Value
X1	AADTT	0.317	32	0.537	0.654	(0.600, 0.698)	0.000
X4	Percent of Trucks in Design Lane (%)	0.554	24	0.480	0.600	(0.546, 0.651)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.635	8	-0.288	0.352	(0.291, 0.412)	0.000
X10	Tire Pressure	0.674	4	0.198	0.200	(0.148, 0.269)	0.000
X27	Subgrade Modulus	0.712	4	-0.193	0.197	(0.139, 0.259)	0.000
X30	Optimum gravimetric water content (%)	0.747	4	-0.185	0.182	(0.126, 0.240)	0.000
X8	Traffic Growth Factor	0.772	3	0.154	0.135	(0.090, 0.189)	0.000
X26	Subgrade Material Type	0.790	2	0.135	0.103	(0.065, 0.152)	0.000
X13	AC Layer Thickness (Top Layer)	0.809	2	-0.137	0.110	(0.072, 0.163)	0.000
X12	Climatic Zones	0.824	1	0.116	0.078	(0.042, 0.124)	0.000
X3	Percent of Trucks in Design Direction (%)	0.834	1	0.101	0.062	(0.032, 0.094)	0.000
X5	Operational Speed	0.841	1	-0.087	0.047	(0.020, 0.081)	0.002
X16	Superpave Binder Grade (Top AC Layer)	0.841	0	0.003	0.000	(0.000, 0.009)	0.053
X21	Superpave Binder Grade (2nd AC Layer)	0.843	0	0.053	0.016	(0.000, 0.038)	0.035
X15	Effective binder content (%) (Top AC Layer)	0.846	0	0.052	0.017	(0.000, 0.038)	0.096

Note:

Estimated Model Summary:

1. *Model: Y6 = f(X1, X4, X18, X10, X27, X30, X8, X26, X13, X12, X3, X5, X16, X21, X15, X22, X24, X17, X29, X14)*
2. $R^2 = 0.8576493$

Table 5.11: Summary of Regression Analysis

Model	Name	Linear Regression					Rank Regression				
		R^2	**A**	**B**	**C**	**D**	**R^2**	**A**	**B**	**C**	**D**
Y1	Terminal IRI	**0.61**	X18, X1		X4, X13	X26, X27, X30, X22, X10, X25, X8	**0.85**	X1, X4, X18		X26, X27, X10, X30	X13, X8, X3, X29, X5, X22, X12, X24
Y2	Longitudinal Cracking	**0.61**	X18	X4, X1	X24, X17, X25	X13, X27, X15, X23	**0.84**	X18	X1, X4, X27	X24, X13, X17, X25	X26, X8
Y3	Alligator Cracking	**0.51**	X18	X1	X4, X22, X13	X25, X24, X12, X27, X3	**0.88**	X18, X4, X1		X22, X13	X20, X24, X8, X25, X27, X3
Y4	Transverse Cracking	**0.01**				X24	**.07**				X16, X12, X24
Y5	Permanent Deformation (AC Only)	**0.86**	X1, X4	X10	X8, X18	X12, X13, X6, X16, X3, X30, X5	**0.88**	X1, X4	X10	X18, X8	X12, X13, X5, X16, X3, X30, X6
Y6	Permanent Deformation (Total Pavement)	**0.85**	X1, X4, X18		X27, X10, X30	X8, X13, X26, X12, X3, X5	**0.86**	X1, X4	X18	X10, X27, X30, X8	X26, X13, X12, X3, X5

Note:

1. A= Explain at least 10% of the variance
2. B= Explain 6% to 9% of the variance
3. C= Explain 3% to 5% of the variance
4. B= Explain 2% or less then 2% of the variance

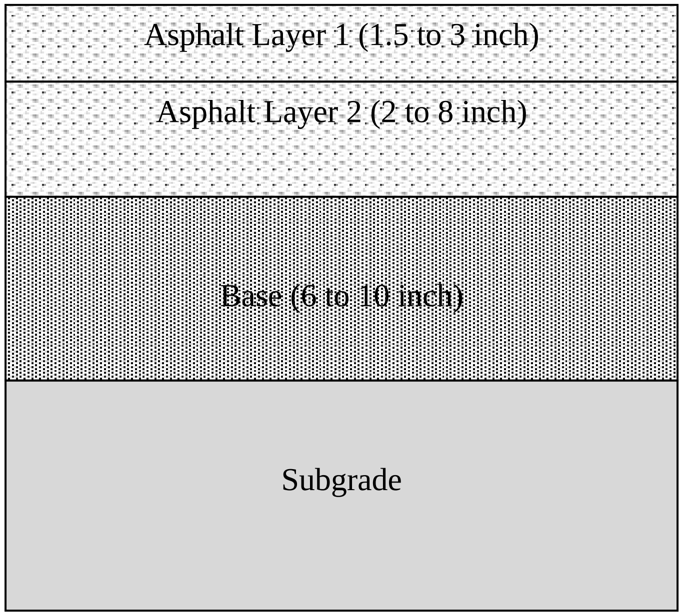


Figure 5.1: Pavement Structure Consideration for the Analysis

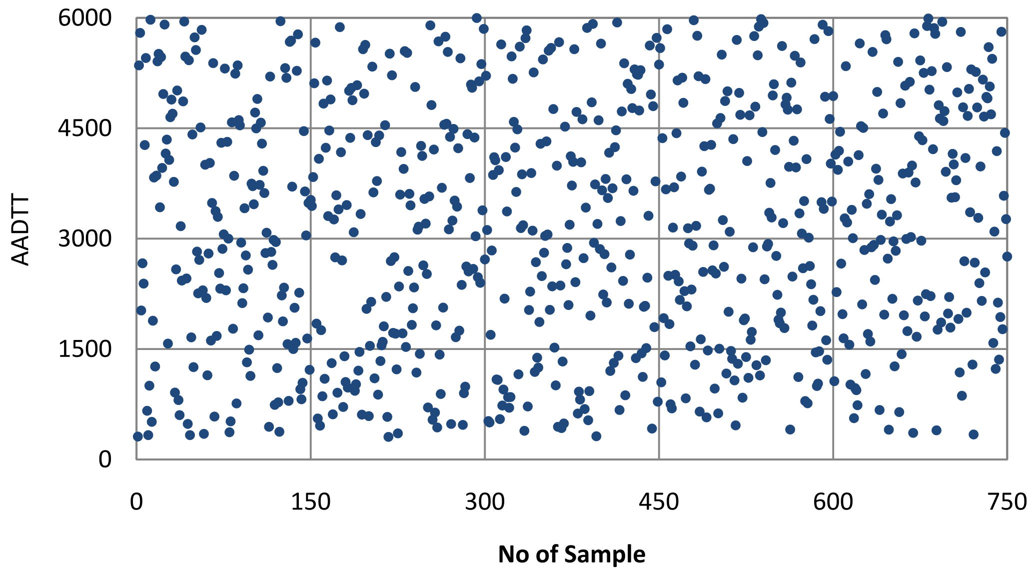


Figure 5.2(a): Latin Hypercube Sampling for AADTT (Variable Type: Integer)

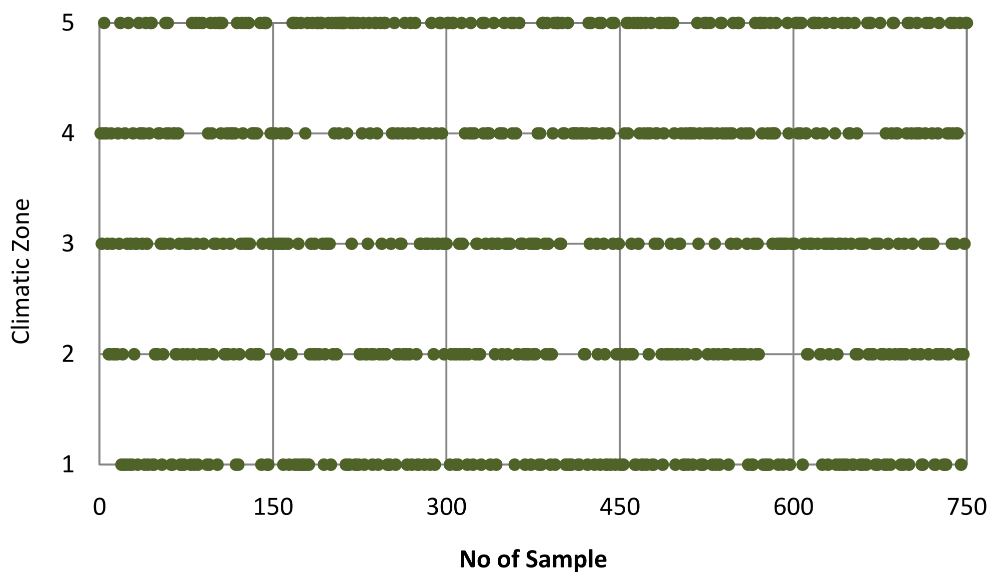


Figure 5.2(b): Latin Hypercube Sampling for Climatic Zones (Variable Type: Discrete)

Figure 5.2: Latin Hypercube Sampling for Different Types of Variable

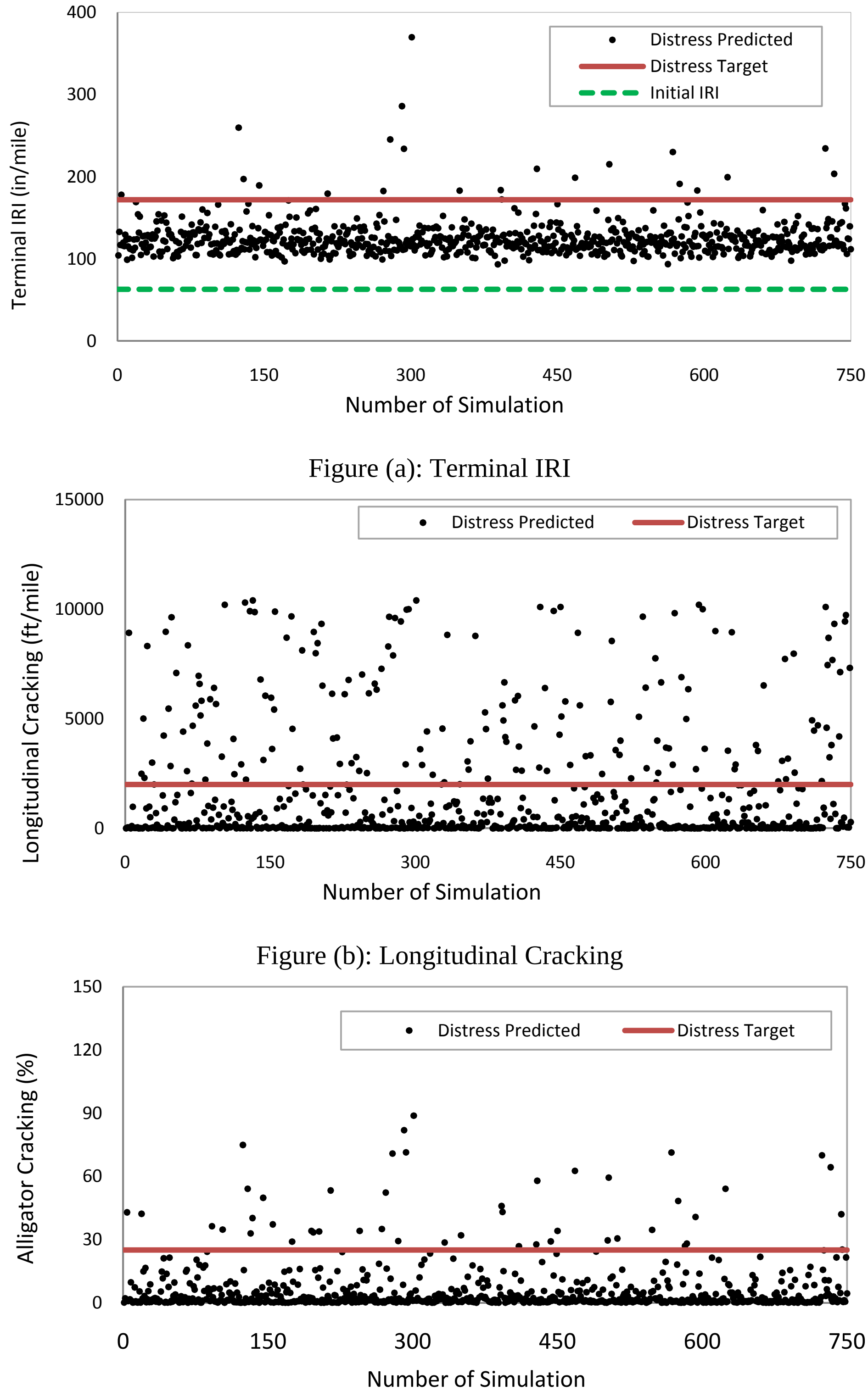


Figure (a): Terminal IRI

Figure (b): Longitudinal Cracking

Figure (c): Alligator Cracking

Figure 5.3: Summary Result of Test Matrix

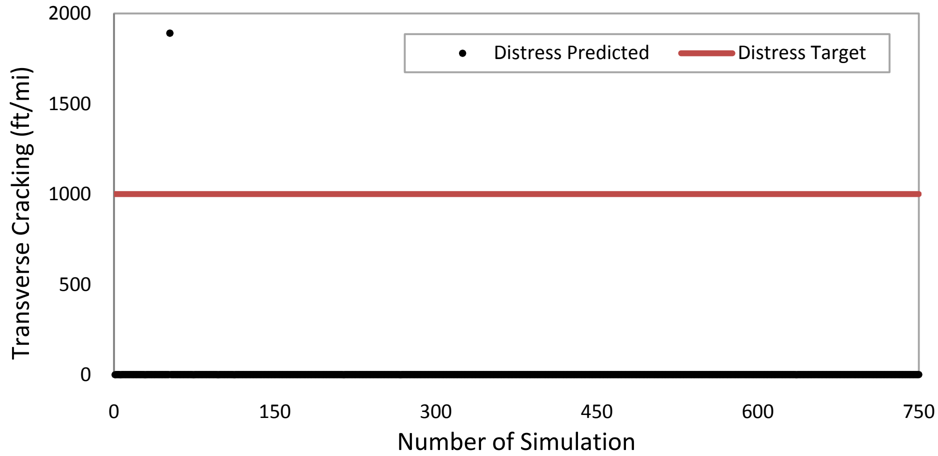


Figure (d): Transverse Cracking

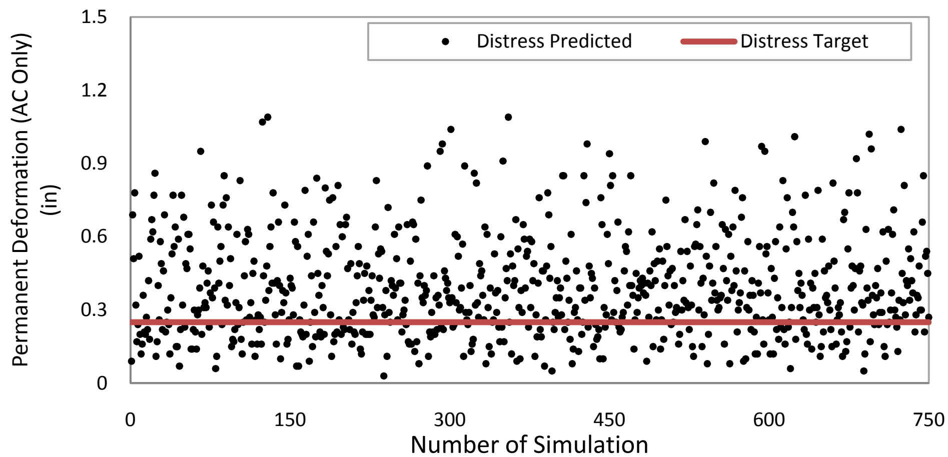


Figure (e): Permanent Deformation (AC only)

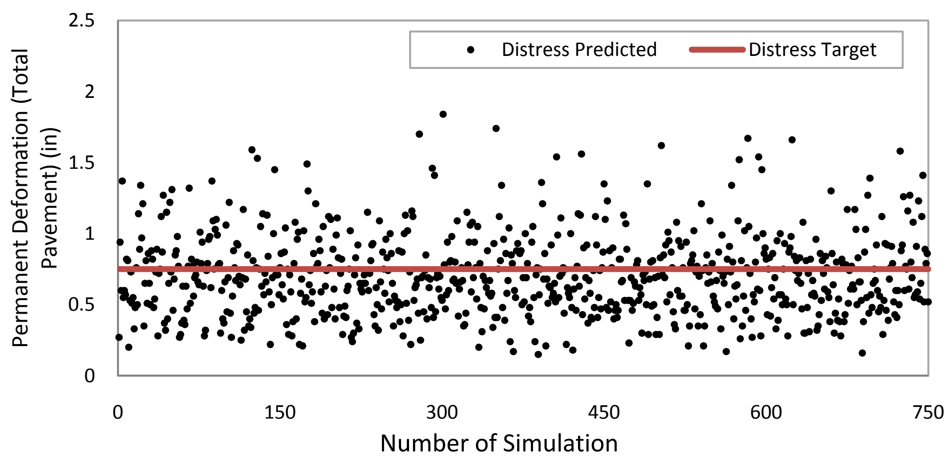
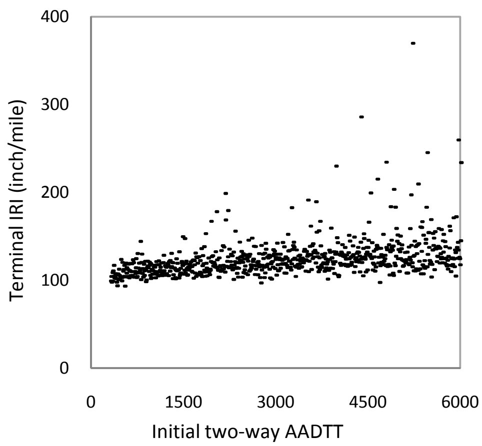
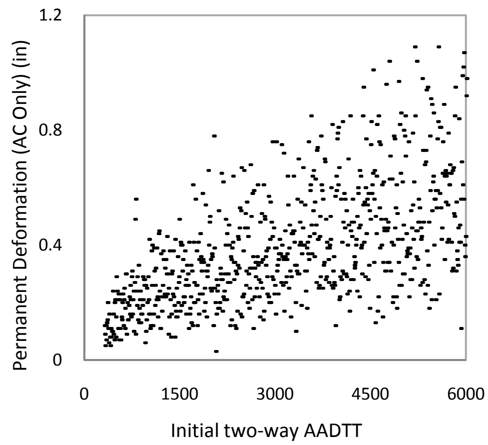


Figure (f): Permanent Deformation (Total Pavement)

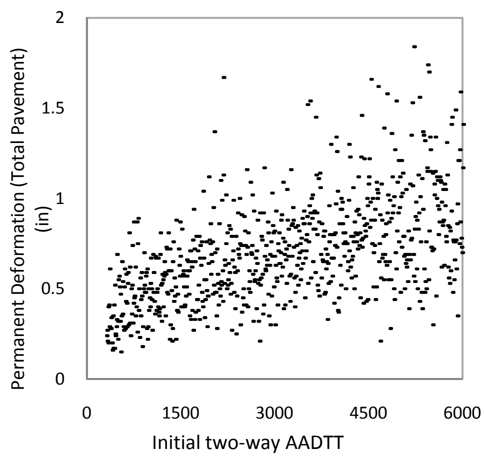
Figure 5.3: Summary Result of Test Matrix (Continued)



(a): Terminal IRI

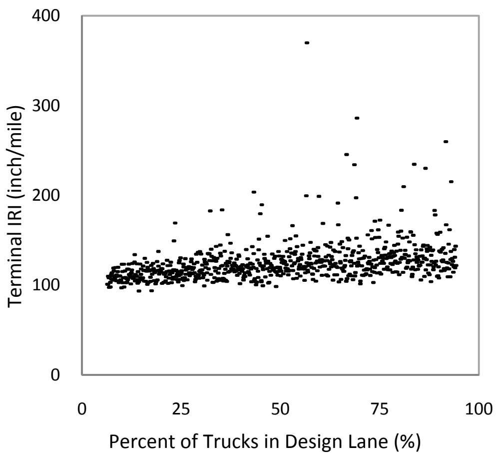


(b): Permanent Deformation (AC only)

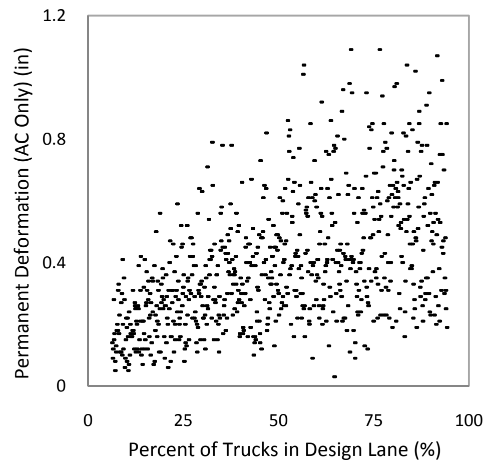


(c): Permanent Deformation (Total Pavement)

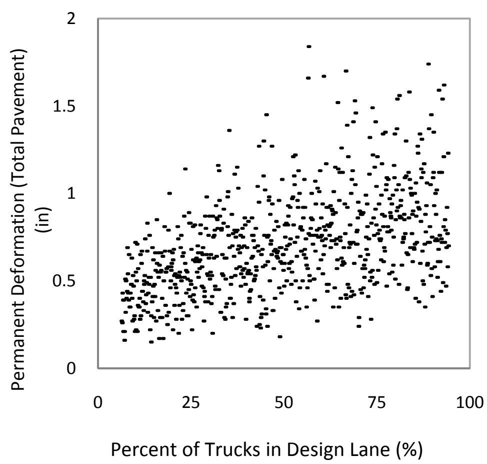
Figure 5.4: Effect of AADTT on Pavement Performance



(a): Terminal IRI

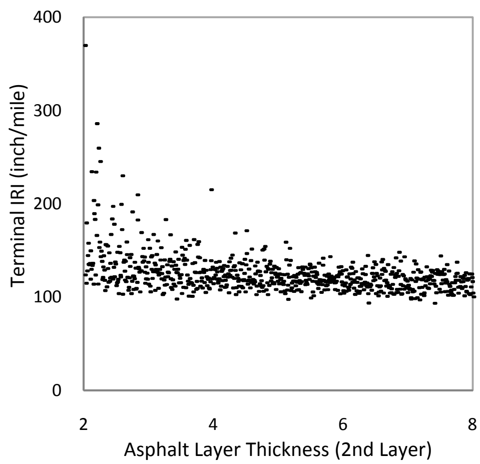


(b): Permanent Deformation (AC only)

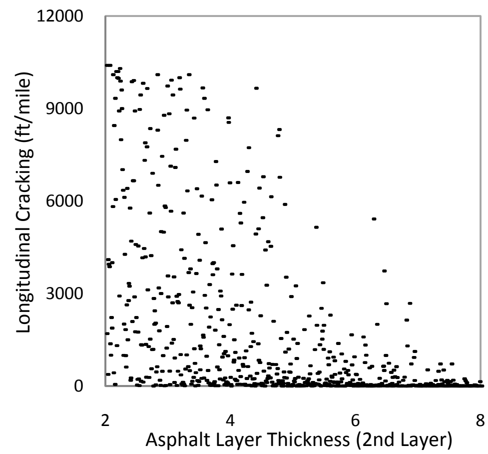


(c): Permanent Deformation (Total Pavement)

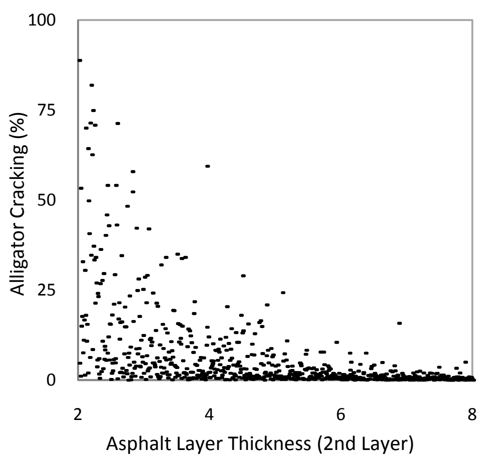
Figure 5.5: Effect of Truck Percentage on Pavement Performance



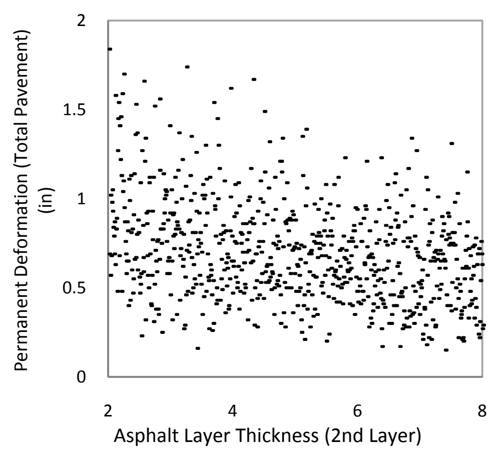
(a): Terminal IRI



(b): Longitudinal Cracking



(c): Alligator Cracking



(d): Permanent Deformation (Total)

Figure 5.6: Effect of Asphalt Layer Thickness (2nd Layer) on Pavement Performance

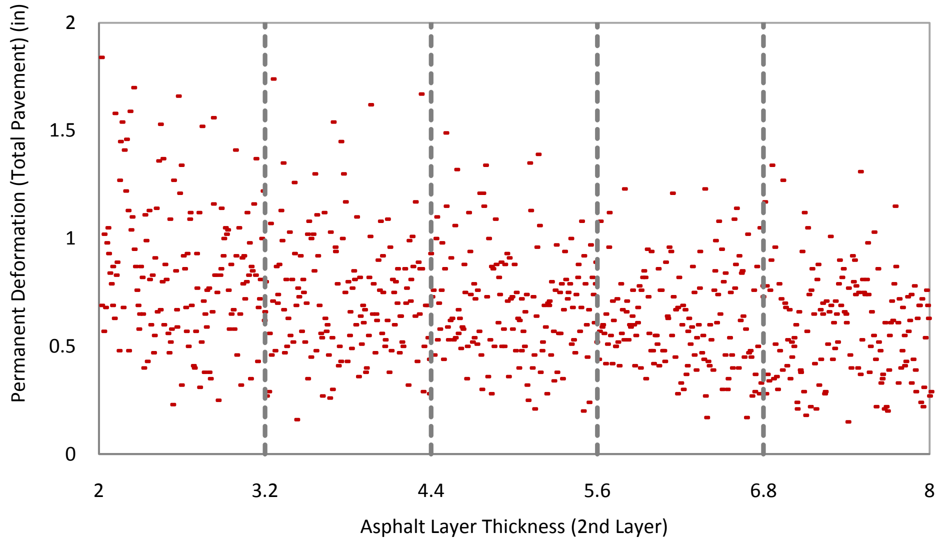


Figure 5.7 (a): Partitioning of Range of x_j for CMN and CL Tests

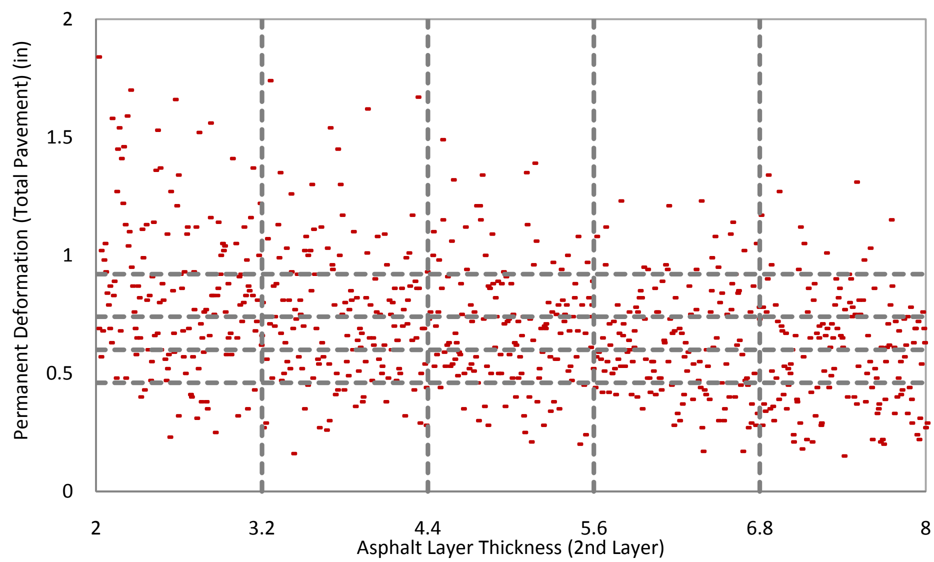


Figure 5.7 (b): Partitioning of Range of x_j and y for SI Test

Figure 5.7: Partitioning of Range of x_j and y for Different Tests based on Gridding

CHAPTER 6

A NONPARAMETRIC APPROACH TO SENSITIVITY ANALYSES

6.1 Introduction

The most significant variables and their interactions among other inputs are identified in this chapter. A sensitivity index is a quantitative measure of the variance in the response that is due to the uncertainty in an input. Different types of models are used in this chapter to estimate the necessary sensitivity index for each input. The sensitivity index helps to determine the sensitivity of one particular input variable with its interaction to output. Linear regression is one of the most popular choices for model construction because of its simplicity and the output is approximately linear to the inputs. If the input variables do not have linear relationship with the analysis result, linear regression methods often fail to quantify the importance of the inputs. Therefore, in this chapter, nonparametric regression procedures are implemented to estimate sensitivity indices and quantify the sensitivity.

