USE OF FALLING WEIGHT DEFLECTOMETER DATA FOR ASSESSING PAVEMENT STRUCTURAL EVALUATION VALUES

Final Report

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by

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16 Abstract

Structural evaluation can be very useful at the network level for project prioritization purposes. In the project priority ranking procedure of the Kansas Department of Transportation (KDOT), a pavement rating attribute, Pavement Structural Evaluation (PSE), is used. These ratings are subjective and based on the condition of the pavement as indicated by the visual distresses and maintenance histories and the ability of the section to provide an adequate surface for the prevailing traffic. PSE is expected to be an indicator of the structural deficiency of the pavement sections. However, since KDOT does not collect any deflection data at the network level, the PSE computation process does not directly take into account any structural evaluation. This study outlines an approach based on the classical multiple regression analysis resulting in a better estimation of the PSE values using the results from the Falling Weight Deflectometer (FWD) tests and network-level distress survey.

The regression models proposed in this study predict the *decrease* in PSE values by taking into account the FWD data, age, thickness, and distress levels of pavements, and very closely approximate the current PSE ratings obtained at the district level. FWD data on approximately 20% of the KDOT network is needed for network level structural evaluation. This translates into 750 lane-miles of FWD testing per year. Three FWD tests per mile are recommended for the network-level evaluation. This testing would also be necessary for using/updating the models developed in this study. The *decrease* in the structural number values obtained from the models developed in this study was about 33% higher than the KDOT design assumption.

A parallel study at Kansas State University used the Bayesian Regression methodology developed by the Canadian Strategic Highway Research Program. The Bayesian regression models developed are very similar in form to the classical regression models and yielded statistically similar results when tested on a different set of pavements. However, the Bayesian regression models appeared to give slightly better results for some pavements during testing.

17 Key Words
Deflection, Falling Weight Deflectometer (FWD), Pavement, Pavement Structural Evaluation (PSE), Regression Analysis

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EXECUTIVE SUMMARY

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1.0 INTRODUCTION

1.1 General Problem Statement

Pavement evaluation in pavement management systems (PMS) is generally directed toward the following objectives *(Haas et al. 1994)*:

1. Selection of projects and treatment strategies at the network level, and
2. Identification of specific maintenance requirements at the project level.

Each of these objectives requires pavement evaluation information to greater or lesser degrees of detail. In the case of lesser detail, aggregation of the individual measures comprising the information, such as a composite or combined measure of pavement quality, is widely used. Such a combined measure for each pavement section is helpful at the network level for technical decisions, e. g., project selection.

At the network level, Nondestructive Testing (NDT) can be used to identify the beginning and end of management sections and group pavement sections with similar structural capacities for condition prediction, and to identify pavement projects for project-level testing and evaluation *(Shahin 1994).* Without NDT testing, there is a risk of defining pavement management sections that may appear uniform based on observed distress alone, but in reality they are not. In Kansas, one type of pavement management section is known as a "control section." A control section is "a segment of roadway with reasonably uniform geometric, traffic, surface, and base characteristics for its entire length." These sections are used for project prioritization purposes by the Kansas Department of Transportation (KDOT).

Due to limited resources and large size of the network (17,660 km or 10,971 miles), network-level structural data collection annually by KDOT at the same intervals (5 to 10 tests per mile) as the project level is not realistic. Although guidelines exist for test intervals at the project level *(Karan et al. 1981; Koole 1979; Way et al. 1981; Mamlouk et al. 1990; Hossain and Zaniewski 1992; Shahin 1994),* not many studies have been conducted to determine the test intervals at the network level. Lytton et al. *(1990)* evaluated the minimum number of Falling Weight Deflectometer (FWD) tests required to provide accurate representation of the structural capacity of the pavement section at the network level. They concluded that a minimum of five tests per mile are required to provide a ranking of a pavement section which is highly correlated to the actual ranking. The actual ranking is the one that would be obtained by doing as many tests as possible. KDOT owns two Dynatest 8000 FWD. Currently, each unit is capable of testing up to 20 lane-miles in a 10-hour day during a deflection survey period which runs from April thru October. With this production level, to test the entire network (17,660 lane km or 10,971 lane miles) annually, 275 days of testing would be necessary just at the network level! This does not include the time spent in travel from one project to the other. Thus, one of the objectives of this study was to determine the test sample size (percent mileage) at the network level as well as the test intervals and frequency.

In the Priority Ranking Procedure of KDOT, a composite measure of pavement quality, Pavement Structural Evaluation (PSE), is used. The rating for pavements is on a scale of 0 to 10, 10 being the best or no work required. In the ranking procedure, PSE is expected to be an indicator of the control section structural deficiency *(Clark 1989)*. The attributes and relative weights used in the prioritization process for the interstate highways are as follows:

Attribute	**Relative Weight**
Commercial Traffic Index	0.140
Rideability	0.189
PSE	0.447
Observed condition	0.224

Thus the relative weight of the PSE attribute in the interstate roadway priority formula is twice the next weighted attribute of observed condition. The same importance is attached to the PSE rating attribute for non-interstate roadways *(Comstock 1992)*.

PSE ratings are furnished by the district offices of KDOT and are based on the condition and strength of base and surface, as indicated by maintenance costs, subgrade failures, and ability of the section to provide an adequate surface for the type of expected traffic *(Chowdhury 1998)*. Table 1.1 shows the rating guide used by the KDOT districts for the bituminous pavements. Since the implementation of a network-level PMS (known as Network Optimization System or NOS) by KDOT in the late eighties, PSE is the only input the Districts have into the project prioritization process.

The Geotechnical unit provides a possible range of PSE values for each control section based on algorithms developed by the experts in that unit using the PMS data. However, these values did not appear to be helpful to the districts and in some cases, led to confusion. Since KDOT does not collect any deflection data at the network level, the PSE computation process does not take into account any structural evaluation. However, some of the distresses considered are structure-related. Engineering judgment indicates that a better measure of structural evaluation can be developed using results from the in-situ deflection tests, such as Falling Weight Deflectometer (FWD) tests and network-level distress survey.

Table 1.1 PSE Rating Guide for Bituminous Surfaces

PSE Value	Pavement Condition
10	Nearly new condition. No maintenance or distress expected for three or more years. When a recent action produces a current condition that is expected to last less than three years, consider making the rating in light of the condition before recent action.
8~9	Slight (<1/4") rutting in at least 1 wheelpath; and/or fine alligator cracks; little or no surface maintenance needed.
6~7	Moderate (½") rutting continuous in 2 or more wheel paths; and/or secondary transverse cracks or moderate (1/4") transverse cracks with little or no roughness associated with crack; and/or alligator cracks associated with ruts; and/or minor shoving, spot edge failures, or hairline block cracks; requires spot patching and major patching.
4~5	Significant (>½") rutting in wheel paths; and/or wide (>½") transverse cracks with roughness developing at cracks and/or shoving may be present; and/or alligator cracks associated with deep ruts, or vertical displacement; and/or edge failures, and/or spalling associated with block cracks; requires frequent patching and major patching.
2~3	Very wide (>3/4") or depressed transverse cracks resulting in unacceptable surface roughness; and/or continual edge failures or shoving along pavement edge at transverse cracks; and/or block cracking that is <4" in any dimension with spalling associated with the cracks; requires major patching; high potential for winter or spring breakup.
0~1	Continual patching and major patching required; or milling required to remove ruts and/or roughness due to depressed transverse cracks; beyond economical maintenance by KDOT forces.

1.2 Objective of the Study

The primary objective of this study was to investigate the potential of FWD deflection data to augment the Pavement Structural Evaluation (PSE) value computation. Another objective was to determine the FWD test sample size (percent mileage) at the network level, and test intervals and frequency needed to provide input into the network-level structural evaluation and PSE computation process.

1.3 Approach of the Study

The following variables, which directly or indirectly influence the pavement structural condition, were investigated as potential predictors of the PSE values:

1. Age of the pavement (in years) *since the last rehabilitation action*,
2. Cumulative 18 kip Equivalent Single Axle Loads (ESAL's) that have passed over the section *since the last action*,
3. Asphalt Concrete (AC) layer thickness,
4. Structural number (SN) of the pavement, and
5. Distress level due to transverse cracking.

It is to be noted that pure deflection values were not used as predictors. Rather the structural number of the pavement which can be derived from the deflection results is used as a predictor. This was done because a pavement with a strong subgrade and weak AC, base and subbase layers may have the same first sensor deflection value as a pavement with a weak subgrade and strong AC, base and subbase layers. The structural number, on the other hand, is known to be more representative of the structural condition of the layers above subgrade. However, since the deflection results are mostly unaffected by transverse cracking (FWD tests are conducted away from the cracks), the distress level of transverse cracking was used as a predictor. Multiple linear regression models were developed with the above predictors as independent variables to objectively quantify the decrease in the PSE values.

A parallel study by the junior author for his master's thesis *(Chowdhury 1998)* used the Bayesian regression modeling approach to objectively quantify the decrease in the PSE values. XLBAYES, an EXCEL-based software, was used to develop similar models using the same variables used in the multiple linear regression analysis done earlier. Bayesian regression modeling has been introduced by the Canadian Strategic Highway Research Program (C-SHRP) for analyzing the Canadian Long-Term Pavement Performance (C-LTPP) data. Chowdhury *(1998)* also tested the models developed by the classical regression and Bayesian regression on a different set of data, and appropriate models were recommended for global use on the KDOT network.

1.4 Synopsis

This report is divided into seven chapters. In Chapter 1, the introduction to the problem, the objectives of this study, and study approach are discussed. In Chapter 2, a literature review of previous work is presented. Chapter 3 deals with the determination of FWD test sample size (percent mileage), and test intervals, and frequency at the network level. It also discusses the network-level pavement structural evaluation. Regression models were developed to predict the decrease in the structural number, and thus, forecasts were made on the structural deterioration of the pavements in Kansas. In Chapter 4, multiple linear regression analysis was performed to predict the decrease in PSE values by using variables which reflect the structural, climatic, traffic and surface condition of the pavements. Chapters 5 and 6 have been borrowed from the master's thesis of Chowdhury *(1998)*. Chapter 5 describes the Bayesian Regression and its application in the determination of PSE values using the same set of variables as in the classical regression analysis. Chapter 6 analyzes the performance of the selected models on a different set of pavements with data from different years. The performances of the classical and Bayesian models are also compared. Finally, Chapter 7 presents the conclusions and recommendations.

2.0 LITERATURE REVIEW

An extensive literature search was conducted to obtain a thorough knowledge about deflection tests, backcalculation of pavement layer moduli, and determination of effective structural number from the NDT tests. Also, the need to predict the deterioration of pavements and the role of empirical study in this respect was assessed from different studies.

2.1 The Need to Predict Deterioration

A World Bank study in 1987 estimated that a quarter of the paved roads outside urban areas in developing countries were in need of reconstruction, and that an additional 40 percent of paved roads required strengthening then or in the next few years *(Paterson et al. 1987)*. Similar situations have been arising in developed countries to varying degrees from the eighties. For example, the accelerated deterioration of federally-aided highways in the United States required a 44 percent increase in funding in 1982 to meet the repair and rehabilitation costs of the system. Extensive rehabilitation programs have also been planned in most European countries *(Paterson et al. 1987)*. A recent journal of the National Asphalt Pavement Association (NAPA) reveals the fact that "America's interstate highway system- 42,700 miles of it, once the envy of the world, is visibly deteriorating" *(NAPA 1998)*. The system already carries 2 ½ times the traffic it did in 1975, and congestion is still increasing. In the past seven years, highway capacity has grown 2% while the traffic has increased to 37% *(NAPA 1998)*. In May of 1998, the Congress passed the TEA-21 (Transportation Equity Act for the 21st Century), the six-year $216 billion highway bill for roads, bridges and mass transit. Until the year 2003, the bill is believed to guarantee that all incoming revenues to the Highway Trust Fund can only be used for highway and mass transit investments. It is also believed that even if the entire $216 billion is spent on repairing interstates, it would not be enough to restore, upgrade, and maintain them *(NAPA: Focus on Hot Mix Asphalt Technology 1998*).

Such projections at the international and national levels exemplify the problems facing the highway planners, financiers, managers and engineers everywhere at national or local levels and to varying degrees. The problem concerns deterioration of an aging road infrastructure and how best to control it, taking into account the best interests and constraints of the economy and resources. Largely because of the worldwide need for extensive rehabilitation programs in the 1980s and 1990s, and in order to avoid such sharp peaks in highway expenditure, increasing efforts are being made to develop and implement improved road management and planning tools. These tools are required for evaluating the allocation of financial needs of the road maintenance and rehabilitation programs, for evaluating the design and maintenance standards appropriate for the funding available to the highway sector, and for planning and prioritizing works in the program. Tools are also needed for evaluating the costs of road use as a basis of pricing and taxation in the transport sector *(Paterson et al. 1987)*.

All such projections and evaluations depend upon predictions of the rate at which roads in the network will deteriorate and of the effectiveness of different maintenance options, dependent on current state and projected trends of traffic, economic growth and available resources. At the heart is a model of road deterioration, which may be as simple as a fixed estimate of life, such as, paved roads need major rehabilitation every 20 years. The model may be more complex, for example, taking into account the traffic projections, existing road structure, and specific standards of service and design. Paterson et al. *(1987)* also argued that the increasing demands for improved management and planning techniques, and for economic justification of expenditures and standards in the highway sector, are placing much more exacting requirements on the models of road deterioration.

2.2 The Roles of Empirical and Mechanistic Methods

While much of the knowledge of pavement behavior historically has been based on theoretical considerations, empirical observations have always provided the basis for formulating the criteria to be applied in practice. The reason for this is clear. Under traffic and climate, the long term behavior of natural and treated road materials is influenced by numerous and complex factors and is highly variable. Thus the criteria for acceptable performance involves subjectively determined limits of riding quality and other modes of distress. The large number of variables involved, however, strains the method, and the capability to improve the structural efficiency of pavements. It also extrapolates design to the magnitude of loading and to the types of material that are beyond the scope of available field data. These have been the factors behind the recent effort toward developing the mechanistic analysis techniques *(Paterson et al. 1987).* Mechanistic methods are based on a theoretical analysis of the stresses included in a pavement under load, mechanical properties of materials, and experimental models of the behavior of materials under repetitive loadings at different environmental conditions. However, the methods need validation and calibration to the full range of real conditions. These methods currently lack the prediction of roughness and surface disintegration which are important determinants for maintenance needs *(Paterson et al. 1987).*

Empirical study can be used to quantify and distinguish the long term parallel effects of mixed traffic loading and environmental factors on pavement performance. Perhaps, it is the only method by which the real rates of distress development, the interaction between distress types, and the relative effectiveness of different maintenance activities can be quantified. On the other hand, mechanistic analyses and accelerated loading studies have been invaluable in identifying the fundamental variables and appropriate functional forms for the development of each type of distress *(Paterson et al. 1987).*

2.3 Structural Evaluation of Existing Pavements

Structural deterioration is defined as any condition that reduces the load-carrying capacity of the pavement *(AASHTO 1993)*. In the AASHTO Pavement Design Guide, the structural capacity of a new pavement is denoted as SC_0 (Figure 2.1). For flexible pavements, structural capacity is expressed by the structural number, SN. For rigid pavements, structural capacity is the slab thickness, D. For existing composite pavements (asphalt concrete overlay over Portland cement concrete, AC/PCC), the structural capacity is expressed as an equivalent slab thickness, D_{eff}. This research deals with the flexible pavements only.

The structural capacity of the flexible pavements declines with time and traffic. The effective structural capacity of existing flexible pavements is expressed as SN_{eff}. The primary objective of a structural evaluation program is to determine the effective structural capacity of the existing pavements. However, no single specific methods exists for evaluating structural capacity. The evaluation of effective structural capacity must consider the current condition of the existing pavement materials, and also consider how those materials will behave in the future. Three alternative methods are recommended by the 1993 AASHTO Guide to determine the effective structural capacity:

1. Structural capacity based on visual survey and material testing.

This involves the assessment of current conditions based on the distress and drainage surveys, and

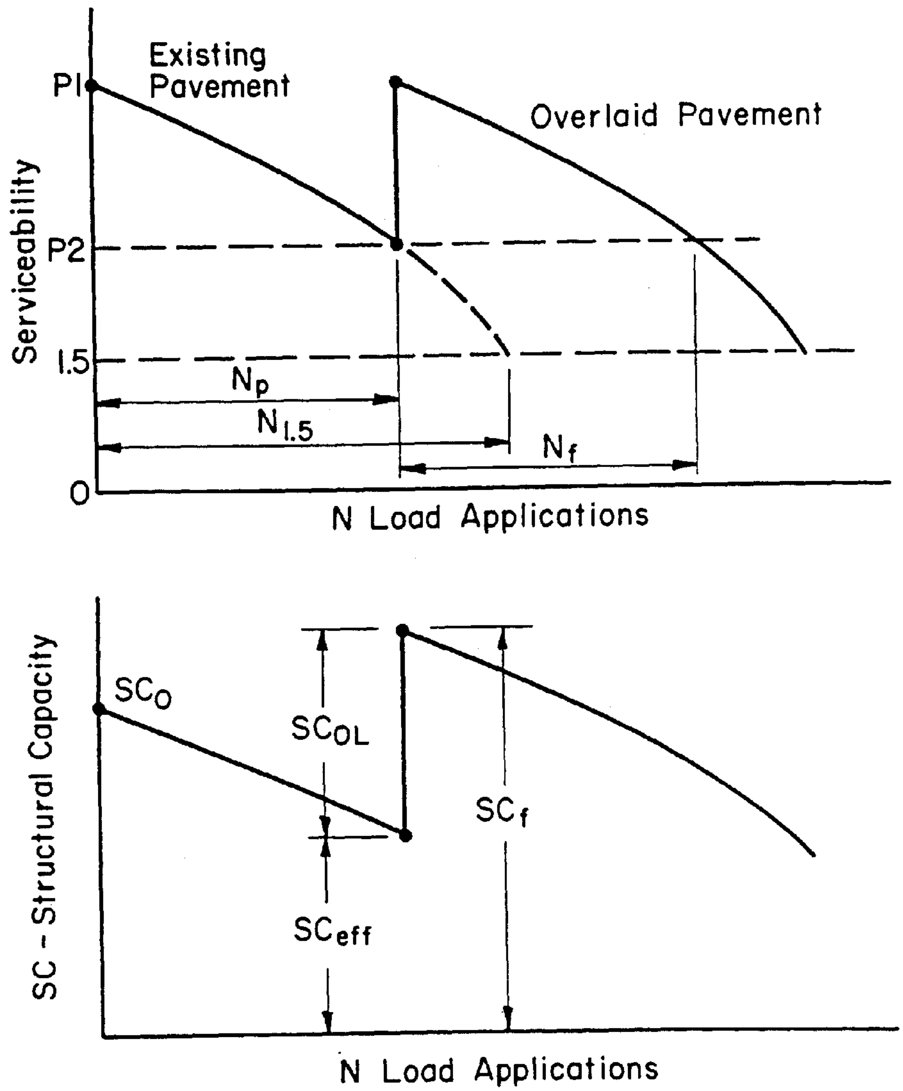

Figure 2.1 Illustration of Structural Capacity Loss Over Time And With Traffic ***(After AASHTO 1993)***

usually some coring and testing materials.

2. Structural capacity based on nondestructive deflection testing.

This approach is a direct evaluation of the in situ subgrade and pavement stiffness along the project.

3. Structural capacity based on fatigue damage from traffic.

Knowledge of past traffic is used to assess the existing fatigue damage in the pavement. This method is most applicable to the pavements which have very little visible deterioration.

2.4 Nondestructive Deflection Testing

Nondestructive deflection testing (NDT) is an extremely valuable and rapidly developing technology. When properly applied, NDT can provide a vast amount of information and analysis at a reasonable expenditure of time, money and effort. The analyses, however, can be quite sensitive to the unknown conditions and must be performed by knowledgeable, experienced personnel *(AASHTO 1993)*. For flexible pavement evaluation, NDT serves two functions:

1. To estimate the roadbed soil resilient modulus, and
2. To provide a direct estimate of SN_{eff} of the pavement structure.

For this research project, NDT data was used to calculate the effective structural number (SN_{eff}) of the pavement. The method recommended in the 1993 AASHTO Guide was followed in the process.

2.4.1 Temperature-Deflection Correction

A wide range in modulus of an asphalt material may occur as the temperature varies from cool to warm conditions. At very cold temperatures, the modulus of an asphalt mix may approach the stiffness values of Portland Cement Concrete (6.9 GPa to 13.78 GPa or 1 to 2 million psi) while at very warm temperatures, the mix may have an elastic modulus slightly greater than the high quality unbound stone base (3.4 MPa to 1.4 GPa or 50,000 to 200,000 psi). This is due to the fact that asphalt is a viscous material and its properties are highly dependent on temperature. Therefore, the FWD first sensor deflection data must be corrected and standardized (at 20ºC or 68°F) before it can be used in the calculation of effective structural number. However, the first task is to determine the average pavement temperature during the FWD deflection test.

2.4.2 Determination of Average Pavement Temperature

The most direct way to determine the temperature of the asphalt layers during an NDT deflection test is to physically measure the temperature. Care must be taken to recognize that with increased depth into the asphalt layer fairly high temperature gradients may occur at a given time. Thus in many cases, the measurement of temperature only at the surface will not suffice as an accurate measurement of the 'average' or 'effective' temperature of the entire layer. The thicker the asphalt layer, the greater the need to evaluate the overall pavement temperature for the entire layer rather than simply relying on the surface temperature measurements.

The 1986 AASHTO Guide recommended an alternative procedure for determination of effective pavement temperature which was adopted in the 1993 Guide. It is generally recommended that the pavement temperature be calculated from the graph provided by AASHTO at three depth locations within the pavement structure: (1) near surface (less than 25 mm or 1-inch depth), (2) mid layer, and (3) bottom of the asphalt concrete layer. The average temperature computed from these values then yields the estimate of the pavement temperature at the time of the FWD deflection testing. This procedure requires the following information:

1. Pavement surface temperature during the FWD test, and

2. Average air temperature data at the site for the five days previous to the FWD test.

Previous research indicated that this procedure showed excellent consistency when applied to some states in the U.S. *(AASHTO 1986)*. Therefore, in this study, the AASHTO approach was followed to calculate the average pavement temperature.