6.2 Sensitivity Measures with Nonparametric Regression Procedure

The previous chapter presents the ranking of most important factors for predicted MEPDG outputs. Statistical approaches performed in previous chapter offer a qualitative measure of sensitivity. The relative importances of variables are not quantified. For this reason, nonparametric regression procedures are applied to quantify the sensitivity of predicted outputs for each input.

Nonparametric regression is a type of regression analysis. In this procedure, the output function does not take any predetermined form. According to the information derived from the data, the model is constructed. Nonparametric regression requires larger sample sizes than conventional regression based on parametric models because the data must supply the model structure as well as the model estimates. There are many types of nonparametric regression procedures. Two different types of methods are applied in this chapter. They are Multivariate Adaptive Regression Splines (MARS) and Gradient Boosting Machine (GBM). In addition, one parametric regression procedure Quadratic Response Surface Regression (QREG) is also applied to compare the results. Table 6.1, Table 6.2 and Table 6.3 give the summary of sensitivity measures for Model Y1 to Y6.

Two basic type of sensitivity measure, which are called Single Variance Index (S) and Total variance Index (T). They are going to be use for the rest of the sections of this chapter. These two indices give quantitative measure of sensitivity which is not possible by p-value. P-value can be varied by changing the sample size. Therefore, it can only provide the qualitative measure or significance of a particular input.

6.2.1 Variance Index

Single Variance Index

Single variance index or S_j indicates the sole influence of x_j without interaction. The value is normalized by the total variance of f. S can be calculated using Eqn. 7.1 given below .

$$S_j = \frac{Var\left(E\left[f(x)|x_j|\right]\right)}{Var\left(f(x)\right)} \qquad 7.1$$

By definition, S_j corresponds to the fraction of the uncertainty in y due to x_j only.

Total Variance Index

T can be calculated using Eqn. 7.2 given below (Homma and Saltelli 1996).

$$T_j = \frac{E\left(Var\left[f(x)\middle|x_j|\right]\right)}{Var\left(f(x)\right)} = \frac{Var\left(f(x)\right) - Var\left(E\left[f(x)\middle|x_{(-j)}|\right]\right)}{Var\left(f(x)\right)} \qquad 7.2$$

where, $x_{-j} = \{x_i, \dots \dots . x_{j-1}, x_{j+1}, \dots \dots . . x_p\}$ to quantify this uncertainty. T_j corresponds to the fraction of the uncertainty in y due to x_j and its interactions with other variables. The calculation of T_j requires the evaluation of p-dimensional integrals (Storlie et al. 2009). These are very good single number summary of the overall importance of an input variable. S_j and T_j are variance index for the true model. The estimated value or calculated value of S_j is expressed by S.hat. The estimated value or calculated value of T_j according to the regression model approximation is denoted by T. To calculate S_j and T_j for every input requires a big number of simulation runs, which would be infeasible for this study. For the remaining sections of this chapter, T will be considered instead of T_j and S will be considered instead of $S_{j.}$ we also obtain confidence intervals for true T_j and S_j based on the regression approximation.

6.2.2 Confidence Intervals

The use of nonparametric regression for estimating sensitivity measures can be more accurate than the use of standard Monte Carlo methods. This is especially true for estimating sensitivity measures with small to moderate sample sizes (Storlie et al. 2009). For a given sample size, accurate estimation is the main concern for sensitivity analysis. It is very important to know how much confidence is available in measuring the importance and rankings for the individual input variables. Therefore, CI is important and need to be considered. It can indicate the reliability of an estimate. By definition, Confidence intervals (CIs) for T_j should contain the true value for all repeated experimentation. By definition, Confidence intervals (CIs) for T_j should contain the true value for all repeated experimentation. As an example, model evaluation is done with n sample size from x distribution. These n values are used to create a confidence interval for T_j. If this experiment is repeated 1,000 times, CI of T_j will contain at least 950 values.

6.3 Sensitivity Measures with QREG

Quadratic response surface regression (QREG) is implemented in this study. The model is applied here with a stepwise model fitting procedure. For an input x_i, first it allows the linear (i.e., x_i) terms and squared (i.e., x^2_i) terms, and all linear × linear interactions (i.e., cross products x_jx_k) with other inputs x_k of the model. Backwards selection is then performed on these interaction terms before the next step (at which time another input is considered for inclusion) (Storlie et al. 2008). Detailed results are presented in Table 6.1(a) to Table 6.1(f).

Output Y1 (Terminal IRI)

Table 6.1(a) represents the result summary for Model Y1 (terminal IRI). Total model summary is given as a note of this table. The model has a R^2 value of 0.87, which means that 87% of uncertainties are captured in this model. Therefore, this model can be said a good model. Total model contains of 18 input variables. Input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown. The most important parameter in this model is X18 (bottom AC layer thickness). Single variance index for this input is 0.23. According to this value, it can be understand that the sole influence of X18 without any interaction is 23%. Total variance index obtained for this parameter is 0.34, which means that X18 alone and its interaction with other inputs all together explains 34% of the uncertainties. The total interaction for this input is 11% (this value can be obtained deducting S.hat value from T.hat value). The confidence interval of T is measured. The estimated T value for X18 is 0.34. We are 95% confident time the value will be within 0.292 to 0.387. It indicates that, 95% of the time X18 and its corresponding interaction can be within 29% to 39%. The variation in the confidence interval is small (±0.05) which indicates that the result is consistent.

In this model, the next important parameter is X1 (AADTT). This input variable is significant, as it obtained zero p-value. According to the S value, X1 itself is responsible for 23% of uncertainties. According to the T value, X1 and its corresponding interaction altogether captured 27% of the uncertainties. The total interaction for this input is 4.2% (this value is obtained deducting S.hat value from T.hat value). The confidence interval for T is 0.231 to 0.325. Therefore, influence of X1 and its interaction can be 23% to 33% in most of the cases. The variation of the upper limit and lower limit is 9.5% that is small. So, the result is steady in this case also.

X4 (percent of trucks in design lane) is also important factor in this model. Single variance index for this input is obtained 0.16. According to this value, it can be interpreted that the sole influence of X4 with any interaction is 16%. Influence of this input variable with its interaction with others has estimated 17%. 95% of time, this value will be from 13% to 21%. The total interaction for this input is around 2%. X13 or top AC layer thickness has T value of 0.1, which also means that this input's effect with the interaction among others can explain 10% of the variance. The range of this value is 7.5 to 15%. It alone can explain 9.4% uncertainties.

Without these parameters, X22 (percent air void of bottom AC layer) can be considered as important parameter for model Y1 because single variance index for this input is 0.046. According to this value, it can be understand that the sole influence of X22 without any interaction is 4.6%. And total variance index of X22 is 0.073 which means this parameter itself with its interaction have explained 7.3% of the uncertainties. Total interaction of this input is 2.7%. This input has upper limit up to 12% and lower limit up to 5%. X26 (type of subgrade material), X3 (percent of trucks in design direction), X25 (Base Modulus) and X8 (traffic growth factor) are considered as somewhat important factors. They all explain with their interactions from 3% to 6%.

<u>Output Y2 (Longitudinal Cracking)</u>

Table 6.1(b) represents the result summary for Model Y2 (Longitudinal Cracking). The model has a R^2 value of 0.89, which means that 89% of uncertainties are captured in this model. Therefore, this model can be said as an excellent model. Total model summary is given as a note of the table. Total model contains of 18 input variables. Among these 18 inputs, 9 input variables with less than 0.05 p-values are considered as significant and presented in this table.

In the first two column of this table, the name and description of the selected input variables are shown. The most important parameter in this model is X18 (bottom AC layer thickness). Single variance index for this input is 0.36. According to this value, it can be understand that the sole influence of X18 without any interaction is 36%. Total variance index obtained for this parameter is 0.56, which means that X18 alone, and its interaction with other inputs all together explains 56% of the uncertainties. Therefore the total interaction of this input is 19%. This can be considered as the most important factor for this model as it including its interaction has explained more than 50% of the variance. The confidence interval of T is measured and presented in the next column. The estimated T value for X18 is 0.56 but 95% time the value will be within 0.513 to 0.607. It indicates that, 95% of the time X18 and its corresponding interaction can be within 51% to 61%. The variation in the confidence interval is small (±0.05) which indicates that the result is consistent.

In this model, the next important parameter is X1 (AADTT). This input variable is significant as it obtained zero p-value. According to the S value, X1 itself is responsible for 13% of uncertainties. According to the T value, X1 and its corresponding interaction altogether captured 16% of the uncertainties. The confidence interval for T is 0.121 to 0.206. Therefore, influence of X1 and its interaction can be 12% to 21% in most of the cases. The variation between the upper limit and lower limit is 8.5%, which is almost negligible. Therefore, the result is steady in this case also. X4 (percent of trucks in design lane) is also important factor in this model which is itself responsible for 13% of uncertainties as well as has estimated T value almost close to X1. Influence of this input variable with its interaction with others has estimated 15%. Total interaction of this input is 1.5%. In most cases (95%), this value will be from 10% to 19%. These two parameter can be considered also as very important factor for this model as they explained more than 10% of the variance individually (including interaction).

X24 (base material type), X17 (percent air void of top AC layer) and X25 (base modulus) can be categorized as important for this model as they all explained 6% to 9% of the variance individually. The estimated T value is 9.2%, 6.4% and 6 % respectively. Input variable X24 need extra attention because most of the case influence can be increased up to 12%, which is greater than 10%.The same comment is also applicable for X25 as the highest limit of T estimated is 10%.

According to S value, it can be understand that the sole influence of X13 or top AC layer thickness without any interaction is 4.6 %. X13 has T value of 0.05 which also means that this input's effect with the interaction among others can explain 5% of the variance. The range of this value is 5% to 8.3%. X27 (subgrade modulus) can be considered as somewhat important parameter like X13 for model Y2 because this parameter itself with its interaction have explained 4% of the uncertainties. This value has upper limit up to 8% and lower limit up to 1%. X15 (effective binder content of top AC layer) with its interaction among others has explained 3% of the variance. Sometime, this effect can be negligible (almost 1%) and it can be up to 6% in some cases.

Output Y3 (Alligator Cracking)

Summary of the Model Y3 (Alligator Cracking) is presented in Table 6.1 (c). It is a very good model because the R^2 value of 0.89, which means that 89% of uncertainties are captured in this model. Total model contains of 17 input variables. Among these 18 inputs, 7 input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown. The most important parameter in this model is

X18 (bottom AC layer thickness). Single variance index for this input is 0.38. According to this value, it can be understand that the sole influence of X18 without any interaction is 38%. Total variance index obtained for this parameter is 0.6, which means that X18 alone, and its interaction with other inputs all together explains 60% of the uncertainties. This can be considered as the most important factor for this model as itself including its interaction has explained more than half of the variance. Interaction of this variable is important because the interaction is 22%. The confidence interval of T is measured and presented in the next column. The estimated T value for X18 is 0.6 but 95% time the value will be within 0.58 to 0.67. It indicates that, 95% of the time X18 and its corresponding interaction can be within 58% to 67%. The variation in the confidence interval is small (±0.05) which indicates that the result is consistent. The next important parameter is X1 (AADTT) for this model. According to S value, it can be understand that the sole influence of X1 without any interaction is 15%. According to the estimated T value, X1 and its corresponding interaction altogether captured 19% of the uncertainties. The confidence interval for T is 0.16 to 0.25. Therefore, influence of X1 and its interaction can be 16% to 25% in most of the cases. The variation between the upper limit and lower limit is 9%, which is very small. Therefore, the result is steady in this case also.

X22 (percent air void of second AC layer) is an important factor in this model because the sole influence of X22 without any interaction is 9% and itself and with its interaction with other inputs all together explains 12% of the uncertainties. Therefore the interaction is 3%. X4 (percent of trucks in design lane) is also important factor in this model because the sole influence of itself is 10% and combining with its individual influence with interaction with others has 12% of uncertainties. Therefore the total interaction is 3%. X13 or top AC layer thickness has S value and T value of 0.88 and 0.088 respectively, which also means that this input's effect without the interaction among others as well as with the interaction can explain 8.8% of the variance for both case. Therefore there is no influence of interaction for this input. The range of this influence can vary from 5% to 13%. Two basic properties of base layer are ranked as somewhat important in this method. They are X24 (base material type) and X25 (base modulus). They can be categorized as somewhat important for this model as they all explained 5% of the variance individually. The estimated T value for these two variables is 5% each. Both of these variables need extra attention because most of the case influence can be increased up to 10%. In some cases, this effect can be negligible (less than 2%).

Output Y4 (Transverse Cracking)

Table 6.1(d) represents the result summary for Model Y4 (Transverse Cracking). The model has a R^2 value of 0.15 which means that only 15% of uncertainties are captured in this model. Therefore, this model is not usable and different method should be applied for this model. Total model contains of 6 input variables. All these variables have less than 0.05 p-values and presented in this table. In the first two column of this table the name and description of the selected input variables are shown.

The most important parameter in this model is X26 (type of subgrade material). Single variance index for this input is 0.06. According to this value, it can be understand that the sole influence of X18 without any interaction is 6%.Total variance index obtained for this parameter is 0.35, which means that X26 alone, and its interaction with other inputs all together explains 35% of the uncertainties. Total interaction of this input is 29%. The confidence interval of T is measured and presented in the next column. The estimated T value for X26 is 0.35 but 95% time the value will be within 0.270 to 0.613. It indicates that, 95% of the time X26 and its corresponding interaction can be within 27% to 61%. The variation in the confidence interval is high (34%) which indicates that the result is not consistent.

Another input variable X7 (AADTT distribution by vehicle class 11) considered as important as X26. Estimated S value is 0.10, which means the sole influence of X7 without any interaction is 10%. Estimated T value is 0.343, which means that X7 with all its interaction can explain 34% of the uncertainties. Total interaction of this input is 25%. The CI for this T value is 0.330 to 0.69 which is also very big. X4 (percent of trucks in design lane) is also important factor in this model like the other two. Influence of this input variable with its interaction with others has estimated 32%. Most of the cases, this value will be from 31% to 53%.

The other three parameters are X28 (plastic limit), X24 (type of base material) and X29 (Liquid limit), used in this model can be considered as very important. They all explained 24% to 27% of the uncertainties. All these three parameter has chance to have influence up to 48% to 53%. X28 explains sole influence without interaction of 19% and influence combining with interaction with other inputs is 27%. X24 explains sole influence without interaction of 19% and influence combining with interaction with other inputs 24%. The last one has no interaction influence. The sole influence of X29 is 24%.

Output Y5 (AC Rut)

Table 6.1(e) represents the result summary for Model Y5 (AC rut). Total model summary is given as a note of this table. The model has a R^2 value of 0.95 which means that 95% of uncertainties are captured in this model. Therefore, this model can be said as very good and usable model. Total model contains of 17 input variables. Input variables with less than 0.05 p-values are considered as significant and presented in this table.

In the first two column of this table, the name and description of the selected input variables are listed. Two variable can be considered as very important factor for this model as they have explained more than 30% of the uncertainties individually. This effect includes its interaction with other inputs too. These inputs are X1 (AADTT) and X4 (percent of trucks in design lane). The individual influence without any interaction with other inputs of X1 and X4 are 34% and 34% respectively. Estimated T value for X1 and X4 are 39% and 36% respectively. Therefore total interactions of this input with others have influence of 5% and 2% respectively. The confidence interval of T for X1 is 0.36 to 0.43. The limit of this interval is very small which indicates that the result is reliable. The confidence interval of T for X4 is 0.33 to 0.40. This limit also indicates that the result is reliable.

From designer's view, these values are very important. The influence of X1 with its interaction can be up to 43% in some cases. Same as X1, the effect of X4 can be up to 40%. The influence for these two cases can decrease up to 36% and 33% respectively. Another important parameter in this model is X10 (tire pressure). Single variance index of X10 is 0.105. According to this value, it can be understand that the sole influence of

X10 without any interaction is 10.5%.Total variance index obtained for this parameter is 0.11, which means that X10 and its interaction with other inputs all together explains 11% of the total uncertainties. The estimated T value for X10 is 0.11 but 95% time the value will be within 0.09 to 0.15. It indicates that, 95% of the time X10 and its corresponding interaction can be within 9% to 15%. The variation in the confidence interval is small (±0.06) which indicates that the result is consistent. This parameter is important as it explain at least 10% of the variance.

In this model, the next parameter is X18 (bottom AC layer thickness) can be considered as quite important. This input variable is significant, as it obtained zero p-value. According to the T value, X18 and its corresponding interaction altogether captured 6% of the uncertainties. The confidence interval for T is 0.026 to 0.081. Therefore, influence of X18 and its interaction can be 3% to 8% in most of the cases.

The variation of the upper limit and lower limit is 5%, which is very small. Therefore, the result is steady in this case also. Three parameters have captured 3% to 4% uncertainties individually (including their interaction). They are X8 (Traffic growth factor), X12 (climatic zone) and X13 (top AC layer thickness). During design, these three parameters need little care as they can have influence up to 5-6% in some cases. In overall, this model is an excellent model for Y5 as it obtained a good R^2 value. The confidence interval for estimated T is reasonable which indicates reliability ion the result. QREG method is good choice for model Y5.

Output Y6 (Total Rut)

Table 6.1(f) represents the result summary for Model Y6 (Total Rut). Total model summary is given as a note of this table. The model has a R^2 value of 0.93 which means that 93% of uncertainties are captured in this model. Therefore, this model can be assigned as an excellent model also like Y5. Total model has selected 19 input variables according to stepwise addition and deletion process and finally build the model. Input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X1 (AADTT). Single variance index for this input is 0.29. According to this value, it can be understand that the sole influence of X1 without any interaction is 29%. Total variance index obtained for this parameter is 0.32 which means that X1 and its interaction with other input variables altogether explains 32% of the uncertainties. Total interaction is 3%. The confidence interval of T is measured and presented in the next column. The estimated T value for X1 is 0.32 but 95% time the value will be within 0.29 to 0.362. It indicates that, 95% of the time X1 and its corresponding interaction can be within 29% to 36%. The variation in the confidence interval is small (7%) which indicates that the result is consistent.

In this model, the next important parameter is X4 (percent of trucks in design lane). This input variable is significant also as it obtained zero p-value. Single variance index for this input is 0.27. According to this value, it can be understand that the sole influence of X4 without any interaction is 27%. According to the T value, X4 and its corresponding interaction altogether captured 29% of the uncertainties. The confidence interval for T is 0.257 to 0.325. Therefore, influence of X4 and its interaction can be 26% to 33% in most of the cases. The variation of the upper limit and lower limit is 9.5% which is small. Therefore, the result is steady in this case also. X18 or bottom AC layer thickness is also important factor in this model. The sole influence of this input without any interaction is 12%. Influence of this input variable with its interaction with others has estimated 13%. So the total interaction is only 1%. 95% of time, this value will be from 10% to 16%. This parameter is important as it explain at least 10% of the variance.

Two subgrade properties are listed in this table and can be considered as somewhat important factor for this model. They are X27 (subgrade modulus) and X30 (Optimum gravimetric water content). They have captured 6.2% and 5.2% of the uncertainties respectively. In some case the effect of subgrade modulus can be up to 9% and can be low up to 4%. Optimum gravimetric water content can play role from 2% to 8%.

Four parameters are listed in this table which are not very important but sometime needs extra attention. These are X10 (tire pressure), X8 (traffic growth factor), X13 (top AC layer thickness) and X21 (Superpave binder grade of bottom Ac layer). They all explained 3% to 5% of total uncertainties individually. Sometimes they can have their influence more than 7%. X26 (type of subgrade material) and X22 (percent air void of bottom AC layer) are considered as less important factors. They all explain with their interactions less than 3%.

6.4 Sensitivity Measures with MARS

Multivariate Adaptive Regression Splines (MARS) is implemented in this study and described in this section. This method is essentially a combination of spline regression, stepwise model fitting, and recursive partitioning. With this procedure, at first, a curve is fitted by adding (usually linear spline) basis functions to a model in a stepwise manner and then linear regression model is fitted. MARS procedure also considers stepwise deletion of basic functions. Detailed results are presented in Table 6.2 (a) to Table 6.2 (f).

<u>Output Y1 (Terminal IRI)</u>

Table 6.2(a) represents the result summary for Model Y1 (Terminal IRI). Total model summary is given as a note of this table. The model has a R^2 value of 0.76, which means that 76% of uncertainties are captured in this model. Therefore, this model can be said as a less confident model. Total model contains of all 30 input variables. Input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X18 (bottom AC layer thickness). Single variance index for this input is 0.29. According to this value, it can be understand that the sole influence of X18 without any interaction is 29%. Total variance index obtained for this parameter is 0.42 that means that X18 alone and its interaction with other inputs all together explains 42% of the uncertainties. Total interaction of this input is 13%. The confidence interval of T is measured and presented in the next column. The estimated T value for X18 is 0.42 but 95% time the value will be within 0.36 to 0.49. It indicates that, 95% of the time X18 and its corresponding interaction can be high as much as 49%. In some cases, this influence can be low up to 36%.

In this model, the next important parameter is X1 (AADTT). This input variable is also very significant, as it obtained zero p-value. Single variance index for this input is 0.25. According to this value, it can be understand that the sole influence of X1 without any interaction is 25%. According to the T value, X1 and its corresponding interaction altogether captured 25% of the uncertainties. The confidence interval for T is 0.169 to 0.29. Therefore, influence of X1 and its interaction can be 17% to 29% in most of the cases. The variation of the upper limit and lower limit is 12%, which is small. Therefore, the result is steady in this case. X4 (percent of trucks in design lane) is also as important as X1 in this model. Influences of this input variable without interaction and with interaction with others have estimated 19% and 22% respectively. Therefore the total interaction is 3%. 95% of time, this value will be from 18% to 29%. These two factors are considered as very important as they both have captures more than 10% of the variance individually.

X13 or top AC layer thickness has sole influence without the interaction 5.8%. It has a T value of 0.07 that also means that this input's effect with the interaction among others can explain 7% of the variance. The range of this value is 3.5% to 13.2%. X22 (percent air void of bottom AC layer) can be considered as important parameter for model Y1 because this parameter itself without interaction has explained 6.6% as well as itself with interaction has explained 6.65 of the uncertainties too. This value has upper limit up to 11% and lower limit up to 2%. These two parameters are somewhat important, as they have explained at least 5% of the uncertainties individually. Another main thing need to be considered that, these two parameters both has chance to have influence more than 10%. X16 (Superpave binder grade of top AC layer) can be considered not very important factor though it has listed in this table. It has explained 2% of the uncertainties that has chance to be up to 4%.

Output Y2 (Longitudinal Cracking)

Table 6.2(b) represents the result summary for Model Y2 (Longitudinal Cracking). The model has a R^2 value of 0.79, which means that 79% of uncertainties are captured in this model. Therefore, this model can be said as less confident model but usable. Total model summary is given as a note of the table. Total model contains of 30 input variables. Among these 30 inputs, 10 input variables with less than 0.05 p-values are considered as significant and presented in this table. The name and description of the selected input variables are listed in the first two column of this table.

The most important parameter in this model is X18 (bottom AC layer thickness). Single variance index for this input is 0.4. According to this value, it can be understand that the sole influence of X18 without any interaction is 40%. Total variance index obtained for this parameter is 0.60, which means that X18 alone, and its interaction with other inputs all together explains 60% of the uncertainties. Total interaction is 20%. This can be considered as the most important factor for this model as it including its interaction has explained more than 50% of the variance. The confidence interval of T is measured and presented in the next column. The estimated T value for X18 is 0.60 but 95% time the value will be within 0.532 to 0.652. It indicates that, 95% of the time X18 and its corresponding interaction can be within 53% to 65%. The variation in the confidence interval is not too big (12%) which indicates that the result is reliable.

In this model, the next important parameter is X1 (AADTT). This input variable is significant as it obtained zero p-value. Single variance index for this input is 0.14. According to this value, it can be understand that the sole influence of X1 without any interaction is 14%. According to the T value, X1 and its corresponding interaction altogether captured 14% of the uncertainties. The confidence interval for T is 0.092 to 0.180. Therefore, influence of X1 and its interaction can be 9% to 18% in most of the cases. The variation between the upper limit and lower limit is 9%, which is almost negligible. Therefore, the result is steady in this case also. X4 (percent of trucks in design lane) is also important factor in this model which has estimated T value almost close to X1. Influence of this input variable with its interaction with others has estimated 13.4%. In most cases (95%), this value will be from 9% to 18%. These two parameter can be considered also as very important factor for this model as they explained more than 10% of the variance individually (including interaction).

X17 (percent air void of top AC layer) and X24 (base material type) can be categorized as important for this model as they all explained 6% to 9% of the variance individually. The estimated T value is 9% and 7% respectively. Both of these input variable X17 need extra attention because most of the case influence can be increased up to 13.4%, which is greater than 10%. The same comment is also applicable for X24 as the highest limit of T estimated is 11.3%.

X25 (Base Modulus), X13 (top AC layer thickness), X27 (Subgrade Modulus) and X23 (base thickness) have estimated T value from 4% to 5%. This means that, any of these input's effect with the interaction among others can explain 5% of the variance. These set of inputs have chance to have influence up to 9% individually in some cases. Another input variable X3 (percent of trucks in design direction) is listed in this table with estimated T value of 2%. This parameter is not important as itself explain 2% of the variance and has a chance of being maximum 5%.

<u>Output Y3 (Alligator Cracking)</u>

Summary of the Model Y3 (Alligator Cracking) is presented in Table 6.2 (c). It is a very good and usable model because the R^2 value of 0.80, which means that 80% of uncertainties are captured in this model. Total model contains of 30 input variables. Among these 30 inputs, eight input variables with less than 0.05 p-values are considered as very significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are given.

The most important parameter in this model is X18 (bottom AC layer thickness). Single variance index for this input is 0.5. According to this value, it can be understand that the sole influence of X18 without any interaction is 50%. Total variance index obtained for this parameter is 0.68, which means that X18 alone, and its interaction with other inputs all together explains 68% of the uncertainties. Total interaction of this input with other inputs is 20%. This can be considered as the most important factor for this model as itself including its interaction has explained more than half of the variance. The confidence interval of T is measured and presented in the next column. The estimated T value for

X18 is 0.7 but 95% time the value will be within 0.6 to 0.74. It indicates that, 95% of the time X18 and its corresponding interaction can be within 60% to 74%.

The next important parameter is X1 (AADTT) for this model. According to S value, X1 itself is responsible for influence of 18% of uncertainties. According to the estimated T value, X1 and its corresponding interaction altogether captured 18% of the uncertainties. The confidence interval for T is 0.01 to 0.22. Therefore, influence of X1 and its interaction can be 10% to 22% in most of the cases. The variation between the upper limit and lower limit is 12%, which is considerable. Therefore, the result can be said steady in this case. X22 (percent air void of second AC layer) and X4 (percent of trucks in design lane) are also important factor in this model because both have estimated T value almost more than 10%. Influence of these input variables with their interaction with others has estimated 13% and 12% respectively. Individual influences without interaction of these two variables are 8% and 11% respectively. Therefore total interactions of these two variables are 5% and 1% respectively. In some cases, the influence of X22 can be up to 21% and the influence of X4 can be up to 17%. X13 or top AC layer thickness has S value of 0.08 and T value of 0.08, which also means that this input's effect with the interaction and without the interaction among others can explain 8% of the variance. The range of this influence can vary from 5% to 16%. Two input variables X25 (base modulus) and X3 (percent of trucks in design direction) can be categorized as somewhat important for this model as they all explained 5% of the variance individually. Both of these variables have chance to be influential up to 9%. In some cases, these effect can be negligible (0%).

Output Y4 (Transverse Cracking)

Table 6.2(d) represents the result summary for Model Y4 (Transverse Cracking). The model has a R^2 value of 0.6 which means that only 60% of uncertainties are captured in this model. Therefore, this model may be usable but cannot be considered as a good model. Different method should be applied for this model. Total model contains of 30 input variables. Among all these, two input variables have less than 0.05 p-values and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X4 (percent of trucks in design lane). Single variance index for this input is 0.05. According to this value, it can be understand that the sole influence of X18 without any interaction is 5%. Total variance index obtained for this parameter is 0.88, which means that X4 alone, and its interaction with other inputs all together explains 88% of the uncertainties. Total interaction of input with other variables is 83% which is very high compared to the individual influence. The confidence interval of T is measured and presented in the next column. The estimated T value for X4 is 0.88 but 95% time the value will be within 0.026 to 1.000. It indicates that, 95% of the time X4 and its corresponding interaction can be within 3% to 100%. The variation in the confidence interval is too high (97%) which indicates that the result is not consistent. Another input variable X7 (AADTT distribution by vehicle class 11) considered as important also. Estimated S value and T value is 0.35 and 0.40 respectively. According to S value, it can be understand that, X7 solely is responsible for 35% of influence. According to T value, sole influence with interaction with other inputs can explain 40% of the uncertainties. The CI for this T value is 0.2 to 0.81 which is also very big. (Comment)

Output Y5 (AC Rut)

Table 6.2(e) represents the result summary for Model Y5 (AC rut). Total model summary is given as a note of this table. The model has a R^2 value of 0.94 that means that 94% of uncertainties are captured in this model. Therefore, this model can be said as very good and usable model. Total model contains of 30 input variables. Input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are listed.

Two variables can be considered as very important factor for this model as they have explained more than 30% of the uncertainties individually. This effect includes its interaction with other inputs too. These inputs are X1 (AADTT) and X4 (percent of trucks in design lane). Single variance index for X1 is 0.34. According to this value, it can be understand that the sole influence of X1 without any interaction is 34%. Single variance index for X4 is 0.33. According to this value, it can be understand that the sole influence of X4 without any interaction is 33%. Estimated T value for X1 and X4 are 40% and 35% respectively. The confidence interval of T for X1 is 0.36 to 0.44. The limit of this interval (8%) is very small which indicates that the result is reliable. The confidence interval of T for X4 is 0.31 to 0.39. This limit also indicates that the result is reliable. From designer's view, these values are very important. The influence of X1 with its interaction can be up to 44% in some cases. Same as X1, the effect of X4 can be up to 39%. The influence for these two cases can decrease up to 36% and 30% respectively.

Another important parameter in this model is X10 (tire pressure). According to S value, X10 itself without its interaction captured 11% of the uncertainties. Total variance index obtained for this parameter is 0.11, which means that X10 and its interaction with other inputs all together explains 11% of the total uncertainties. There is no influence of the interactions. The estimated T value for X10 is 0.11 but 95% time the value will be within 0.09 to 0.14. It indicates that, 95% of the time X10 and its corresponding interaction can be within 9% to 14%. The variation in the confidence interval is small (±0.05) which indicates that the result is consistent. This parameter is important as it explain at least 10% of the variance.

In this model, the next parameter is X18 (bottom AC layer thickness) can be considered as quite important. This input variable is significant, as it obtained zero p-value. Estimated S value is 0.034, which means it solely is responsible for 3.4% of uncertainties. According to the T value, X18 and its corresponding interaction altogether captured 6% of the uncertainties. The confidence interval for T is 0.016 to 0.074. Therefore, influence of X18 and its interaction can be 2% to 8% in most of the cases. The variation of the upper limit and lower limit is 6%, which is very small. Therefore, the result is steady in this case also.

Two parameters have captured 2% uncertainties individually (including their interaction). They are X30 (Optimum gravimetric Water Content) and X25 (Base Modulus). These parameters are not as important as they have captured less than 5% of the variance individually. In overall, this model is an excellent model for Y5 as it obtained a good R^2 value. The confidence interval for estimated T is reasonable which indicates reliability ion the result. MARS method is good choice for model Y5.

Output Y6 (Total Rut)

Table 6.2(f) represents the result summary for Model Y6 (Total Rut). Total model summary is given as a note of this table. The model has a R^2 value of 0.91, which means that 91% of uncertainties are captured in this model. Therefore, this model can be said as an excellent and usable model also like Y5. Total model has selected 30 input variables according to stepwise addition and deletion process and finally build the model. Input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X1 (AADTT). Single variance index for this input is 0.30. According to this value, it can be understand that the sole influence of X18 without any interaction is 30%. Total variance index obtained for this parameter is 0.34, which means that X1, and its interaction with other input variables altogether explains 34% of the uncertainties. Therefore the total interaction of the input is 4%. The confidence interval of T is measured and presented in the next column. The estimated T value for X1 is 0.34 but 95% time the value will be within 0.31 to 0.39. It indicates that, 95% of the time X1 and its corresponding interaction can be within 31% to 39%. The variation in the confidence interval is small (9%) which indicates that the result is consistent.

In this model, the next important parameter is X4 (percent of trucks in design lane). This input variable is significant also as it obtained zero p-value. According to S value, it can be understand that the sole influence of X4 without any interaction is 26%. According to the T value, X4 and its corresponding interaction altogether captured 27% of the uncertainties. Therefore, only 1% influence of the interaction is exclaimed by this input. The confidence interval for T is 0.234 to 0.31. Therefore, influence of X4 and its interaction can be 23% to 31% in most of the cases. The variation of the upper limit and lower limit is 8%, which is small. Therefore, the result is steady in this case also. X18 or bottom AC layer thickness is also important factor in this model. Influence of this input variable with its interaction with others has estimated 13%. Among them all 13% is from sole interaction. Therefore there is no influence of interaction of inputs. 95% of time, this value will be from 8% to 15%. This parameter is important as it explain at least 10% of the variance.

X10 (tire pressure) is somewhat important in this model because it has explained 5.3% of sole and 6.4% sole with interaction influence of the uncertainties. The confidence interval for T is 0.05 to 0.1. Therefore, influence of X10 and its interaction can be 5% to 10% in most of the cases. The variation of the upper limit and lower limit is 5%, which is small.

X27 (subgrade modulus) and X30 (Optimum gravimetric water content), X8(Traffic Growth factor) and X13 (top AC layer thickness) have captured 3% to 6% of total uncertainties. In some cases, the effect of subgrade modulus can be up to 8% and can be low up to 2%. Optimum gravimetric water content can play role from 0% to 6%. For traffic growth factor, the variation is from 2% to 7%. Top AC layer thickness can have influence from 1% to 5%.

Three parameters are listed in this table which are not very important but sometime needs extra attention. These are X3 (Percent of Trucks in Design Direction (percentage)), X26 (type of subgrade material) and X21 (Superpave binder grade of bottom Ac layer). They all explained 2% to 3% of total uncertainties individually. Sometimes they can have their influence more than 5%.

6.5 Sensitivity Measures with GBM

Gradient Boosting Machine (GBM) is implemented in this study and described in this section. The general idea behind boosting trees is to compute a sequence of simple trees, where each successive tree is built for the prediction of the residuals from the preceding tree. These trees are then put together in an additive expansion to produce the final estimator. Detailed results are presented in Table 6.3 (a) to Table 6.3 (f).

Output Y1 (Terminal IRI)

Table 6.3(a) represents the result summary for Model Y1 (Terminal IRI). Total model summary is given as a note of this table. The model has a R^2 value of 0.90, which means that 90% of uncertainties are captured in this model. Therefore, this model can be said as an excellent and usable model. Total model contains of 27 input variables. Input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X18 (bottom AC layer thickness). Single variance index for this input is 0.42. According to this value, it can be understand that the sole influence of X18 without any interaction is 42%. Total variance index obtained for this parameter is 0.54 which means that X18 alone and its interaction with other inputs all together explains 54% of the uncertainties. Therefore total interaction for this input is 12%. The confidence interval of T is measured and presented in the next column. The estimated T value for X18 is 0.54 but 95% time the value will be within 0.442 to 0.602. It indicates that, 95% of the time X18 and its corresponding interaction can be within 44% to 60%.

In this model, the next important parameter is X1 (AADTT). This input variable is very significant, as it obtained zero p-value. According to the S value, X1 solely is responsible for influencing of 29% of uncertainties. According to the T value, X1 and its corresponding interaction altogether captured 29% of the uncertainties. Therefore no influence is exclaimed by interactions. The confidence interval for T is 0.21 to 0.342. Therefore, influence of X1 and its interaction can be 21% to 34% in most of the cases. X4 (percent of trucks in design lane) is also important factor in this model. X4 solely is responsible for the influence of 17%. Influence of this input variable with its interaction with others has estimated 20%. Therefore total interaction of this input is 3%. For most of the cases, this value will be from 16% to 29%. These three parameters are considered as most important factor for this model as they all explained more than 20% of the uncertainties individually.

X22 (percent air void of bottom AC layer) can be considered as somewhat important parameter for model Y1 because this parameter itself without its interaction have explained 1.7% of the uncertainties and with interaction have explained 3.5% of the uncertainties. This value has upper limit up to 7% and lower limit up to 2%. X8 (traffic growth factor), X13 (top AC layer thickness) and X14 (aggregate gradation of top AC layer) are considered not so important factors. They all explain with their interactions less than 5% individually. These parameters can be influential up to 5% to 6%.

Output Y2 (Longitudinal Cracking)

Table 6.3(b) represents the result summary for Model Y2 (Longitudinal Cracking). The model has a R^2 value of 0.90, which means that 90% of uncertainties are captured in this model. Therefore, this model can be said as an excellent model. Total model summary is given as a note of the table. Among all 30 inputs, 9 input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X18 (bottom AC layer thickness). Single variance index for this input is 0.57. According to this value, it can be understand that the sole influence of X18 without any interaction is 57%. Total variance index obtained for this parameter is 0.73, which means that X18 alone, and its interaction with other inputs all together explains 73% of the uncertainties. Total interaction for this input is 16%. This can be considered as the most important factor for this model as itself including its interaction has explained more than 73% of the variance. The confidence interval of T is measured and presented in the next column. The estimated T value for X18 is 0.73 but 95% time the value will be within 0.61 to 0.69. It indicates that, 95% of the time X18 and its corresponding interaction can be within 61% to 69%. The variation in the confidence interval is small (9%). However, the result obtained in this model, exceeded the limit value.

In this model, X4 (percent of trucks in design lane) is also important factor in this model which has estimated S value and T value 0.12 and 0.15 respectively. According to S value, X4 solely is responsible of exclaiming 12% of uncertainties. Influence of this input variable with its interaction with others has estimated 15%. Total interaction of this input is 3%. In most cases (95% of the time), this value will be from 13% to 22%. The next important parameter is X1 (AADTT). This input variable is significant, as it obtained zero p-value. X1 itself has an influence of 11.6% of uncertainties. According to the T value, X1 and its corresponding interaction altogether captured 12.3% of the uncertainties. The confidence interval for T is 0.10 to 0.19. Therefore, influence of X1 and its interaction can be 10% to 19% in most of the cases. The variation between the upper limit and lower limit is 9%, which is almost negligible. Therefore, the result is steady in this case. These two parameter can be considered also as very important factor for this model as they explained more than 10% of the variance individually (including interaction).

X25 (base modulus), X24 (base material type) and X17 (percent air void of top AC layer) can be categorized as important for this model as they all explained 5% to 10% of the variance individually. Estimated S value is 2.2%, 6.6%, and 4.6% respectively. On the other hand, the estimated T value is 5.4%, 5.2% and 5 % respectively. Input variable X25 need extra attention because most of the case influence can be increased up to 11%, which is greater than 10%. The same comment is also applicable for X24 and X17 as the highest limit of T estimated is 11% and 10% respectively. X13 or top AC layer thickness, X3 (Percent of Trucks in Design Direction (%)) and x26 (subgrade material type) are also listed in this table. These inputs have effect with the interaction among others can explain less than 5% of the variance. Sometime, these effect can be negligible (almost 0%) and can be up to 5% in some cases.

Output Y3 (Alligator Cracking)

Summary of the Model Y3 (Alligator Cracking) is presented in Table 6.3 (c). It is a very good model because the R^2 value of 0.93, which means that 93% of uncertainties are captured in this model. Among all inputs, 7 input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X18 (bottom AC layer thickness). Single variance index for this input is 0.61. According to this value, it can be understand that the sole influence of X18 without any interaction is 61%. Total variance index obtained for this parameter is 0.8, which means that X18 alone, and its interaction with other inputs all together explains 80% of the uncertainties. Total interaction for this input is 19%. This can be considered as the most important factor for this model as itself including its interaction has explained more than half of the variance. The confidence interval of T is measured and presented in the next column. The estimated T value for X18 is 0.8 but 95% time the value will be within 0.71 to 0.79. It indicates that, 95% of the time X18 and its corresponding interaction can be within 71% to 79%. The variation in the confidence interval is small (9%). However, the result obtained in this model, exceeded the limit value.

The next important parameter is X1 (AADTT) for this model. According to the S value, X1 itself is responsible for 14% of uncertainties. According to the estimated T value, X1 and its corresponding interaction altogether captured 17% of the uncertainties. Total interaction of this input is 3%. The confidence interval for T is 0.15 to 0.26. Therefore, influence of X1 and its interaction can be 15% to 26% in most of the cases. The variation between the upper limit and lower limit is 11%, which is ok. Therefore, the result is steady in this case.

X22 (percent air void of second AC layer) and X4 (percent of trucks in design lane) are also important factor in this model because both have estimated T value almost more than 10%. Influence of these input variables with their interaction with others has estimated 8.4% individually. In some cases, the influence of X22 can be up to 16% and the influence of X4 can be up to 17%.

X13 or top AC layer thickness has T value of 0.04, which also means that this input's effect with the interaction among others can explain 4% of the variance. The range of this influence can vary from 1% to 7.3%. X25 (base modulus) and X28 (plastic limit) are ranked in this method. They can be categorized as not very important for this model as they have explained less than 5% of the variance individually. The estimated T value for these variables is 3%. In some cases, influence can be increased up to 8%. In some cases, this effect can be negligible (0%).

<u>Output Y4 (Transverse Cracking)</u>

Table 6.3(d) represents the result summary for Model Y4 (Transverse Cracking). The model has a R^2 value of 0.39 which means that only 39% of uncertainties are captured in this model. Therefore, this model is not usable and different method should be applied for this model. Total six input variables have less than 0.05 p-values and presented in this

table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X28 (plastic limit). Single variance index for this input is 0.76. According to this value, it can be understand that the sole influence of X18 without any interaction is 76%.Total variance index obtained for this parameter is 0.87, which means that X28 alone, and its interaction with other inputs all together explains 87% of the uncertainties. Total interaction of this input is 11%. The confidence interval of T is measured and presented in the next column. The estimated T value for X28 is 0.87 but 95% time the value will be within 0.2 to 1.0. It indicates that, 95% of the time X26 and its corresponding interaction can be within 20% to 100%. The variation in the confidence interval is high (80%) which indicates that the result is not consistent.

Another input variable X4 (percent of trucks in design lane) considered as important. According to the S value, X4 itself is responsible for 17% of uncertainties. Estimated T value is 0.17, which means that X4 with all its interaction can explain 17% of the uncertainties. The CI for this T value is 0.0 to 0.35 which is also very big. X12 (climatic zone) is also important factor in this model like the other two. Influence of this input variable with its interaction with others has estimated 11%. Among them all influence is exclaimed by the interaction of inputs with other inputs. Most of the cases, this value will be from 11% to 22%.

The other three parameters are X23 (thickness of base layer)and X11 (depth of water table used in this model can be considered as important. They both explained 9% of the uncertainties. But there is no influence of both of them solely. All influence is due to the interaction of the input with other inputs. All these three parameter has chance to have influence up to 23% and 22% respectively. X21 (superpave binder grade of second AC layer) has obtained T value of .05 which means that it is able to explain 5% of the uncertainties. This parameter's effect can vary from 0% to 10%.

<u>Output Y5 (AC Rut)</u>

Table 6.3(e) represents the result summary for Model Y5 (AC rut). Total model summary is given as a note of this table. The model has a R^2 value of 0.93 which means that 93% of uncertainties are captured in this model. Therefore, this model can be said as very good and usable model. Total six input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are listed.

Two variable can be considered as very important factor for this model as they have explained more than 30% of the uncertainties individually. This effect includes its interaction with other inputs too. These inputs are X1 (AADTT) and X4 (percent of trucks in design lane). Single variance index for this input is 0.42. According to this value, it can be understand that the sole influence of X1 without any interaction is 42%. Single variance index for this input is 0.36. According to this value, it can be understand that the sole influence of X18 without any interaction is 36%.Estimated T value for X1 and X4 are 49% and 40% respectively. Total interactions for these inputs are 7% and 2% respectively. The confidence interval of T for X1 is 0.41 to 0.50. The limit of this interval (9%) is very small which indicates that the result is reliable. The confidence interval of T for X4 is 0.34 to 0.43. This limit also indicates that the result is reliable. From designer's view, these values are very important. The influence of X1 with its interaction can be up to 50% in some cases. Same as X1, the effect of X4 can be up to 43%. The influence for these two cases can decrease up to 41% and 34% respectively.

Another important parameter in this model is X10 (tire pressure). According to the S value, X10 itself is responsible for 11% of uncertainties. Total variance index obtained for this parameter is 0.12, which means that X10 and its interaction with other inputs all together explains 12% of the total uncertainties. The estimated T value for X10 is 0.12 but 95% time the value will be within 0.01 to 0.17. It indicates that, 95% of the time X10 and its corresponding interaction can be within 10% to 17%. The variation in the confidence interval is small (7%) which indicates that the result is consistent. This parameter is important as it explain at least 10% of the variance.

In this model, the next parameter is X18 (bottom AC layer thickness) can be considered as quite important. This input variable is significant, as it obtained zero p-value. According to the S and T value, X18 solely without corresponding interaction captured 3.6% of the uncertainties. There is no influence of the interaction. The confidence interval for T is 0.02 to 0.07. Therefore, influence of X18 and its interaction can be 2% to 7% in most of the cases. The variation of the upper limit and lower limit is 5%, which is very small. Therefore, the result is steady in this case also.

Two parameters have captured less than 3% of total uncertainties individually (including their interaction). They are X8 (Traffic growth factor) and X13 (top AC layer thickness). They can have influence up to 5% in some cases. In overall, this model is an excellent model for Y5 as it obtained a good R^2 value. The confidence interval for estimated T is reasonable which indicates reliability ion the result. GBM method is good choice for model Y5.

Output Y6 (Total Rut)

Table 6.3(f) represents the result summary for Model Y6 (Total Rut). Total model summary is given as a note of this table. The model has a R^2 value of 0.91 which means that 91% of uncertainties are captured in this model. Therefore, this model can be assigned as an excellent model also like Y5. Input variables with less than 0.05 p-values are considered as significant and presented in this table. In the first two column of this table, the name and description of the selected input variables are shown.

The most important parameter in this model is X1 (AADTT). Single variance index for this input is 0.4. According to this value, it can be understand that the sole influence of X1 without any interaction is 40%. Total variance index obtained for this parameter is 0.45 which means that X1 and its interaction with other input variables altogether explains 45% of the uncertainties. Total interaction for this input is 5%. The confidence interval of T is measured and presented in the next column. The estimated T value for X1 is 0.45 but 95% time the value will be within 0.35 to 0.45. It indicates that, 95% of the time X1 andi its corresponding interaction can be within 35% to 45%. The variation in the confidence interval is small (10%) which indicates that the result is consistent.

In this model, the next important parameter is X4 (percent of trucks in design lane). This input variable is significant also as it obtained zero p-value. According to the S value, X4 itself is responsible for 34% of uncertainties. According to the T value, X4 and its corresponding interaction altogether captured 36% of the uncertainties. Therefore total interaction of the input is 2%. The confidence interval for T is 0.28 to 0.38 Therefore, influence of X4 and its interaction can be 28% to 8% in most of the cases. The variation of the upper limit and lower limit is 10%, which is small. Therefore, the result is steady in this case also. X18 or bottom AC layer thickness is also important factor in this model. Influence of this input variable without its interaction with others has estimated 12.4%. there is no influence of interaction. 95% of time, this value will be from 10% to 17%. This parameter is important as it explain at least 10% of the variance.

Two input variables are listed in this table and can be considered as not so important factor for this model. They are X10 (tire pressure) and X27 (subgrade modulus). They have captured less than 4% of the uncertainties respectively. In some case, the effect of subgrade modulus can be up to 7% and can be low up to 2%. Tire pressure can play role from 3% to 8%. Three parameters are listed in this table which are not important because they have captured less than 3% of the uncertainties individually. These are X30 (Optimum gravimetric water content), X3 (Percent of Trucks in Design Direction) and X11 (Depth of Water table). Sometimes they can have their influence about 4%.

6.5 Discussion

In this section, the results obtained from the nonparametric regression methods are investigated. For this study, total 6 output variables and 30 input variables are used. Not all of the inputs have an effect on each of the six outputs. Three meta-models are used in this study and they are Quadratic regression (QREG), Multivariate Adaptive Regression Splines (MARS) and Gradient Boosting Method (GBM). All of the meta-models considered are constructed using the *CompModSA* R package available at http://www.stat.unm.edu/_storlie. To obtain the outputs, MEPDG model is evaluated with sample size n=750. Using these meta-models, the bootstrap confidence interval is estimated for the T_j for each output. For comparing the meta-models, the input variables are divided in four groups. These groups are called as Group A to D. If any input variable (including the interaction among other input variables) explains at least 10% of the variance, than it will be categorized as A. If the input and its interaction is able to explain 6% to 9% of the variance, then it will be grouped as B. for C group the range is 3-5% and for D group the range is 2% or less than 2%. This category will be maintained also for quantifying interaction effect in the rest of the sections of this chapter.

6.5.1 Output Y1 (Terminal IRI)

Table 6.4 summarizes the analysis results for output Y1 (terminal IRI) for different methods. In the first row of this table, R^2 obtained by these methods are given. The highest R^2 value (0.91) obtained by GBM method. The second highest value is obtained by QREG (0.87) and the lowest value is obtained by MARS (0.76). By comparing these R^2 values, it can be said that the output model by GBM method is an excellent and usable one. Three type of variance are described in Table 6.4. These variances are expressing total effects (T.hat), individual effect (S.hat) and effect of interaction (S.hat value is deducted from T.hat). For total effect, four input variables have fallen in A group for QREG method. Rest of the models has three inputs in this group individually. Among this group, three inputs are common for all Methods. They are X18 (bottom AC layer thickness), X1 (AADTT) and X4 (percent of trucks in design lane). Therefore, these three inputs are most important factor for this output. X13 (top AC layer thickness) is also important factor for this output because this input variable is obtained by all three methods though in different group. X22 (percent air void of bottom AC layer) is also common for all meta-models. It has captured 6-9% of variance for QREG and MARS, but 3-5% for GBM. Overall, these five parameters can be said important factor for this output without any doubt for total effect. For all these three methods, the order of top listed parameters is same and consistent. Without these five parameters, rest of the input variables is also common for all three methods and the order also. Therefore, it can be said that the models obtained for output Y1 are reliable. GBM is the best method for this output and QREG is fine.

For main effect, three input variables have fallen in A group for all three methods. These three inputs are common for all Methods. They are X18 (bottom AC layer thickness), X1 (AADTT) and X4 (percent of trucks in design lane). Therefore, these three inputs are most important factor for this output for their sole effect. X13 (top AC layer thickness) is also important factor for this output because this input variable is obtained by all three methods though in different group. It is personally responsible for 6% to 9% of uncertainties in QREG and MARS method but less than 2% for GBM. X22 (percent air void of bottom AC layer) is also common for all meta-models. It has captured 6-9% of variance for QREG, 3-5% for MARS and 2% or less than 2% for GBM. X30 or gravimetric water content is obtained in B group for QREG but it is not found as important in other two methods for main effect. For all these three methods, the order of top listed parameters is almost same and consistent. Without these mentioned parameters, rest of the input variables is also common for all three methods and the order also.