2.4.3 Effective Structural Number (SN_{eff})

At sufficiently large distances from the load, deflections measured at the pavement surface are due to the subgrade deformation only and are also independent of the size of the load plate *(AASHTO 1993)*. This permits the backcalculation of the subgrade resilient modulus (M_r) from a single deflection measurement and load magnitude using the following equation:

$$M_r = (0.24 * P)/ (d_r * r) \qquad (2.1)$$

where,

M_r = backcalculated subgrade resilient modulus, psi,
P = applied load, pounds,
d_r = deflection at a distance r from the center of the load, inches, and
r = distance from the center of the load, inches.

It should be noted that no temperature adjustment is needed in determining M_r since the deflection used is only due to subgrade deformation. The deflection used to backcalculate the subgrade resilient modulus must be measured far enough away that it provides a good estimate of the subgrade modulus, independent of the effects of any layers above, but also close enough that it is not too small to be measured accurately. The minimum distance may be found from the following relationship:

$$r \quad 0.7\, a_e \qquad (2.2)$$

$$a_e = [\, a^2 + D^2 * (E_p/M_r)^{2/3}]^{1/2} \qquad (2.3)$$

where, a_e = radius of the stress bulb at the subgrade-pavement interface, inches
a = NDT load plate radius, inches
D = total thickness of pavement layers above the subgrade, inches
E_p = effective modulus of all pavement layers above the subgrade, psi.

E_p values may be determined from the ratio E_p/M_r (Figure 1.2) or based on the following equation:

$$d_0 = 1.5pa\left\{ 1 \Big/ M_R\sqrt{1+\left(\frac{D}{a}\sqrt[3]{\frac{E_p}{M_R}}\right)^2} + \left[1-\frac{1}{\sqrt{1+\left(\frac{D}{a}\right)^2}}\right] \Big/ E_p \right\} \qquad (2.4)$$

where, d_0 = deflection measured at the center of the load plate *(and adjusted to a standard temperature of 20°C or 68°F)*, inches

Once the E_p value is calculated, the effective structural number can be easily determined by the Equation 2.5 provided by AASHTO:

$$SN_{eff} = 0.0045 * D * (E_p)^{1/3} \qquad (2.5)$$

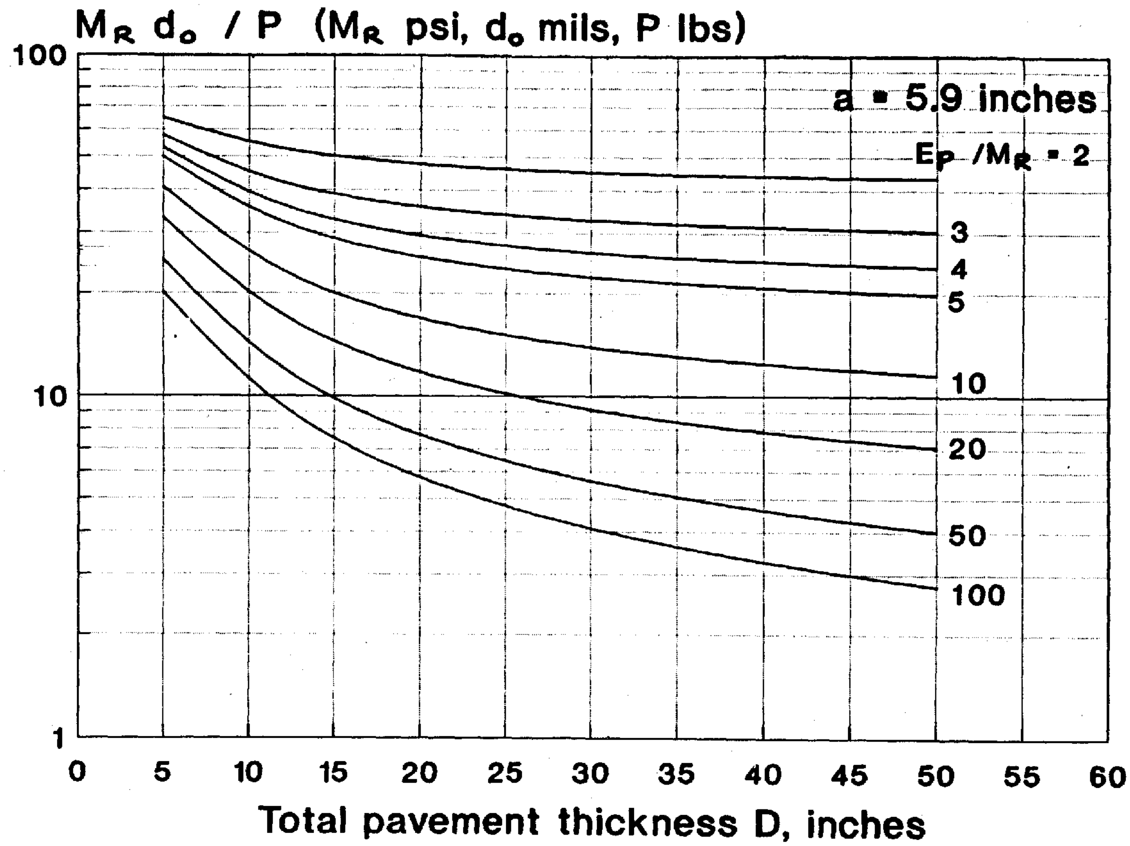

Figure 2.2 Determination of E_p/M_r *(After AASHTO 1993)*

3.0 NETWORK-LEVEL FWD TESTING

3.1 Introduction

Structural evaluation provides a wealth of information concerning the expected behavior of pavements *(Haas et al. 1994)*. However, due to the expense of data collection and analysis, structural capacity is not currently evaluated at the network level of pavement management by many agencies. The practice is more common at the project level of management. It has been argued that the structural capacity information, even derived from less intensive sampling than for project level purposes, can be very useful at the network work level for project prioritization purposes. The practice exists in a few states and Canadian provinces, such as Idaho, Minnesota, Utah, Alberta, and Prince Edward Island *(Haas et al. 1994)*. As mentioned earlier, due to limited resources and the large size of the network, network-level structural data collection annually in Kansas at the same rate (5 to 10 tests per mile) as the project level is not realistic. One of the objectives of this research was to determine the sample size (percent mileage), test intervals and frequency to be used as guides by KDOT for network-level FWD testing so that the deflection data can be used as input into the PSE computation process.

3.2 Data Collection

Deflection data was collected on the asphalt pavements in District IV from 1993 to 1996. KDOT maintains two types of flexible pavements - Full-Design and Partial-Design Bituminous Pavements. Full-Design Bituminous (FDBIT) pavements were designed for the current and projected traffic and usually carry heavier traffic than the Partial-Design Bituminous (PDBIT) pavements which resulted from the paving and maintenance of the original “farm to market” roads in the forties and fifties. District IV was chosen as the test network since its mileage most closely approximates the pavement types on the whole KDOT network and thus, deflection data collected on this district would be very representative of the KDOT network. The FDBIT and PDBIT pavement mileages in District IV are 545 and 695 miles, respectively. They represent roughly 15% and 14%, respectively, of the total network mileage in Kansas for the two pavement types. Data for this study was collected on the non-Interstate routes in District IV.

Pavement surface deflections were measured by a Dynatest 8000 Falling Weight Deflectometer (FWD). Ten (10) FWD tests per mile were performed on the outer wheel path of the travel lane. Table 3.1 summarizes the project details for data collection. FWD tests were conducted each year of the study period on the projects selected by NOS for the long-term rehabilitation program.. Thus the projects tested in a given year are the candidates for rehabilitation for a certain future year and should be in a "similar" condition state. The condition states are defined by NOS based on roughness, rutting, transverse cracking, fatigue cracking and/or block cracking. In total, approximately 20% of the FDBIT pavements and 36% of the PDBIT pavements from 96 "control" sections in District IV were included in the study.

Table 3.2 shows some geometric and loading characteristics of the sections selected. The annual ESAL's varied from 42,000 to 264,000 and are fairly representative of the traffic loads on KDOT's non-Interstate network. On average, the loading on the FDBIT pavements was three to four times the loading on the PDBIT pavements.

Table 3.1 Data Collection Summary

Year	Pavement Type				No. of Control Sections
	Full Design		Partial Design		
	Miles	% of	Miles	% of	
1993	36	6.6	107	15.4	43
1994	15	2.7	71	10.2	25
1995	25	4.6	9	1.3	11
1996	34	6.2	60	8.6	17
Total	110	20.1	247	35.5	96

Table 3.2 Characteristics of the Study Sections

Year	Pavement Type	Average Length (mile)	Average Annual ESALs	No. of Control Sections
1993	FDBIT	3.027	198,000	12
	PDBIT	3.359	71,000	31
1994	FDBIT	3.003	264,000	5
	PDBIT	3.548	58,000	20
1995	FDBIT	3.116	128,000	8
	PDBIT	2.686	44,000	3
1996	FDBIT	5.654	188,000	6
	PDBIT	6.624	42,000	15

3.3 Response Variables and Analysis Method

The following attributes were selected as response variables:

1. Normalized and Temperature-corrected first sensor deflection (d_1),

2. Subgrade Resilient Modulus (M_r), backcalculated from the FWD data following the

AASHTO Guide algorithm, and

3. Effective Pavement Modulus (E_p), also computed following the AASHTO Guide algorithm.

The FWD first sensor deflection values were normalized to 40 kN (9,000 lb) load level and then corrected to a temperature of 20° C (68° F) following the methodology proposed by Southgate and Deen and adopted by AASHTO *(AASHTO Guide 1993)*.

3.4 Trends of Response Variables

Table 3.3 shows the summary statistics for d_1, $M_{r,}$ and E_p for the years 1993 thru 1996 for the control sections. It appears that the coefficients of the variations for the backcalculated subgrade moduli were similar over the years, indicating the effects of spatial variation rather than variation over the time period considered. The coefficients of the variations are the highest for the E_p's which is derived from the other two parameters. It appears that the variabilities in those parameters are magnified in the calculation process. Table 3.3 shows the results of the student's t-tests between the means of these variables for the four years of study period. For all variables, there were no significant differences among the means of these variables for 1993, 1994, and 1995. Thus, the mean values of d_1, $M_{r,}$ and E_p did not change significantly over three years. However, significant differences were noted between the first-sensor deflection values for 1996 and 1993 for both pavement types.

These results imply that the average structural capacity of the pavement network in Kansas most likely change over a three year period. In other words, it takes about three years of traffic and climatic affect to significantly change the average structural condition of the network.

3.5 Limit of Accuracy Curves

It is well known that tests conducted on pavement analysis units provide an estimate of the actual mean and standard deviation of the attribute under investigation. As the number of test

Table 3.3 Summary Statistics of the Response Variables

Variable	Year	Pavement Type							
		Full Design				Partial Design			
		Mean	Std. Dev.	C.V. (%)	n	Mean	Std. Dev.	C.V. (%)	n
d_1 (mils)	1993	11.3	5.6	50	12	23.6	10.3	44	31
	1994	9.6	0.8	9	5	24.3	10.5	43	20
	1995	14	5	36	8	19.7	5.5	28	3
	1996	19.3	9	47	6	19.7	7.2	37	11
M_r (ksi)	1993	17.7	4.3	25	12	12.5	3.3	26	31
	1994	14.9	3.1	21	5	10.7	3.1	29	20
	1995	16.4	4.2	26	8	13.2	2.6	20	3
	1996	12.7	3.2	25	6	12.6	2.0	16	11
E_P (ksi)	1993	250	190	75	12	318	241	76	31
	1994	267	110	40	5	447	412	92	20
	1995	149	58	39	8	352	167	48	3
	1996	207	115	56	6	317	285	90	11

Note: 1 psi = 6.89 kPa
1 mil = 0.025 mm

Table 3.4 Students t-test Results at 5% level of Significance

Response Variable	Pavement Type	Test	t-statistic	d.o.f.	Results
d_1	FDBIT	1996 vs. 1995	-1.413	7*	not significant
		1996 vs. 1994	-2.207	8*	not significant
		1996 vs. 1993	-2.309	16	significant
	PDBIT	1996 vs. 1995	-0.0076	12	not significant
		1996 vs. 1994	1.284	29	not significant
		1996 vs. 1993	2.141	40	significant
M_r	FDBIT	1996 vs. 1995	1.824	12	not significant
		1996 vs. 1994	1.183	9	not significant
		1996 vs. 1993	2.499	16	significant
	PDBIT	1996 vs. 1995	0.45	12	not significant
		1996 vs. 1994	-1.794	29	not significant
		1996 vs. 1993	0.059	31*	not significant
E_p	FDBIT	1996 vs. 1995	-1.118	7*	not significant
		1996 vs. 1994	0.902	9	not significant
		1996 vs. 1993	2.596	15*	significant
	PDBIT	1996 vs. 1995	0.199	12	not significant
		1996 vs. 1994	0.928	29	not significant
		1996 vs. 1993	2.287	34**	not significant

* unequal variances
** a few projects were eliminated due to unreliable thickness data

increases, the estimated value more closely approximates the true value. However, as mentioned earlier, more tests translate to more expenses and in some cases, unrealistic data collection and analysis expenses. The principles of statistical confidence levels can be used to determine how many tests will be necessary to ensure that the estimated mean is within a certain limit of the actual mean. Statistical limit of the accuracy curves helps assess the impact of the number of tests conducted on the precision of the estimate. The limit of accuracy, R, represents the probable range of the variation of the "true" mean from the average obtained by "n" tests at a given degree of confidence. Mathematically,

$$R = K\ (\quad /\ n) \tag{3.1}$$

where,

	K	=	standardized normal deviate, which is a function of the desired confidence level,
		=	standard deviation of the variable (d_1),
	n	=	number of FWD tests conducted or percent network mileage tested at a fixed interval, and
	R	=	allowable error in the random variable being considered.

It is to be noted that for a given confidence interval, standard deviation and number of tests, the corresponding error could be computed using Equation 3.1. For a given variable (e.g., deflection), if the confidence level (e.g., 95%), K and are known, the R value would be inversely proportional to the square root of the number of tests randomly selected. The relationship between the R value and the number of tests is depicted in Figure 3.1. AASHTO defines three zones along the accuracy curve. In Zone I, characterized by a steep slope, the precision of the estimate significantly increases with each additional test or sample and the benefit-cost ratios for increasing the number of tests per analysis are quite high. Zone III, on the other hand, is a region with little slope, where even large increases in the number of tests/samples obtained will not significantly improve the precision

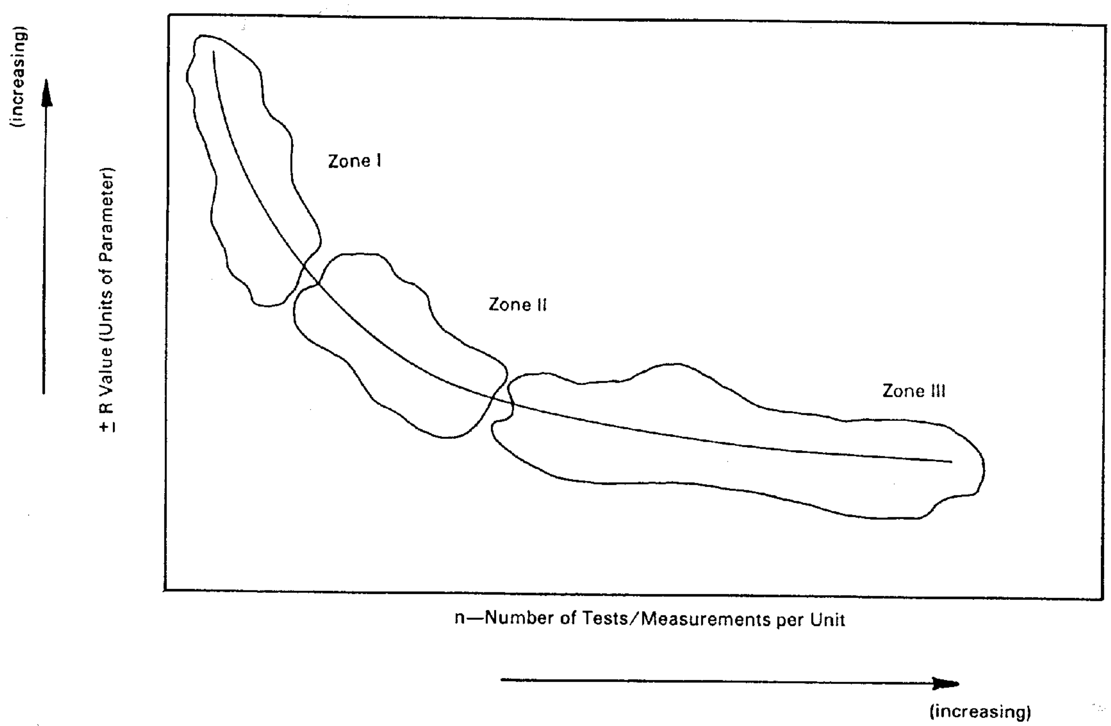

Figure 3.1 Typical Limit of Accuracy Curve for All Pavement Variables (*after AASHTO 1993)*

of the estimate, and the costs associated with additional testing may outweigh the benefits. Zone II represents the "optimal" range in developing a test program, because it represents the area where accurate estimates will be made using a minimum number of tests *(AASHTO Guide 1993)*.

3.6 Error Analysis

For this analysis, the temperature-corrected first sensor deflection (d_1) was chosen as the response variable and the values of d_1 for 1993, 1994 and 1995 were aggregated for the analysis. The error values associated with d_1 were computed as:

$$\% \text{ Error} = (\text{Absolute Error}/ \text{Average value}) * 100 \qquad (3.2)$$

All error calculations were done at 95% confidence level for which the value of K is 1.96.

For each project, the average and standard deviation of the first-sensor deflections were computed. For error analysis of the FWD tests on the percentage of network mileage covered, it was assumed that the "true" standard deviation of the first-sensor deflections of each project is equal to the standard deviation obtained from the tests on 100% of the network covered without errors.

Table 3.4 shows the error analysis results for the network mileage tested. It is interesting to note that the percent error values corresponding to the percent network mileage tested are similar for the FDBIT and PDBIT pavements. Thus the percent error values for the two pavement types were combined and the following regression equation for the percent error was developed:

$$\text{percent } (\%) \text{ error} = \exp(4.096 - 0.5115 \ln(\% \text{ network mileage})) \qquad (3.3)$$

$$(R^2 = 0.976, \text{ Standard Error} = 1.142)$$

Figure 3.2 shows a plot of Equation 3.3. It is apparent that the FWD tests on more than approximately 20 percent of network mileage will not significantly increase the precision of the estimate or the first-sensor deflection value. Hence 20 percent mileage could be selected as a reasonable sample size in network-level structural evaluation of flexible pavements. This would

Table 3.5 Error Analysis Results

Pavement Type					
Full Design			Partial Design		
% Network	R	Error (%)	% Network	R	Error (%)
14	1.9	16	27	2.7	11
10.5	2.3	19	20	2.9	13
7	2.55	22	13.5	3.2	16
3.5	3.4	33	7	3.7	20

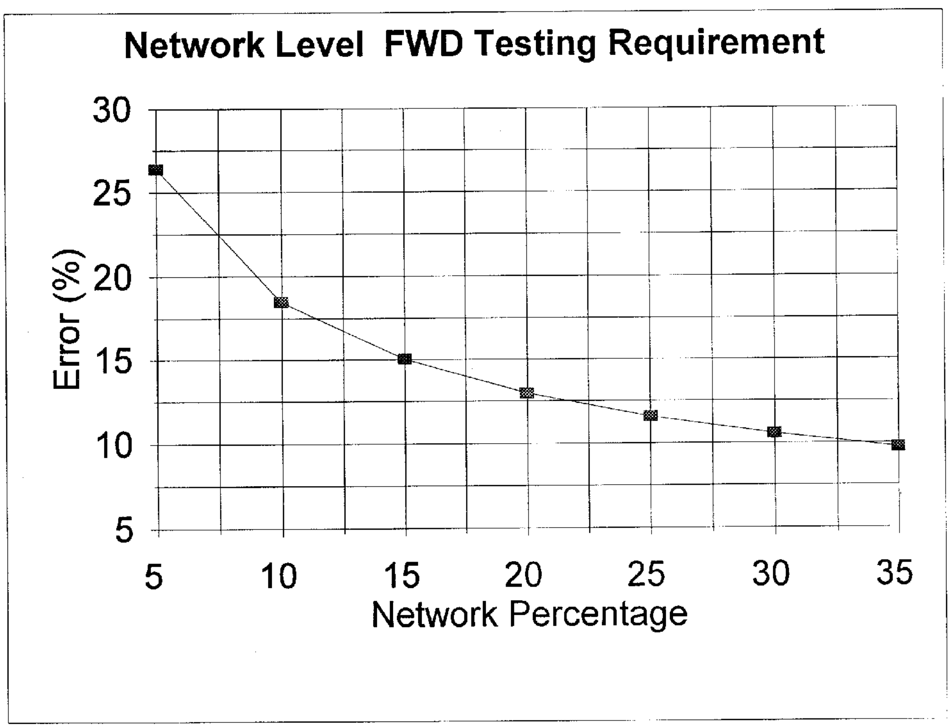

Figure 3.2 Network Level FWD Testing Requirements

translate into approximately 3,542 lane-km (2,200 lane-miles) of testing in three years. Thus, KDOT should test its system on a 3-year cycle or approximately 1,208 lane-km (750 lane-miles) each year for network evaluation. With two FWD units, this would require 19, 10-hour work days of testing each year.

For the error analysis of the FWD test rate on a particular project, it was assumed that the "true" standard deviation of the first-sensor deflections of each project is equal to the standard deviation obtained from 10 tests per mile. Percentage errors for the test intervals of seven, five, three, and one test per mile were computed. The 10 tests were done at about 160 m intervals. For seven tests per mile, every third test point was ignored. For five tests per mile, every other test point was ignored. For three tests per mile, the first, fourth and seventh test points were taken for analysis. The one test per mile was assumed to be at the beginning of each project. Results in Table 3.5 show that the average error does not vary significantly for seven, five, or three tests per mile. Thus, the lowest test rate, three tests per mile could be taken as the spatial test frequency at the network level.

The suggested test coverage of 20% mileage and spatial frequency of three tests per mile were tested with the FWD data collected in 1995. That year, 25 miles of FDBIT pavements were tested. Twenty percent mileage translated to only five miles of testing in 1995. Different combinations of the control sections which would result in five miles of testing showed that the average error for the spatial frequency of three tests per mile ranged from 14% to 16%, compared to 13% to 15% for five tests per mile, and 12% to 13% for seven tests per mile.

This testing would be necessary for network level structural evaluation of the KDOT pavements and also for using/updating the models to be developed in this study.

Table 3.6 Determination of the Number of Tests Per Mile at the Network Level

Percent error in FWD 1st sensor deflection for various test intervals *(1995 data)*				
Route	**Number of Tests Per Mile**			
	7	**5**	**3**	**1**
US 54	14	16	18	39
US 59	6	8	9	15
US 59	12	14	17	35
US 59	8	9	13	25
K 68	15	18	21	44
K 68	10	12	21	44
K 68	14	16	19	40
K 103	9	10	12	25
K 103	7	9	11	22
K 126	16	21	23	47
US 169	9	10	12	25
Average	11	12	14	29

3.7 Prediction of the Decrease in Structural Number

In this study, the network-level structural deterioration was predicted through quantification of the decrease in the structural number of the existing pavements estimated from the FWD data. This was necessary because this decrease in structural number will be used as a predictor for estimating PSE values for the control section. It is apparent that in the future, FWD test results will not be available for all control sections on the network. However, the decrease in structural number still could be estimated for any section based on the models to be developed.

The approach for structural evaluation was based on the second technique for pavement structural evaluation suggested by the 1993 AASHTO Pavement Design Guide. The technique, based on nondestructive testing (NDT) as discussed in Chapter 2 of this report, was used. Following this approach, the effective structural numbers (SN_{eff}) of the pavement sections were calculated using FWD data collected in 1993, 1994, and 1995.

The FWD first sensor deflection values were normalized to 40 kN (9,000 lb) load and were also corrected for temperature at 20° C (68° F). The deflection values were then used to calculate the subgrade resilient modulus (M_r). The effective E_p values were determined from Equation (2.4). Once the E_p value had been calculated, the effective structural number was found by the following formula provided by AASHTO:

$$SN_{eff} = 0.0045 * D * (E_p)^{1/3} \qquad (3.4)$$

The original structural numbers of the existing flexible pavements after rehabilitation actions, calculated according to the algorithms in KDOT's HYNELIFE program, were obtained from the KDOT's CANSYS database.

The decrease in structural number (SN) was then computed as:

$$SN = SN\ (CANSYS) - SN_{eff} \qquad (3.5)$$

3.7.1 Model Development

The major factors contributing to the structural deterioration of asphalt pavements are traffic and climate. In this study, the age of the pavement was taken as a surrogate variable for the climatic affect or aging. Three variables were selected to predict the decrease in structural number (SN) to assess structural deterioration at the network level:

1. Age (in years) of the pavement *since the last rehabilitation action*,

2. Cumulative number of ESAL's that have passed over the pavement *since the last rehabilitation action*, and

3. Thickness (in inches) of the *asphalt concrete (AC) layer*.

The thickness and rehabilitation histories of the pavement sections under study were collected from the HYNERES database of KDOT. Specifically, the following information was obtained:

(i) Years corresponding to different rehabilitation actions,

(ii) Type of rehabilitation action, and

(iii) Thickness of the overlay (s).

The AC layer thickness, the total thickness of the pavement sections above subgrade, and the age of the pavement since the last rehabilitation action were then calculated. The total thickness of the pavement sections is necessary during computation of the effective pavement modulus, E_p.

During this analysis, the FDBIT and PDBIT pavements were treated separately since the structural behavior of these pavements is different. By doing simple linear regression analysis, it was apparent that the decrease in structural number was highly correlated with the age, cumulative number of ESAL's and AC layer thickness for the FDBIT pavements, and the age and cumulative ESAL's for the PDBIT pavements. To select the correct variables, three variable selection methods of the Statistical Analysis System (SAS) software were used:

a. Forward Selection Method,
b. Backward Elimination Method, and
c. Stepwise Method

The results of these three variable selection methods are shown in Table 3.6. All three variables were selected for the FDBIT pavements, but the AC layer thickness was not selected for the PDBIT pavements. As mentioned earlier, PDBIT pavements are "built up" pavements- basically asphalt surfaced pavements which trace back to "farm to market roads" in the mid forties and fifties. The thicknesses of such pavements were really not designed to carry a specific traffic. This fact also is supported by the three independent variable selection methods of SAS indicating that the AC layer thickness of the existing pavement does not play an important role in determining the decrease in structural number of the PDBIT pavements. Therefore, thickness was dropped from the PDBIT model as a predictor variable. Also, a correlation study among the proposed variables revealed that the age and cumulative ESAL's are highly correlated to each other (64.3% for FDBIT and 62.1% for PDBIT pavements). Thus, to avoid multicolinearity, only one of them was included in the model, and the variable 'age' was selected because of its greater contribution to the R^2 value. Two types of models were selected in each case. The first one was a regular regression model with an intercept. The other model was forced to have a zero intercept. From a practical point of view, a zero-intercept model is more justifiable since it implies that the structural number will remain unchanged if the age since the last action is zero *(i.e., just after the rehabilitation action)* and the AC layer thickness is zero. For FDBIT pavements, the R^2 value for the intercept model was 83.4% and for the zero-intercept model, 81.3%. These values for the PDBIT pavements were 75.8% and 72.0%, respectively. For both types of pavements, the zero-intercept model was selected for being practical.

Table 3.7 Variable Selection Process Summary

Method of Selection	Variables selected by SAS	
	FDBIT Pavements	PDBIT Pavements
Forward Selection	1. Age 2. AC layer thickness 3. Cumulative ESAL	1. Age 2. Cumulative ESAL
Backward Elimination	1. Age 2. Cumulative ESAL 3. AC layer thickness	1. Age 2. Cumulative ESAL
Stepwise Method	1. Age 2. AC layer thickness 3. Cumulative ESAL	1. Age 2. Cumulative ESAL

3.8 Models Obtained and the 'Model Utility' Test

FDBIT Pavements: For the FDBIT pavements, the model to predict a *decrease* in structural number is:

$$SN = 0.0218 * \text{age} + 0.001 * \text{AC layer thickness} \qquad (3.6)$$

As shown in Table 3.7, the R^2 of the FDBIT pavements model is 0.8127. The significance values (p-values) for the parameters are: age: 0.0001 and AC layer thickness: 0.0176, indicating that both variables are significant at a level of more than 98%. The analysis of variance (ANOVA) for this model showed that the model has an F-value of 320 and its significance value is 0.0001. Since the selected model has a high F-value and a very low p-value, it satisfactorily passes the model utility test. The test shows that the model is helpful and adequate in predicting the dependent variable, SN. Also, the estimated root mean square error ( ) value for the model is 0.044, which indicates the selected model will predict the decrease in structural number (SN) at the network level with a variability of ±2 or ±0.088 for a confidence level of 99.99%.

Table 3.8 SAS ANOVA Results for the Model Developed for FDBIT Pavements

Source	Degrees of Freedom	Sum of Squares	Mean Square	F Value	Prob > F
Model	2	1.29274	0.6463	320.03	0.0001
Error	37	0.07473	0.0020		
Total	39	1.36747			
Root MSE: 0.04494 R-square: 0.8127 Dep. Mean: 0.15758 Adj. R-sq: 0.8095 C.V. 28.51995					
Parameter Estimates					
Variable	**Deg. of Freedom**	**Parameter Estimate**	**Standard Error**	**T for Ho: Parameter = 0**	**Prob > {T}**
AGE	1	0.021872	0.00189	11.56	0.0001
THICKNESS	1	0.001025	0.00099	1.034	0.0176

PDBIT Pavements: For the PDBIT pavements, the selected model is:

$$SN = 0.0166 * age \qquad (3.7)$$

The R^2 value for this model is 0.7195 and the significance (p) value for the parameter age is 0.0001; i.e., the variable age is significant at a level more than 99%. The ANOVA results in Table 3.8 for this model indicates that the model has an F-value of 842, and its significance value is 0.0001. Since the selected model also has a high F-value and a very low p-value, it satisfactorily passes the model utility test. Also the estimated root mean square error ( ) value for the model is 0.046, which reveals that the selected model will predict the decrease in structural number at a variability of ±2 or ±0.092 with a confidence level of 99%.

The FDBIT and PDBIT models indicate that a 25-mm (1.0-inch) AC overlay with a structural

Table 3.9 SAS ANOVA Results for the Model Developed for PDBIT Pavements

Source		Degrees of Freedom	Sum of Squares	Mean Square	F Value	Prob > F
Model		1	1.84718	1.84718	841.8	0.0001
Error		84	0.18432	0.00219		
Total		85	2.03150			
Root MSE: 0.04684 R-square: 0.7195 Dep. Mean: 0.14286 Adj. R-sq: 0.7098 C.V.: 32.79012						
Parameter Estimates						
Variable	**Deg. of Freedom**	**Parameter Estimate**	**Standard Error**	**T for Ho: Parameter = 0**		**Prob > {T}**
AGE	1	0.016685	0.000575	29.014		0.000

layer coefficient of 0.42 on 200-mm (8.0-in) thick asphalt pavements will have no affect on the *decrease* of the structural number of the pavement in about 19 and 25 years, respectively, for these two types of pavement. In other words, the fatigue lives of these AC layers will be fully consumed by that time. According to the algorithms in HYNELIFE, in 10 years the *decrease* in structural number of this *overlay* would be 0.08 *(= 0.42-0.34)*. Moreover, the *decrease* in the structural number of a 25-mm (1-inch) AC layer which has been overlaid two times over a period of 20 years *(one overlay every 10 years)* is 0.28 (i.e., SN=0.28). However, the models in this study (Equations 3.6 & 3.7) show that after 20 years, on average, the decrease in structural number of a 25-mm (1-inch) overlay would be 0.42. Thus, these models overestimate the damage by 0.42/0.28 (= *150%)* or 50% *higher* compared to the assumptions in HYNELIFE.

4.0 CLASSICAL REGRESSION ANALYSIS TO PREDICT THE DECREASE IN PSE VALUES

4.1 Multiple Regression Analysis

The major objective of this research was to objectively and quantitatively determine the PSE values of the pavements since the last rehabilitation action. However, the *decrease* in PSE value was taken as the dependent variable because it somewhat represents a "normalized" value. Classical multiple regression analysis was performed to estimate the *decrease* in the PSE (PSE) values. One of the most important aspects of classical regression analysis is the selection of independent variables which are strong indicators of the dependent variable. The selection was done in two steps *(Ott 1993)*:

(i) Enumerating the independent variables, and
(ii) Evaluating and selecting independent variables subjectively or by analyzing correlation.

4.2 Selection of Independent Variables for the Prediction of Decrease in the PSE Values

Extensive literature search was done to select the independent variables to predict the *decrease* in the PSE values. Expert opinion was also sought for this purpose. Since PSE ratings are based on the condition of the base and surface, as indicated by the maintenance costs, subgrade failures, and ability of the section to provide an adequate surface for the prevailing traffic, the following variables were selected to reflect those conditions:

1. Age of the pavement *since the last rehabilitation action* (in years),
2. Cumulative ESAL's that have passed over the pavement *since the last action*,
3. AC layer thickness (in inches),
4. PSE value assigned to the pavement *immediately after the last action*,
5. Decrease in structural number (SN), and
6. Distress level due to transverse cracking.

The selected variables were plotted on scatter plots against the dependent variable, PSE values, and were inspected for possible trends. Also, correlation coefficients for different pairs were determined. It was apparent from the scatter plot that age and SN were not linearly related to PSE values. In the case of age, the rationale is that PSE values do not decrease at the same rate with time. During the initial years this rate is lower, but after a certain period, the PSE values start to decrease drastically. A trial-and-error approach was followed to determine the transformed functional form for an independent variable *(Chowdhury 1998)*. After several trials, the variable age was transformed to $(\text{age})^{1.5}$. For the relationship between the dependent variable, PSE, and the independent variable, age, the Pearson's correlation coefficients improved from 0.35 to 0.68 for the FDBIT and 0.39 to 0.56 for the PDBIT pavements, when the transformation was performed. Similarly, the variable, decrease in structural number, SN, was transformed to exp(SN) to improve the correlation coefficient of the relationship from 0.49 to 0.61 for the FDBIT and 0.48 to 0.55 for the PDBIT pavements, respectively. The variable AC layer thickness was dropped from the PDBIT model as a predictor since the thickness of this type of pavement was not designed to carry the expected traffic. Another important fact to note is that the variables age and cumulative ESALs have a very high correlation between themselves (correlation coefficient of 0.65 for FDBIT and 0.58 for PDBIT). Therefore, only one of them, (age), was included in the model to avoid possible multicolinearity or overspecification of the model *(Chowdhury 1998)*.

Transverse cracking was included in the model as a binary variable. Transverse cracking on the pavements in Kansas is measured by the number of equivalent roadway-width cracks. According to the KDOT PMS rating guide *(KDOT 1996)*, the crack severity is categorized using three severity codes:

Code 1: No roughness, 6 mm (0.25 in.) or wider with no secondary cracking; or any width with secondary cracking less than 1.2 m (4 ft) per lane.

Code 2: Any width crack with noticeable roughness due to depression or bump. Also includes cracks that have greater than 1.2 m (4 ft) of secondary cracking, but no roughness.

Code 3: Any width crack with significant roughness due to depression or bump. Secondary cracking will be more severe than code 2.

Different combinations of the coded cracks will result in different distress levels due to transverse cracking *(KDOT 1996)*. Distress levels due to transverse cracking are defined as shown in Table 4.1.

Table 4.1 Distress Levels Due to Transverse Cracks

DISTRESS LEVELS	TRANSVERSE CRACK CODES		
	CODE 1	CODE 2	CODE 3
DL 1	< 3	0	0
DL 2	3	< 3	< 2
DL 3	ANY NO.	3	2

4.3 Criteria Used to Select a Model

The following criteria were used to select a model:

(i) *Minimize mean sum square errors (MSE)*: The smallest MSE will result in the narrowest confidence intervals and largest test statistics. The model with the smallest MSE involving the least number of independent variables can generally be considered as the best model *(Ott 1993)*.

(ii) *Maximize the Coefficient of Determination (R^2):* R^2 is a measure of how well the estimated model fits the observed data. The best model selected is generally the one with the largest R^2.

(iii) *Minimum increase of R^2 :* The best model is selected as the model associated with the smallest increase in R^2 with the addition of an extra variable.

(iv) *Mallows C_p statistic:* The best model is usually thought to have a C_p value closest to p, where, p is the number of regression coefficients. Models associated with C_p greater than p are usually thought to be biased or misspecified models *(Ott 1993)*.

4.4 Models Obtained and the 'Model Utility' Tests

FDBIT Pavements: Detailed analyses and summary statistics of the model development have been described by Chowdhury *(1998)*. For FDBIT pavements, the selected models are:

<u>Distress Level 1</u>

$$PSE = 0.216*(AGE)^{1.5} - 20.82*\exp[\ SN] + 0.138*TH + 0.328*PSE + 17.65*DL1 \quad (4.1)$$

<u>Distress Level 2</u>

$$PSE = 0.216*(AGE)^{1.5} - 20.82*\exp[\ SN] + 0.138*TH + 0.328*PSE + 18.06*DL2 \quad (4.2)$$

<u>Distress Level 3</u>

$$PSE = 0.216*(AGE)^{1.5} - 20.82*\exp[\ SN] + 0.138*TH + 0.328*PSE + 18.38*DL3 \quad (4.3)$$

where,

	PSE=	Predicted *decrease* in the PSE value,
	AGE=	Age of the pavement *since the last rehabilitation action* (in years),
	TH =	AC layer thickness (in inches),
	PSE=	PSE value assigned to the pavement *immediately after the last action*,
	SN=	Decrease in structural number, and
	DL_i=	Distress level due to transverse cracking (i = 1, 2 and 3).

The p-values for the parameters imply that all the variables are significant at a level of more than 95%. The ANOVA shown in Table 4.2 for the models implies that the model has an F-value of 37 and its significance value is 0.0001. Since the selected model has a high F-value and a very low p-value, it satisfactorily passes the model utility test, which indicates that the model is helpful and adequate in predicting the dependent variable. Also the estimated root mean square error ( ) value for the model is 0.47, which reveals the fact that the selected model will predict the decrease in PSE values at a variability of ±2 or ±0.94 with a confidence of 99%.

It should be noted that the decrease in structural number, SN, values can be computed from the FWD data following the methodology described in Chapter 3 or can be estimated using Equations 3.6 & 3.7 developed previously in Chapter 3.

PDBIT Pavements : For PDBIT pavements, the selected models are:

<u>Distress Level 1</u>

$$PSE = 0.024^{*} (AGE)^{1.5} - 1.145^{*}exp[\ \ SN] + 0.171^{*} PSE + 0.229^{*}DL1 \quad \textit{(4.4)}$$

<u>Distress Level 2</u>

$$PSE = 0.024^{*} (AGE)^{1.5} - 1.145^{*}exp[\ \ SN] + 0.171^{*} PSE + 0.958^{*}DL2 \quad \textit{(4.5)}$$

<u>Distress Level 3</u>

$$PSE = 0.024^{*} (AGE)^{1.5} - 1.145^{*}exp[\ \ SN] + 0.171^{*} PSE + 0.2.27^{*}DL3 \quad \textit{(4.6)}$$

The variables in the above equations have been described before. The p-values for the parameters imply that all the variables are significant at a level of more than 95%. The ANOVA shown in Table 4.3 for the models implies that the model has an F-value of 132 and its significance value is 0.0001. Since the selected model has a high F-value and a very low p-value, it satisfactorily passes the model utility test, which indicates that the model is helpful and adequate in predicting the dependent variable. Also the estimated root mean square error ( ) value for the model is 0.47, which reveals the fact that the selected model will predict the decrease in PSE values at a variability of ±2 or ±0.94 with a confidence of 99%.

Table 4.2 SAS ANOVA Results for the Model Developed for FDBIT Pavements

Source	Degrees of Freedom	Sum of Squares	Mean Square	F Value	Prob > F
Model	7	59.413	8.487	37.011	0.0001
Error	20	4.586	0.229		
Total	27	64.000			

Root MSE: 0.478 *R-square: 0.7835*
Dep. Mean: 1.259 Adj. R-sq: 0.7717
C.V. 38.028

Parameter Estimates

Variable	Deg. of Freedom	Parameter Estimate	Standard Error	T for Ho: Parameter = 0	Prob > {T}
$(AGE)^{1.5}$	1	0.21668	0.239	0.906	0.0105
exp[SN]	1	-20.820	29.999	-0.694	0.0512
THICKNESS	1	0.138	0.049	2.785	0.0114
PSE	1	0.328	0.109	2.989	0.0073
DL1	1	17.655	30.628	0.576	0.0487
DL2	1	18.064	30.636	0.590	0.0197
DL3	1	18.381	30.636	0.600	0.0185

Table 4.3 SAS ANOVA Results for the Model Developed for PDBIT Pavements

Source	Degrees of Freedom	Sum of Squares	Mean Square	F Value	Prob > F
Model	6	138.178	23.029	131.67	0.0001
Error	39	6.821	0.174		
Total	45	145.000			

Root MSE: 0.412 *R-square: 0.8665*
Dep. Mean: 1.444 Adj. R-sq: 0.855
C.V. 28.953

Parameter Estimates

Variable	Deg. of Freedom	Parameter Estimate	Standard Error	T for Ho: Parameter = 0	Prob > {T}
(AGE)1.5	1	0.0246	0.0182	1.352	0.0184
exp[SN]	1	-1.145	0.5559	-2.061	0.0460
PSE	1	0.171	0.0619	2.766	0.0086
DL1	1	0.229	0.4534	0.506	0.0415
DL2	1	0.958	0.4292	2.233	0.0314
DL3	1	2.227	0.4439	5.017	0.0010

5.0 BAYESIAN REGRESSION ANALYSIS

5.1 Bayesian Regression Methodology

5.1.1 Introduction

Predictive equations are very important tools for the pavement management systems. However, databases to support the developments and updating of these models are lacking. These databases are often inadequate in sample size, noisy, or incomplete. Conventional statistical modeling tools, such as classical regression analysis, may have limited success in these applications *(Kajner et al. 1996)*. A promising solution lies in the use of Bayesian regression, which explicitly allows experts to be used to supplement poor quality data *(Kwaeski and Nickeson 1997)*. Bayesian regression methodology was adopted by the Canadian Strategic Highway Research Program (C-SHRP) for the Canadian Long Term Pavement Performance (C-LTPP) monitoring program. Nesbit and Sparks *(1990)* discussed the complete rationale for employing the Bayesian approach for the C-LTPP program in the report "Design of Long Term Pavement Monitoring System for the Canadian Strategic Highway Research Program."

5.1.2 An Overview of the Bayesian Regression Approach

In its simplest sense, Bayesian regression is a specialized adaption of the Bayes' Theorem involving development of multivariate regression models which explicitly consider two disparate sources of information:

1. A prior information, i.e. information that is known prior to an experiment, and
2. Experimental data, i.e. information that is derived from an experiment.