For interaction effects, X18 (bottom AC layer thickness) is the most responsible for all cases. X1 and X22 are responsible for 3% to 5% of uncertainties in QREG method. X4 is responsible for same amount of uncertainties in MARS and GBM but not in QREG. X10 is in Group B for MARS but no other method else.

Figure 6.1 represents graphically the summary result of most important factors by all three methods. Figure 6.1 (a), Figure 6.2 (b) and Figure 6.3 (c) present the most significant factors (p-value < 0.05) by QREG, MARS and GBM Method respectively. By QREG method total nine variables are listed as significant which is the highest among three meta-models. By MARS and GBM, total six and seven input variables listed respectively. From these figures, it can be seen that X18 or bottom AC layer thickness with its interaction among others has captured the most percentage of uncertainties for all three methods. The total uncertainty captured by this input variable is highest in GBM (42%) and the lowest in QREG (23%). The interaction effect due to this parameter is almost same in all three methods.

X1 (AADTT) has ranked second important factor in all three meta-models. The total uncertainties explained by this input variable are almost same in three cases (25~30%). In QREG method some interaction effects is obtained for this input variable but for the other methods interaction effect is null.X4 or percent of trucks in design lane placed third in the ranking order for all three methods. It is very clear from the figures that the effect of this input is also same in all cases (17%~20%). The interaction effect for this input variable is also same in all three methods (2%~3%). X13 or top AC layer thickness has different S. hat value in these figures. It has ranked fourth in all QREG and MARS but seventh in GBM. It is able to explain around 10% of the uncertainties in QREG model but less than 10% in other methods. The interaction effects for this input variable are almost negligible in all cases. It is quite interesting that sole effect and interaction effect of this input variable is same in GBM method.

X22 or percent air void of bottom AC layer is also common for all these three methods with almost same rank. In all three models, it has S.hat value less than 10%. In GBM model, it has the lowest S.hat value, which is 3%. There is no interaction effect in MARS model for this input variable. In GBM model, interaction effect due to this variable is greater than Main effect.

Without these five parameters, QREG and GBM both have X8 (traffic growth factor) which is not listed by MARS. X8 has explained 4% of the uncertainties in QREG and no interaction effects. In GBM, it has interaction effects more than main effects. X26 (subgrade material type), X3 (percent of trucks in design direction) and X25 (base modulus) have ranking in QREG method but they are absent in MARS and GBM method. X16 (Superpave binder grade of bottom AC layer) is ranked in MARS meta-model but not any other methods. X14 (aggregate gradation of top AC layer) is ranked in GBM meta-model but not by others.

Figure 6.2 summarizes the results of estimating T_j over Y1. In this figure, the most important factors (discussed in Table 6.4 and Figure 6.1) are presented. In the vertical axis of these figures, total variance index is scaled in percent value. The true T_j of each input factor obtained by all three meta-models are shown. The 95% CI for T is presented as the high low line. Figure 6.2(a) gives the summary for X18 or bottom AC layer thickness. GBM has the largest total variance T for Y1. 95% CI of T value has 16% coverage for GBM. QREG has 10% and MARS has 13% coverage. This is due to the nonlinear approximation to model the curvature in Y1 across X18 and the interaction effect between X18 and other inputs. T.hat for QREG is an excellent measure in this example as it has almost the same limit value from upper and lower boundary. This comment is also applicable for MARS and GBM. According to GBM the effect of X18 can be up to 60%. The lowest effect of X18 is 34%, which is obtained by QREG model. Figure 6.2 (b) presents summary of Tj value for X1 or AADTT. T.hat value for all three methods is almost same for all three methods (25%~28%). The result is very consistent in this case also. QREG and GBM have the highest influence of X1 (33%~34%). The upper limit of CI for MARS is 30%. MARS has the lowest limit of Tj for X1, which is less than 20%. QREG and GBM have lowest limit of T value above 20%. The total result in this case for QREG and GBM is almost same to each other and MARS has very little difference, which is almost negligible. Therefore, for this case the result is very consistent. Figure 6.2 (c) presents the summary result for X4 or percent of trucks in design lane. The T.hat for QREG is less than 20%. MARS and GBM have T.hat value more than 20%. The upper limit of CI for QREG is 21%, which is even lower than t.hat value of MARS and GBM. Upper limit of Tj for MARS and GBM are same and the value is 29%. Lower limit of CI for QREG is 13%, for MARS is 18% and for GBM is 16%. T.hat value and the CI are almost same in all three methods for this input variable. Figure 6.2 (d) presents the summary result for X13 or top AC layer thickness. In this case, QREG result varies little bit with MARS and GBM result. T.hat for QREG is 10% but MARS and GBM have T.hat less than 10%. QREG has CI for Tj is 8 to 15%. Mars has the CI from 3% to 13% and GBM has CI from 2% to 7%. QREG has considered this parameter as an important factor but for GBM and MARS it is not so important. Figure

6.2 (e) presents the result for X22 or percent air void of bottom AC layer. QREG and MARS have T.hat almost same (6~7%) and GBM has T.hat for this input variable is 3%. QREG and MARS have described that, X22 has the probability for being influential up to 12%. For GBM, this effect can be up to 6% only.

6.5.2 Output Y2 (Longitudinal Cracking)

Table 6.5 summarizes the analysis results for output Y2 (Longitudinal Cracking) for different meta-models. In the first row of this table, R^2 obtained by these methods are given. The highest R^2 value (0.90) obtained by GBM method. QREG has R^2 value (0.89) almost close to GBM. MARS has the lowest R^2 value (0.79) among the three methods. By comparing these R^2 values, it can be said that the output model by GBM and QREG methods are excellent and usable also. For total effect, three input variables have fallen in A group for all three methods and they are common for all Methods. They are X18 (bottom AC layer thickness), X1 (AADTT) and X4 (percent of trucks in design lane). Therefore, these three inputs are most important factor for this output. Ranking order of these inputs is same for QREG and MARS. X18 (bottom AC layer thickness) is ranked first in all three methods. X1 (AADTT) has achieved second position in QREG and Mars but third position in GBM. X4 (percent of trucks in design lane) is ranked second in GBM but third in both QREG and MARS. X24 or base material type has grouped in B group for all methods. It has explained 6 to 9% uncertainties for all three cases. X17 (percent air void for top AC layer) has grouped in B group in both QREG and MARS. It has explained 6 to 9% uncertainties in these two methods. GBM has this input in Group C that means X24 has explained 3 to 5% uncertainties. X25 (Base modulus) is in group C for GBM and MARS but it has more importance in QREG. These six input factors mentioned above are considered as main factors for Y2. Though they have different ranking order but the difference is negligible. Therefore, the result obtained for Y2 is consistent among all three methods. Without these inputs, the rest of the order is almost same for all three meta-model. All three meta-models are consisted of 15 input variables individually and the first ten inputs of all meta-models are almost same order. The other common inputs are X13 (top AC layer thickness), X27 (subgrade modulus), X23 (base thickness) and X3 (percent of trucks in design direction). Some of the inputs are not common for all three methods but may be common in two methods (i.e., X15 (effective binder content of top AC layer). Overall, it can be said that the models obtained for output Y2 are reliable.

For main effect, the same result for total effect is obtained for group A. They are X18 (bottom AC layer thickness), X1 (AADTT) and X4 (percent of trucks in design lane). Therefore, these three inputs are most important factor for this output for their sole effect. X24 or base material type is also important factor for this output because this input variable is obtained by all three methods though in group B. It is personally responsible for 6% to 9% of uncertainties as main effect. X17 (percent air void for top AC layer) has grouped in B group in both QREG and MARS. It has explained 6 to 9% uncertainties by itself in these two methods but less than 2% for GBM.

X25 or base modulus is responsible only for main effect for all three cases for 3% to 5% of uncertainties. X13 (top AC layer thickness) is also common for all meta-models for main effect. It has captured 3-5% of variance for QREG and MARS but 2% or less than 2% for GBM. For all these three methods, the order of top listed parameters is almost same and consistent. Without these mentioned parameters, rest of the input variables is also common for all three methods and the order also. For interaction effects, X18 (bottom AC layer thickness) is the most responsible for all cases. X1 and X27 are responsible for 3% to 5% of uncertainties in QREG method. X4 and X25 are responsible for same amount of uncertainties in GBM. Rest of the parameters for all three methods has very negligible interaction effects.

Figure 6.3 represents graphically the summary result of most important factors by all three methods. Figure 6.3 (a), Figure 6.3 (b) and Figure 6.3 (c) present the most significant factors (p-value < 0.05) by QREG, MARS and GBM Method respectively. QREG and GBM method have total nine variables listed as significant. MARS has list of total ten input variables. From these figures, it can be seen that X18 or bottom AC layer thickness with its interaction among others has captured the most percentage of uncertainties for all three methods. The total uncertainty captured by this input variable only is 57% in GBM and 40% in MARS and 36% in QREG. The interaction effects due to this input variable are almost same for all three cases (16% to 20%).

Rest of the inputs for Y2 model in all three meta-models have explained less than 20 % of uncertainties individually.X1 (AADTT) and X4 or percent of trucks in design lane are also very important factor for output Y2 and they have explained more than 10% of the uncertainties individually for all three meta-models. No interaction effects for X1 are obtained in MARS but very small amount are obtained in the rest of the two cases. All other inputs in these meta-models are considered somewhat important as they all have captured less than 10% of the uncertainties. X17, X24 and X25 are almost in same order for all these three meta-models. These three have explained 5% to 10% of the uncertainties individually as main effect. Interaction effects obtained for these three inputs in all meta-models are less than 3% which have no importance. X13 is one of the input variable which is common for the significant list of all three methods and has captured 2% to 5% of the uncertainties. Rest of the inputs shown in the graphs is less important as they have explained less than 2% of the variance individually.

Figure 6.4 summarizes the results of estimating T_j over Y2. In this figure, the most important factors (discussed in Table 6.5 and Figure 6.3) are presented. In the vertical axis of these figures, total variance index is scaled in percent value. The true T_j of each input factor obtained by all three meta-models are shown. The 95% CI for T is presented as the high low line. This is due to the nonlinear approximation to model the curvature in Y2 across the input variables and the interaction effects between that the input variable and other inputs.

Figure 6.4(a) gives the summary for X18 or bottom AC layer thickness. GBM has the largest total variance T for Y2 (73%). 95% CI of T value has 8% coverage for GBM. The estimated T value for this model by GBM has exceeded the CI limit (61% to 69%). QREG has 9% and MARS has 12% coverage. The highest uncertainties possible by X18 are around 60% by QREG. GBM has shown that, the lowest influence of X18 is 60%. T.hat value obtained for GBM is 60%, which is same to the upper limit of CI for QREG. Overall, the T.hat obtained by these three methods are close to each other.

Figure 6.4 (b) presents summary of Tj value for X1 or AADTT. T.hat value for all three methods is almost same for all three methods (12%~16%). The result is very consistent in this case also. The highest limit of CI for Tj value for three case are almost same (around 20%). The lower boundary of CI is relatively close to each other for all three methods

(9% to 12%). The T.hat for this model by three meta-models do not very so much (12% to 16%). So, the result is very reliable in this case.

Figure 6.4 (c) presents the summary result for X4 or percent of trucks in design lane. The T.hat for QREG and GBM are same (15%) which is very close to T.hat of MARS (13%). The upper limit of CI for GBM is 22%, which is the highest among these three. Rest of two methods has CI upper boundary less than 20%. Lower limit of CI for QREG is 10%, for MARS is 9% and for GBM is 13%. T.hat value and the CI are almost same in all three methods for this input variable.

Figure 6.4 (d) presents the summary result for X24 or type of base material. In this case, GBM result varies little bit with MARS and QREG result. T.hat for QREG is 9%, MARS and GBM have T.hat 7% and 5% respectively. QREG has CI for Tj is 9 to 12%. Mars has the CI from 3% to 11% and GBM has CI from 5% to 10%. All these three meta model consider this parameter is not so important for this model Y2 because it has explained less than 10% of variance in each case. However, from CI, it is clear that it has the probability to have influence greater than 10%.

Figure 6.4 (e) presents the result for X17 or percent air void of top AC layer. QREG and GBM have T.hat almost same (5~6%) and MARS has T.hat for this input variable is 9%. For all three methods, the upper limit of CI is 10 % or greater than 10%. The lower boundary of CI for QREG is almost negligible (2%). QREG and GBM have lower limit 5% and 3%, which is the case of less importance.

Figure 6.4 (f) presents the result summary of X25 (base modulus). The T.hat value for all three meta-models is almost same (5%~6%). According to CI upper boundary obtained by QREG and GBM, base modulus can have influence up to 10%~11%. For MARS, upper limit of CI is less than 10%. The lower limit of CI is 0% that means, there is chance to have no effect due to this input variable. For QREG and GBM, the lowest effect can be up to 2% and 5% respectively overall, the result is consistent in this case also.

6.5.3 Output Y3 (Alligator Cracking)

Table 6.6 summarizes the analysis results for output Y3 (Alligator Cracking) for different meta-models. In the first row of this table, R^2 obtained by these methods are given. The highest R^2 value (0.94) obtained by GBM method. QREG has R^2 value (0.89). MARS has the lowest R^2 value (0.80) among the three methods. By comparing these R^2 values, it can be said that the output model by all three methods are excellent and usable also.

For total effects, four input variables have fallen in A group for QREG and MARS method. The inputs and their ranking order are same in this case. These inputs are X18 (bottom AC layer thickness), X1 (AADTT), X22 (percent air void of bottom AC layer) and X4 (percent of trucks in design lane). These inputs are most important factor for this output obtained by these two methods. Because they have explained more than 10% of the variance in each case. Among these four inputs, X18, X1 and X22 are grouped in A for GBM method as they have explained more than 10% of the variance in this meta-model. X4 is grouped in Group B for GBM as they have explained less than 10% of the total uncertainties individually in GBM meta-model. X13 or top AC layer thickness has explained 6% to 9% for QREG and MARS method. So, it has ranked in B group for these two methods. However, for GBM it has grouped in C because it has explained 3% to 5%

in GBM method. These total five parameters have the same ranking order for all these three methods. X25 or base modulus is grouped as Group C in all three cases. Therefore, the results obtained from all three methods are consistent for output Y3.

All these meta-models are consisting of 15 input variables each. Without these main six inputs, rest of them is more or less common for all three cases. As an example, X24 or type of base material is considered in group C for QREG and group D in MARS but absent in GBM. Rest of the inputs are provided in the table are considered as less important as they explained less than 3% of the uncertainties individually.

For main effect, three input variables have fallen in A group for all three methods. These three inputs are common for QREG and MARS. They are X18 (bottom AC layer thickness), X1 (AADTT) and X4 (percent of trucks in design lane). In GBM, the inputs are X18, X1 and X22. X22 has grouped in B for QREG and MARS. X4 has grouped in B in GBM. These four parameters are almost have same order in all three cases. Therefore, these four inputs are most important factor for this output for their sole effect. X13 (top AC layer thickness) is also important factor for this output because this input variable is obtained by all three methods though in different group. It is personally responsible for 6% to 9% of uncertainties in QREG and MARS method but less than 6% for GBM.

X25 (base modulus) is also common for all meta-models. It has captured 3-5% of variance for QREG and MARS and 2% or less than 2% for GBM. For all these three methods, the order of top listed parameters is almost same and consistent for main effect. Without these mentioned parameters, rest of the input variables is also common for all three methods and the order also.

For interaction effects, X18 (bottom AC layer thickness) is the most responsible for all cases. X1 is responsible for 3% to 5% of uncertainties in QREG and GBM but 2% or less than 2% for MARS. X22 is responsible for 3% to 5% of uncertainties in QREG and MARS. X28 is responsible for same amount of uncertainties in GBM. Overall, it can be said that the models obtained for output Y3 are reliable.

Figure 6.5 represents graphically the summary result of most important factors by all three methods. Figure 6.5 (a), Figure 6.5 (b) and Figure 6.5 (c) present the most significant factors (p-value < 0.05) by QREG, MARS and GBM Method respectively. QREG and GBM method have total seven variables listed as significant. MARS has list of total eight input variables. From these figures, it can be seen that X18 or bottom AC layer thickness with its interaction among others has captured the most percentage of uncertainties for all three methods for its sole effect. The total uncertainty captured by this input variable is more than 60% in GBM, 45% in MARS and 40% in QREG. The interaction effects for this input variable is almost same for all three cases (20% to 25%). Rest of the inputs for Y3 model in all three meta-models have explained less than 20 % of uncertainties individually. X1 (AADTT)is also considered as very important factor for output Y3 and they have explained more than 10% of the uncertainties individually for all three meta-models. It has almost interaction effects for QREG and GBM but not in MARS.

For QREG and GBM the ranking order and percent of variance index are almost same. These two methods have another two important factor for output Y3. They are X22 percent air void of bottom AC layer and X4 or percent of trucks in design lane. The amount of interaction effects obtained for these two variables are same for these two methods. The interaction effect of X22 is greater than interaction effect of X4. All other inputs in these meta-models are considered somewhat important as they all have captured less than 10% of the uncertainties.

X13, X24 and X25 are almost in same order for all these three meta-models. These three have explained 5% to 10% of the uncertainties individually. X13 is one of the input variables, which is common for the significant list of all three meta-models. It has captured around 10% of the uncertainties in QREG and MARS but less than 5% in GBM. The interaction effect for this input variable is negligible in all cases. Rest of the inputs shown in the graphs is less important as they have explained less than 5% of the variance individually. From these three figures, it can be visualize clearly that the ranking order and amount of explainable uncertainties are almost same for each three cases. Therefore, the results obtained for output Y3 are reliable and consistent.

Figure 6.6 summarizes the results of estimating T_j over Y3. In this figure, the most important factors (discussed in Table 6.6 and Figure 6.5) are presented. In the vertical axis of these figures, total variance index is scaled in percent value. The true T_j of each input factor obtained by all three meta-models are shown. The 95% CI for T is presented as the high low line. This is due to the nonlinear approximation to model the curvature in Y3 across the input variables and the interaction effects between that the input variable and other inputs.

Figure 6.6(a) gives the summary for X18 or bottom AC layer thickness. GBM has the largest total variance T for Y3 (80%). 95% CI of T value has 8% coverage for GBM. The estimated T value for this model by GBM has exceeded the CI limit (71% to 79%).

QREG has 9% and MARS has 14% coverage. The estimated T value for QREG and MARS are 60% and 68%. The highest uncertainties possible by X18 are around 80% by GBM. QREG has shown that, the lowest influence of X18 is 58%. CI lower boundary for GBM is around 70% which us even greater then upper boundary of CI for QREG. Overall, the T.hat obtained by these three methods are not so close to each other.

Figure 6.6 (b) presents summary of Tj value for X1 or AADTT. T.hat value for all three methods is almost same for all three methods (17%~19%). The T.hat for this model by three meta-models do not very so much. Therefore, the result is very reliable in this case. The result is very consistent in this case. The highest limit of CI for Tj value for three cases are almost close to each other (22% to 26%). The lower boundary of CI is almost same for QREG and GBM methods (15% to 16%). The lowest boundary of CI for MARS is 9% which is less than 10%. As a summary result of all these three methods, the influence of X1 can be 10% to 20%.

Figure 6.6 (c) presents the summary result for X22 or percent air void of bottom AC layer. The T.hat for QREG and MARS are almost same (12%~13%) which is not so close to T.hat of GBM (8%). The upper limit of CI for MARS is 21%, which is the highest among these three. Rest of two methods has CI upper boundary less than 20%. Lower limit of CI for QREG and MARS are 9%, for GBM is 6%. This input variable X22 has chance of being less important and also has chance of being one of the most important factor for all three methods.

Figure 6.6 (d) presents the summary result for X4 or percent of trucks in design lane. The T.hat for QREG and MARS are same (12%) which is close to T.hat of GBM (8%). The limit of CI for all these three methods are almost same to each other (7%~17%). This factor is considered as very important factor in QREG and MARS method and somewhat important for GBM method. But for all three methods, it has chance to have influence up to 20%.

Figure 6.6 (e) presents the summary result for X13 or top AC layer thickness. For this input variable, result obtained by QREG and MARS are almost same to each other. The t.hat for X13 by these two methods is 8% which means it is important factor for these two methods. For GBM, t.hat value is 4%, which indicates that X13 is somewhat important factor for output Y3. The CI obtained for GBM is (1% to 7%) which also indicates that in maximum cases it has no probability to being very important. For QREG and MARS, X13 has the chance to be a very important factor as it has CI upper limit greater than 10%.

6.5.4 Output Y4 (Transverse Cracking)

Table 6.7 summarizes the analysis results for output Y4 (Transverse Cracking) for different meta-models. In the first row of this table, R^2 obtained by these methods are given. The highest R^2 value (0.60) obtained by MARS method. QREG has R^2 value (0.15 and GBM has R^2 value (0.38). None of the three methods is able to obtain a good R^2 value. so, it can be said that these three methods are not applicable for Y4 or transverse cracking.

For total effects, six input variables are grouped as GROUP A in QREG method. Five input variables are ranked as Group A in MARS and three input variables have fallen in A group for GBM method. Among all these input variables, only two input variables are common in three cases. They are X28 (plastic limit) and X4 (percent of trucks in design lane). X7 (percentage AADTT distribution by class 11 %) is in Group A for both QREG and MARS but in GBM it is in Group C. X26 (type of subgrade material) is considered as very important factor in QREG method but not even captured in rest of the methods. X24 (type of base material) is captured by QREG and GBM in Group A and D respectively but not by MARS. X29 (liquid limit) is grouped in A for QREG only. X23 (thickness of base) and X15 (effective binder content for top AC layer) is captures by MARS and GBM in Group A and C respectively but not by QREG. All these inputs mentioned above can be said important factors for Y4 because they are at least common in two cases. X2, X9 and X10 are also common for both Mars and GBM but they all are able to explain less than 5% of the uncertainties. The other inputs like X12, X25are captured by single methods and not so important. That is why they are not mentioned in the discussion.

For main effect, six input variables have fallen in A group for QREG, three for MARS and two for GBM. Only one input is common for all Methods and the input is X28 (plastic limit). X7 is common for QREG and MARS. X4 is common for QREG and GBM. X24 and X29 are very important for QREG model. X23 (base thickness) is very important for MARS model. rest of the inputs are not common for all three cases and ranking order is totally different.

For interaction effects, no common input is obtained for all three cases. X4 or percent of truck is common for QREG and MARS for interaction effect. For QREG model, very interacting inputs are X26 and X7 but not for the other methods. X28 and X12 have found as very interactive input variable for GBM model but not for the other cases. X28 has interacting effect in QREG model but the amount is less than GBM Model. X23, X11 and X17 are important for GBM model as they have interaction effects that can explain 6% to 9% of the uncertainties individually.

Figure 6.7 represents graphically the summary result of most important factors by all three methods. Figure 6.7 (a), Figure 6.7 (b) and Figure 6.7 (c) present the most significant factors (p-value < 0.05) by QREG, MARS and GBM Method respectively. Figure 6.7 (a) represents that all the significant inputs obtained by QREG method are of almost same importance. X4, X28, X24 and X29 have captured around 20% to 25% of the uncertainties as their main effect. Rests of them are X26 and X7 and they all have captured around 10% of uncertainties individually as main effect. For X26 and X7. Effect due to interaction is greater than main effect. For X26, the amount is almost three times bigger. Figure 6.7 (b) represents only two significant inputs obtained by MARS. They are X7 and X4. X7 has captured more than 30% of the uncertainties as main effect and less than 10% as interacting effect. X4 has captured around 5% of uncertainties as main effect but more than 80% as effect due to interaction. Figure 6.7 (c) represents that all the significant inputs obtained by GBM method are of almost same importance. X28 has captured more than 70% of the uncertainties as main effect and more than 10% as interaction. It has ranked first in the input list. Rests of them are X4, X12, X23, X11 and X21considered as significant inputs and presented in the graph. X4 and X12 have explained around 20% as main effect X12 has explained around 10% of variance as interaction. Rest of them has captured less than 10% of the variance only for interaction.

QREG has total seven input variables listed as significant. MARS has list of only two input variables. GBM has total six input variables listed as significant. From these figures, it can be seen that X4 or percent of trucks in design lane with its interaction among others has captured by all three methods. It has explained around 90% of uncertainties and ranked first among all other inputs in MARS method. In QREG it has explained around 30% of the variance and ranked third in the list. Though the amount of explained uncertainties is different in all three cases, but it is the only input variable common for all. So, this input can be said as very important factor for model Y4.

Figure 6.8 further summarizes the results of estimated T_j over Y4. In this figure, the most important factors (discussed in Table 6.7 and Figure 6.7) are presented. In the vertical axis of these figures, total variance index is scaled in percent value. The true T_j of each input factor obtained by all three meta-models are shown. The 95% CI for T is presented as the high low line. This is due to the nonlinear approximation to model the curvature in Y4 across the input variables and the interaction effects between that the input variable and other inputs.

Figure 6.8(a) gives the summary for X4 or percent of trucks in design lane. MARS has the largest total variance T for Y4 (87%). 95% CI of T value has 97% coverage for MARSM. QREG and GBM have 34% coverage individually. The estimated T value for QREG and GBM are 31% and 17%. The highest uncertainties possible by X4 are 100% by MARS. GBM has shown that, the lowest influence of X4 is 0%. CI lower boundary for QREG is around 31% which is even greater then upper boundary of CI for MARS. Overall, the T.hat obtained by these three methods is not so close to each other.

Figure 6.8 (b) presents summary of Tj value for X7 or percent AADTT distribution by vehicle class 11. This input variable is considered as significant by QREG and MARS only. T.hat value for all these two methods are close to each other (34%~41%).

According to CI value for QREG, the effect of X7 can be 33% to 69%. For MARS, the CI limit is 19% to 81%. As a summary result of all these two methods, the influence of X7 can be 20% to 90%.

Figure 6.8 (c) presents summary of Tj value for X28 or plastic limit. This input variable is considered as significant by QREG and GBM only. T.hat value for all these two methods differ a lot (27%~87%). According to CI value for QREG, the effect of X7 can be 23% to 53%. For MARS, the CI limit is 20% to 100%. As a summary result of all these two methods, the influence of X28 can be 20% to 100%.

6.5.5 Output Y5 (AC Rut)

Table 6.8 summarizes the analysis results for output Y5 (AC Rut) for different Methods. In the first row of this table, R^2 obtained by these methods are given. The highest R^2 value (0.95) obtained by QREG method. The second highest value is obtained by MARS (0.94) and the lowest value is obtained by MARS (0.93). By comparing these R2 values, it can be said that the output model Y5 by all these three methods are excellent and usable one.

For total effect, three input variables have fallen in A group for all three methods and these three inputs are common for all methods. They are X1 (AADTT), X4 (percent of trucks in design lane) and X10 (tire pressure). Therefore, these three inputs are most important factor for this output. X18 (bottom AC layer thickness) is also important factor for this output because this input variable is obtained by all three methods though in different group. X8 (traffic growth factor) is also common for all meta-models. It has captured 3-5% of variance for QREG and MARS, but 0-2% for GBM. Overall, these five parameters can be said important factor for this output without any doubt for total effects. For all these three methods, the order of top listed parameters is same and consistent. Without these six parameters, rest of the input variables is also common for all three methods and the order also.