The interpretation and conclusion drawn from the experimental data can be quite different depending on what other evidence exists on the subject at hand. However, this difference in interpretation does not simply mean biasing a result. Interpretation of results using Bayes' Theorem is a mathematically consistent way to interpret new evidence/information *(Kwaeski and Nickeson 1997).*

The Bayesian statistical method for model development, represented in Figure 5.1, is to systematically combine prior knowledge and experience with data to improve the predictive relationship. The Bayes approach calculates a meaningful and credible answer without relying solely on a small database. In doing so, the Bayes technique allows decisions to be made in the short term while improvements to the data, judgement and the model continue to be made *(Kwaeski and Nickeson 1997).*

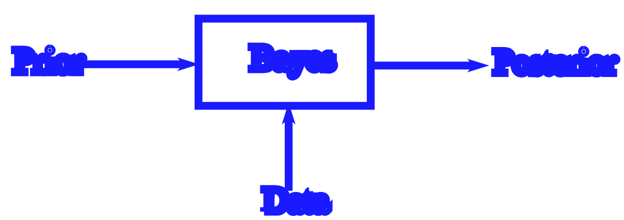

Figure 5.1 The Bayesian Statistical Approach *(Kwaeski and Nickeson 1997)*

In assembling information for Bayesian regression, data collected in the traditional manner is supplemented with prior knowledge. This approach is summarized in the Figure 5.1. The so-called 'prior' may be drawn from expert judgement, "old" data sets, or knowledge that is generally accepted in the field. Expert judgement can also be encoded by polling experts and asking them to estimate the value of the dependent variable for a combination of contributory variables. Once collected, the experts' observations are interpreted similar to the traditional data.

5.1.3 Bayesian Regression Software

Two Bayesian regression software packages, B-STAT and XLBayes, were developed by VEMAX Management, Inc., Canada, under contract to C-SHRP. B-STAT provides an EXCEL spreadsheet interface to a FORTRAN based Bayesian regression program, PC-BRAP. XLBayes, on the other hand, is a much faster Bayesian regression program based entirely in the EXCEL environment *(Kwaeski and Nickeson 1997)*. The analysis features and numerical results of the two programs are identical. XLBayes was selected for this research because it is relatively straightforward and faster.

5.2 Bayesian Regression to Predict the Decrease in PSE Values

The Bayesian regression analysis using the XLBayes software requires prior data to be combined with the sample data to obtain the desired posteriors. The prior data can be drawn from the expert judgement, old data sets or knowledge that is generally accepted in the field. For this research project, the data set for a number of pavements from Districts I and IV for 1993 and 1994 were used as prior data, and the data for 1995 were used as the sample data. The same functional form and transformations of the independent variables as in the classical regression were used.

5.2.1 Developing Prior and Assembling Sample Data

The prior can be derived either subjectively using expert judgement or objectively based on existing data or models. Both approaches require that the prior information be put into either an N-prior or G-prior format. Both the N-prior or G-prior summarize a linear regression which represents the prior state of knowledge in the Bayesian regression calculation. The prior includes the coefficients of the linear regression equation along with the corresponding regression statistics such as the variance of the regression coefficients. The regression statistics indicate the certainty of the prior and are used to weigh the balance between the prior and the data in the Bayesian regression calculation. A brief overview of the information required to define the N-prior or a G-prior is provided in Table 5.1 *(Kwaeski and Nickeson 1997)*. The G-prior option is typically used when the coefficient means have been estimated directly by the experts. The G-prior derives the variance/covariance matrix for the coefficient means based on a set of independent variable data. The G-prior factor is used to increase or decrease the influence of the prior in the calculation of the posterior. The G-prior factor is denoted by g. A typical value for g is 1. This essentially gives the prior variance/covariance matrix weight equal to that of the experimental data. The greater the value of g, the more influence the prior will have on the posterior. Since the pseudo/prior data used in this research were not derived from expert opinion only, the N-prior option of Bayesian regression was used in this analysis.

Table 5.1 Required Prior Information *(After Kwaeski and Nickeson 1997)*

Prior Information	Required for N-prior	Required for G-prior
Means vector		
Variance/Covariance Matrix		-
G-prior data set	-	
G-prior factor	-	
Residual variance		
Degrees of freedom		

5.2.2 Results of Bayesian Regression and Selected Posterior Models

The classical regression results using pseudo data, development of the N-prior and the posterior regression coefficients for the FDBIT and PDBIT pavements have been reported in detail by Chowdhury *(1998)*. The selected posterior models using N-prior Bayesian regression analysis are shown below.

FDBIT Pavements: The selected models for FDBIT pavements are :

<u>Distress Level 1</u>

$$PSE = 0.123*(AGE)^{1.5} - 9.329*\exp[\ SN] + 0.106*TH + 0.374*PSE + 5.89*DL1 \quad (5.1)$$

<u>Distress Level 2</u>

$$PSE = 0.123*(AGE)^{1.5} - 9.329*\exp[\ SN] + 0.106*TH + 0.374*PSE + 6.04*DL2 \quad (5.2)$$

<u>For Distress Level 3</u>

$$PSE = 0.123*(AGE)^{1.5} - 9.329*\exp[\ SN] + 0.106*TH + 0.374*PSE + 6.47*DL3 \quad (5.3)$$

PDBIT Pavements: The selected models for PDBIT pavements are :

<u>Distress Level 1</u>

$$PSE = 0.021*(AGE)^{1.5} - 1.873*\exp[\ SN] + 0.303*PSE + 0.392*DL1 \quad (5.4)$$

<u>Distress Level 2</u>

$$PSE = 0.021*(AGE)^{1.5} - 1.873*\exp[\ SN] + 0.303*PSE + 0.881*DL2 \quad (5.5)$$

<u>Distress Level 3</u>

$$PSE = 0.021*(AGE)^{1.5} - 1.873*\exp[\ SN] + 0.303*PSE + 1.974*DL3 \quad (5.6)$$

where,

	PSE=	Predicted *decrease* in PSE value,
	AGE=	Age of the pavement *since the last rehabilitation action* (in years),
	TH =	AC layer thickness (in inches),
	PSE=	PSE value assigned to the pavement *immediately after the last action*,
	SN=	Decrease in structural number, and
	DL_i=	Distress level due to transverse cracking (i = 1, 2, 3).

5.3 Model Evaluation

The purpose of evaluating the model results is to draw conclusions about the Bayesian posterior results. Evaluation emphasizes comparisons between the data, the prior, and the posterior. These comparisons may be used for additional iterations for analysis later on. The statistical performance of a classical regression model is typically measured by evaluating the standard error (S_e), coefficient of determination (R^2), F-statistic, and t-statistic. In Bayesian regression, only S_e and t-statistic can be evaluated. Neither R^2 nor the F-statistic can be calculated because they rely on the experimental data which does not exist for the posterior results *(Kaweski et al 1997)*.

5.3.1 Data, Prior, and Posterior PDF Plots

An important output of XLBayes is the PDF (Probability Density Function) plots for each coefficient in the model. These plots graphically compare the distribution of the same coefficient when based on the data alone, the prior alone, or the Bayesian posterior. Figures 5.2 through 5.14 show the PDF plots for all coefficients in the models developed in this study.

Under the assumptions of both classical linear regression and the Bayesian regressions, the model coefficients follow t-distribution. The width of the bell shaped curve shows the confidence in the estimating coefficients. The PDF plots of all coefficients reveal the fact that the probability distribution for the posterior estimate is 'tighter' than either the prior or the data. This is intuitively reasonable as the prior and the data reinforce each other with similar estimates of the coefficients. Bayesian regression models can always be updated by inserting more data in the model which makes the posterior more and more definitive.

5.3.2 t-Statistic

The t-test is used to determine whether a regression coefficient is significantly different from zero. The t-value for a regression coefficient is calculated by dividing the mean of the regression coefficient by its standard deviation:

$$t = b_i / \quad _{bi}$$

The null hypothesis in this test is :

$$H_0 : b_n = 0$$

which is tested against the alternative hypothesis :

$$H_1 : b_n \quad 0$$

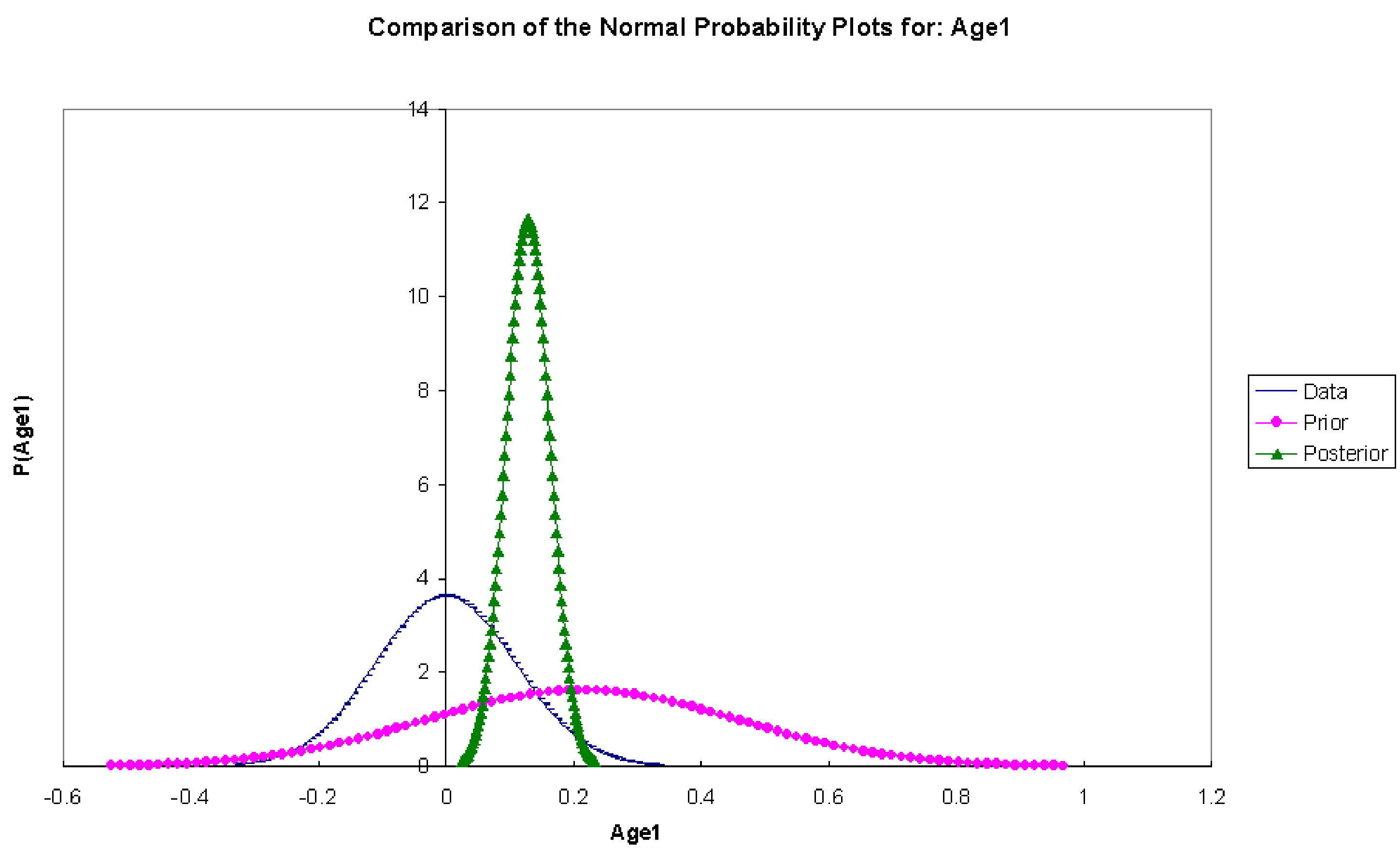

Figure 5.2 PDF Plot for Age for FDBIT Pavements

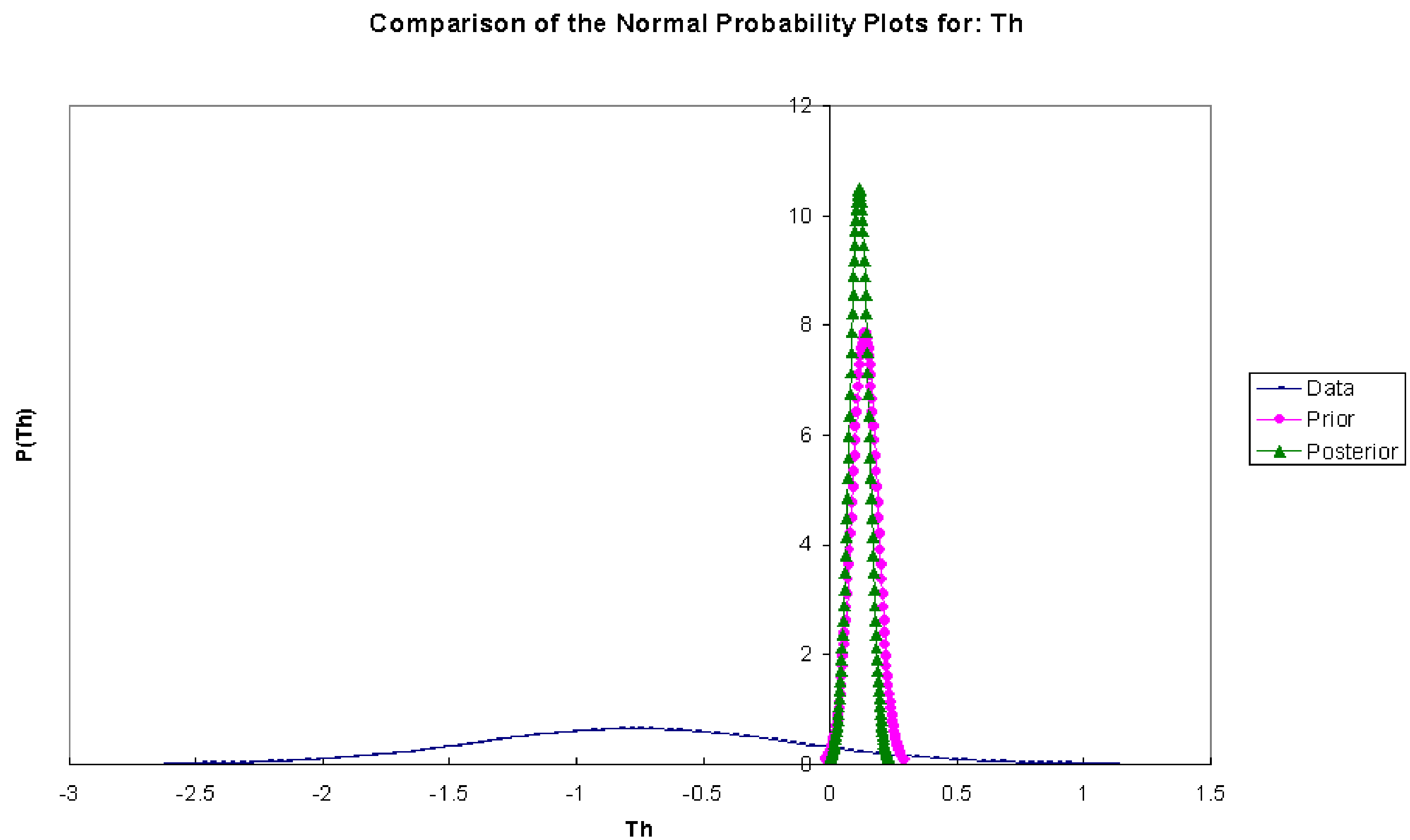

Figure 5.3 PDF Plot for Thickness for FDBIT Pavements

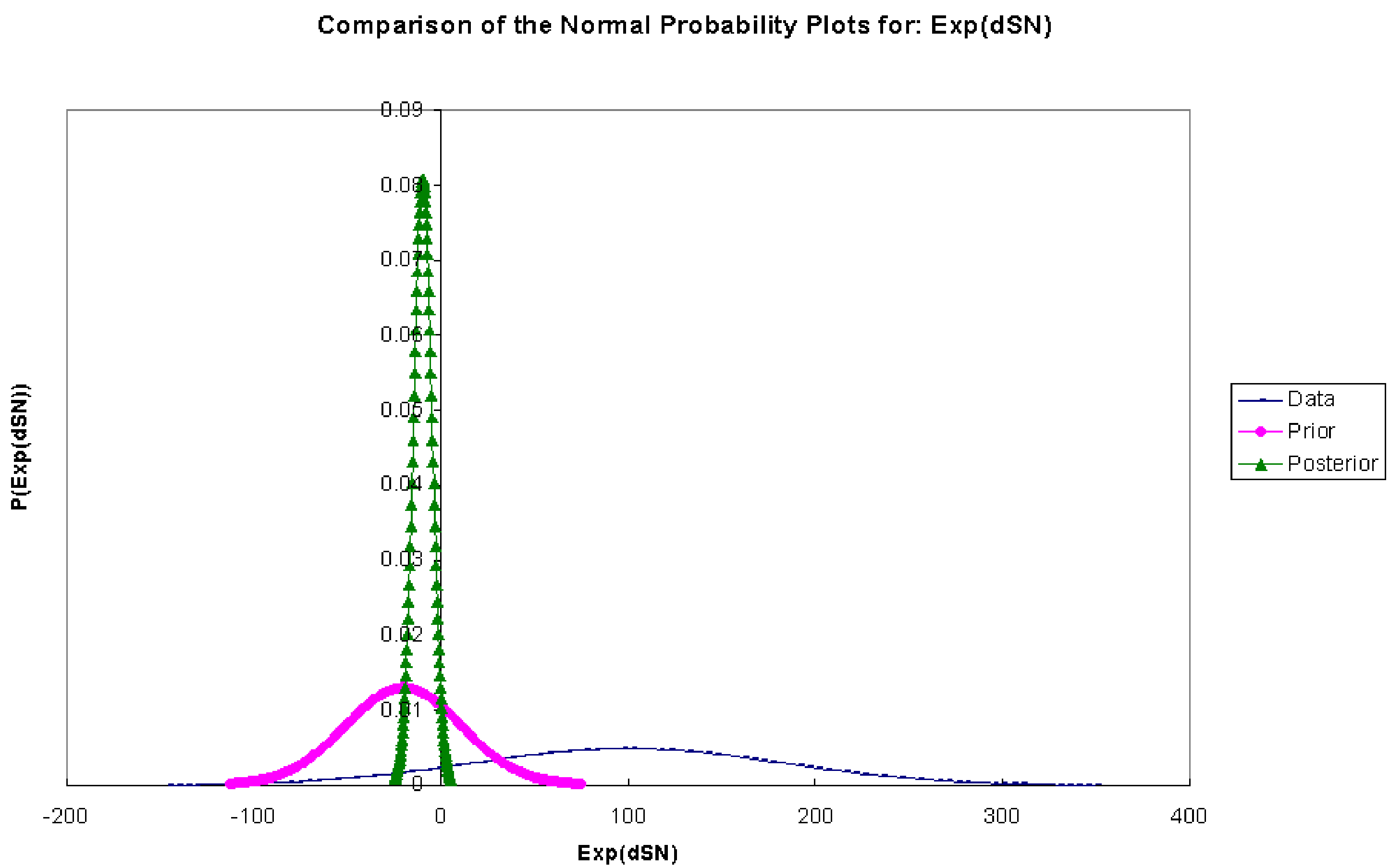

Figure 5.4 PDF Plot for Decrease in Structural Number for FDBIT Pavements

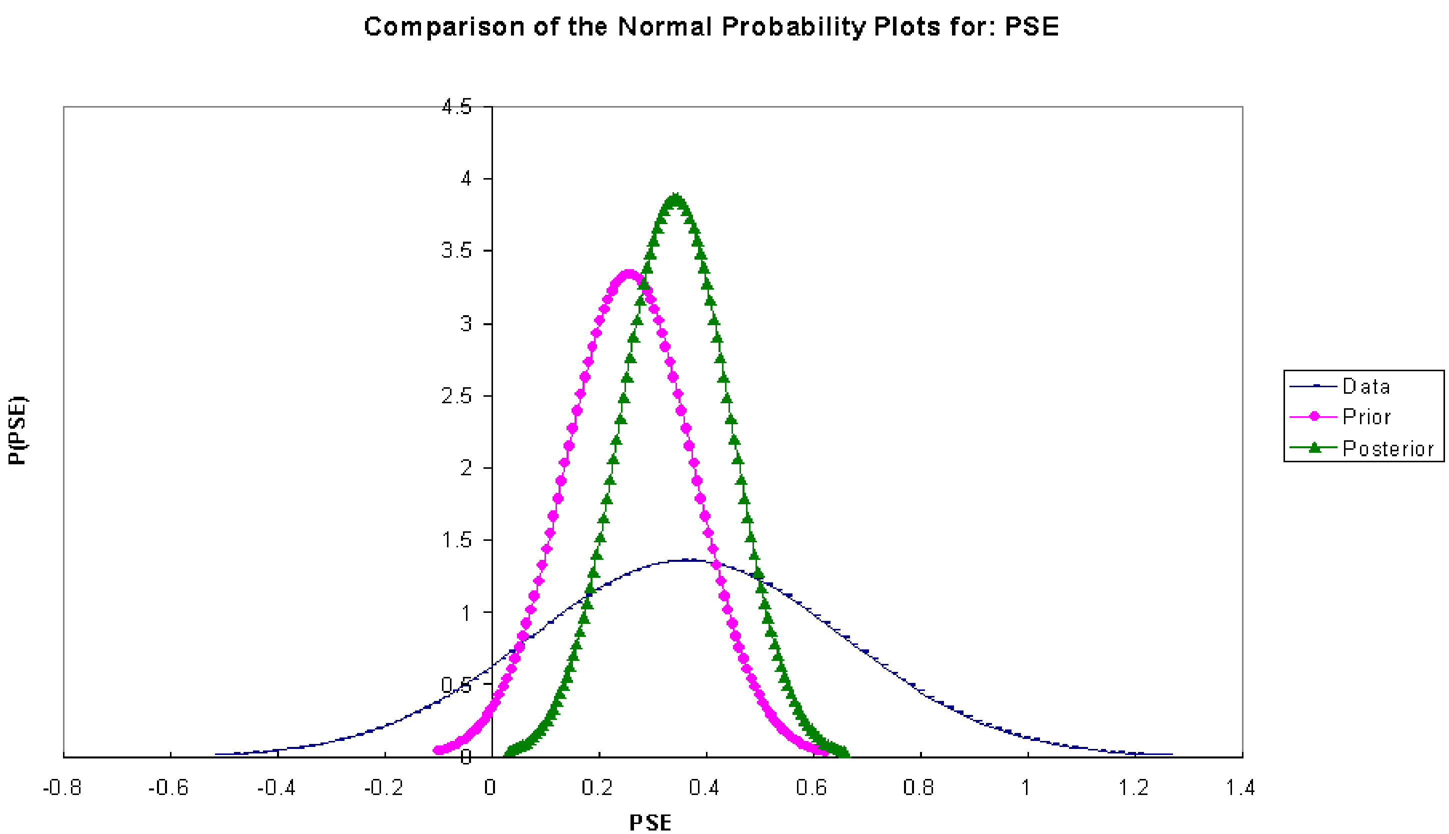

Figure 5.5 PDF Plot for PSE for FDBIT Pavements

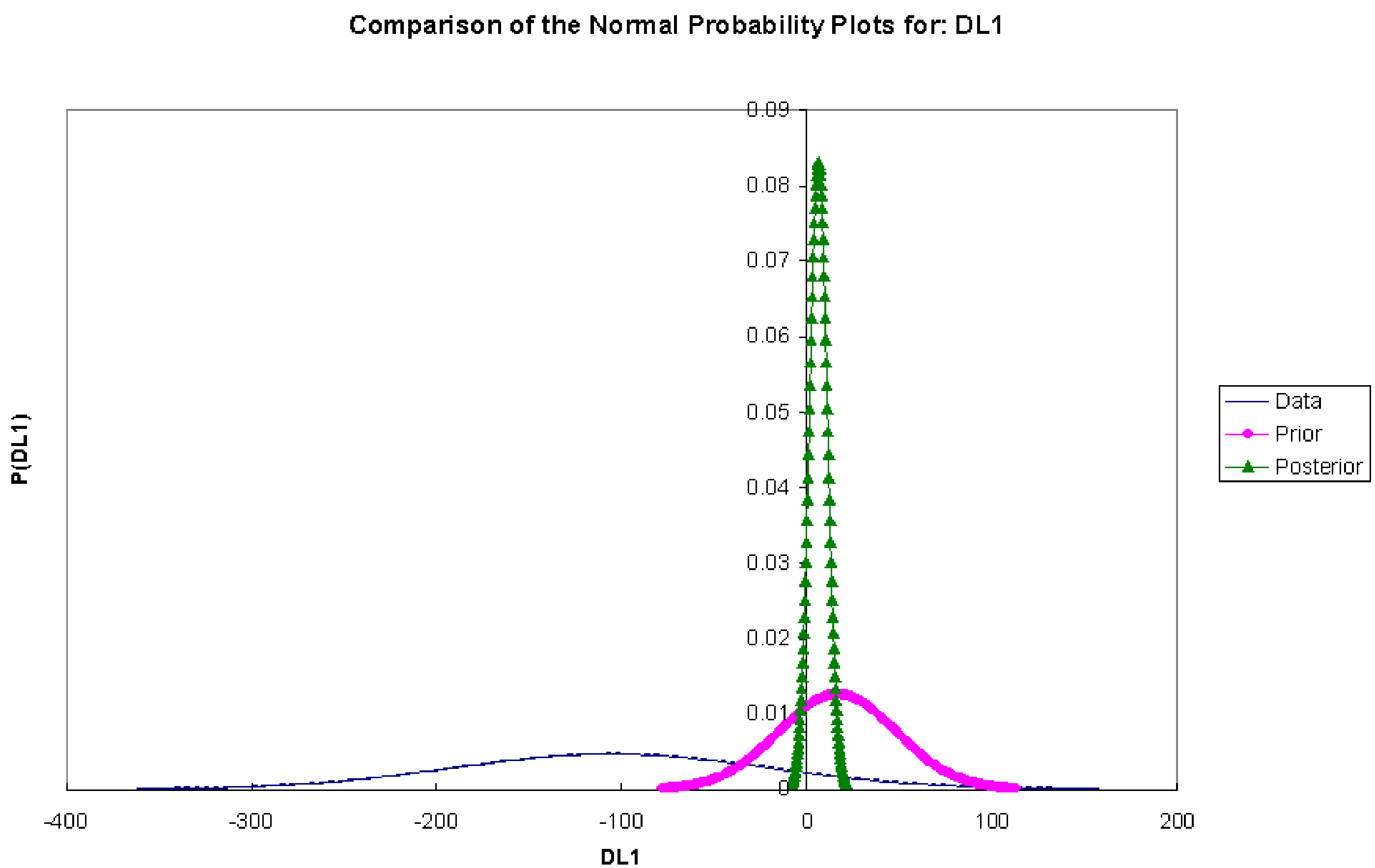

Figure 5.6 PDF Plot for Distress Level 1 for FDBIT Pavements

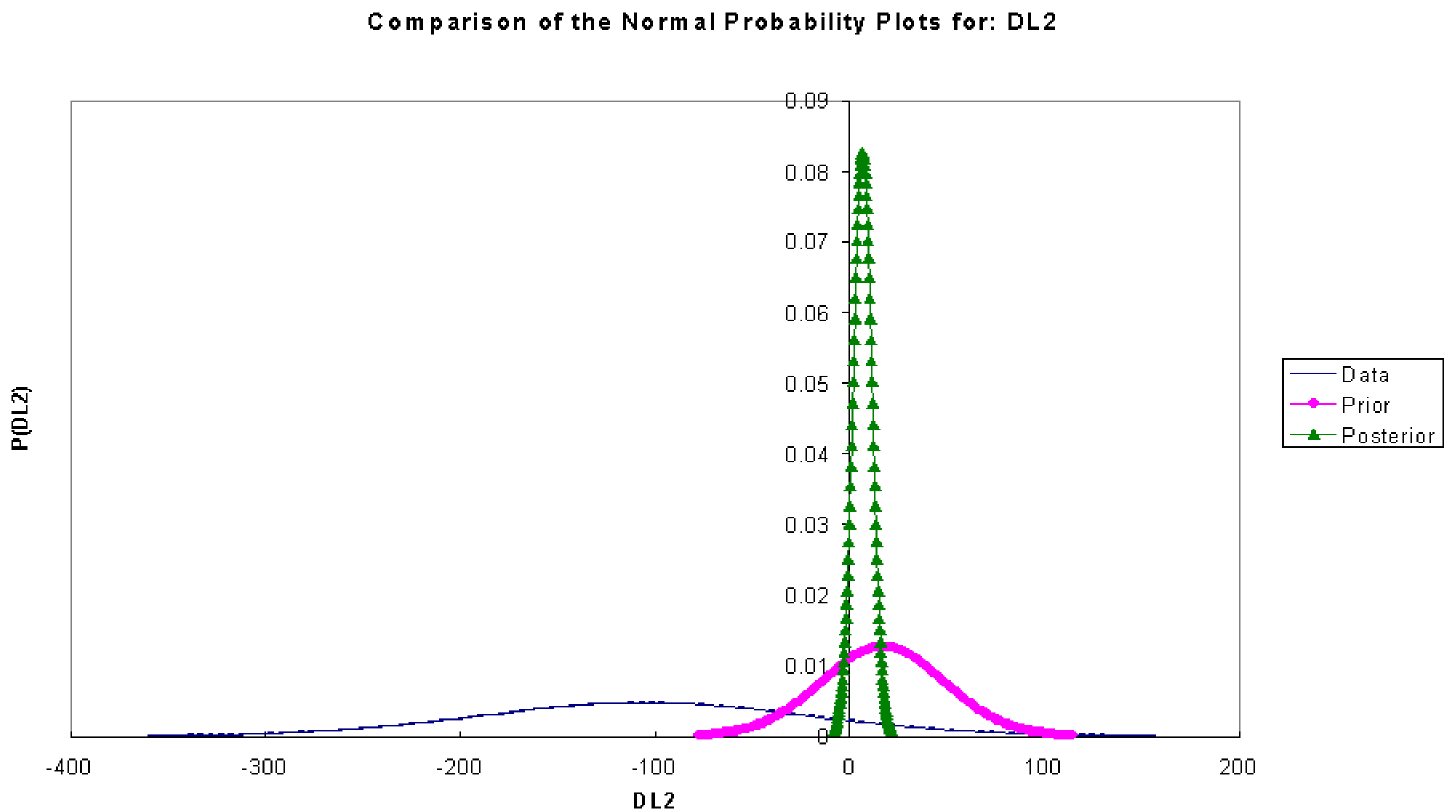

Figure 5.7 PDF Plot for Distress Level 2 for FDBIT Pavements

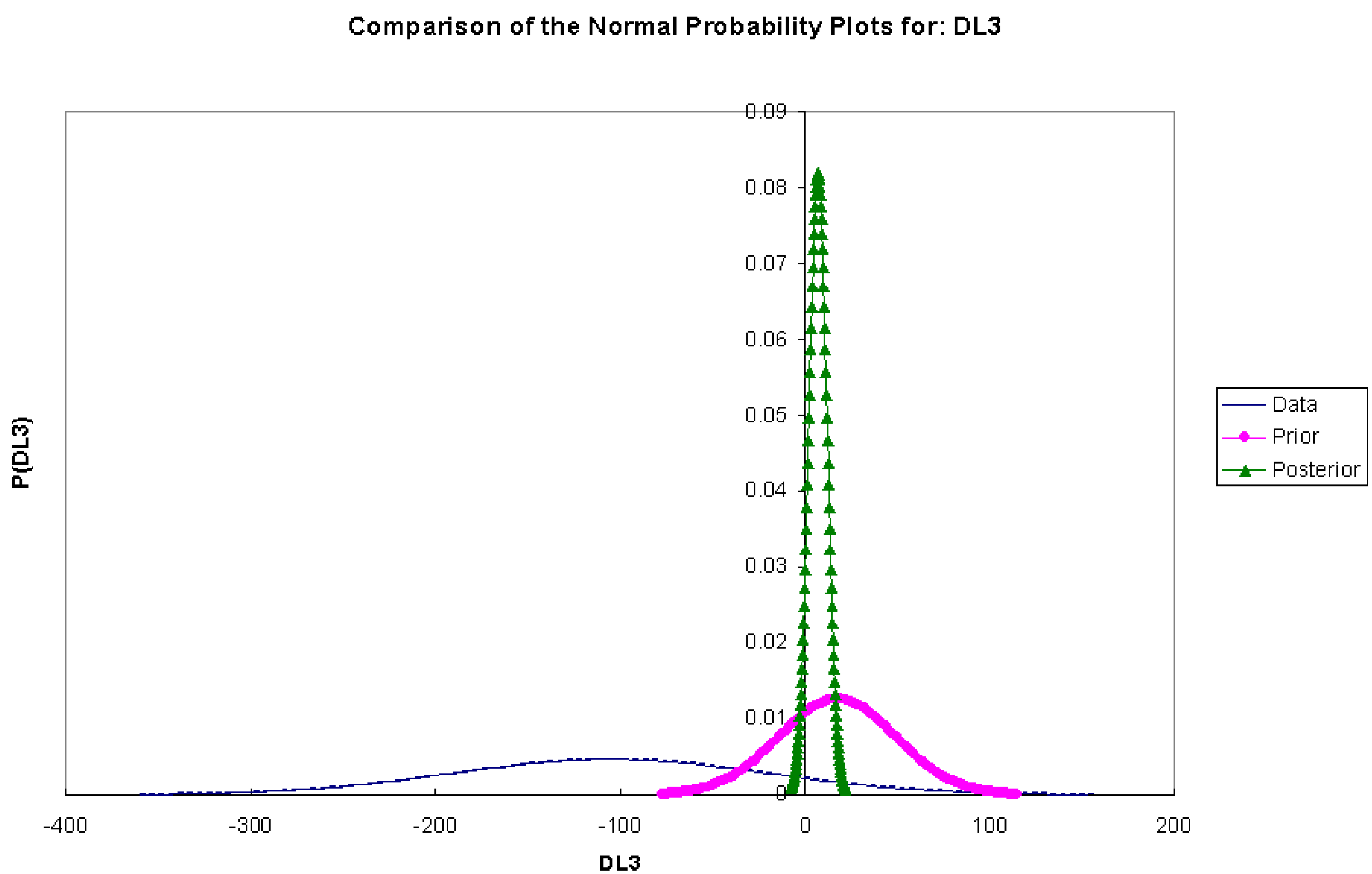

Figure 5.8 PDF Plot for Distress Level 3 for FDBIT Pavements

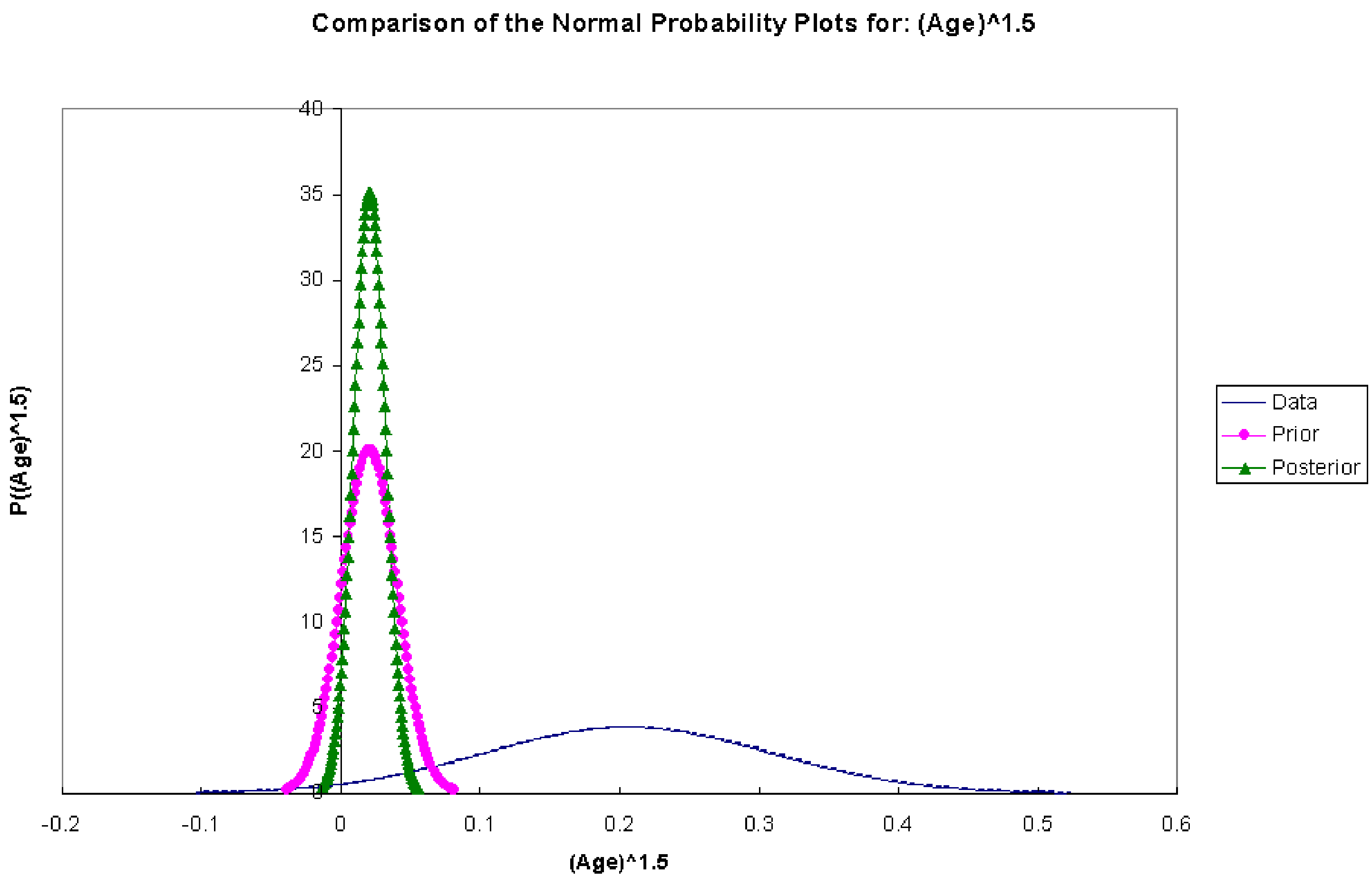

Figure 5.9 PDF Plot for Age for PDBIT Pavements

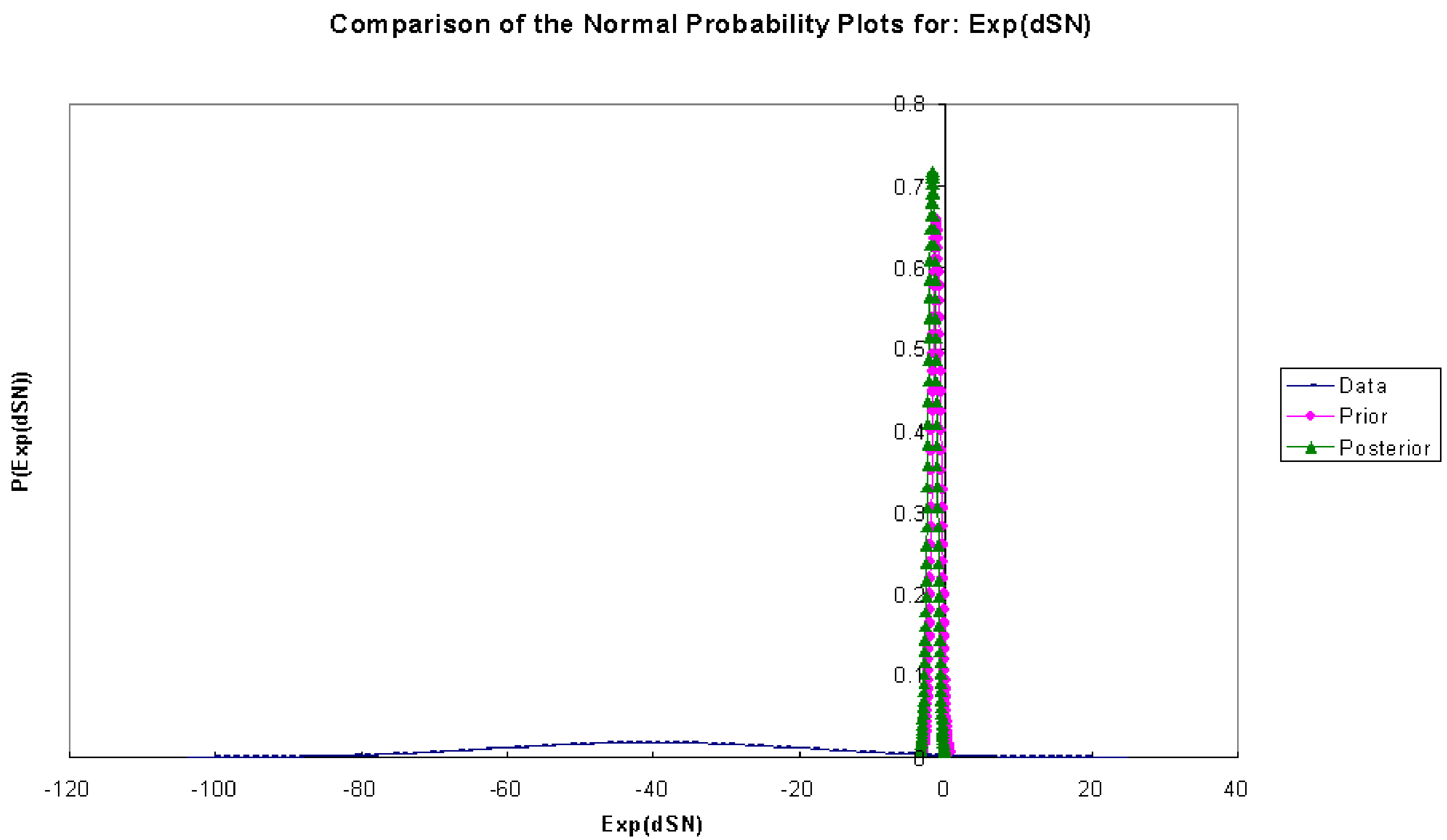

Figure 5.10 PDF Plot for Decrease in Structural Number for PDBIT Pavements

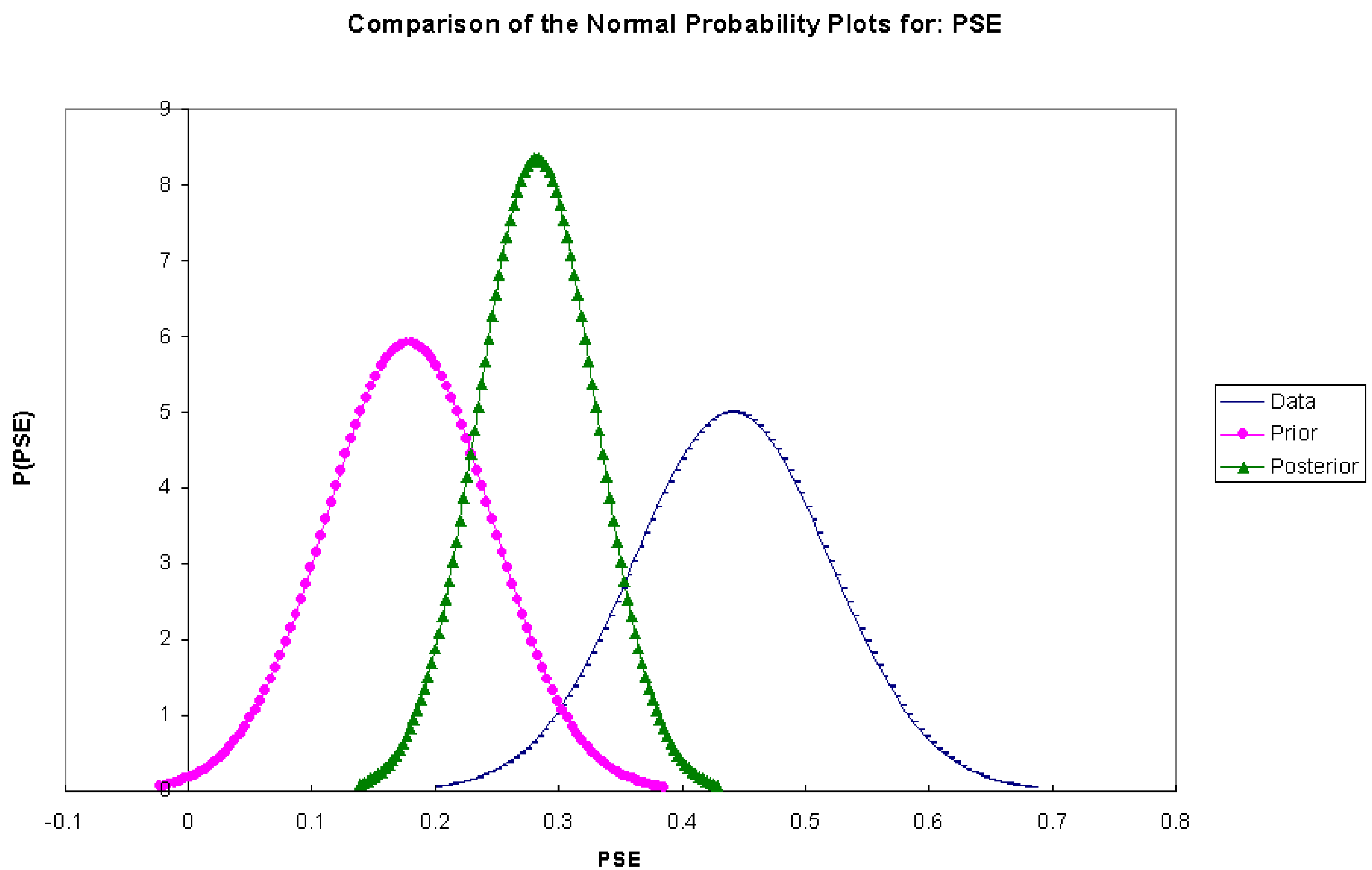

Figure 5.11 PDF Plot for PSE for PDBIT Pavements

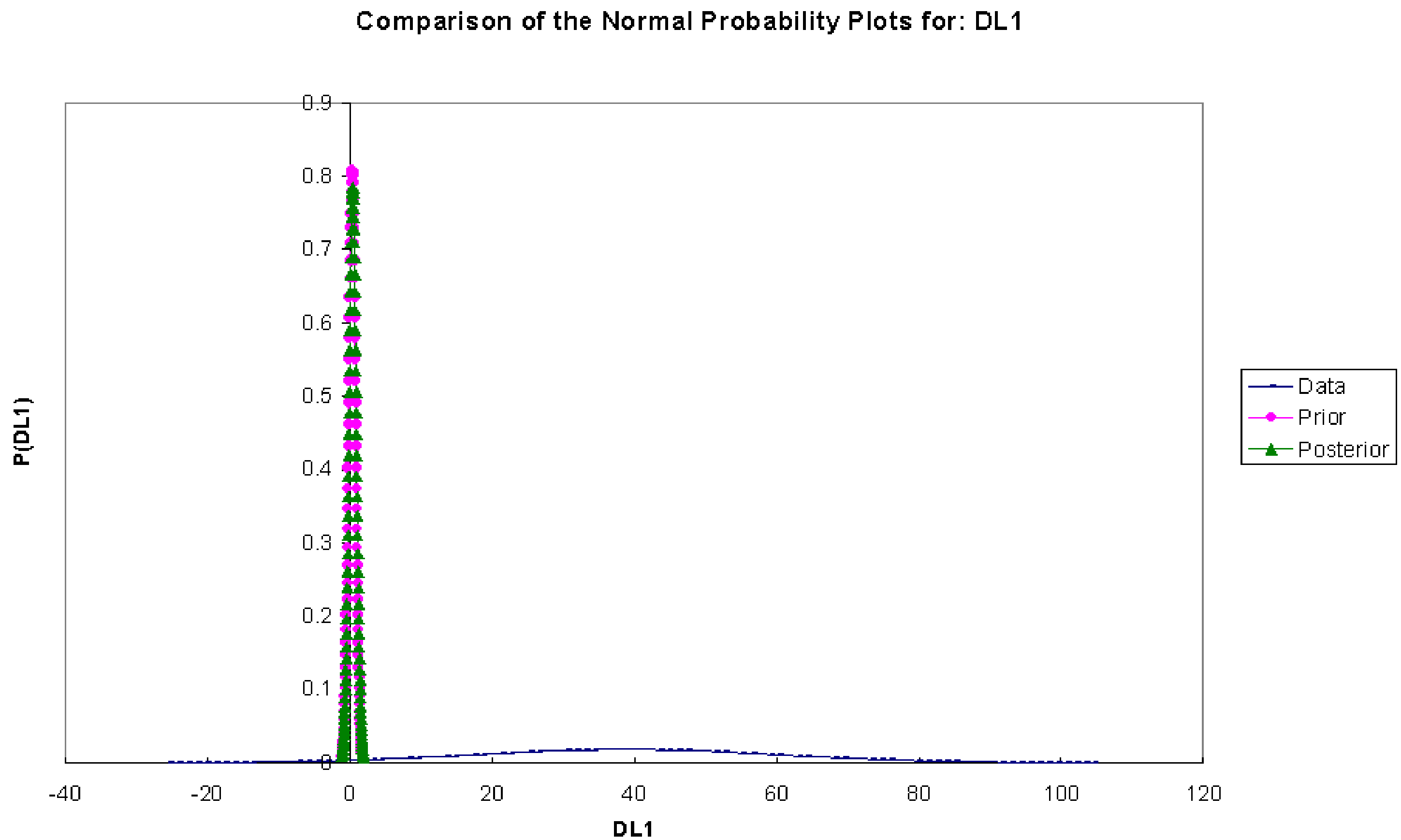

Figure 5.12 PDF Plot for Distress Level 1 for PDBIT Pavements

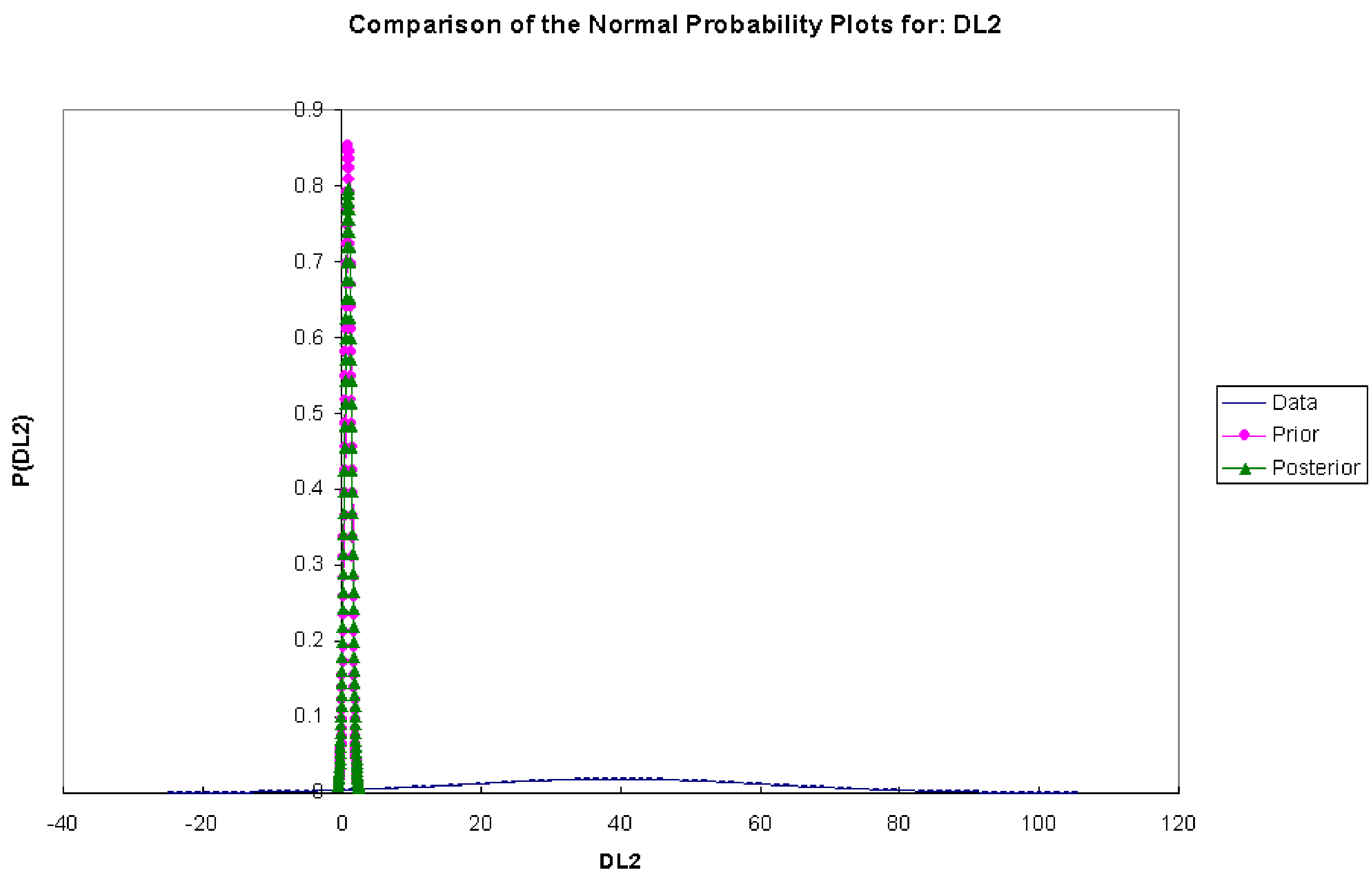

Figure 5.13 PDF Plot for Distress Level 2 for PDBIT Pavements

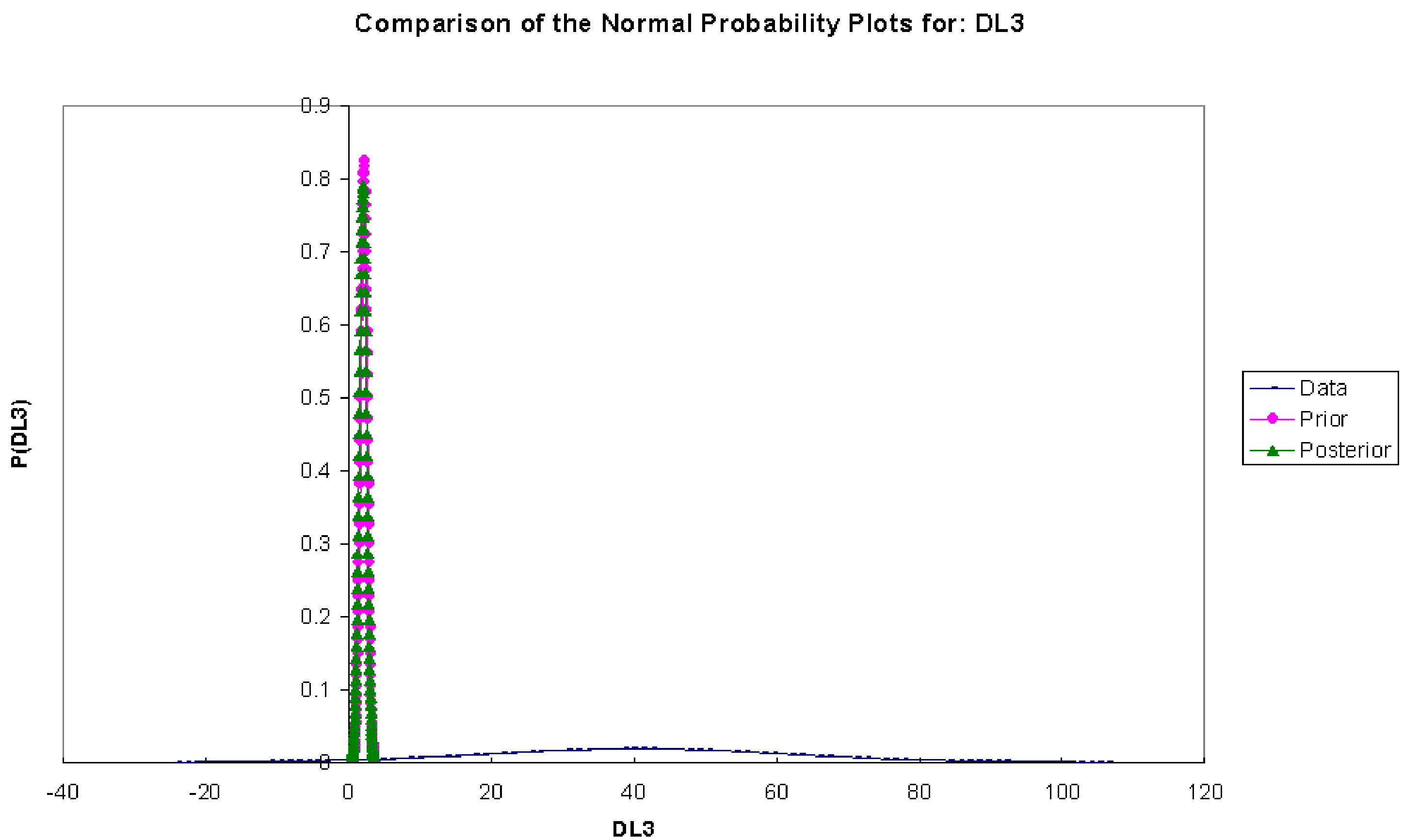

Figure 5.14 **PDF Plot for Distress Level 3 for PDBIT Pavements**

At 5% level of significance, where the number of degrees of freedom is very large (i.e., the t distribution is approximately the same as the normal distribution), the critical value of t is ± 1.96. If the t-value is greater than 1.96 or less -1.96, the null hypothesis is rejected and it is accepted that the estimate of b_n is statistically significant. The higher the value of t, the more is the confidence about its value and significance. If the t-value is between 1.96 and -1.96, the null hypothesis is accepted and it is concluded that the estimate of b_n is not statistically significant. The values calculated for the coefficients may only be different from zero due to chance. If the regression coefficients in the prior and posterior are not statistically significant it may be useful to re-run the analysis after excluding the variable in question. If the standard error term does not increase significantly, the excluded variable may not be a statistically significant contributory variable.

The ideal result is for the data and prior to reinforce each other, resulting in a posterior coefficient that has a smaller standard error than either one individually. This is not always the case, however, and the posterior may in fact have a larger standard error. Irrespective of how much the variance has changed, it is desirable that the coefficients in the posterior model all be statistically significant.

The t-statistics and the standard deviations of different coefficients are presented in Table 5.8. It is observed that the t-statistics of all selected variables are outside the range of 1.96 and -1.96 which means that the null hypothesis is rejected in all cases. Thus, the variables used in the models are significant at 5% level of significance.

5.3.3 Standard Error of the Residuals (S_e)