The result obtained for Group A for main effects is same as the result for total effects of Group A. no input variable is available in Group B for any methods. It means that no input has sole effect to explain 6% to 9% of the uncertainties. X18 is in Group C for all cases. X8 is able to explain 3% to 5% of uncertainties as main effect for QREG and MARS but not for GBM. For GBM, the amount is less than 3%. Rests of the input parameters are not important in case of main effect as they all explain 2% or less than 2% individually.

For interaction effects, no input variable is obtained for Group A in any of the models. It means that interaction effects due to the input variables are not able to explain more than 10% of the variance. X1 is obtained in Group B for GBM and Group C for QREG and MARS. It has explained 6% to 9% of the uncertainties for its interaction in GBM. It has explained 3% to 5% of the uncertainties for its interaction in QREG and MARS. X4 is responsible for same amount of uncertainties in GBM but not in others. Rest of the parameters is not mentioned in this case, as they are not able to explain not more than 2% of the variances. As a conclusion of this table, it can be said that the models obtained for output Y5 are dependable and usable. All the three methods can be said workable, as the variation of R^2 value is negligible.

Figure 6.9 represents graphically the summary result of most important factors by all three methods. Figure 6.9 (a), Figure 6.9 (b) and Figure 6.9 (c) present the most significant factors (p-value < 0.05) by QREG, MARS and GBM Method respectively. By QREG method total seven variables are listed as significant which is the highest among three meta-models. By MARS and GBM, total six input variables listed individually. By visual inspection at a glance for all these three methods, it can be said that the pattern of the bar chart is same for all cases. First two parameters are contributing a lot (around 40%) compare to other parameters in the bar chart as main effect. Rest of the parameters explains 10% or less than 10% of the variances. This is the common trend for all three bar charts. From these figures, it can be seen that X1 or AADTT for its main effect among others has captured the most percentage of uncertainties for all three methods. The total uncertainty captured by this input variable is highest in GBM (42%) and the lowest in QREG (30%). The amount of interaction effect for this input variable is around 5% for all three methods. X4 or percent of trucks in design lane has ranked second important factor in all three meta-models. The total uncertainties explained by this input's main effect are almost same in three cases (35~40%). he amount of interaction effect for this input variable is less than 4% for all three methods.

X10 or tire pressure placed third in the ranking order for all three methods. It is very clear from the figures that the effect of this input is also same in all cases (10%~12%). The interaction effect due to X10 is negligible for all cases.

X18 or bottom AC layer thickness has almost same S. hat value in these figures. It has ranked fourth in all methods. It is able to explain less than 10% of the uncertainties in all cases. Without these parameters, QREG and GBM both have X8 (traffic growth factor) which is not listed by MARS. X8 has explained around 3% of the uncertainties in these two models each. This same comment is applicable for X13 or top AC layer thickness. Without all these parameters, there are some parameters which are just captured by one particular method. They are X12, X30 and X25. These are all less important variables as they are not able to explain more than 3% of uncertainties. Figure 6.10 further summarizes the results of estimating T_j over Y5. In this figure, the most important factors (discussed in Table 6.8 and Figure 6.9) are presented. In the vertical axis of these figures, total variance index is scaled in percent value. The true T_j of each input factor obtained by all three meta-models are shown. The 95% CI for T is presented as the high low line.

Figure 6.10 (a) gives the summary for X1 or AADTT. GBM has the largest total variance T for Y5 (50%). T.hat for QREG and MARS are same in this model (40%). 95% CI of T value has 9% coverage for GBM. QREG has 7% and MARS has 8% coverage. This is due to the nonlinear approximation to model the curvature in Y5 across X1 and the interaction effect between X1 and other inputs. According to GBM the effect of X1 can be up to 50%. The lowest effect of X1 is 36%, which is obtained by QREG and MARS model. So, the result obtained in these cases is consistent. Figure 6.10 (b) presents summary of Tj value for X4 or percent of trucks in design lane. T.hat value for all three methods is almost same for all three methods (35%~40%). The limit of CI for all cases is around 7% to 9%. The upper value and lower value of CI are very close to each other. The result is very consistent in this case also.

Figure 6.10 (c) presents summary of Tj value for X10 or tire pressure. T.hat value for all three methods is same for all three methods (11%~12%). The limit of CI for all cases is around 6% to 7%. The upper value and lower value of CI are same for QREG and MARS and a very little difference with GBM. According to lower limit of CI obtained by all three methods for this model explains that this effect can be as low as less than 10%. The result is very consistent in this case also. Figure 6.10 (d) presents the summary result for X18 or bottom AC layer thickness. In this case, QREG and MARS result vary little bit with GBM result. T.hat for QREG and MARS are around 6% but GBM have T.hat less than 5%. The 95% CI obtained for this parameter is same for all three methods. According to them, the effect can be any of the values within the limit of 2% to 8%. Overall, the model Y5 is reliable as the same result is obtained for all three different methods.

6.5.6 Output Y6 (Total Rut)

Table 6.9 summarizes the analysis results for output Y6 (AC rut) for different Methods. In the first row of this table, R^2 obtained by these methods are given. The highest R^2 value (0.95) obtained by QREG method. The second highest value is obtained by MARS (0.94) and the lowest value is obtained by MARS (0.93). By comparing these R^2 values, it can be said that the output model Y6 by all these three methods are excellent and usable one. In this table, three common input variables have fallen in A group for all three methods following same order for total effect and main effect. They are X1 (AADTT), X4 (percent of trucks in design lane) and X18 (bottom AC layer thickness). Therefore, these three inputs are most important factor for this output. X27 (subgrade modulus) is also important factor for this output for total effect and main effect. This input variable is obtained by all three methods though in different group. X30 (optimum gravimetric water content) is also common for all meta-models. It has captured 3-5% of variance for QREG, 6% to 9% for MARS and 0-2% for GBM. For main effect, it has the same result.

X10 (tire pressure) is also common for all meta-models. It has captured 6% to 9% of variance for QREG and MARS, but 3-5% for GBM as total effect. It has captured 6-9% of variance for QREG but 3-5% for MARS and GBM as main effect. Overall, these six parameters can be said important factor for this output without any doubt. For all these three methods, the order of top listed parameters is same and consistent. Without these six parameters, rest of the input variables is also common for all three methods and the order also. Therefore, it can be said that the models obtained for output Y6 are dependable and usable. All the three methods can be said workable as the variation of R^2 value is negligible. For interaction effects no input variable is obtained for Group A and B. it means that, this output is just the result of the main effects for all the input variables. No significant interaction occurs in this case.

Figure 6.11 represents graphically the summary result of most important factors by all three methods. Figure 6.11 (a), Figure 6.11 (b) and Figure 6.11 (c) present the most significant factors (p-value < 0.05) by QREG, MARS and GBM Method respectively. By MARS method total eleven variables are listed as significant which is the highest among three meta-models. By MARS and GBM, total ten and eight input variables listed respectively. By visual inspection at a glance for all these three methods, it can be said that the pattern of the bar chart is same for all cases. First two parameters are contribution a lot (more than 20%) compare to other parameters in the bar chart. Rest of the parameters less than 15% of the variances as main effect. This is the common trend for all three bar charts.

From these figures, it can be seen that X1 or AADTT with its sole effect has captured the most percentage of uncertainties for all three methods. The total uncertainty captured by this input variable is highest in GBM (40%) and the lowest in QREG and MARS (30%). The interaction effect due to this parameter is less than 5% for all cases. X4 or percent of trucks in design lane has ranked second important factor in all three meta-models. The total uncertainties explained by this input variables are almost same in three cases (around 30%). The interaction effect due to this parameter is less than 2% for all cases. X18 or bottom AC layer thickness placed third in the ranking order for all three methods. It is very clear from the figures that the effect of this input is also same in all cases (10%~12%). No interaction effect is working for this case, too.

X10 or tire pressure placed fourth in two case and sixth in one case in the ranking order. It is very clear from the figures that the effect of this input is also same in all cases (4%~6%). X27 and X30 are working like X10 in all these three methods. Without all these parameters, there are some parameters that are just captured by one or two particular method. Some of them are X8, X13, etc. These are all less important variables as they are not able to explain more than 3% of uncertainties.

Figure 6.12 further summarizes the results of estimating T_j over Y6. In this figure, the most important factors (discussed in Table 6.9 and Figure 6.11) are presented. In the vertical axis of these figures, total variance index is scaled in percent value. The true T_j of each input factor obtained by all three meta-models are shown. The 95% CI for T is presented as the high low line. Figure 6.12 (a) gives the summary for X1 or AADTT. GBM has the largest total variance T for Y5 (45%). T.hat for QREG and MARS are same in this model (around 33%). 95% CI of T value has 10% coverage for GBM. QREG has

7% and MARS has 8% coverage. This is due to the nonlinear approximation to model the curvature in Y6 across X1 and the interaction effect between X1 and other inputs. According to GBM the effect of X1 can be up to 45%. The lowest effect of X1 is 30%, which is obtained by QREG and MARS model. So, the result obtained in these cases is consistent.

Figure 6.12 (b) presents summary of Tj value for X4 or percent of trucks in design lane. T.hat value for all three methods is almost same for all three methods (30%~36%). The limit of CI for all cases is around 7% to 11%. The upper value and lower value of CI are very close for QREG and MARS. For GBM, the value can rise upto 39% which indicates that this parameter can be very important in some cases. The lower limit of CI for all three methods is close to each other (32 to 38%). The result can be said as consistent in this case also. Figure 6.12 (c) presents the summary result for X18 or bottom AC layer thickness. In this case, T.hat for all three methods is same (12%). The 95% CI obtained for this parameter is same for all three methods. According to them, the effect can be any of the values within the limit of 8% to1 8%. The model Y5 is reliable as the same result is obtained for all three different methods.

Figure 6.12 (d) presents summary of Tj value for X10 or tire pressure. T.hat value for all three methods is same for all three methods (around 5%). The upper value and lower value of CI are same for QREG and GBM and a very little difference with MARS. According to lower limit of CI obtained by all three methods for this model explains that this effect can be as high as 10%. The result is very consistent in this case also. Figure 6.12(e) gives the summary for X27 or subgrade modulus. T.hat for all three methods is almost same to each other for all three cases. The CI for QREG is 4% to 9%. For MARS, the limit is 1% to 7% and for GBM the limit is 2% to 7%. Considering the T,hat and Upper limit of CI, it can be said that the obtained result is consistent for X27 for this model Y6.

Figure 6.12(f) gives the summary for X30 or optimum gravimetric water content. T.hat for QREG and MARS makes this input variable is somewhat important as it is able to explain at least 4% uncertainties. For GBM, it is less important variable as it has explained 2% of the uncertainties only. The CI for QREG is 2% to 8%. For MARS, the limit is 0% to 6% and for GBM the limit is 1% to 4%. Considering T,hat and Upper limit of CI, it can be said that the obtained result is consistent for X30 for this model Y6.

6.6 Conclusions

Nonparametric and parametric regression procedures are employed to determine the sensitivity measures of the input variables. Total three methods are performed in this case. They are QREG, MARS and GBM. These test results provides the sensitivity indexes for input variables considering the interaction effect among them. The significant variables are obtained for different pavement performances are given below:

List of Highly Sensitive variables

- Terminal IRI: Bottom AC layer Thickness, AADTT and percent of trucks in design Direction
- Longitudinal Cracking: Bottom AC layer Thickness, AADTT and Percent of trucks in Design Lane
- Alligator Cracking: Bottom AC layer Thickness, AADTT and Percent Air void of Bottom AC Layer

- Transverse cracking: AADTT and Percent of Vehicle class 11
- AC Rut: AADTT, Percent of trucks in Design Lane and Tire Pressure
- Total Rut: AADTT, Percent of trucks in Design Lane and Bottom AC layer Thickness

<u>List of Sensitive variable</u>

- Terminal IRI: Top AC layer Thickness, Percent Air void of Bottom AC Layer
- Longitudinal Cracking: Type of base Material, Modulus of Base Layer, Percent Air void of Top AC Layer
- Alligator Cracking: Bottom AC layer Thickness, Percent of trucks in Design Lane
- Transverse Cracking: Plastic Limit, Type of subgrade material, Type of Base Material, Liquid Limit, climatic zone, Effective binder content of Top AC layer, Thickness of Base
- AC Rut: Bottom AC layer Thickness, Traffic Growth Factor, climatic zones and Top AC layer thickness
- Total Rut: Modulus of Subgrade, Tire Pressure and Optimum Gravimetric Water Content

The sensitivity chart presented in this chapter can be used to get an idea about pavement distresses for some specific combinations of input variables. It will also help the designer to pick up the input values that need to be studied to take care of a particular pavement distress.

Table 6.1 (a): Results for Y1 (Terminal IRI) Using the Meta Model QREG

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.226	0.337	0.111	(0.292, 0.387)	0.000
X1	AADTT	0.228	0.270	0.042	(0.231, 0.325)	0.000
X4	Percent of Trucks in Design Lane (%)	0.155	0.174	0.019	(0.128, 0.211)	0.000
X13	AC Layer Thickness (Top Layer)	0.094	0.104	0.010	(0.075, 0.151)	0.000
X22	Air Void (%) (AC 2nd Layer)	0.046	0.073	0.027	(0.045, 0.120)	0.000
X26	Subgrade Material Type	0.033	0.054	0.021	(0.019, 0.098)	0.001
X3	Percent of Trucks in Design Direction (%)	0.041	0.045	0.004	(0.026, 0.091)	0.000
X25	Base Modulus	0.015	0.039	0.024	(0.000, 0.073)	0.039
X8	Traffic Growth Factor	0.040	0.030	0.000	(0.000, 0.064)	0.035

Note:

Estimated Model Summary:

1. *Model: Y1 = f(X18, X1, X4, X13, X22, X26, X3, X25, X8, X24, X27, X30, X9, X16, X10, X12, X21, X6)*
2. $R^2 = 0.8674323$

Table 6.1 (b): Results for Y2 (Longitudinal Cracking) Using the Meta Model QREG

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.364	0.551	0.187	(0.513, 0.607)	0.000
X1	AADTT	0.125	0.157	0.032	(0.121, 0.206)	0.000
X4	Percent of Trucks in Design Lane (%)	0.130	0.145	0.015	(0.104, 0.185)	0.000
X24	Base Material Type	0.086	0.092	0.006	(0.041, 0.116)	0.000
X17	Percent Air Void (Top AC Layer)	0.079	0.079	0.000	(0.019, 0.096)	0.000
X25	Base Modulus	0.053	0.059	0.006	(0.023, 0.100)	0.000
X13	AC Layer Thickness (Top Layer)	0.046	0.046	0.000	(0.005, 0.083)	0.014
X27	Subgrade Modulus	0.007	0.041	0.034	(0.007, 0.081)	0.009
X15	Effective binder content (%) (Top AC layer)	0.029	0.029	0.000	(0.010, 0.058)	0.004

Note:

Estimated Model Summary:

1. *Model: Y2 = f(X18, X1, X4, X24, X17, X25, X13, X27, X15, X23, X21, X30, X8, X16, X3, X2, X22, X26)*
2. $R^2 = 0.8862138$

Table 6.1 (c): Results for Y3 (Alligator Cracking) Using the Meta Model QREG

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.380	0.600	0.220	(0.576, 0.671)	0.000
X1	AADTT	0.148	0.187	0.039	(0.156, 0.248)	0.000
X22	Air Void (%) (AC 2nd Layer)	0.091	0.121	0.030	(0.093, 0.174)	0.000
X4	Percent of Trucks in Design Lane (%)	0.103	0.115	0.012	(0.067, 0.150)	0.000
X13	AC Layer Thickness (Top Layer)	0.088	0.088	0.000	(0.045, 0.126)	0.000
X24	Base Material Type	0.037	0.050	0.013	(0.012, 0.095)	0.004
X25	Base Modulus	0.052	0.052	0.000	(0.006, 0.082)	0.015

Note:

Estimated Model Summary:

1. *Model: Y3 = f(X18, X1, X22, X4, X13, X24, X25, X16, X23, X6, X3, X21, X8, X20, X30, X27, X12)*
2. $R^2 = 0.8883755$

Table 6.1 (d): Results for Y4 (Transverse Cracking) Using the Meta Model QREG

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X26	Subgrade Material Type	0.056	0.346	0.290	(0.270, 0.613)	0.000
X7	AADTT Distribution by Vehicle Class 11 (%)	0.097	0.343	0.246	(0.330, 0.686)	0.000
X4	Percent of Trucks in Design Lane (%)	0.219	0.324	0.105	(0.314, 0.649)	0.000
X28	Plastic Limit	0.194	0.266	0.072	(0.231, 0.531)	0.000
X24	Base Material Type	0.192	0.243	0.051	(0.120, 0.437)	0.003
X29	Liquid Limit	0.242	0.242	0.000	(0.218, 0.485)	0.000

Note:

Estimated Model Summary:

1. *Model: Y4 = f(X26, X7, X4, X28, X24, X29)*
2. $R^2 = 0.1471916$

Table 6.1 (e): Results for Y5 (Permanent Deformation (AC Only)) Using the Meta Model QREG

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X1	AADTT	0.337	0.387	0.050	(0.359, 0.428)	0.000
X4	Percent of Trucks in Design Lane (%)	0.337	0.357	0.020	(0.332, 0.401)	0.000
X10	Tire Pressure	0.105	0.110	0.005	(0.088, 0.146)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.046	0.057	0.011	(0.026, 0.081)	0.000
X8	Traffic Growth Factor	0.040	0.040	0.000	(0.011, 0.064)	0.000
X12	Climatic Zones	0.029	0.031	0.002	(0.007, 0.060)	0.006
X13	AC Layer Thickness (Top Layer)	0.016	0.029	0.013	(0.002, 0.054)	0.017

Note:

Estimated Model Summary:

1. *Model: Y5 = f(X1, X4, X10, X18, X8, X12, X13, X3, X21, X16, X30, X27, X22, X5, X17, X6, X26)*
2. $R^2 = 0.9548097$

Table 6.1 (f): Results for Y6 (Permanent Deformation (Total Pavement)) Using the Meta Model QREG

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X1	AADTT	0.288	0.322	0.034	(0.290, 0.362)	0.000
X4	Percent of Trucks in Design Lane (%)	0.274	0.290	0.016	(0.257, 0.325)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.122	0.130	0.008	(0.099, 0.160)	0.000
X27	Subgrade Modulus	0.055	0.062	0.007	(0.035, 0.090)	0.000
X30	Optimum gravimetric water content	0.052	0.052	0.000	(0.017, 0.075)	0.000
X10	Tire Pressure	0.057	0.057	0.000	(0.014, 0.072)	0.003
X8	Traffic Growth Factor	0.016	0.036	0.020	(0.014, 0.070)	0.001
X13	AC Layer Thickness (Top Layer)	0.029	0.035	0.006	(0.006, 0.060)	0.007
X21	Superpave Binder Grade (2^{nd} AC Layer)	0.010	0.028	0.018	(0.017, 0.057)	0.001
X22	Air Void (%) (AC 2nd Layer)	0.000	0.017	0.017	(0.000, 0.036)	0.041

Note:

Estimated Model Summary:

1. *Model: Y6 = f(X1, X4, X18, X27, X30, X10, X8, X13, X21, X26, X22, X3, X25, X12, X5, X19, X15, X16, X11)*
2. $R^2 = 0.9328149$

Table 6.2 (a): Results for Y1 (Terminal IRI) Using the Meta Model MARS

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.287	0.418	0.131	(0.355, 0.488)	0.000
X1	AADTT	0.247	0.249	0.002	(0.169, 0.287)	0.000
X4	Percent of Trucks in Design Lane (%)	0.191	0.218	0.027	(0.178, 0.285)	0.000
X13	AC Layer Thickness (Top Layer)	0.058	0.069	0.011	(0.033, 0.132)	0.001
X22	Air Void (%) (AC 2nd Layer)	0.066	0.066	0.000	(0.016, 0.110)	0.008
X16	Superpave Binder Grade (Top AC Layer)	0.000	0.020	0.020	(0.001, 0.040)	0.023

Note:

Estimated Model Summary:

1. *Model: Y1 = f(X18, X1, X4, X13, X22, X8, X3, X10, X27, X26, X16, X24, X25, X30, X15, X12, X23, X6, X2, X7, X5, X9, X11, X14, X17, X19, X20, X21, X28, X29)*
2. $R^2 = 0.7635875$

Table 6.2 (b): Results for Y2 (Longitudinal Cracking) Using the Meta Model MARS

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.404	0.600	0.196	(0.532, 0.652)	0.000
X1	AADTT	0.144	0.144	0.000	(0.092, 0.180)	0.000
X4	Percent of Trucks in Design Lane (%)	0.121	0.134	0.013	(0.085, 0.180)	0.000
X17	Percent Air Void (Top AC Layer)	0.067	0.086	0.019	(0.047, 0.134)	0.000
X24	Base Material Type	0.062	0.065	0.003	(0.028, 0.113)	0.001
X25	Base Modulus	0.053	0.053	0.000	(0.000, 0.085)	0.046
X13	AC Layer Thickness (Top Layer)	0.039	0.041	0.002	(0.003, 0.081)	0.014
X27	Subgrade Modulus	0.044	0.044	0.000	(0.001, 0.076)	0.025
X23	Base Thickness	0.016	0.036	0.020	(0.008, 0.072)	0.010
X3	Percent of Trucks in Design Direction (%)	0.021	0.021	0.000	(0.000, 0.045)	0.032

Note:

Estimated Model Summary:

1. *Model: Y2 = f(X18, X1, X4, X17, X24, X25, X13, X27, X23, X3, X9, X8, X22, X15, X30, X14, X7, X29, X26, X19, X2, X5, X6, X10, X11, X12, X16, X20, X21, X28)*
2. $R^2 = 0.7914227$

Table 6.2 (c): Results for Y3 (Alligator Cracking) Using the Meta Model MARS

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.449	0.680	0.231	(0.600, 0.737)	0.000
X1	AADTT	0.177	0.178	0.001	(0.094, 0.217)	0.000
X22	Percent Air Void (2nd AC Layer)	0.080	0.133	0.053	(0.093, 0.206)	0.000
X4	Percent of Trucks in Design Lane (%)	0.110	0.120	0.010	(0.062, 0.166)	0.000
X13	AC Layer Thickness (Top Layer)	0.079	0.080	0.001	(0.044, 0.161)	0.000
X25	Base Modulus	0.031	0.045	0.014	(0.010, 0.089)	0.013
X3	Percent of Trucks in Design Direction (%)	0.032	0.035	0.003	(0.000, 0.069)	0.023
X24	Base Material Type	0.000	0.022	0.022	(0.000, 0.046)	0.029

Note:

Estimated Model Summary:

1. *Model: Y3 = f(X18, X1, X22, X4, X13, X25, X3, X24, X7, X27, X21, X29, X5, X14, X12, X19, X2, X6, X8, X9, X10, X11, X15, X16, X17, X20, X23, X26, X28, X30)*
2. $R^2 = 0.8003899$

Table 6.2 (d): Results for Y4 (Transverse Cracking) Using the Meta Model MARS

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X4	Percent of Trucks in Design Lane (%)	0.049	0.874	0.825	(0.026, 1.000)	0.000
X7	AADTT Distribution by Vehicle Class 11 (%)	0.354	0.406	0.052	(0.194, 0.812)	0.013

Note:

Estimated Model Summary:

1. *Model: Y4 = f(X4, X7, X28, X23, X15, X11, X22, X30, X29, X14, X2, X25, X3, X9, X10, X18, X21, X17, X1, X5, X6, X8, X12, X13, X16, X19, X20, X24, X26, X27)*
2. R^2 *=0.6021314*

Table 6.2 (e): Results for Y5 (Permanent Deformation (AC Only)) Using the Meta Model MARS

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X1	AADTT	0.343	0.395	0.052	(0.363, 0.443)	0.000
X4	Percent of Trucks in Design Lane (%)	0.334	0.347	0.013	(0.305, 0.386)	0.000
X10	Tire Pressure	0.112	0.112	0.000	(0.081, 0.139)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.034	0.053	0.019	(0.016, 0.074)	0.001
X30	Optimum gravimetric water content	0.016	0.019	0.003	(0.002, 0.038)	0.017
X25	Base Modulus	0.004	0.016	0.012	(0.005, 0.032)	0.013

Note:

Estimated Model Summary:

1. *Model: Y5 = f(X1, X4, X10, X18, X8, X30, X25, X5, X12, X23, X13, X26, X24, X19, X28, X6, X16, X3, X15, X7, X21, X20, X22, X17, X2, X9, X11, X14, X27, X29)*
2. $R^2 = 0.940641$

Table 6.2 (f): Results for Y6 (Permanent Deformation (Total Pavement)) Using the Meta Model MARS

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X1	AADTT	0.299	0.338	0.039	(0.305, 0.384)	0.000
X4	Percent of Trucks in Design Lane (%)	0.261	0.274	0.013	(0.234, 0.309)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.134	0.134	0.000	(0.083, 0.149)	0.000
X10	Tire Pressure	0.053	0.064	0.011	(0.047, 0.103)	0.000
X27	Subgrade Modulus	0.047	0.052	0.005	(0.014, 0.074)	0.002
X30	Optimum gravimetric water content	0.055	0.055	0.000	(0.000, 0.058)	0.038
X8	Traffic Growth Factor	0.028	0.038	0.010	(0.016, 0.071)	0.001
X13	AC Layer Thickness (Top Layer)	0.030	0.030	0.000	(0.001, 0.053)	0.019
X3	Percent of Trucks in Design Direction (%)	0.013	0.024	0.011	(0.000, 0.053)	0.045
X26	Subgrade Material Type	0.028	0.028	0.000	(0.001, 0.047)	0.020
X21	Superpave Binder Grade (Second AC Layer)	0.000	0.016	0.016	(0.000, 0.036)	0.041

Note:

Estimated Model Summary:

1. *Model: Y6 = f(X1, X4, X18, X10, X27, X30, X8, X13, X3, X26, X21, X5, X16, X9, X15, X28, X19, X24, X14, X7, X12, X2, X6, X11, X17, X20, X22, X23, X25, X29)*
2. $R^2 = 0.9075568$

Table 6.3 (a): Results for Y1 (Terminal IRI) Using the Meta Model GBM

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.415	0.538	0.123	(0.442, 0.602)	0.000
X1	AADTT	0.285	0.285	0.000	(0.205, 0.342)	0.000
X4	Percent of Trucks in Design Lane (%)	0.171	0.200	0.029	(0.156, 0.286)	0.000
X22	Air Void (%) (AC 2nd Layer)	0.017	0.035	0.018	(0.019, 0.069)	0.007
X8	Traffic Growth Factor	0.008	0.029	0.021	(0.007, 0.058)	0.013
X13	AC Layer Thickness (Top Layer)	0.022	0.027	0.005	(0.000, 0.058)	0.034
X14	Aggregate Gradation (Top AC Layer)	0.000	0.024	0.024	(0.003, 0.048)	0.021

Note:

Estimated Model Summary:

1. *Model: Y1 = f(X18, X1, X4, X22, X8, X13, X14, X2, X3, X27, X16, X26, X15, X28, X6, X9, X29, X24, X19, X5, X7, X10, X11, X12, X17, X20, X21, X23, X25, X30)*
2. *R^2 = 0.9074214*

Table 6.3 (b): Results for Y2 (Longitudinal Cracking) Using the Meta Model GBM

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.571	0.730	0.159	(0.605, 0.689)	0.000
X4	Percent of Trucks in Design Lane (%)	0.121	0.148	0.027	(0.131, 0.217)	0.000
X1	AADTT	0.116	0.123	0.007	(0.100, 0.189)	0.000
X25	Base Modulus	0.025	0.054	0.029	(0.054, 0.108)	0.000
X24	Base Material Type	0.066	0.066	0.000	(0.048, 0.104)	0.000
X17	Percent Air voids (Top AC layer)	0.046	0.048	0.002	(0.031, 0.095)	0.000
X13	AC Layer Thickness (Top Layer)	0.024	0.024	0.000	(0.001, 0.041)	0.023
X3	Percent of Trucks in Design Direction (%)	0.001	0.020	0.019	(0.007, 0.040)	0.007
X26	Subgrade Material Type	0.000	0.016	0.016	(0.000, 0.035)	0.031

Note:

Estimated Model Summary:

1. *Model: Y2 = f(X18, X4, X1, X25, X24, X17, X13, X3, X27, X26, X11, X2, X12, X22, X23, X16, X30, X21, X5, X6, X7, X8, X9, X10, X14, X15, X19, X20, X28, X29)*
2. $R^2 = 0.9011435$

Table 6.3 (c): Results for Y3 (Alligator Cracking) Using the Meta Model GBM

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X18	AC Layer Thickness (2nd AC Layer)	0.610	0.802	0.192	(0.713, 0.787)	0.000
X1	AADTT	0.138	0.166	0.028	(0.145, 0.261)	0.000
X4	Percent of Trucks in Design Lane (%)	0.064	0.084	0.020	(0.071, 0.169)	0.000
X22	Air Void (%) (AC 2nd Layer)	0.102	0.102	0.000	(0.055, 0.160)	0.000
X13	AC Layer Thickness (Top Layer)	0.028	0.036	0.008	(0.006, 0.073)	0.014
X25	Base Modulus	0.018	0.027	0.009	(0.000, 0.055)	0.027
X28	Plastic Limit	0.000	0.025	0.025	(0.000, 0.051)	0.036

Note:

Estimated Model Summary:

1. *Model: Y3 = f(X18, X1, X4, X22, X13, X25, X28, X19, X27, X20, X21, X17, X26, X5, X9, X30, X2, X12, X14, X3, X6, X7, X8, X10, X11, X15, X16, X23, X24, X29)*
2. $R^2 = 0.9370997$

Table 6.3 (d): Results for Y4 (Transverse Cracking) Using the Meta Model GBM

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X28	Plastic Limit	0.756	0.872	0.116	(0.196, 1.000)	0.000
X4	Percent of Trucks in Design Lane (%)	0.172	0.172	0.000	(0.000, 0.346)	0.033
X12	Climatic Zones	0.000	0.109	0.109	(0.115, 0.218)	0.000
X23	Base Thickness	0.000	0.085	0.085	(0.000, 0.228)	0.038
X11	Depth of Water Table	0.000	0.081	0.081	(0.000, 0.217)	0.047
X21	Superpave Binder Grade (2nd AC Layer)	0.000	0.048	0.048	(0.000, 0.106)	0.036

Note:

Estimated Model Summary:

1. *Model: Y4 = f(X28, X4, X12, X23, X11, X17, X21, X7, X18, X2, X13, X15, X9, X24, X10, X25, X27, X1, X3, X5, X6, X8, X14, X16, X19, X20, X22, X26, X29, X30)*
2. $R^2 = 0.381959$

Table 6.3 (e): Results for Y5 (Permanent Deformation (AC Only)) Using the Meta Model GBM

Input	**Name**	**S.hat**	**T.hat**	**Interactions**	**95% T CI**	**p-value**
X1	AADTT	0.424	0.485	0.061	(0.405, 0.501)	0.000
X4	Percent of Trucks in Design Lane (%)	0.362	0.400	0.038	(0.340, 0.433)	0.000
X10	Tire Pressure	0.109	0.116	0.007	(0.099, 0.165)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.036	0.036	0.000	(0.019, 0.068)	0.000
X8	Traffic Growth Factor	0.020	0.021	0.001	(0.003, 0.042)	0.012
X13	AC Layer Thickness (Top Layer)	0.027	0.027	0.000	(0.001, 0.031)	0.022

Note:

Estimated Model Summary:

1. *Model: Y5 = f(X1, X4, X10, X18, X8, X13, X11, X15, X3, X20, X9, X21, X17, X23, X12, X25, X6, X2, X27, X14, X24, X5, X7, X16, X19, X22, X26, X28, X29, X30)*
2. $R^2 = 0.9255857$

Table 6.3 (f): Results for Y6 (Permanent Deformation (Total Pavement)) Using the Meta Model GBM

Input	Name	S.hat	T.hat	Interactions	95% T CI	p-value
X1	AADTT	0.397	0.446	0.049	(0.347, 0.451)	0.000
X4	Percent of Trucks in Design Lane (%)	0.343	0.356	0.013	(0.279, 0.384)	0.000
X18	AC Layer Thickness (2nd AC Layer)	0.123	0.124	0.001	(0.099, 0.169)	0.000
X10	Tire Pressure	0.037	0.038	0.001	(0.031, 0.076)	0.000
X27	Subgrade Modulus	0.024	0.035	0.011	(0.015, 0.069)	0.001
X30	Optimum gravimetric water content (%)	0.021	0.022	0.001	(0.009, 0.044)	0.002
X3	Percent of Trucks in Design Direction (%)	0.000	0.020	0.020	(0.013, 0.041)	0.000
X11	Depth of Water Table	0.000	0.012	0.012	(0.000, 0.025)	0.034

Note:

Estimated Model Summary:

1. *Model: Y6 = f(X1, X4, X18, X10, X27, X30, X3, X13, X11, X8, X24, X12, X20, X28, X26, X19, X21, X22, X2, X14, X5, X6, X7, X9, X15, X16, X17, X23, X25, X29)*
2. $R^2 = 0.9012907$

Table 6.4: Summary Result for Output Y1

Type	**Total Effects**			**Main Effects**			**Interaction Effects**		
Model	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**
R^2	**0.87**	**0.76**	**0.91**	**0.87**	**0.76**	**0.91**	**0.87**	**0.76**	**0.91**
A	X18 X1 X4 X13	X18 X1 X4	X18 X1 X4	X18 X1 X4	X18 X1 X4	X18 X1 X4	X18	X18	X18
B	X22 X30	X13 X22		X13 X30	X13 X22				
C	X26 X3 X25 X8 X24 X27	X8 X3 X10 X27 X26	X22 X8 X13 X27	X22 X26 X3 X8	X3 X27 X26	X27	X1 X22	X4 X10	X4
D	X9 X16 X10	X16 X24 X25 X30 X15	X14 X2 X3 X16 X26 X15 X28 X6	X25 X24 X27 X9 X16 X10	X8 X10 X16 X24 X25 X30 X15	X22 X8 X13 X14 X2 X3 X16 X26 X15 X28 X6	X13 X26 X3 X25 X8 X24 X27 X30 X9 X16 X10	X1 X13 X22 X8 X3 X27 X26 X16 X24 X25 X30 X15	X1 X22 X8 X13 X14 X2 X3 X27 X16 X26 X15 X28 X6

Note:

5. A= Explain at least 10% of the variance
6. B= Explain 6% to 9% of the variance
7. C= Explain 3% to 5% of the variance
8. B= Explain 2% or less than 2% of the variance

Table 6.5: Summary Result for Output Y2

Type	Total Effects			Main Effects			Interaction Effects		
Model	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**
R^2	**0.89**	**0.79**	**0.90**	**0.89**	**0.79**	**0.90**	**0.89**	**0.79**	**0.90**
A	X18 X1 X4	X18 X1 X4	X18 X4 X1	X18 X1 X4	X18 X1 X4	X18 X4 X1	X18	X18	X18
B	X24 X17 X25	X17 X24	X24	X24 X17	X17 X24	X24			
C	X13 X27 X15 X23	X25 X13 X27 X23	X25 X17	X25 X13 X15 X23	X25 X13 X27	X25 X17	X1 X27		X4 X25
D	X21 X30 X8 X16 X3	X3 X9 X8 X22 X15 X30	X13 X3 X27 X26 X11 X2 X12 X22 X23	X27 X21 X30 X8 X16 X3	X23 X3 X9 X8 X22 X15 X30	X13 X3 X27 X26 X11 X2 X12 X22 X23	X4 X24 X17 X25 X13 X15 X23 X21 X30 X8 X16 X3	X1 X4 X17 X24 X25 X13 X27 X23 X3 X9 X8 X22 X15 X30	X1 X24 X17 X13 X3 X27 X26 X11 X2 X12 X22 X23

Note:

1. A= Explain at least 10% of the variance
2. B= Explain 6% to 9% of the variance
3. C= Explain 3% to 5% of the variance
4. B= Explain 2% or less than 2% of the variance

Table 6.6: Summary Result for Output Y3

Type	Total Effects			Main Effects			Interaction Effects		
Model	QREG	MARS	GBM	QREG	MARS	GBM	QREG	MARS	GBM
R^2	0.89	0.80	0.94	0.89	0.80	0.94	0.89	0.80	0.94
A	X18 X1 X22 X4	X18 X1 X22 X4	X18 X1 X22	X18 X1 X4	X18 X1 X4	X18 X1 X22	X18	X18	X18
B	X13	X13	X4	X22 X13	X22 X13	X4			
C	X24 X25 X6	X25 X3	X13 X25 X28 X27	X24 X25 X6	X25 X3	X13 X27	X1 X22	X22	X1 X28
D	X16 X23 X3 X21 X8 X20 X30	X24 X7 X27 X21 X29 X5 X14 X12	X19 X20 X21 X17 X26 X5 X9	X16 X23 X3 X21 X8 X20 X30	X24 X7 X27 X21 X29 X5 X14 X12	X25 X28 X19 X20 X21 X17 X26 X5 X9	X4 X13 X24 X25 X16 X23 X6 X3 X21 X8 X20 X30	X1 X4 X13 X25 X3 X24 X7 X27 X21 X29 X5 X14 X12	X4 X22 X13 X25 X19 X27 X20 X21 X17 X26 X5 X9

Note:

1. A= Explain at least 10% of the variance
2. B= Explain 6% to 9% of the variance
3. C= Explain 3% to 5% of the variance
4. B= Explain 2% or less than 2% of the variance

Table 6.7: Summary Result for Output Y4

Type	Total Effects			Main Effects			Interaction Effects		
Model	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**
R^2	0.15	0.60	0.38				0.15	0.60	0.38
A	X26 X7 X4 X28 X24 X29	X4 X7 X28 X23 X15	X28 X4 X12	X7 X4 X28 X24 X29	X7 X28 X23	X28 X4	X26 X7 X4	X4	X28 X12
B		X11	X13 X11 X17	X26	X15 X11		X28		X23 X11 X17
C		X22 X30 X29 X14 X2	X21 X7 X18 X2 X13 X15		X4		X24	X7 X28 X22 X30 X29 X2	X21 X7 X18 X2 X13 X15
D		X25 X3 X9 X10	X9 X24 X10		X22 X30 X29 X14 X2 X25 X3 X9 X10	X12 X23 X11 X17 X21 X7 X18 X2 X13 X15 X9 X24 X10	X29	X23 X15 X11 X14 X25 X3 X9 X10	X4 X9 X24 X10

Note:

1. A= Explain at least 10% of the variance
2. B= Explain 6% to 9% of the variance
3. C= Explain 3% to 5% of the variance
4. B= Explain 2% or less than 2% of the variance

Table 6.8: Summary Result for Output Y5

Type	**Total Effects**			**Main Effects**			**Interaction Effects**		
Model	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**
R^2	0.95	0.94	0.93				0.95	0.94	0.93
A	X1 X4 X10	X1 X4 X10	X1 X4 X10	X1 X4 X10	X1 X4 X10	X1 X4 X10			
B	X18								X1
C	X8 X12 X13	X18 X8	X18 X13	X18 X8 X12	X18 X8	X18 X13	X1	X1	X4
D	X3 X21 X16 X30 X27 X22 X5 X17	X30 X25 X5 X12 X23 X13 X26 X24 X19 X28	X8 X11 X15 X3 X20 X9 X21 X17 X23 X12	X13 X3 X21 X16 X30 X27 X22 X5 X17	X30 X25 X5 X12 X23 X13 X26 X24 X19 X28	X8 X11 X15 X3 X20 X9 X21 X17 X23 X12	X4 X10 X18 X8 X12 X13 X3 X21 X16 X30 X27 X22 X5 X17	X4 X10 X18 X8 X30 X25 X5 X12 X23 X13 X26 X24 X19 X28	X10 X18 X8 X13 X11 X15 X3 X20 X9 X21 X17 X23 X12

Note:

5. A= Explain at least 10% of the variance
6. B= Explain 6% to 9% of the variance
7. C= Explain 3% to 5% of the variance
8. B= Explain 2% or less than 2% of the variance

Table 6.9: Summary Result for Output Y6

Type	Total Effects			Main Effects			Interaction Effects		
Model	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**	**QREG**	**MARS**	**GBM**
R^2	0.95	0.94	0.93				0.95	0.94	0.93
A	X1 X4 X18	X1 X4 X18	X1 X4 X18	X1 X4 X18	X1 X4 X18	X1 X4 X18			
B	X27 X10	X10 X30		X27 X10	X30				
C	X30 X8 X13 X21	X27 X8 X13 X26	X10 X27 X13	X30	X10 X27 X8 X13 X26	X10 X13	X1	X1	X1
D	X26 X22 X3 X25 X12 X5	X3 X21 X5 X16 X9 X15	X30 X3 X11 X8 X24 X12 X20 X28 X26	X8 X13 X21 X26 X22 X3 X25 X12 X5	X3 X21 X5 X16 X9 X15	X27 X30 X3 X11 X8 X24 X12 X20 X28 X26	X4 X18 X27 X30 X10 X8 X13 X21 X26 X22 X3 X25 X12 X5	X4 X18 X10 X27 X30 X8 X13 X3 X26 X21 X5 X16 X9 X15	X4 X18 X10 X27 X30 X3 X13 X11 X8 X24 X12 X20 X28 X26

Note:

5. A= Explain at least 10% of the variance
6. B= Explain 6% to 9% of the variance
7. C= Explain 3% to 5% of the variance
8. B= Explain 2% or less than 2% of the variance

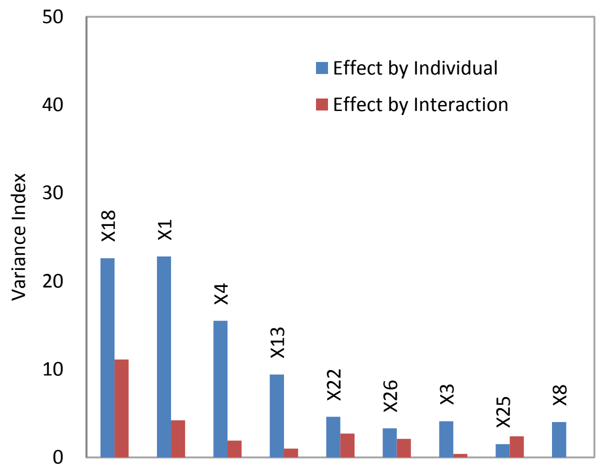


Figure 6.1(a): QREG Method

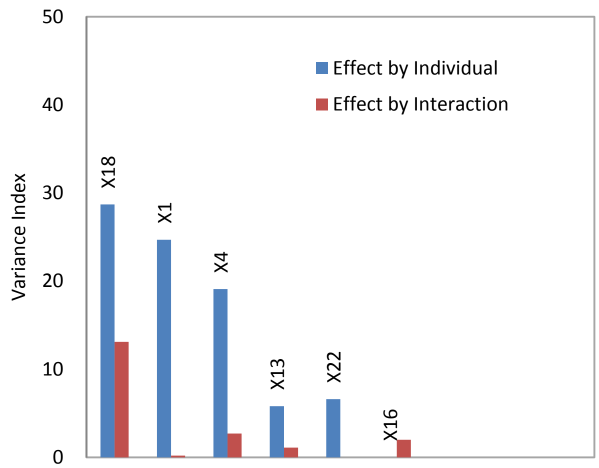


Figure 6.1(b): MARS Method

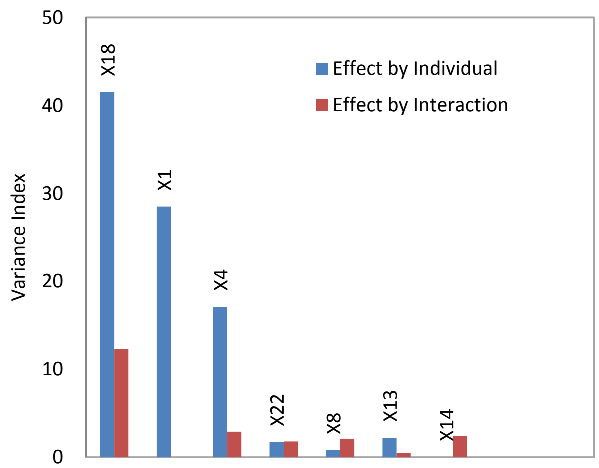


Figure 6.1(c): GBM Method

Figure 6.1: Summary of Nonparametric Regression Methods for Output Y1

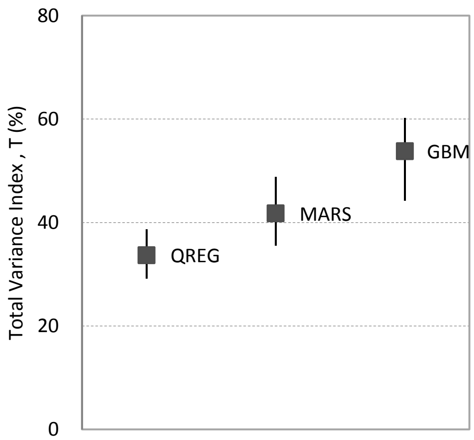


Figure 6.2(a): X18 (Bottom AC Layer Thickness)

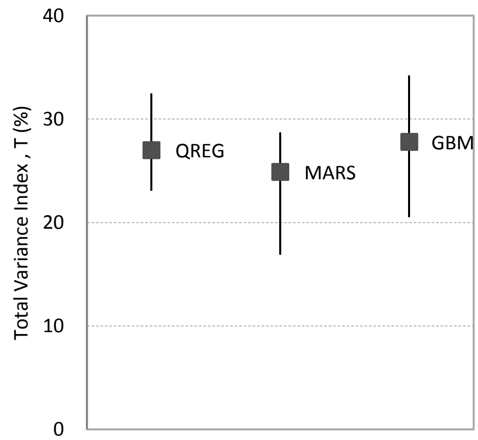


Figure 6.2(b): X1 (AADTT)

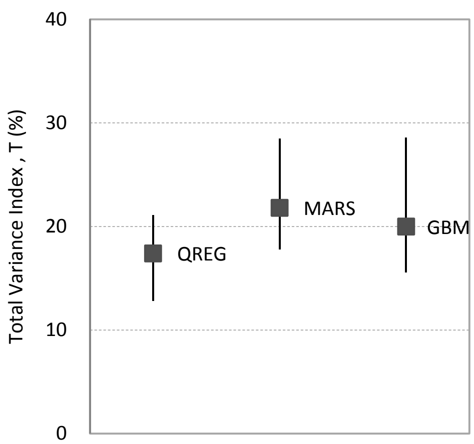


Figure 6.2(c): X4 (Percent of Trucks in Design Lane)

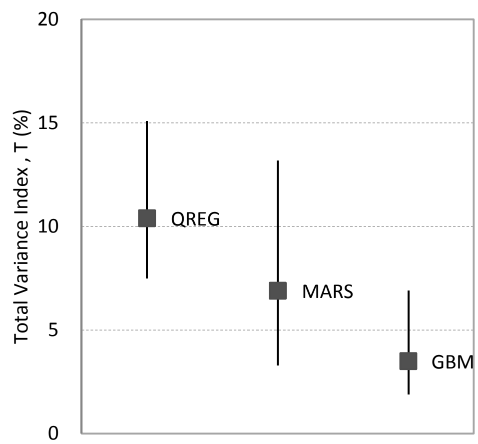


Figure 6.2(d): X13 (Top AC Layer Thickness)

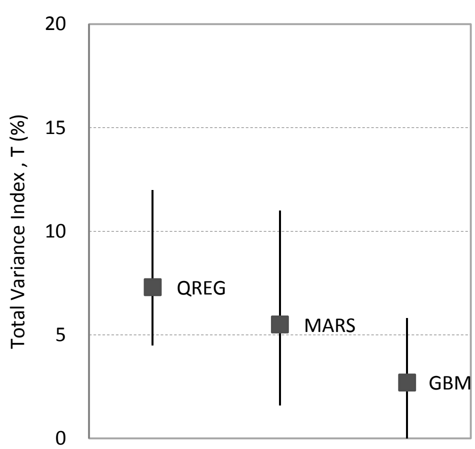


Figure 6.2(e): X22 (Percent Air Void of Bottom AC Layer)

Figure 6.2: Summary of Total Variance Indexes for Output Y1

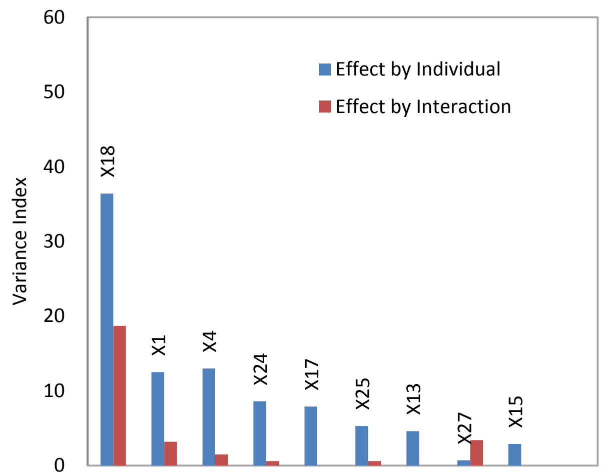


Figure 6.3(a): QREG Method

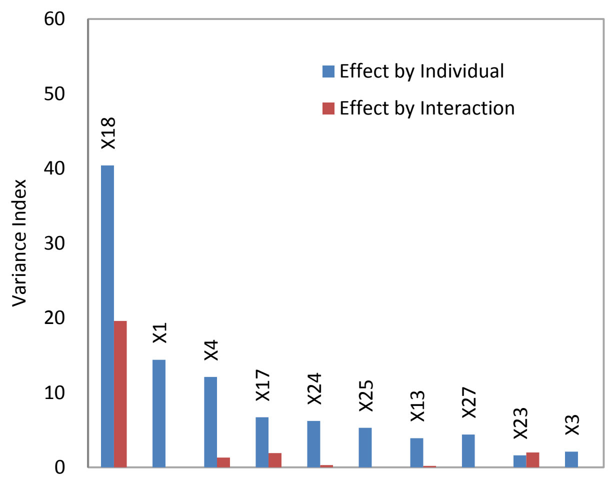


Figure 6.3(b): MARS Method

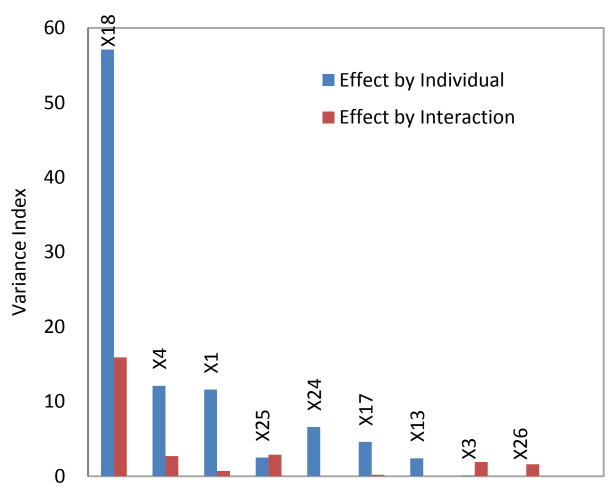
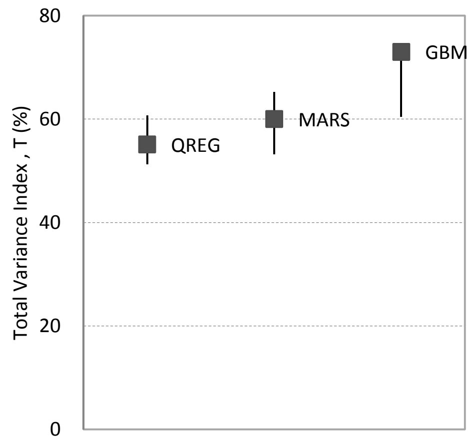
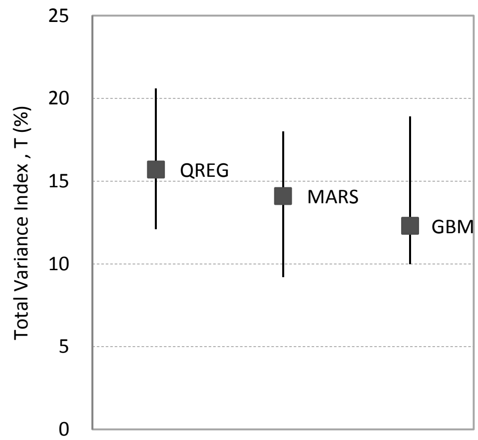


Figure 6.3(c): GBM Method

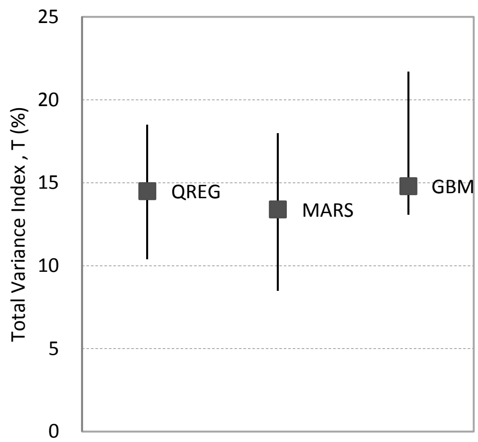
Figure 6.3: Summary of Nonparametric Regression Methods for Output Y2



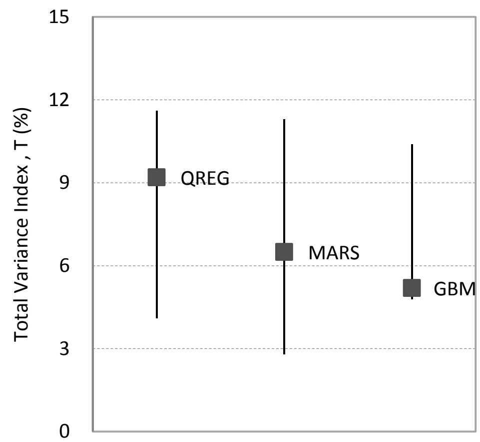
(a): X18 (Bottom AC Layer Thickness)