The standard error of the residuals, S_e, is a basic measure of regression model performance. The standard error (or standard deviation) of the residuals is simply the square root of the residual variance, S_e^2. The lower the S_e, the closer the predictions made by the model are to the actual

Table 5.2 Standard Deviation and t-Statistic of the Posterior Coefficients

Pavement type	Variable	Std. Deviation	t-value	Res. Var. (S_e^2)
FDBIT	$(Age)^{1.5}$	0.034	3.620	0.329
	Thickness	0.041	2.547	
	Exp[(SN)]	4.240	-2.200	
	PSE	0.107	3.486	
	DL1	2.979	1.98	
	DL2	2.876	2.101	
	DL3	2.424	2.670	
PDBIT	$(Age)^{1.5}$	0.008	2.349	0.203
	Exp[(SN)]	0.500	-3.746	
	PSE	0.038	7.850	
	DL1	0.196	1.990	
	DL2	0.383	2.301	
	DL3	0.466	4.234	

observations of the dependent variable, and therefore, the better the model.

Under the assumptions of regression, the residual has a mean of zero and is normally distributed. Thus the confidence interval for the forecasts made by the model can be calculated using a table of areas under the standard normal curve. For example, 95% confidence interval for a forecast corresponds to the mean forecast plus or minus 1.96 times the standard deviation of the residual. Therefore, the selected models will predict the (PSE) values within ±1.1 units of actual ratings for FDBIT and ±0.88 units for PDBIT pavements with 95% confidence.

6.0 RESULTS AND DISCUSSION

6.1 Prediction of PSE Values Using the Selected Models

As mentioned earlier, data from 1993, 1994, and 1995 were used in the regression analysis. Statistical tests were performed on the models which yielded very convincing and satisfactory results. To get an idea about how well the models would perform in the field, data from a different set of control sections collected in different years were selected. These sections were not included in the regression analyses. For 1996, 12 FDBIT and 26 PDBIT sections and for 1997, 10 FDBIT and 19 PDBIT sections were chosen randomly to test the models developed in this study. Both classical and Bayesian regression models were used to predict the PSE values on those pavement sections. At the same time, the rated decrease in the PSE values assigned by the KDOT engineers were also collected. Figures 6.1 through 6.4 show the results graphically.

The PSE values are always assigned as integer numbers. Since the coefficients of regression equations are not integers nor the independent variables, the output from the models are evidently nonintegers. So the output values were rationally rounded up or down to the nearest integer. The predicted PSE values for most of the pavement sections, very closely, approximate the rated PSE values. A few cases of discrepancies were encountered in the KDOT ratings. For example, Project No. 18 in Figure 6.3 (Route K-68), the PSE rating has been increased by two although no rehabilitation action had been taken on this pavement for the last four years. On the other hand, both the Bayesian and Classical regression models suggest that the PSE value should decrease by two. Similarly, other discrepancies in the present rating system were rationally and objectively addressed by the selected models as evident in Figures 6.1 through 6.4.