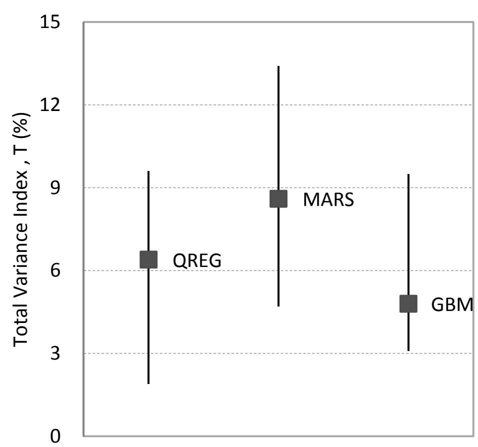
(b): X1 (AADTT)



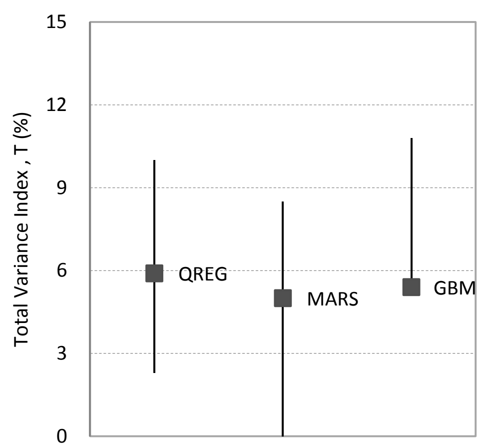
(c): X4 (Percent of Trucks in Design Lane)



(d): X24 (Type of Base Material)



(e): X17 (Percent Air Void of Top AC Layer)



(f): X25 (Base Modulus)

Figure 6.4: Summary of Total Variance Indexes for Output Y2

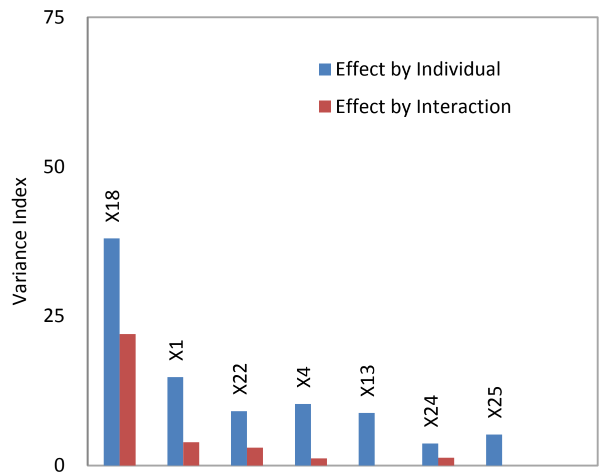


Figure 6.5(a): QREG Method

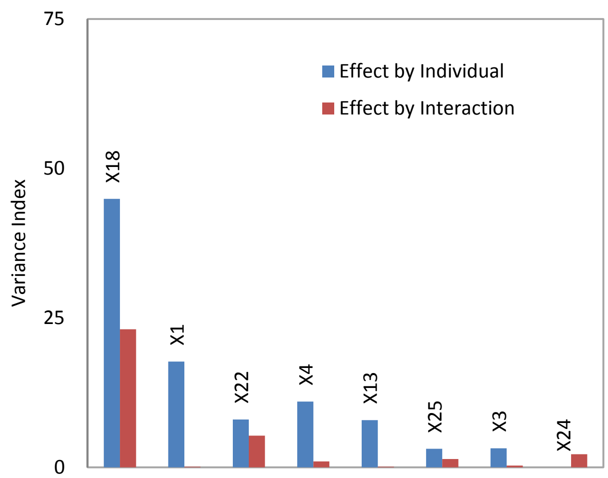


Figure 6.5(b): MARS Method

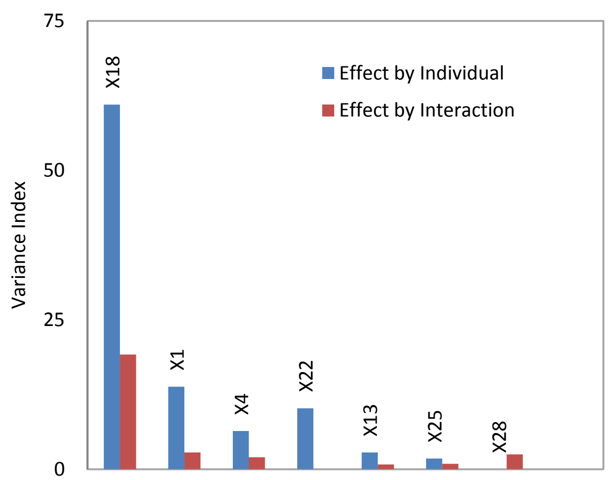
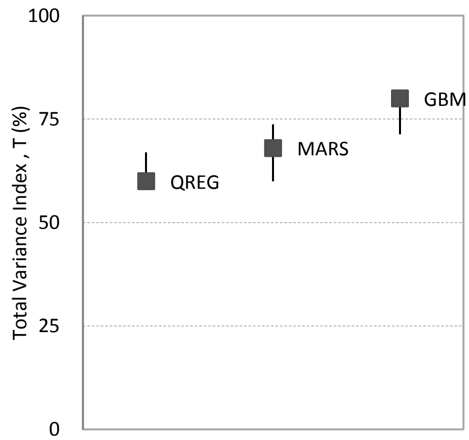
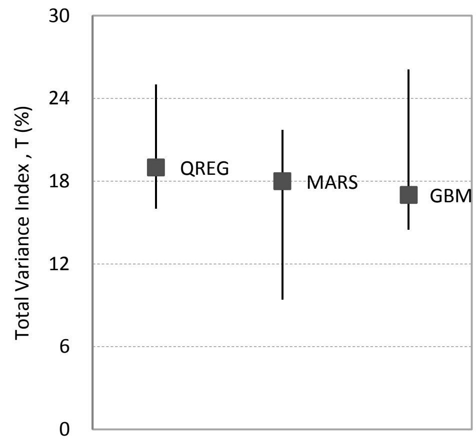


Figure 6.5(c): GBM Method

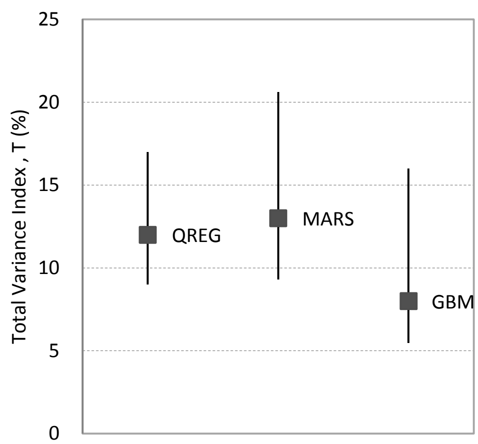
Figure 6.5: Summary of Nonparametric Regression Methods for Output Y3



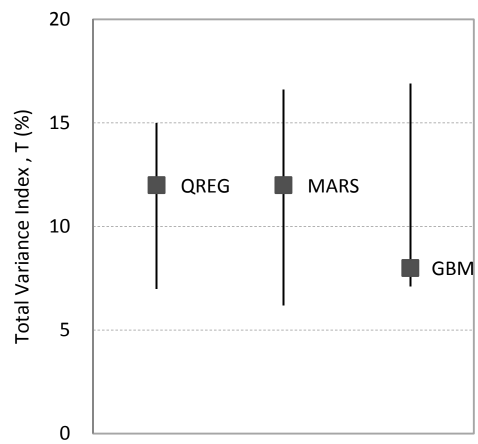
(a): X18 (Bottom AC Layer Thickness)



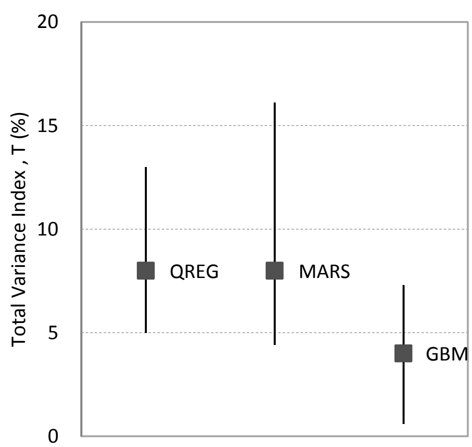
(b): X1 (AADTT)



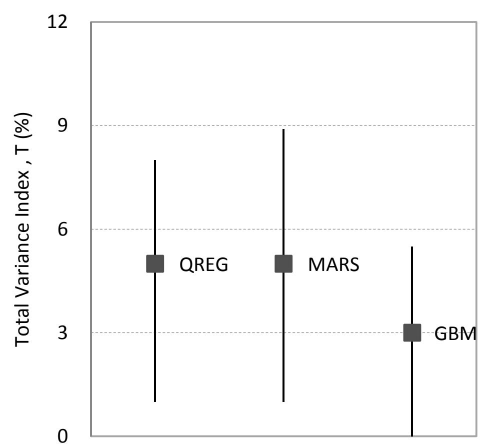
(c): X22 (Percent Air Void of Bottom AC Layer)



(d): X4 (Percent of Trucks in Design Lane)



(e): X13 (Top AC Layer Thickness)



(f): X25 (Base Modulus)

Figure 6.6: Summary of Total Variance Indexes for Output Y3

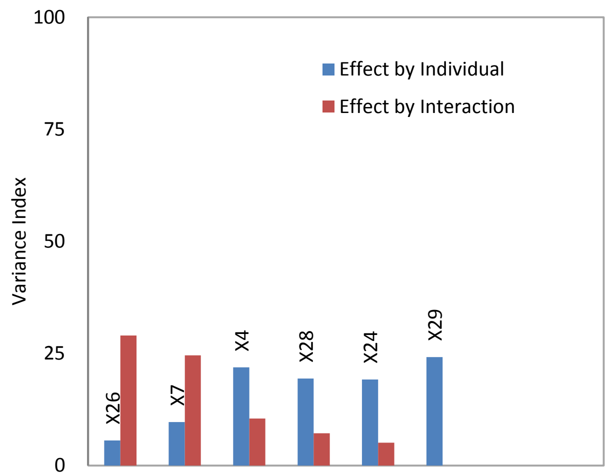


Figure 6.7 (a): QREG Method

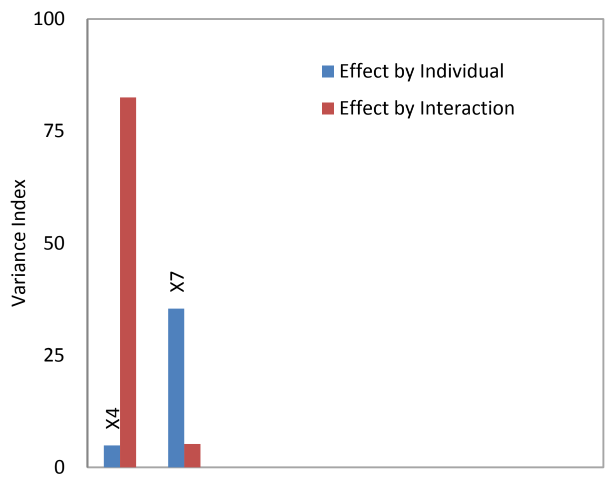


Figure 6.7 (b): MARS Method

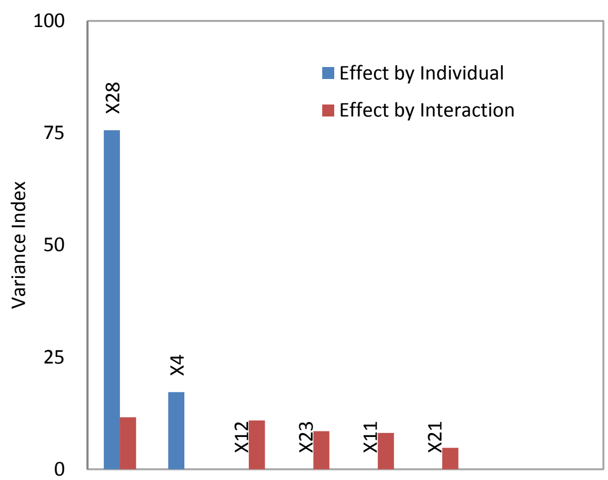
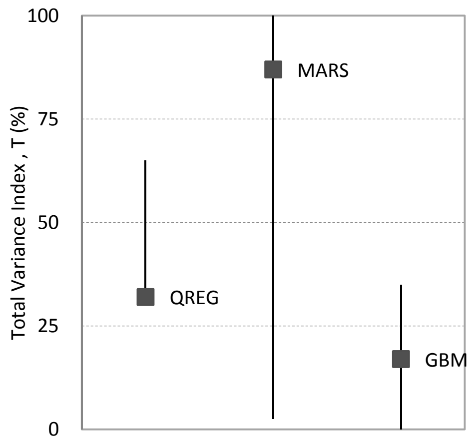
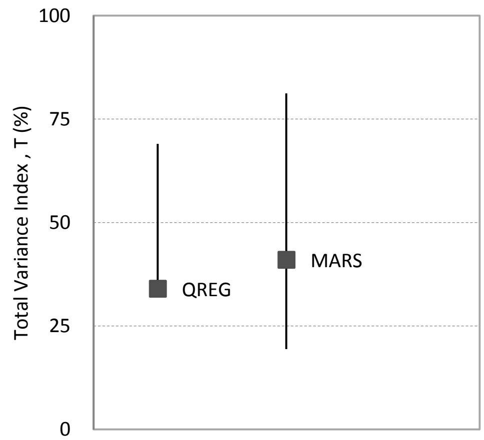


Figure 6.7 (c): GBM Method

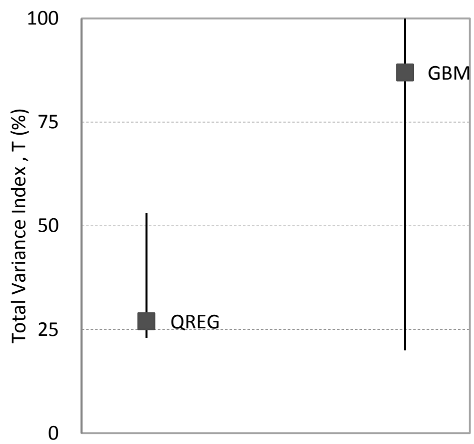
Figure 6.7: Summary of Nonparametric Regression Methods for Output Y4



(a): X4 (Percent of Trucks in Design Lane)



(b): X7 (% AADTT Distribution By Vehicle Class 11)



(c): X28 (Plastic Limit)

Figure 6.8: Summary of Total Variance Indexes for Output Y4

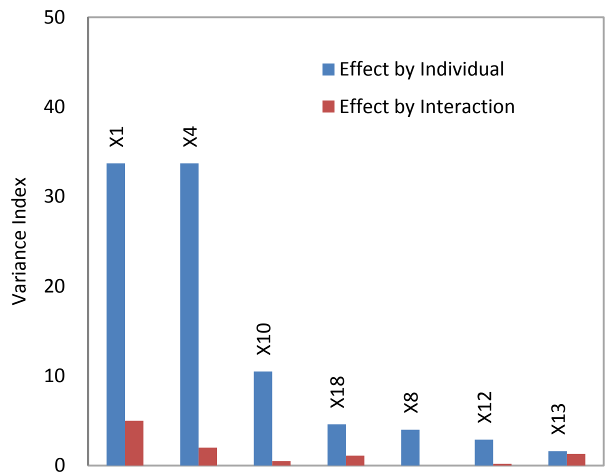


Figure 6.9 (a): QREG Method

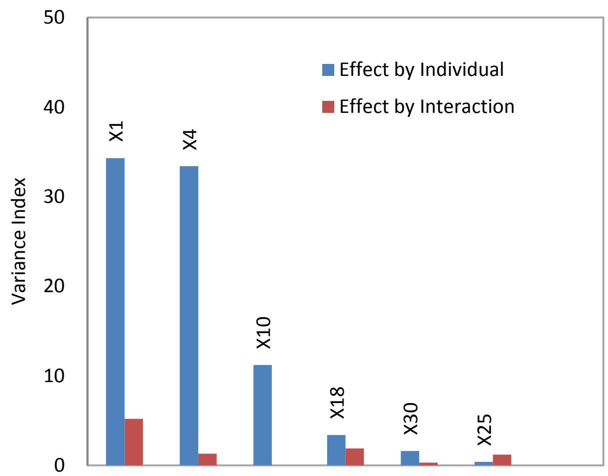


Figure 6.9 (b): MARS Method

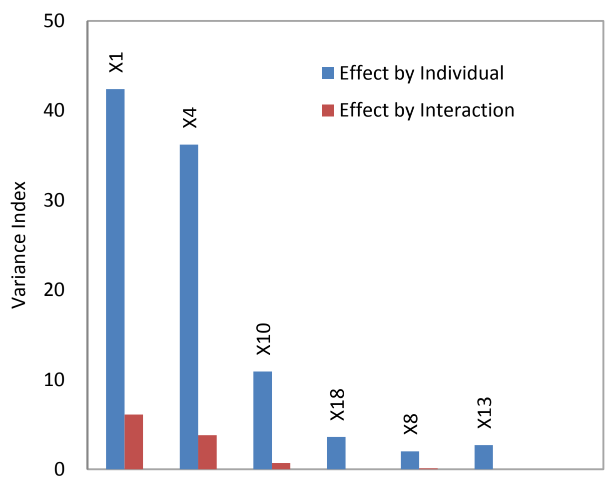
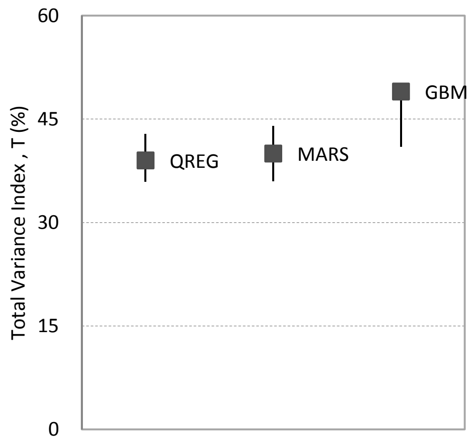
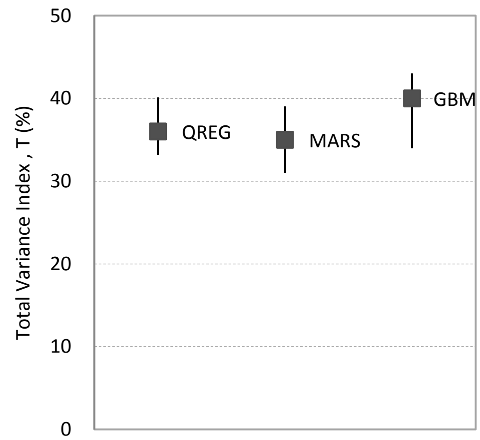


Figure 6.9 (c): GBM Method

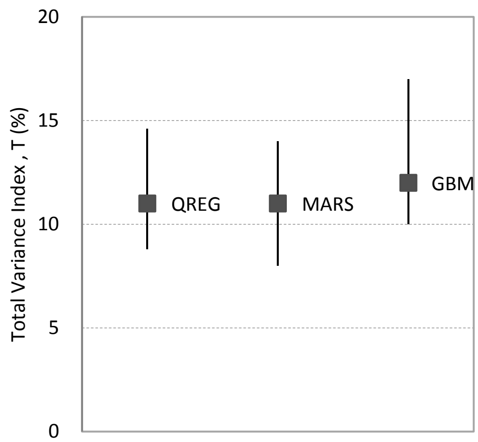
Figure 6.9: Summary of Nonparametric Regression Methods for Output Y5



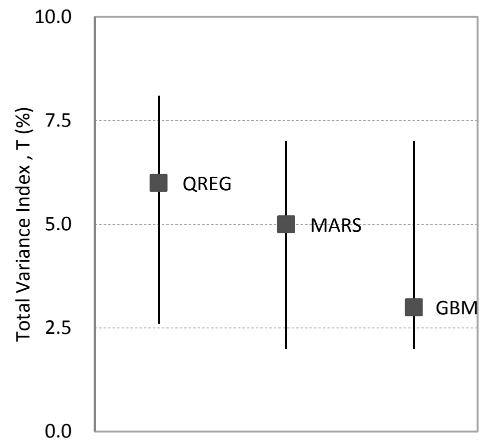
(a): X1 (AADTT)



(b): X4 (Percent of Trucks in Design Lane)



(c): X10 (Tire Pressure)



(d): X18 (Bottom AC Layer Thickness)

Figure 6.10: Summary of Total Variance Indexes for Output Y5

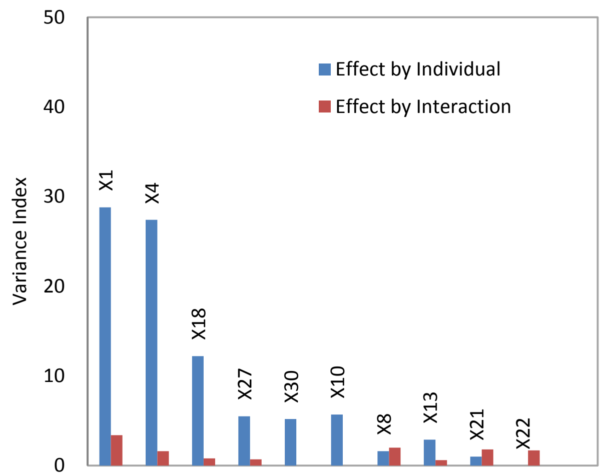


Figure 6.11 (a): QREG Method

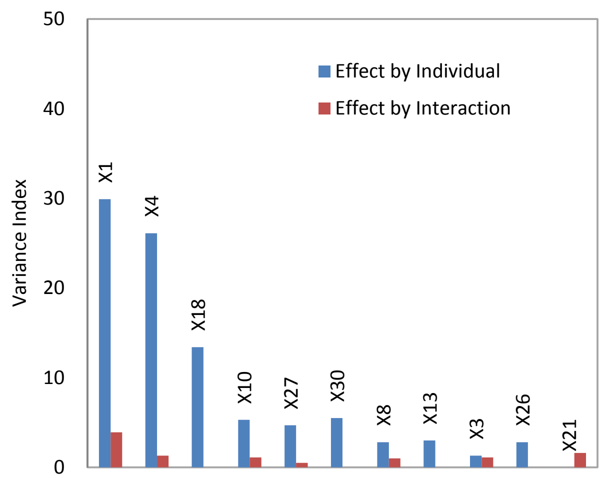


Figure 6.11 (b): MARS Method

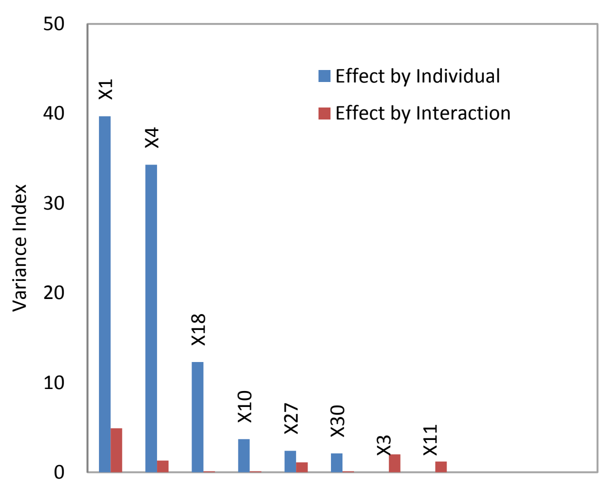
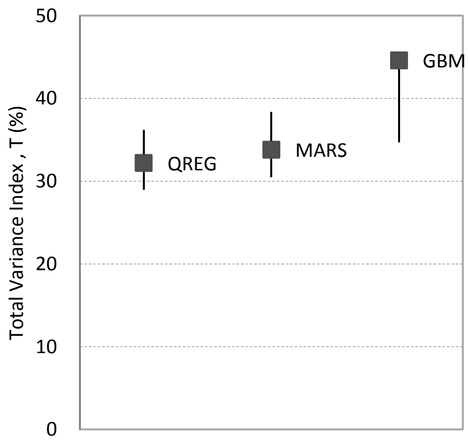
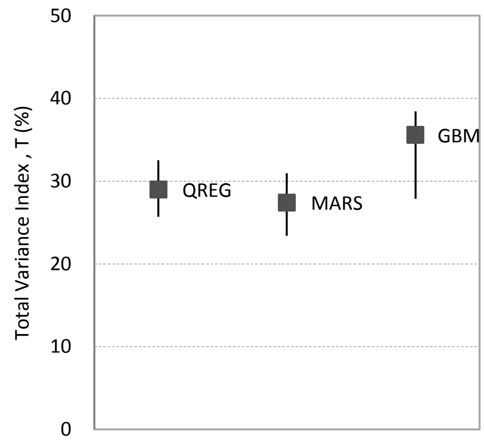


Figure 6.11 (c): GBM Method

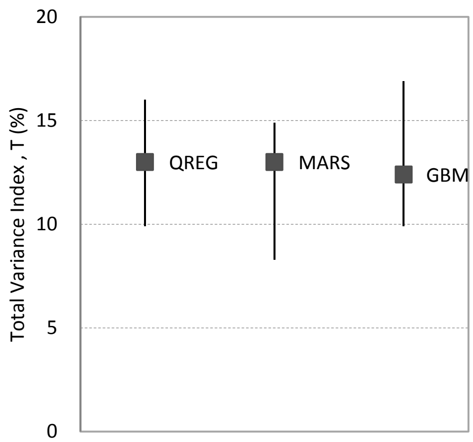
Figure 6.11: Summary of Nonparametric Regression Methods for Output Y6



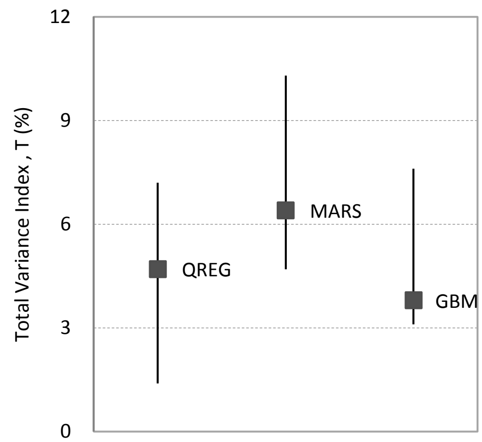
(a): X1 (AADTT)



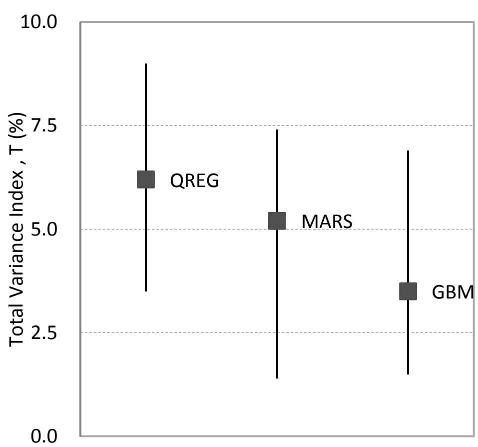
(b): X4 (Percent of Trucks in Design Lane)



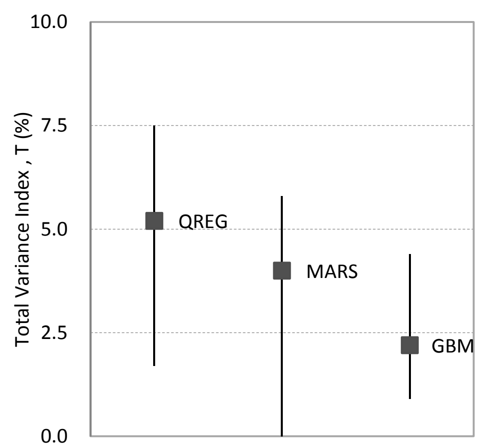
(c): X18 (Bottom AC Layer Thickness)



(d): X10 (Tire Pressure)



(e): X27 (Modulus of Subgrade)



(f): X30 (Optimum Gravimetric Water Content)

Figure 6.12: Summary of Total Variance Indexes for Output Y6

CHAPTER 7

CONCLUSIONS

7.1 Summary and Conclusions

Sensitivity analyses are performed in order to identify the MEPDG input variables that significantly influence the predicted MEPDG outputs or flexible pavement performances. As a first step, all input variables related to New Mexico pavements are collected. The inputs are then analyzed to determine their statistical mean, distributions, and range. Thirty input variables are selected based on past literature. These inputs are used to investigate the effect of individual input variables on performance. Pavement Design simulations are conducted by varying one input at a time, while keeping other inputs constant in MEPDG. Sensitivity analysis of MEPDG predicted outputs is performed using line and bar plots. A detailed sensitivity analysis is performed using a full factorial design matrix considering the interaction effects of input variables among themselves. Parametric approaches such as test for nonrandomness, linear and nonlinear regression analysis and nonparametric regression analysis such as GBM, MARS are performed. Based on the analyses performed, several conclusions are made and are summarized below.