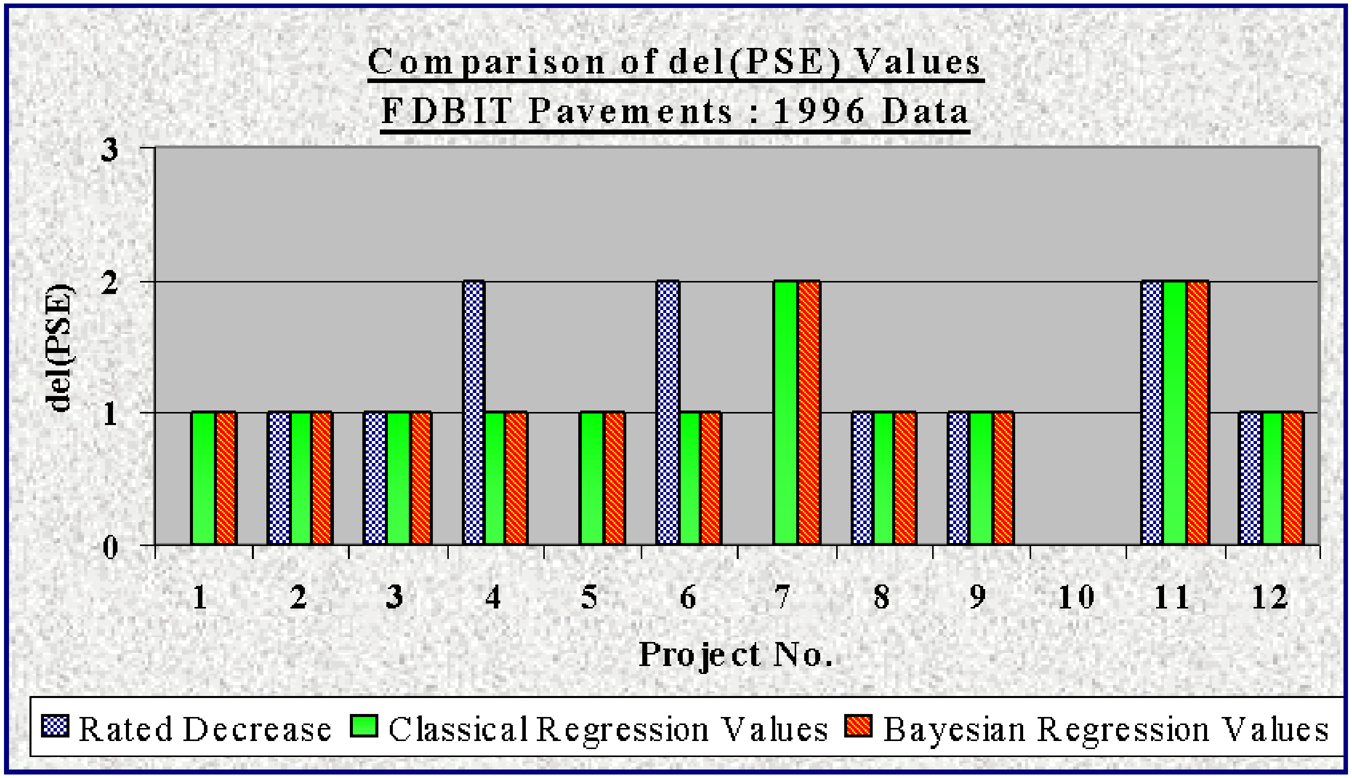

Figure 6.1 Graphical Comparison of Rated and Predicted PSE Values

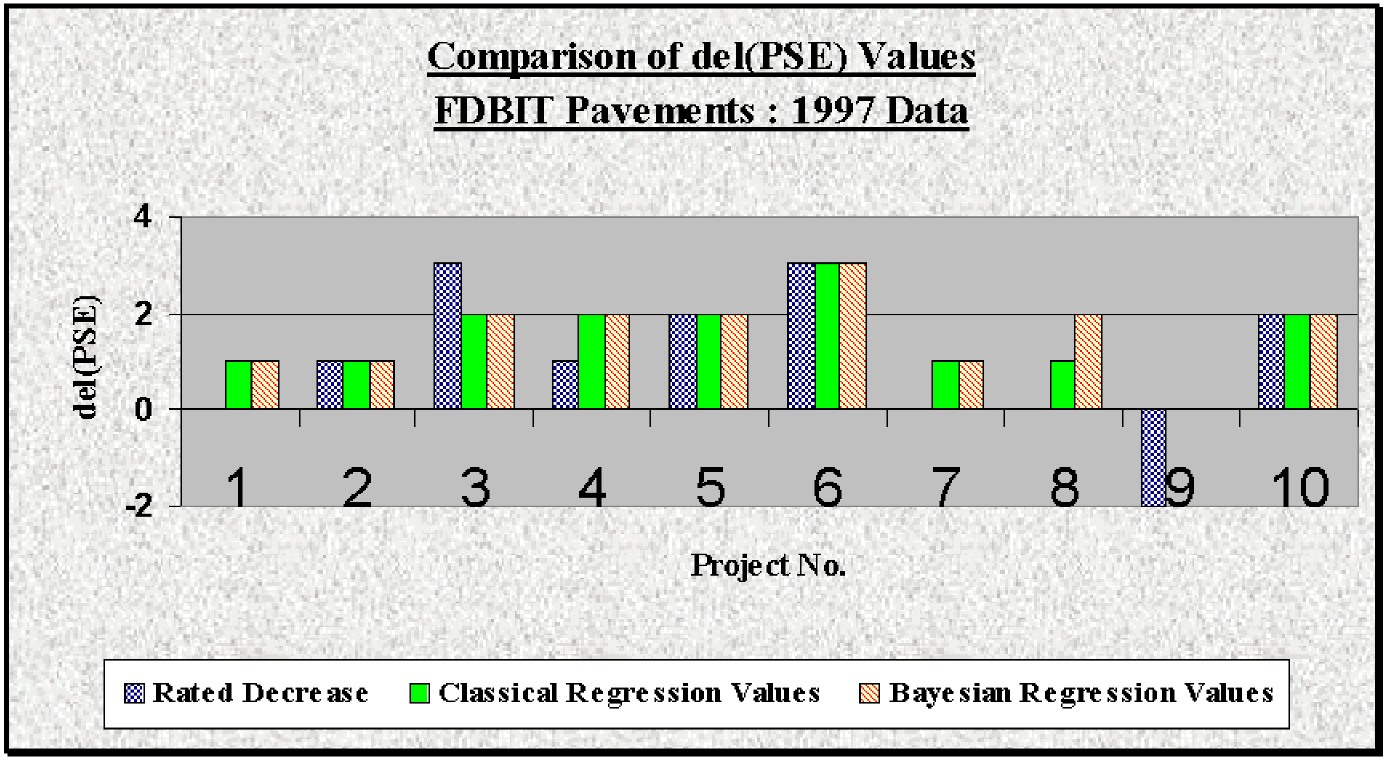

Figure 6.2 Graphical Comparison of Rated and Predicted PSE Values

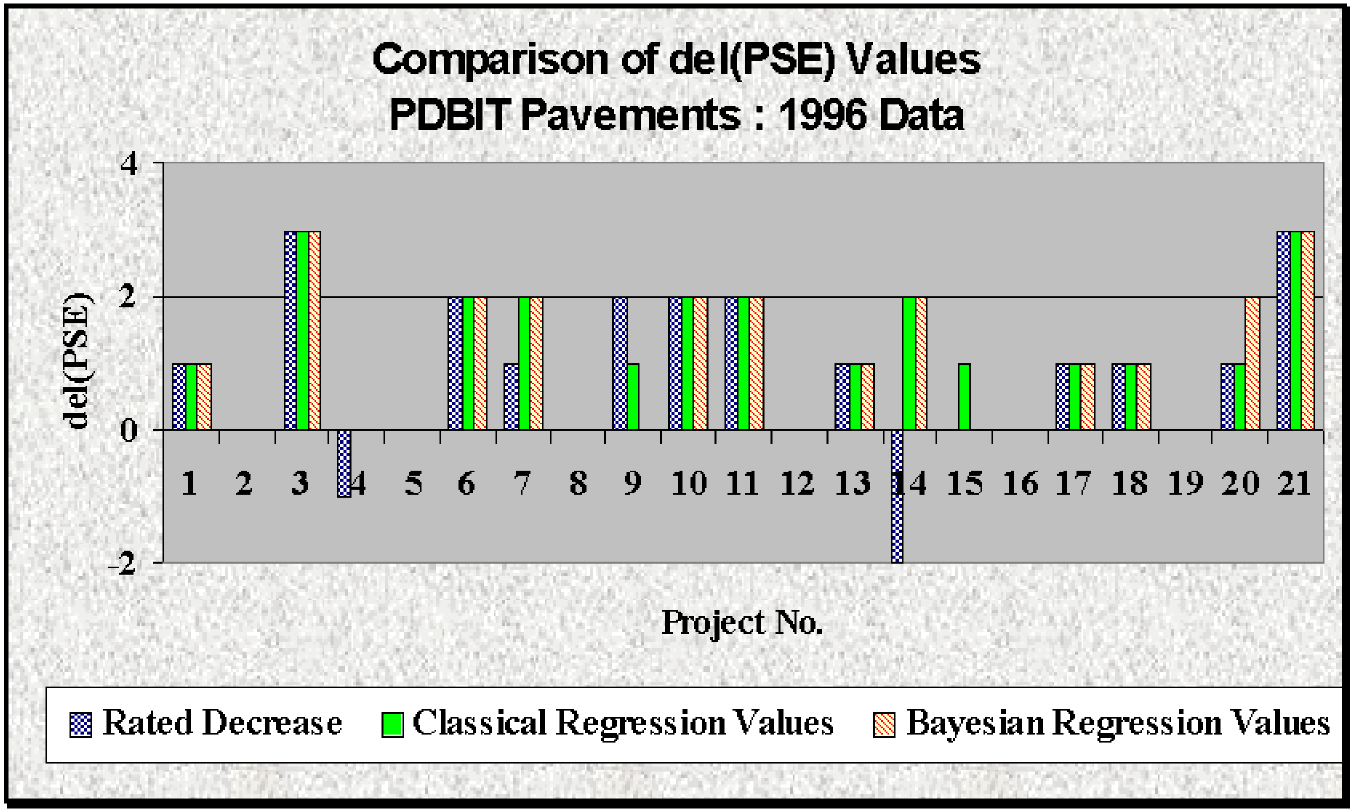

Figure 6.3 Graphical Comparison of Rated and Predicted PSE Values

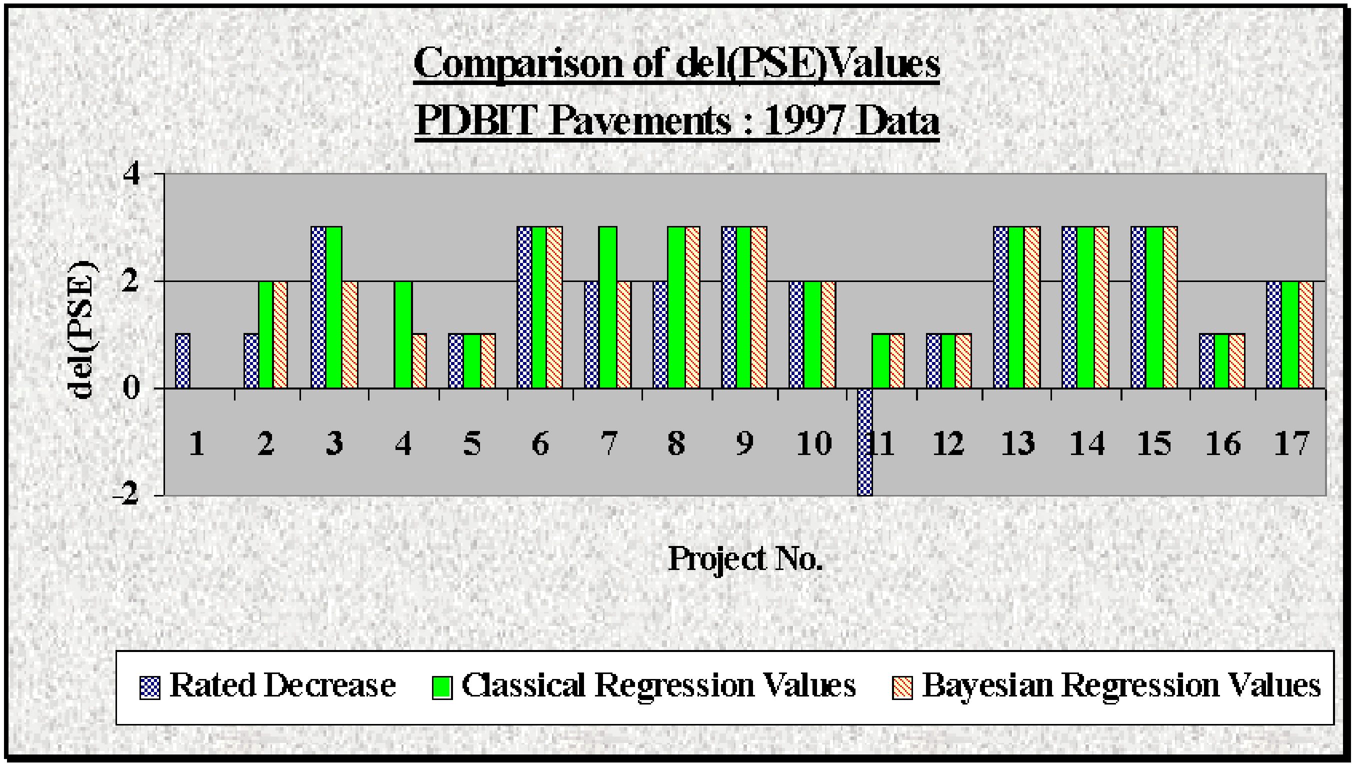

Figure 6.4 Graphical Comparison of Rated and Predicted PSE Values

6.2 Range of the Independent Variables

Like all other regression equations, there is a range of each independent variable for which the selected models are expected to predict the dependent variable with sufficient accuracy. The prediction interval band will be wider outside that range, and it is statistically inaccurate to use the model in those cases. The suggested ranges of the independent variables of the selected models are:

1. Age since last rehabilitation action: (1 to 18 years),
2. AC layer thickness: (4 to 30 inches),
3. PSE rating at the base year: (2 to 10),
4. Decrease in structural number SN: (0.001 to 2.5), and
5. Distress level due to transverse cracking: (1 to 3)

6.3 Paired t-Test Results

Paired t-tests were performed to determine whether the data from two different sources have the same mean or in other words whether they are statistically similar. Rated decrease in the PSE values were compared with the predicted decrease derived from both classical and Bayesian regression. The null hypothesis was:

$H_0 : {}_1 = {}_2$ (or the two sets of data have the equal means)

which was tested against the alternate hypothesis:

$H_a : {}_1 \quad {}_2$ (or the two sets of data are significantly different)

The results of the t-tests are tabulated in Table 6.1. The results indicate that for all regression models for both FDBIT and PDBIT pavements the absolute t-value was less than the critical value of t, which implies that the null hypothesis was accepted in all cases. In other words,

Table 6.1 Results of Paired t-Test

PAVEMENT TYPE	RESULTS OF PAIRED t-TEST	
	BAYESIAN	**CLASSICAL**
FDBIT	t_{crit} (two tail) = 2.079	t_{crit} (two tail) = 2.079
	t = -1.46	t = -1.89
	sum of sq. err. = 16.74	sum of sq. err. = 16.87
PDBIT	t_{crit} (two tail) = 2.015	t_{crit} (two tail) = 2.015
	t = -1.39	t = -1.93
	sum of sq. err. = 7.78	sum of sq. err. = 12.41

there was no significant difference between the two sets of data. From the sum of squared errors, it can be concluded that for the FDBIT pavements the Bayesian and classical regression models yield similar results, while for the PDBIT pavements, the Bayesian regression models appear to be more accurate.

7.0 SUMMARY

7.1 Conclusions

The following conclusions can be drawn based on the results of this study:

1. There were no significant differences among the means of the response variables, first sensor deflection (d_1), subgrade resilient modulus (M_r), and effective pavement modulus (E_p), for the years 1993, 1994, and 1995. However, significant differences were observed between the first sensor deflection values in 1996 and 1993 for both FDBIT and PDBIT pavements. Therefore, FWD tests up to a 3-year interval at the network level would yield statistically similar pavement responses and layer properties.

2. At the network level, FWD tests on more than 20% of network mileage will not significantly increase the precision of the mean first sensor deflection value. Therefore, at the network level, FWD tests on 20% of the mileage appear to be a valid statistical choice and could be selected as a reasonable sample size in structural evaluation of asphalt pavements. For KDOT, it would translate into approximately 2,200 lane-miles of testing over three years or approximately 750 lane-miles each year. The average percentage of error for seven, five, and three FWD tests per mile does not vary significantly. Therefore, three tests per mile can be taken as the minimum test frequency at the network level. This testing would be necessary for network level structural evaluation of the KDOT pavements and also for using/updating the models developed in this study. The *decrease* in the structural number values obtained from the models developed in this study was about 50% higher than the KDOT design assumption.

3. PSE rating is a very important attribute in the project prioritization process of KDOT and

the current PSE rating system has discrepancies. The classical regression models proposed in this study predict the PSE values by taking into account the FWD data, age, thickness, and distress level of pavements and hence, is representative of the actual structural condition of the pavement. The proposed models very closely approximate the present PSE ratings obtained at the district level.

The following conclusion was drawn by Chowdhury *(1998)* in his study of the Bayesian regression methodology:

1. The models obtained from the classical and Bayesian regression are very similar in form and they yield statistically similar results when tested on a different set of pavements. Both the classical and the Bayesian regression models appear to be statistically sound from the view point of predicting capability and model utility since they pass the individual statistical tests. Although very similar in form, the Bayesian regression models yielded slightly better results during testing.

7.2 Recommendations

1. FWD tests are recommended to be performed at 3-year intervals at the network level since there is no significant difference in pavement responses during those years. Three tests per mile is the minimum recommended test interval required for network level structural evaluation and also for using/updating the models developed in this study.
2. The PSE values obtained by the proposed models are recommended to be used as "suggested PSE values" along with the KDOT's recommended maximum and minimum PSE values currently in use.

The following recommendations were made by Chowdhury *(1998)*:

1.. The Bayesian regression models perform slightly better than the Classical regression models when tested on a different set of pavements and are, therefore, recommended for use for predicting PSE values.

2. The Bayesian regression is a continuous process of updating the existing "partial state of knowledge" *(Kaweski et al. 1997)*. As the existing database is enriched with more data, the Bayesian regression will result in a posterior with an even smaller confidence interval. Hence, it is highly recommended that the existing models be updated every third year with more recent data.

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APPENDIX A : Typical SAS Code Files, Log Files, and Output of the Selected Models for the Prediction of Decrease in Structural Number

Statistical Analysis System (SAS) Codes

```
Title1 ' FDBIT PAVEMENTS' ;
Title2 'Prediction of del(SN) from age, thickness and cumulative ESAL' ;
options ls= 80 ps= 60;
data;
input dsn age th cumESAL;
cards;
0.098 4 16.5 599087
0.0924 6 13.9 745738
0.0582 3 13.8 129687
0.0876 5 9.8 301154
0.023 1 11.8 53125
0.1116 6 10.3 925514
0.1292 6 12.4 810048
0.1225 7 13.5 407297

0.204 13 7.8 965029
0.08 5 19 298817
0.09 6 14.4 385079
0.13 8 12.6 889037
0.08 5 14.7 461194

0.09 6 11.4 238113
0.099 6 17.5 394265
0.236 15 14 1782951

0.18 6 15.6 1326061
0.168 6 18.8 1722453
0.171 6 17 1636727
0.151 5 14.1 531323
0.171 5 12.2 675370
0.14 5 12.2 675370
0.184 7 11.9 1126211
0.16 6 15.6 2135526
0.281 9 19.4 623234
0.219 10 19.8 3723550

0.055 2 14.6 995321
0.19 7 14.9 2087479
0.131 5 17.4 2388042
```

```
0.059 2 17.6 1119591
0.204 7 10.5 176723

0.49 17 18.7 4041889
0.09 3 10 227849
0.08 3 12.3 267089
0.1 3 12.3 267089
0.09 3 12.3 365729
0.27 9 19.1 2013217
0.39 16 16.2 3295945
0.44 16 16.7 1363570
proc anova;
class dsn;
model dsn= age th;
proc reg;
model dsn =  age th cumESAL;
model dsn =  age th cumESAL/noint;
model dsn =  age cumESAL;
model dsn =  age cumESAL/noint;
model dsn =  age th;
model dsn =  age th/noint;
proc stepwise;
model dsn =  age th cumESAL/F B stepwise;
proc rsquare;
model dsn =  age th cumESAL/adjrsq cp rmse;
proc corr;
run;
```

The SAS System : Log File

```
NOTE: Copyright ©1989-1996 by SAS Institute Inc., Cary, NC, USA.
NOTE: SAS (r) Proprietary Software Release 6.12  TS020
      Licensed to KANSAS STATE UNIVERSITY, Site 0003010005.

This message is contained in the SAS news file, and is presented upon
initialization.  Edit the files "news" in the "misc/base" directory to
display site-specific news and information in the program log.
The command line option "-nonews" will prevent this display.

NOTE: AUTOEXEC processing beginning; file is /usr/local/lic/sas612/autoexec.sas.

NOTE: SAS initialization used:
      real time           0.760 seconds
      cpu time            0.533 seconds

NOTE: AUTOEXEC processing completed.
1
2          Title1 'FDBIT PAVEMENTS';
3          Title2 'Prediction of del(SN) from age, thickness and cumulative ESAL';
4          options ls= 80 ps= 60;
5          data;
6          input dsn age th cumESAL;
7          cards;

NOTE: SAS went to a new line when INPUT statement reached past the end of a  line.
NOTE: DATA statement used:
      real time           0.230 seconds
      cpu time            0.113 seconds

52         proc anova;
53         class dsn;
54         model dsn= age th;
```

```
NOTE: PROCEDURE ANOVA used:
      real time           0.020 seconds
      cpu time            0.019 seconds

proc reg;
model dsn =  age th cumESAL;
model dsn =  age th cumESAL/noint;
model dsn =  age cumESAL;
model dsn =  age cumESAL/noint;
model dsn =  age th;
model dsn =  age th/noint;

NOTE: The PROCEDURE REG printed pages 1-6.
NOTE: PROCEDURE REG used:
      real time           0.410 seconds
      cpu time            0.141 seconds

proc stepwise;
model dsn =  age th cumESAL/F B stepwise;

NOTE: The PROCEDURE STEPWISE printed pages 7-10.
NOTE: PROCEDURE STEPWISE used:
      real time           0.310 seconds
      cpu time            0.082 seconds

proc rsquare;
model dsn =  age th cumESAL/adjrsq cp rmse;

NOTE: The PROCEDURE RSQUARE printed page 11.
NOTE: PROCEDURE RSQUARE used:
      real time           0.290 seconds
      cpu time            0.059 seconds

proc corr;
run;

NOTE: The PROCEDURE CORR printed page 12.
NOTE: PROCEDURE CORR used:
      real time           0.010 seconds
      cpu time            0.018 seconds

NOTE: The SAS System used:
```

real time 2.110 seconds
cpu time 1.029 seconds
NOTE: SAS Institute Inc., SAS Campus Drive, Cary, NC USA 27513-2414

Output : FDBIT PAVEMENTS

Model: MODEL6 Selected Model

NOTE: No intercept in model.
Dependent Variable: DSN

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	*F Value*	*Prob> F*
Model	2	1.29274	0.64637	*320.035*	*0.0001*
Error	37	0.07473	0.00202		
U Total	39	1.36747			

Root MSE	0.04494	*R-square*	*0.8127*
Dep Mean	0.15758	Adj R-sq	0.8095
C.V.	28.51995		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter= 0	Prob > | T|
AGE	1	**0.021872**	0.00189214	11.560	*0.0001*
TH	1	**0.001025**	0.00099054	1.034	*0.0176*

Forward Selection Procedure for Dependent Variable DSN

Step 1 Variable AGE Entered R-square = 0.80739593 C(p) = 7.25384676

	DF	Sum of Squares	Mean Square	F	Prob> F
Regression	1	0.32221333	0.32221333	155.10	0.0001
Error	37	0.07686390	0.00207740		
Total	38	0.39907723			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob> F
INTERCEP	0.00160524	0.01449521	0.00002548	0 . 0 1	0.9124
AGE	0.02339575	0.00187856	0.32221333	155.10	0.0001

Bounds on condition number: 1, 1

Step 2 Variable TH Entered R-square = 0.83423771 C(p) = 3.36524639

	DF	Sum of Squares	Mean Square	F	Prob> F
Regression	2	0.33292527	0.16646264	90.59	0.0001
Error	36	0.06615196	0.00183755		
Total	38	0.39907723			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob> F
INTERCEP	-0.07279728	0.03369669	0.00857622	4.67	0.0375
AGE	0.02235521	0.00181859	0.27766797	151.11	0.0001
TH	0.00563853	0.00233535	0.01071194	5.83	0.0210

Bounds on condition number: 1.059501, 4.238002

All variables have been entered into the model.

Summary of Forward Selection Procedure for Dependent Variable DSN

Step	Variable Entered	Number In	Partial R**2	Model R**2	C(p)	F	Prob> F
1	AGE	1	0.8074	0.8074	7.2538	155.1039	0.0001
2	TH	2	0.0268	0.8342	3.3652	5.8295	0.0210
3	CUMESAL	3	0.0062	0.8405	4.0000	1.3652	0.2505

Backward Elimination Procedure for Dependent Variable DSN

Step 0 All Variables Entered R-square = 0.84046086 C(p) = 4.00000000

	DF	Sum of Squares	Mean Square	F	Prob> F
Regression	3	0.33540879	0.11180293	61.46	0.0001
Error	35	0.06366844	0.00181910		
Total	38	0.39907723			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob> F
INTERCEP	-0.05017719	0.03871490	0.00305571	1.68	0.2034
AGE	0.02062992	0.00233545	0.14194129	78.03	0.0001
TH	0.00392011	0.00274992	0.00369669	2.03	0.1629
CUMESAL	0.00000001	0.00000001	0.00248352	1.37	0.2505

Bounds on condition number: 2.389366, 16.9151

Step 1 Variable CUMESAL Removed R-square = 0.83423771 C(p) = 3.36524639

	DF	Sum of Squares	Mean Square	F	Prob> F
Regression	2	0.33292527	0.16646264	90.59	0.0001
Error	36	0.06615196	0.00183755		
Total	38	0.39907723			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob> F
INTERCEP	-0.07279728	0.03369669	0.00857622	4.67	0.0375
AGE	0.02235521	0.00181859	0.27766797	151.11	0.0001
TH	0.00563853	0.00233535	0.01071194	5.83	0.0210

Bounds on condition number: 1.059501, 4.238002

All variables left in the model are significant at the 0.1000 level.