- Data are collected from LTPP and NMDOT database for flexible pavement design inputs. These data are further reviewed and analyzed to determine the range, mean and distributions. This will be helpful for the pavement engineers to determine the practical ranges of the significant input variables.

- Using the collected data, one-at-a-time sensitivity analysis is performed considering New Mexico pavement sections. This analysis is performed using ten input variables. The variables are AC mix properties, AC thickness, GWT depth, operational speed, AADTT and base material properties. The result obtained in this study matched with national trend. It implies that, MEPDG outputs are sensitive to input variables for New Mexico condition.
- Sensitivity analysis are performed using different type of advanced statistical approaches. Parametric regression procedures are mainly used to measure the strength of the relationship between input and output variables. These tests are scatterplot test, linear regression, rank regression analysis. Based on these analysis results, input variables are ranked according to their significance and influence on outputs. The top ranked variables are listed below:

Terminal IRI

1. Bottom AC layer Thickness
2. AADTT
3. Percent of trucks in Design Lane
4. Type of Subgrade Material
5. Top AC layer Thickness

Longitudinal Cracking

1. Bottom AC layer Thickness
2. AADTT
3. Percent of trucks in Design Lane
4. Modulus of Base Layer
5. Percent Air void of Top AC Layer

Alligator Cracking

1. Bottom AC layer Thickness

2. Percent of trucks in Design Lane
3. AADTT
4. Percent Air void of Bottom AC Layer
5. Top AC layer Thickness

Transverse Cracking

1. PG grade of Top AC layer
2. Type of Base Material
3. Aggregate gradation of Top AC layer
4. Aggregate gradation of Bottom AC layer
5. PG grade of Bottom AC layer

AC Rut

1. AADTT
2. Percent of trucks in Design Lane
3. Tire Pressure
4. Bottom AC layer Thickness
5. Traffic Growth Factor

Total Rut

1. AADTT
2. Percent of trucks in Design Lane
3. Bottom AC layer Thickness
4. Modulus of Subgrade
5. Tire Pressure

- Parametric and Nonparametric regression procedures are employed to determine the sensitivity measures of the input variables. Total three methods are performed in this case. They are QREG (parametric regression), MARS and GBM (nonparametric regression). These test results provides the sensitivity indexes for input variables considering the interaction effect among them. The significant variables are obtained for different pavement performances are given below:

Terminal IRI

1. Highly Sensitive: Bottom AC layer Thickness, AADTT and Percent of Trucks in Design Direction
2. Sensitive: Top AC layer Thickness, Percent Air void of Bottom AC Layer

Longitudinal Cracking

3. Highly Sensitive: Bottom AC layer Thickness, AADTT and Percent of trucks in Design Lane
4. Sensitive: Type of base Material, Modulus of Base Layer, Percent Air void of Top AC Layer

Alligator Cracking

1. Highly Sensitive: Bottom AC layer Thickness, AADTT and Percent Air void of Bottom AC Layer
2. Sensitive: Bottom AC layer Thickness, Percent of trucks in Design Lane

Transverse Cracking

1. Highly Sensitive: AADTT and Percent of Vehicle class 11
2. Sensitive: Plastic Limit, Type of subgrade material, Type of Base Material, Liquid Limit, climatic zone, Effective binder content of Top AC layer, Thickness of Base

AC Rut

1. Highly Sensitive: AADTT, Percent of trucks in Design Lane and Tire Pressure
2. Sensitive: Bottom AC layer Thickness, Traffic Growth Factor, climatic zones and Top AC layer thickness

Total Rut

1. Highly Sensitive: AADTT, Percent of trucks in Design Lane and Bottom AC layer Thickness

2. Sensitive: Modulus of Subgrade, Tire Pressure and Optimum Gravimetric Water Content

- In this study, AC rut and total rut are found to be the most severe case among all the pavement distresses. Compare to other pavement performance measures, the predicted AC rutting and total rutting are influenced by most input parameters. The MEPDG models for rutting specifically needs local calibration to represent New Mexico materials and climate.
- Traffic input variables, such as Annual Average Daily Truck Traffic (AADTT) and Percent of Trucks in Design lane are obtained to be the most critical parameter
- For New Mexico, AC mix properties and AC thickness are very important for roughness, longitudinal crack and fatigue crack. Base properties (modulus and thickness) have significant impact on long and fatigue crack.
- Bottom AC layer thickness has most interacting effects with other input variables for all type of distresses.

7.2 Recommendations

- Due to lack of data, data ranges of inputs are used to perform sensitivity analysis. To have more accuracy in result, information about ranges and distributions for the input variables are recommended to collect for future analysis.
- Number of materials input in MEPDG at level 3 is large. Ideally, all the layers such as base, asphalt layers, subgrade materials gradation can be given as inputs in MEPDG. To keep this study simple, individual sieve analysis result are not

considered. This would lead slight change in some gradation proportions, like percent fines, which can lead to appreciable difference in the overall performance. Gradation issues should be addressed through future studies.

- The HMA mixtures used in New Mexico needs to be characterized using fundamental mechanical testing such as E*, creep compliance and tensile strength for sensitivity analysis. These inputs have significant influence on predicted fatigue and thermal cracking.
- AADTT and percent of trucks are found in the list of most significant input variable. To characterize the real effect of these traffic data, use of vehicle class distribution for all class is recommended to use for further study.

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APPENDICES

APPENDIX A

Sample Data Used for Preliminary Sensitivity Analysis

Table A.1: Traffic Data for LTPP Sections

SHRP ID	AADTT	No of Lane in Design Direction	Vehicle Class Distribution											Growth Factor (%)
			Yesr	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13	
0101	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0102	1662	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0103	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0104	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0105	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0106	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0107	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0108	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0109	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0110	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0111	1661	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
0112	1176	2	2003	4.86	32.74	3.65	0.09	17.13	37.33	0.59	2.12	1.38	0.11	3.2
2006	686	2	2007	2.17	36.75	4.2	0.3	9.96	39.83	1.09	3.76	1.75	0.19	23
6035	4708	3	2007	2.58	9.62	0.56	0.03	34.13	47.02	0.27	3.65	2.1	0.04	5.7

Table A.2: Structure Data for LTPP Sections

Section	Layer No	Layer Type	Thickness (inch)	Name	Material Type
0101	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	6.6	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	GB	7.9	Base Layer	Crushed Stone
	4	TS	6	Subbase Layer	Lime-Treated Soil
	5	SS		Subgrade	Fine-Grained Soils: Sandy Lean Clay
0102	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	4.2	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	GB	12.2	Base Layer	Crushed Stone
	4	TS	6	Subbase Layer	Lime-Treated Soil
	5	SS		Subgrade	Fine-Grained Soils: Fat Inorganic Clay
0103	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	4.7	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	7.2	Base Layer	HMAC
	4	TS	6	Subbase Layer	Lime-Treated Soil
	5	SS		Subgrade	Fine-Grained Soils: Fat Inorganic Clay
0104	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	7.5	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	11.1	Base Layer	HMAC
	4	TS	6	Subbase Layer	Lime-Treated Soil
	5	SS		Subgrade	Fine-Grained Soils: Lean Clay with Sand
0105	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	5.3	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	4	Base Layer	HMAC
	4	GB	3.7	Base Layer	Crushed Stone
	5	TS	6	Subbase Layer	Lime-Treated Soil
	6	SS		Subgrade	Fine-Grained Soils: Fat Inorganic Clay
0106	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	7	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	8	Base Layer	HMAC
	4	GB	2.9	Base Layer	Crushed Stone
	5	TS	6	Subbase Layer	Lime-Treated Soil
	6	SS		Subgrade	Fine-Grained Soils: Sandy Fat Clay
0107	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	5.3	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	3.7	Base Layer	Open Graded, Hot Laid, Central Plant Mix
	4	GB	4	Base Layer	Crushed Stone
	5	TS	6	Subbase Layer	Lime-Treated Soil
	6	SS	132	Subgrade	Fine-Grained Soils: Fat Clay with Sand
0108	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	7.2	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	4.2	Base Layer	Open Graded, Hot Laid, Central Plant Mix
	4	GB	8	Base Layer	Crushed Stone
	5	TS	6	Subbase Layer	Lime-Treated Soil
	6	SS		Subgrade	Fine-Grained Soils: Fat Inorganic Clay

Table A.2: Structure Data for LTPP Sections (Continued)

Section	Layer No	Layer Type	Thickness (inch)	Name	Material Type
0109	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	7.4	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	4.5	Base Layer	Open Graded, Hot Laid, Central Plant Mix
	4	GB	11.9	Base Layer	Crushed Stone
	5	TS	6	Subbase Layer	Lime-Treated Soil
	6	SS		Subgrade	Fine-Grained Soils: Sandy Fat Clay
0110	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	7.3	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	4.6	Base Layer	HMAC
	4	TB	3.7	Base Layer	Open Graded, Hot Laid, Central Plant Mix
	5	EF	0.1	Interlayer	Woven Geotextile
	6	TS	6	Subbase Layer	Lime-Treated Soil
	7	SS		Subgrade	Fine-Grained Soils: Lean Clay with Sand
0111	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	4.3	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	7.6	Base Layer	HMAC
	4	TB	3.7	Base Layer	Open Graded, Hot Laid, Central Plant Mix
	5	EF	0.1	Interlayer	Woven Geotextile
	6	TS	6	Subbase Layer	Lime-Treated Soil
	7	SS		Subgrade	Coarse-Grained Soil: Clayey Sand
0112	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	4.4	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	11.7	Base Layer	HMAC
	4	TB	3.1	Base Layer	Open Graded, Hot Laid, Central Plant Mix
	5	EF	0.1	Interlayer	Woven Geotextile
	6	TS	6	Subbase Layer	Lime-Treated Soil
	7	SS		Subgrade	Fine-Grained Soils: Lean Inorganic Clay
2006	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	4.5	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	3	TB	4.8	Base Layer	Dense Graded, Cold Laid, Mixed In-Place
	4	GS	6.1	Subbase Layer	Other
	5	SS		Subgrade	Coarse-Grained Soil: Silty Sand
6035	1	AC	0.6	Friction Course	Hot Mixed, Hot Laid AC, Open Graded
	2	AC	1.7	Overlay	Hot Mixed, Hot Laid AC, Dense Graded
	3	EF	0.1	Interlayer	Nonwoven Geotextile
	4	AC	2	AC Layer Below Surface	Hot Mixed, Hot Laid AC, Dense Graded
	5	AC	3.6	Original Surface Layer	Hot Mixed, Hot Laid AC, Dense Graded
	6	GB	6	Base Layer	Soil-Aggregate Mix (predominantly coarse-grained)
	7	TS	9.2	Subbase Layer	Cement Aggregate Mixture
	8	SS		Subgrade	Coarse-Grained Soil: Silty Sand

APPENDIX B

Sample Result of Preliminary Sensitivity Analysis

Table B.1: Reliability Summary for 35-6035

No	Variable	Value	Terminal IRI (in/mile)		Long. Cracking (ft/mi)		Alligator Cracking (%)		Permanent Deformation (AC Only) (in)		Permanent Deformation (Total Pavement) (in)	
			Extent	Reliability	Extent	Reliability	Extent	Reliability	Extent	Reliability	Extent	Reliability
1	Air Void (%)	2	145.6	75.76	1.4	99.99	37.4	19.01	0.32	23	0.69	69.49
		4	147.3	74.2	10.2	99.34	38.3	17.33	0.34	18.66	0.71	62.85
		6	150.4	71.21	56	92.32	39.7	14.91	0.38	12.51	0.75	50.3
		8.1	155.2	66.51	262	82.3	41.8	11.72	0.44	6.66	0.81	32.98
		10	161	60.76	867	69.98	44	8.94	0.51	3.13	0.9	18.02
2	Binder Content	4	149.8	71.76	777	71.6	39.5	15.24	0.37	13.44	0.74	52.51
		4.5	151.4	70.2	552	75.79	40.2	14.1	0.39	10.9	0.76	46.19
		5	153	68.7	405	78.82	40.9	13.02	0.41	8.93	0.78	40.54
		5.8	155.2	66.51	262	82.3	41.8	11.72	0.44	6.66	0.81	32.98
		7.5	159.2	62.55	125	87.33	43.3	9.76	0.49	3.94	0.87	21.9
3	Performance Grade	PG 58-28	163.9	57.82	455	77.75	43.9	9.05	0.59	1.59	0.97	10.17
		PG 64-28	159	62.69	347	80.13	42.9	10.26	0.5	3.56	0.88	20.46
		PG 70-22	152.5	69.17	213	83.77	41.2	12.58	0.39	11.12	0.76	46.06
		PG 76-22	149.4	72.19	164	85.53	40.4	13.79	0.34	19.95	0.71	63.3
		PG 82-22	147.7	73.78	140	86.59	39.8	14.75	0.31	26.07	0.68	71.45
		AC 20	155.2	66.51	262	82.3	41.8	11.72	0.44	6.66	0.81	32.98
4	% Passing #200 Sieve	2	160.9	60.83	378	79.39	43.9	9.05	0.51	3.15	0.9	18.12
		4	157.7	64.05	310	81.03	42.8	10.39	0.47	4.8	0.85	25.66
		6	155.8	65.95	273	81.99	42	11.45	0.44	6.17	0.82	31.14
		7.3	155.2	66.51	262	82.3	41.8	11.72	0.44	6.66	0.81	32.98
		10	155.4	66.28	267	82.16	41.9	11.58	0.44	6.43	0.82	32.12
		12	157	64.75	296	81.38	42.5	10.78	0.46	5.25	0.84	27.54
5	AC thickness (in)	3.1	155.2	66.51	262	82.3	41.8	11.72	0.44	6.66	0.81	32.98
		5	132.9	86.42	1.9	99.99	16.7	72.15	0.45	6.11	0.77	44.13
		7	123.3	92.53	0	99.99	6.1	90.99	0.39	10.4	0.68	70.24
		9	116.3	95.93	0	99.99	2.5	99.88	0.3	30.26	0.55	96.52
		10	113.1	97.06	0.1	99.99	1.6	99.999	0.24	53.94	0.48	99.7

Table B.1: Reliability Summary for 35-6035 (Continued)

No	Variable	Value	Terminal IRI (in/mile)		Long. Cracking (ft/mi)		Alligator Cracking (%)		Permanent Deformation (AC Only) (in)		Permanent Deformation (Total Pavement) (in)	
			Extent	Reliability	Extent	Reliability	Extent	Reliability	Extent	Reliability	Extent	Reliability
6	Depth to GWT (ft)	1	169.8	52.06	942	68.63	51.8	2.89	0.43	6.88	0.85	24.69
		5	156.4	65.33	272	82.02	42.2	11.18	0.46	5.41	0.83	28.87
		7	156.4	65.29	275	81.94	42.2	11.18	0.46	5.41	0.83	28.7
		10	156.5	65.27	274	81.96	42.2	11.18	0.46	5.43	0.83	99.99
		12	156.5	65.23	275	81.94	42.2	11.18	0.46	5.44	0.83	28.53
		20	156.6	65.16	279	81.83	42.3	11.04	0.45	5.55	0.83	28.56
7	Operational Speed (mph)	15	172.3	49.73	486	77.12	48.1	5.1	0.66	0.92	1.05	5.65
		20	168.3	53.57	435	78.17	46.8	6.14	0.6	1.44	0.99	8.8
		30	163	58.74	366	79.69	45	7.85	0.53	2.61	0.92	15.36
		50	157.2	64.55	288	81.58	42.6	10.65	0.46	5.25	0.84	27.52
		60	155.2	66.51	262	82.3	41.8	11.72	0.44	6.66	0.81	32.98
		70	153.6	68.1	241	82.9	41.1	12.73	0.42	8.09	0.79	37.89
		90	151.1	70.49	209	83.9	39.9	14.58	0.39	10.96	0.76	99.99
8	AADTT	800	117.4	95.33	18.1	97.9	9.3	86.69	0.19	83.95	0.48	99.83
		1000	119.9	94.26	25.4	96.55	11.6	82.85	0.21	72.79	0.51	99.3
		1200	122.2	93.12	33.5	95.24	13.8	78.6	0.23	62.2	0.54	98.16
		1500	125.5	91.31	47	93.38	17	71.44	0.25	48.71	0.58	94.96
		2000	130.7	88.02	72.5	90.76	21.9	58.68	0.29	32.81	0.63	86.06
9	Base Thickness (inch)	4	161.2	60.6	558	75.68	46.9	6.06	0.42	7.71	0.81	33.56
		6	155.2	66.51	262	82.3	41.8	11.72	0.44	6.66	0.81	32.98
		8	151.4	70.27	154	85.95	38	17.88	0.45	5.89	0.82	32.43
		10	148.7	72.84	111	88.07	35.1	23.74	0.46	5.3	0.82	31.87
		12	146.8	74.57	97.9	88.86	32.9	28.8	0.47	4.84	0.82	31.73
		15	144.8	76.44	103	88.54	30.5	34.85	0.48	4.31	0.82	31.64
		18	143.4	77.76	129	87.12	28.7	39.67	0.49	3.94	0.82	99.99
10	Base Resilient Modulus (psi)	15000	182.1	40.81	2640	39.21	59.2	0.78	0.41	9.03	0.83	29.7
		20000	172.2	49.78	1430	59.99	54	2.01	0.42	8.15	0.82	31.23
		25000	164.9	56.88	792	71.33	49.5	4.15	0.43	7.53	0.82	32.1
		30000	159.5	62.27	450	77.86	45.4	7.44	0.43	7.05	0.81	32.62
		35000	155.2	66.51	262	82.3	41.8	11.72	0.44	6.66	0.81	32.98
		40000	151.7	69.95	156	85.88	38.5	16.97	0.44	6.35	0.81	33.23
		45000	148.8	72.74	94	89.13	35.5	22.87	0.45	6.09	0.81	99.99

APPENDIX C

Sample Result of Statistical Analysis

Summary Result of Regression Analysis

```
R version 2.9.2 (2009-08-24)
###############################################
        Output = Y1
###############################################
###### Fitting Model #####
surface = reg
Stepwise Addition:
 Model                                         GCV Score
 18                                            631.26
 18  1                                         510.22
 18  1  4                                      421.64
 18  1  4 13                                   399.8
 18  1  4 13 26                                379.73
 18  1  4 13 26 27                             365.93
 18  1  4 13 26 27 30                          354.96
 18  1  4 13 26 27 30 22                       344.76
 18  1  4 13 26 27 30 22 10                    335.87
 18  1  4 13 26 27 30 22 10 25                 327.81
 18  1  4 13 26 27 30 22 10 25  8              321.65
 18  1  4 13 26 27 30 22 10 25  8  3           315.73
 18  1  4 13 26 27 30 22 10 25  8  3 24        316.15
 18  1  4 13 26 27 30 22 10 25  8  3 24 29     314.30
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  313.64
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6           312.38
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6 12        314.21
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6 12  5     313.56
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6 12  5  9  313.45
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6 12  5  9 17  313.41

Stepwise Deletion:
 Model                                         GCV Score
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6 12  5  9  313.45
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6 12  5     313.56
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6 12        314.21
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  6           312.38
 18  1  4 13 26 27 30 22 10 25  8  3 24 29 21  313.64
 18  1  4 13 26 27 30 22 10 25  8  3 24 29     314.30
 18  1  4 13 26 27 30 22 10 25  8  3 24        316.15
 18  1  4 13 26 27 30 22 10 25  8  3           315.73
 18  1  4 13 26 27 30 22 10 25  8              321.65
 18  1  4 13 26 27 30 22 10 25                 327.81
 18  1  4 13 26 27 30 22 10                    335.87
 18  1  4 13 26 27 30 22                       344.76
 18  1  4 13 26 27 30                          354.96
 18  1  4 13 26 27                             365.93
 18  1  4 13 26                                379.73
 18  1  4 13                                   399.8
 18  1  4                                      421.64
 18  1                                         510.22
 18                                            631.26
```

Final Model: 18 1 4 13 26 27 30 22 10 25 8 3 24 29 21 6

##

```
> reg.ans
####### Output = Y1 #######

#### surface = reg ####

Estimated Model Summary:
Model: Y1 = f(X18, X1, X4, X13, X26, X27, X30, X22, X10, X25, X8, X3, X24, X29, X21, X6)
Rsq = 0.610531
dfmod = 24
```

Input	Rsq	src	pcc^2	95% pcc^2 CI	p-val
X18	0.164	-0.392	0.277	(0.186, 0.421)	0.000
X1	0.326	0.397	0.284	(0.183, 0.413)	0.000
X4	0.445	0.336	0.219	(0.127, 0.351)	0.000
X13	0.475	-0.174	0.070	(0.032, 0.134)	0.000
X26	0.502	0.145	0.050	(0.019, 0.101)	0.000
X27	0.521	-0.135	0.044	(0.018, 0.096)	0.000
X30	0.536	-0.116	0.032	(0.011, 0.073)	0.001
X22	0.551	0.110	0.029	(0.010, 0.072)	0.003
X10	0.564	0.105	0.027	(0.006, 0.059)	0.010
X25	0.575	-0.096	0.023	(0.006, 0.057)	0.015
X8	0.584	0.102	0.025	(0.007, 0.062)	0.004
X3	0.593	0.094	0.021	(0.006, 0.053)	0.012
X24	0.596	0.067	0.011	(0.000, 0.029)	0.156
X29	0.600	0.060	0.009	(0.000, 0.031)	0.185
X21	0.603	0.054	0.007	(0.000, 0.023)	0.282

Summary Result of Rank Regression Analysis

```
R version 2.9.2 (2009-08-24)

###############################################
        Output = Y1
###############################################

###### Fitting Model #####

surface = rank
Stepwise Addition:
 Model                                        GCV Score
  1                                         25989372
  1  4                                       18001874
  1  4 18                                     13012093
  1  4 18 26                                   11026255
  1  4 18 26 27                                 10006792
  1  4 18 26 27 10                               9051602
  1  4 18 26 27 10 30                             8155817
  1  4 18 26 27 10 30 13                           7402965
  1  4 18 26 27 10 30 13  8                         6829029
  1  4 18 26 27 10 30 13  8  3                       6576706
  1  4 18 26 27 10 30 13  8  3 29                     6340158
  1  4 18 26 27 10 30 13  8  3 29  5                   6111576
  1  4 18 26 27 10 30 13  8  3 29  5 22                 5924903
  1  4 18 26 27 10 30 13  8  3 29  5 22 12               5820933
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24             5788255
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16           5722933
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16 15         5668976
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16 15 21       5640394
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16 15 21 28     5608465
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16 15 21 28 14   5593668

Stepwise Deletion:
 Model                                        GCV Score
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16 15 21 28     5608465
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16 15 21       5640394
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16 15         5668976
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24 16           5722933
  1  4 18 26 27 10 30 13  8  3 29  5 22 12 24             5788255
  1  4 18 26 27 10 30 13  8  3 29  5 22 12               5820933
  1  4 18 26 27 10 30 13  8  3 29  5 22                 5924903
  1  4 18 26 27 10 30 13  8  3 29  5                   6111576
  1  4 18 26 27 10 30 13  8  3 29                     6340158
  1  4 18 26 27 10 30 13  8  3                       6576706
  1  4 18 26 27 10 30 13  8                         6829029
  1  4 18 26 27 10 30 13                           7402965
  1  4 18 26 27 10 30                             8155817
  1  4 18 26 27 10                               9051602
  1  4 18 26 27                                 10006792
  1  4 18 26                                   11026255
  1  4 18                                     13012093
  1  4                                       18001874
  1                                         25989372

Final Model: 1 4 18 26 27 10 30 13 8 3 29 5 22 12 24 16 15 21 28 14
############################################################
```

```
> rank.ans

####### Output = Y1 #######

#### surface = rank ####

Estimated Model Summary:
Model: Y1 = f(X1, X4, X18, X26, X27, X10, X30, X13, X8, X3, X29, X5, X22, X12, X24, X16, X15, X21, X28, X14)
Rsq = 0.8547123
dfmod = 32
```

Input	Rsq	src	pcc^2	95% pcc^2 CI	p-val
X1	0.267	0.503	0.604	(0.551, 0.653)	0.000
X4	0.493	0.465	0.565	(0.505, 0.617)	0.000
X18	0.635	-0.373	0.457	(0.397, 0.512)	0.000
X26	0.684	0.209	0.201	(0.145, 0.263)	0.000
X27	0.712	-0.173	0.153	(0.100, 0.208)	0.000
X10	0.739	0.168	0.143	(0.098, 0.197)	0.000
X30	0.764	-0.158	0.129	(0.084, 0.177)	0.000
X13	0.786	-0.147	0.116	(0.075, 0.172)	0.000
X8	0.801	0.140	0.106	(0.065, 0.151)	0.000
X3	0.809	0.091	0.047	(0.019, 0.079)	0.000
X29	0.816	0.086	0.042	(0.018, 0.076)	0.001
X5	0.824	-0.090	0.046	(0.022, 0.082)	0.000
X22	0.828	0.061	0.021	(0.004, 0.046)	0.011
X12	0.828	-0.006	0.000	(0.000, 0.008)	0.039
X24	0.832	0.059	0.020	(0.000, 0.042)	0.083