Summary of Backward Elimination Procedure for Dependent Variable DSN

Step	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob> F
1	CUMESAL	2	0.0062	0.8342	3.3652	1.3652	0.2

Stepwise Procedure for Dependent Variable DSN

Step 1 Variable AGE Entered R-square = 0.80739593 C(p) = 7.25384676

	DF	Sum of Squares	Mean Square	F	Prob> F
Regression	1	0.32221333	0.32221333	155.10	0.0001
Error	37	0.07686390	0.00207740		
Total	38	0.39907723			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob> F
INTERCEP	0.00160524	0.01449521	0.00002548	0.01	0.9124
AGE	0.02339575	0.00187856	0.32221333	155.10	0.0001

Bounds on condition number: 1, 1

Step 2 Variable TH Entered R-square = 0.83423771 C(p) = 3.36524639

	DF	Sum of Squares	Mean Square	F	Prob> F

Regression	2	0.33292527	0.16646264	90.59	0.0001
Error	36	0.06615196	0.00183755		
Total	38	0.39907723			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob> F
INTERCEP	-0.07279728	0.03369669	0.00857622	4.67	0.0375
AGE	0.02235521	0.00181859	0.27766797	151.11	0.0001
TH	0.00563853	0.00233535	0.01071194	5.83	0.0210

Bounds on condition number: 1.059501, 4.238002

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable DSN

Step	Variable Entered/ Removed		Partial R**2	Model R**2	C(p)	F	Prob> F
1	AGE	1	0.8074	0.8074	7.2538	155.1039	0.0001
2	TH	2	0.0268	0.8342	3.3652	5.8295	0.001

Number in Model	R-square	Adjusted R-square	C(p)	Root MSE	Variables in Model
1	0.80739593	0.80219041	7.25385	0.04557853	AGE
1	0.48461521	0.47068589	78.06610	0.07455786	CUMESAL
1	0.13846268	0.11517788	154.00569	0.09639725	TH
2	0.83423771	0.82502869	3.36525	0.04286670	AGE TH
2	0.83119775	0.82181985	4.03216	0.04325799	AGE CUMESAL
2	0.48478711	0.45616418	80.02838	0.07557368	TH CUMESAL
3	0.84046086	0.82678607	4.00000	0.04265089	AGE TH CUMESAL

Correlation Analysis

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
DSN	39	0.15758	0.10248	6.14550	0.02300	0.49000
AGE	39	6.66667	3.93589	260.00000	1.00000	17.00000
TH	39	14.42564	3.06497	562.60000	7.80000	19.80000
CUMESAL	39	1081320	988399	42171493	53125	4041889

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho= 0

	DSN	AGE	TH	CUMESAL
DSN	1.00000 0.0	0.89855 0.0001	0.37211 0.0197	0.69614 0.0001
AGE	0.89855 0.0001	1.00000 0.0	0.23698 0.1463	0.64328 0.0001
TH	0.37211 0.0197	0.23698 0.1463	1.00000 0.0	0.55025 0.0003
CUMESAL	0.69614 0.0001	0.64328 0.0001	0.55025 0.0003	1.00000 0.0

APPENDIX B : Typical SAS Code Files, Log Files, and Output of the Selected Models for the Prediction of Decrease in PSE Values

Statistical Analysis System (SAS) Codes

```
Title1 ' FDBIT PAVEMENTS' ;
Title2 ' Prediction of del(PSE)' ;
options ls= 80 ps= 60;
data;
input age th cumESAL pse dpse DL1 DL2 DL3;
age1 =  age**1.5;
dsn =  age*0.021872+ th*0.001025;
expdsn =  exp(dsn);
cards;
3 13.8 129687 8 1 0 1 0
5 9.8 301154 7 1 0 0 1
1 11.8 53125 6 0 1 0 0
6 10.3 925514 8 2 0 0 1
6 12.4 810048 7 1 0 1 0

5 19 298817 6 1 1 0 0
6 14.4 385079 6 1 0 0 1
5 14.7 461194 8 2 0 1 0

6 11.4 238113 6 1 0 1 0
6 17.5 394265 9 4 0 0 1

6 15.6 1326061 9 2 0 0 1
6 18.8 1722453 7 2 1 0 0
6 17 1636727 7 2 0 0 1
5 14.1 531323 8 1 0 1 0
5 12.2 675370 8 1 1 0 0
5 12.2 675370 8 1 1 0 0
6 15.6 2135526 9 2 0 0 1
6 18 1722453 9 2 1 0 0

2 14.6 995321 7 1 1 0 0
7 14.9 2087479 8 1 1 0 0
5 17.4 2388042 8 2 0 1 0
2 17.6 1119591 7 1 0 1 0
7 10.5 176723 8 2 0 1 0

3 10 227849 6 0 1 0 0
3 12.3 267089 7 0 1 0 0
```

```
3 12.3 267089 7 0 1 0 0
3 12.3 365729 7 0 1 0 0

proc reg;
model dpse =  age1 expdsn th pse DL1 DL2 DL3;
model dpse =  age1 expdsn th pse DL1 DL2 DL3/ noint;
model dpse =  age1 dsn pse DL1 DL2 DL3;
model dpse =  age1 dsn pse DL1 DL2 DL3/noint;
model dpse =  age1 dsn th pse DL1 DL2 DL3;
model dpse =  age1 dsn th pse DL1 DL2 DL3/noint;
model dpse =  age1 expdsn pse DL1 DL2 DL3;
model dpse =  age1 expdsn pse DL1 DL2 DL3/noint;
proc stepwise;
model dpse =  age1 expdsn th pse DL1 DL2 DL3/F B stepwise;
proc rsquare;
model dpse =  age1 expdsn th pse DL1 DL2 DL3/adjrsq cp rmse;
proc corr;
run;
```

The SAS System : Log File

```
NOTE: Copyright ©1989-1996 by SAS Institute Inc., Cary, NC, USA.
NOTE: SAS (r) Proprietary Software Release 6.12  TS020
      Licensed to KANSAS STATE UNIVERSITY, Site 0003010005.

This message is contained in the SAS news file, and is presented upon
initialization.  Edit the files "news" in the "misc/base" directory to
display site-specific news and information in the program log.
The command line option "-nonews" will prevent this display.

NOTE: AUTOEXEC processing beginning; file is /usr/local/lic/sas612/autoexec.sas.

NOTE: SAS initialization used:
      real time           1.290 seconds
      cpu time            0.639 seconds

NOTE: AUTOEXEC processing completed.

1
2          Title1 'FDBIT PAVEMENTS';
3          Title3 'Prediction of del(PSE)';
```

```
options ls= 80 ps= 60;
data;
input age th cumESAL pse dpse DL1 DL2 DL3;
age1 = age**1.5;
dsn = age*0.021872+ th*0.001025;
expdsn = exp(dsn);
cards;
NOTE: SAS went to a new line when INPUT statement reached past the end of a
      line.
NOTE: The data set WORK.DATA1 has 27 observations and 11 variables.
NOTE: DATA statement used:
      real time           0.450 seconds
      cpu time            0.188 seconds
proc reg;
model dpse = age1 expdsn th pse DL1 DL2 DL3;
model dpse = age1 expdsn th pse DL1 DL2 DL3/noint;
model dpse = age1 dsn pse DL1 DL2 DL3;
model dpse = age1 dsn pse DL1 DL2 DL3/noint;
model dpse = age1 dsn th pse DL1 DL2 DL3;
model dpse = age1 dsn th pse DL1 DL2 DL3/noint;
model dpse = age1 expdsn pse DL1 DL2 DL3
model dpse = age1 expdsn pse DL1 DL2 DL3/noint;
NOTE: The PROCEDURE REG printed pages 1-8.
NOTE: PROCEDURE REG used:
      real time           0.930 seconds
      cpu time            0.258 seconds
proc stepwise;
model dpse = age1 expdsn th pse DL1 DL2 DL3/F B stepwise;
NOTE: 27 observations read.
NOTE: 27 observations used in computations.
NOTE: The PROCEDURE STEPWISE printed pages 9-16.
NOTE: PROCEDURE STEPWISE used:
      real time           0.340 seconds
      cpu time            0.114 seconds
proc rsquare;
model dpse = age1 expdsn th pse DL1 DL2 DL3/adjrsq cp rmse;
NOTE: The PROCEDURE RSQUARE printed pages 17-19.
NOTE: PROCEDURE RSQUARE used:
      real time           0.370 seconds
      cpu time            0.103 seconds

proc corr;
```

```
58         run;
NOTE: PROCEDURE CORR used:
     real time           0.060 seconds
     cpu time            0.041 seconds

59
NOTE: The SAS System used:
     real time           3.710 seconds
     cpu time            1.436 seconds

NOTE: SAS Institute Inc., SAS Campus Drive, Cary, NC USA 27513-2414
```

Output: FDBIT PAVEMENTS

Model: MODEL2 Selected Model

NOTE: No intercept in model.
Dependent Variable: DPSE

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob> F
Model	7	59.41349	8.48764	37.011	0.0001
Error	20	4.58651	0.22933		
U Total	27	64.00000			

Root MSE	0.47888	R-square	0.7835
Dep Mean	1.25926	Adj R-sq	0.7717
C.V.	38.02865		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter= 0	Prob > |T|
AGE1	1	0.216685	0.23914791	0.906	0.0105
EXPDSN	1	-20.820483	29.99936689	-0.694	0.0512
TH	1	0.138074	0.04958408	2.785	0.0114
PSE	1	0.328737	0.10999755	2.989	0.0073
DL1	1	17.655164	30.62681612	0.576	0.0875
DL2	1	18.064029	30.63639956	0.590	0.0975
DL3	1	18.381956	30.63624915	0.600	0.0885

In	R-square	Adjusted R-square	C(p)	Root MSE	Variables in Model
1	0.4412660	0.4189166	28.6161	0.6880954	EXPDSN
1	0.4242109	0.4011794	30.1917	0.6985184	PSE
1	0.4063750	0.3826300	31.8394	0.7092547	AGE1
1	0.2644231	0.2350000	44.9529	0.7895146	DL1
1	0.2509777	0.2210168	46.1950	0.7966976	TH
1	0.2447552	0.2145455	46.7699	0.8000000	DL3
1	0.0071885	-.0325239	68.7164	0.9172327	DL2
2	0.6033276	0.5702715	15.6448	0.5917340	EXPDSN PSE
2	0.5872546	0.5528591	17.1296	0.6036034	AGE1 PSE
2	0.5638447	0.5274984	19.2922	0.6204847	AGE1 TH
2	0.5600446	0.5233817	19.6433	0.6231819	EXPDSN TH
2	0.5518015	0.5144516	20.4048	0.6289929	PSE DL1
2	0.5462266	0.5084121	20.9198	0.6328926	TH PSE
2	0.5395534	0.5011828	21.5363	0.6375293	PSE DL3
2	0.5223561	0.4825525	23.1250	0.6493257	EXPDSN DL1
2	0.5062316	0.4650842	24.6146	0.6601949	EXPDSN DL3
2	0.5056879	0.4644952	24.6648	0.6605583	TH DL1
2	0.4930660	0.4508215	25.8308	0.6689386	AGE1 DL1
2	0.4815786	0.4383768	26.8920	0.6764754	AGE1 EXPDSN
2	0.4766080	0.4329920	27.3512	0.6797106	AGE1 DL3
2	0.4732349	0.4293378	27.6628	0.6818974	TH DL3
2	0.4451075	0.3988665	30.2612	0.6998661	EXPDSN DL2
2	0.4278426	0.3801628	31.8562	0.7106705	PSE DL2
2	0.4103105	0.3611697	33.4758	0.7214765	AGE1 DL2
2	0.3332605	0.2776989	40.5937	0.7671647	DL1 DL3
2	0.3332605	0.2776989	40.5937	0.7671647	DL2 DL3
2	0.3332605	0.2776989	40.5937	0.7671647	DL1 DL2
2	0.2604255	0.1987942	47.3223	0.8079816	TH DL2
3	0.6887634	0.6481673	9.7522	0.5354236	AGE1 TH PSE
3	0.6866526	0.6457812	9.9472	0.5372362	TH PSE DL1
3	0.6837208	0.6424670	10.2180	0.5397437	EXPDSN TH PSE
3	0.6657695	0.6221742	11.8764	0.5548496	TH PSE DL3
3	0.6630709	0.6191236	12.1257	0.5570850	AGE1 TH DL1
3	0.6609352	0.6167093	12.3230	0.5588478	EXPDSN PSE DL1
3	0.6593062	0.6148678	12.4735	0.5601887	EXPDSN TH DL1
3	0.6494018	0.6036716	13.3884	0.5682731	EXPDSN PSE DL3

3	0.6469807	0.6009347	13.6121	0.5702318	AGE1 PSE DL1
3	0.6389619	0.5918700	14.3529	0.5766718	AGE1 TH DL3
3	0.6357582	0.5882484	14.6488	0.5792248	EXPDSN TH DL3
3	0.6354413	0.5878901	14.6781	0.5794767	AGE1 PSE DL3
3	0.6212076	0.5717998	15.9930	0.5906808	AGE1 EXPDSN PSE
3	0.6060122	0.5546225	17.3968	0.6024120	EXPDSN PSE DL2
3	0.5899411	0.5364551	18.8814	0.6145757	AGE1 PSE DL2
3	0.5868383	0.5329477	19.1681	0.6168964	PSE DL1 DL2
3	0.5868383	0.5329477	19.1681	0.6168964	PSE DL2 DL3
3	0.5868383	0.5329477	19.1681	0.6168964	PSE DL1 DL3
3	0.5694920	0.5133388	20.7705	0.6297132	AGE1 TH DL2
3	0.5679853	0.5116355	20.9097	0.6308142	AGE1 EXPDSN DL
3	0.5655092	0.5088365	21.1385	0.6326194	EXPDSN TH DL2
3	0.5642544	0.5074180	21.2544	0.6335323	AGE1 EXPDSN TH
3	0.5637505	0.5068484	21.3009	0.6338984	TH DL2 DL3
3	0.5637505	0.5068484	21.3009	0.6338984	TH DL1 DL3
3	0.5637505	0.5068484	21.3009	0.6338984	TH DL1 DL2
3	0.5515024	0.4930028	22.4324	0.6427355	TH PSE DL2
3	0.5514541	0.4929481	22.4369	0.6427701	AGE1 EXPDSN DL3
3	0.5426597	0.4830066	23.2493	0.6490407	EXPDSN DL1 DL2
3	0.5426597	0.4830066	23.2493	0.6490407	EXPDSN DL1 DL3
3	0.5426597	0.4830066	23.2493	0.6490407	EXPDSN DL2 DL3
3	0.5153431	0.4521270	25.7728	0.6681430	AGE1 DL2 DL3
3	0.5153431	0.4521270	25.7728	0.6681430	AGE1 DL1 DL3
3	0.5153431	0.4521270	25.7728	0.6681430	AGE1 DL1 DL2
3	0.4855279	0.4184228	28.5272	0.6883878	AGE1 EXPDSN DL2
4	0.7615447	0.7181892	5.0286	0.4791906	AGE1 TH PSE DL1
4	0.7573542	0.7132368	5.4157	0.4833828	EXPDSN TH PSE DL1
4	0.7436757	0.6970713	6.6794	0.4968207	AGE1 TH PSE DL3
4	0.7397534	0.6924359	7.0417	0.5006074	EXPDSN TH PSE DL3
4	0.7206141	0.6698167	8.8098	0.5186890	TH PSE DL1 DL2
4	0.7206141	0.6698167	8.8098	0.5186890	TH PSE DL1 DL3
4	0.7206141	0.6698167	8.8098	0.5186890	TH PSE DL2 DL3
4	0.6928186	0.6369674	11.3776	0.5438790	AGE1 TH PSE DL2
4	0.6925526	0.6366530	11.4021	0.5441144	AGE1 EXPDSN TH PSE
4	0.6876838	0.6308991	11.8519	0.5484058	EXPDSN TH PSE DL2
4	0.6853437	0.6281335	12.0681	0.5504565	AGE1 TH DL1 DL3
4	0.6853437	0.6281335	12.0681	0.5504565	AGE1 TH DL2 DL3
4	0.6853437	0.6281335	12.0681	0.5504565	AGE1 TH DL1 DL2
4	0.6833599	0.6257889	12.2514	0.5521890	AGE1 EXPDSN PSE DL1
4	0.6820114	0.6241953	12.3759	0.5533636	EXPDSN TH DL1 DL2

4	0.6820114	0.6241953	12.3759	0.5533636	EXPDSN TH DL1 DL3
4	0.6820114	0.6241953	12.3759	0.5533636	EXPDSN TH DL2 DL3
4	0.6756293	0.6166528	12.9655	0.5588890	EXPDSN PSE DL1 DL2
4	0.6756293	0.6166528	12.9655	0.5588890	EXPDSN PSE DL1 DL3
4	0.6756293	0.6166528	12.9655	0.5588890	EXPDSN PSE DL2 DL3
4	0.6712764	0.6115085	13.3676	0.5626266	AGE1 EXPDSN PSE DL3
4	0.6645175	0.6035207	13.9920	0.5683812	AGE1 EXPDSN TH DL1
4	0.6625829	0.6012343	14.1708	0.5700177	AGE1 PSE DL2 DL3
4	0.6625829	0.6012343	14.1708	0.5700177	AGE1 PSE DL1 DL2
4	0.6625829	0.6012343	14.1708	0.5700177	AGE1 PSE DL1 DL3
4	0.6397344	0.5742316	16.2815	0.5890012	AGE1 EXPDSN TH DL3
4	0.6240152	0.5556544	17.7337	0.6017137	AGE1 EXPDSN PSE DL2
4	0.5901095	0.5155840	20.8659	0.6282590	AGE1 EXPDSN DL1 DL2
4	0.5901095	0.5155840	20.8659	0.6282590	AGE1 EXPDSN DL1 DL3
4	0.5901095	0.5155840	20.8659	0.6282590	AGE1 EXPDSN DL2 DL3
4	0.5700067	0.4918261	22.7230	0.6434809	AGE1 EXPDSN TH DL2
5	0.7782900	0.7255019	5.4817	0.4729325	AGE1 TH PSE DL1 DL2
5	0.7782900	0.7255019	5.4817	0.4729325	AGE1 TH PSE DL1 DL3
5	0.7782900	0.7255019	5.4817	0.4729325	AGE1 TH PSE DL2 DL3
5	0.7746173	0.7209548	5.8210	0.4768335	EXPDSN TH PSE DL1 DL2
5	0.7746173	0.7209548	5.8210	0.4768335	EXPDSN TH PSE DL1 DL3
5	0.7746173	0.7209548	5.8210	0.4768335	EXPDSN TH PSE DL2 DL3
5	0.7668402	0.7113259	6.5394	0.4849906	AGE1 EXPDSN TH PSE DL1
5	0.7478856	0.6878583	8.2905	0.5043190	AGE1 EXPDSN TH PSE DL3
5	0.6995658	0.6280338	12.7543	0.5505303	AGE1 EXPDSN PSE DL1 DL2
5	0.6995658	0.6280338	12.7543	0.5505303	AGE1 EXPDSN PSE DL1 DL3
5	0.6995658	0.6280338	12.7543	0.5505303	AGE1 EXPDSN PSE DL2 DL3
5	0.6968404	0.6246595	13.0060	0.5530217	AGE1 EXPDSN TH PSE DL2
5	0.6868211	0.6122547	13.9316	0.5620859	AGE1 EXPDSN TH DL2 DL3
5	0.6868211	0.6122547	13.9316	0.5620859	AGE1 EXPDSN TH DL1 DL3
5	0.6868211	0.6122547	13.9316	0.5620859	AGE1 EXPDSN TH DL1 DL2
6	0.7835040	0.7185553	7.0000	0.4788793	AGE1 EXPDSN TH PSE DL2 DL3
6	0.7835040	0.7185553	7.0000	0.4788793	AGE1 EXPDSN TH PSE DL1 DL3
6	0.7835040	0.7185553	7.0000	0.4788793	AGE1 EXPDSN TH PSE DL1 DL2

NOTE: Models of not full rank are not included

Correlation Analysis

Simple Statistics

Variable	Mean	Std Dev	Sum	Minimum	Maximum
AGE	4.77778	1.64862	129.00000	1.00000	7.00000
TH	14.09259	2.81109	380.50000	9.80000	19.00000
CUMESAL	826563	696944	22317191	53125	2388042
PSE	7.44444	0.97402	201.00000	6.00000	9.00000
DPSE	1.25926	0.90267	34.00000	0	4.00000
DL1	0.44444	0.50637	12.00000	0	1.00000
DL2	0.29630	0.46532	8.00000	0	1.00000
DL3	0.25926	0.44658	7.00000	0	1.00000
AGE1	10.92259	5.00700	294.90990	1.00000	18.52026
DSN	0.11894	0.03667	3.21150	0.03397	0.16838
EXPDSN	1.12703	0.04078	30.42982	1.03455	1.18338

Pearson's Correlation Coefficients : FDBIT Pavements

	Age	Th	C.ESAL	PSE	DSN	Age1	EXPDSN	DPSE
Age	1.00	0.18	0.65	0.42	0.61	0.99	0.42	0.35
Th	-	1.00	0.51	0.25	0.38	0.17	0.25	0.51
C.ESAL	-	-	1.00	0.45	0.69	0.60	0.55	0.55
PSE	-	-	-	1.00	0.43	0.42	0.28	0.65
DSN	-	-	-	-	1.00	0.58	0.99	0.49
Age1	-	-	-	-	-	1.00	0.43	0.68
EXPDSN	-	-	-	-	-	-	1.00	0.61
DPSE	-	-	-	-	-	-	-	1.00