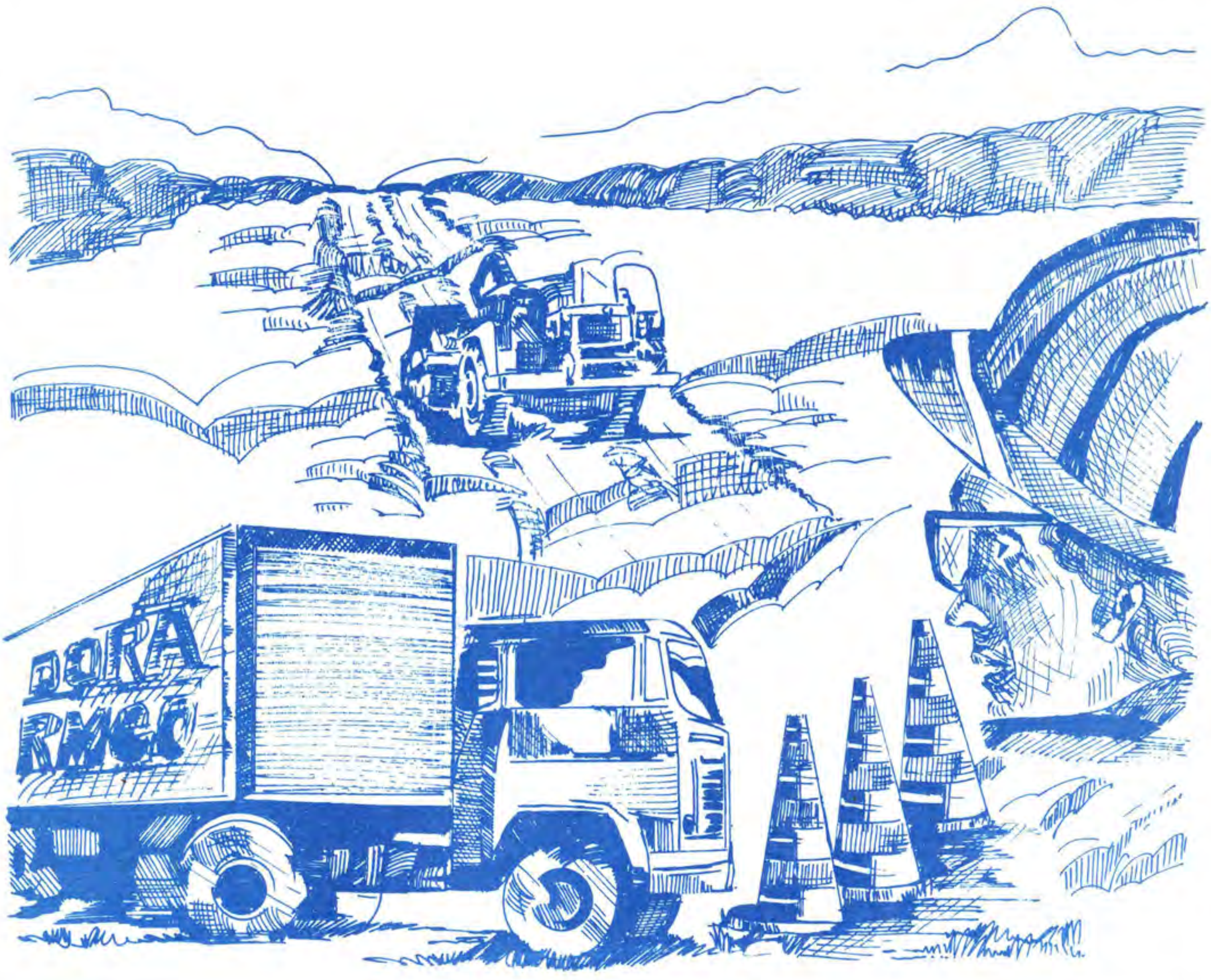
REPÚBLICA FEDERATIVA DO BRASIL
MINISTÉRIO DOS TRANSPORTES
United Nations Development Programme (UNDP)

Research on the Interrelationships Between Costs of Highway Construction, Maintenance and Utilization

Final Report - 1981



VOLUME 7 — Study of Pavement Maintenance and Deterioration

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VOLUME 7 — Study of Pavement Maintenance and Deterioration

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Conteúdo: v.1 Summary of the ICR Research v.2 Methods and organization v.3 Instrumentation v.4 Statistical guide v.5 Study of road user costs v.6 Study of vehicle behavior and performance v.7 Study of pavement maintenance and deterioration v.8 Highway cost model (MICR) v.9 Model of time and fuel consumption (MTC) v.10 Model for simulating traffic (MST) v.11 Fundamental equations v.12 Index to PICR documents.

1. Rodovias - custos - Brasil 2. Rodovias conservação - Brasil 3. Rodovias - utilização - Brasil - I. Título.

PREFACE

This research project was funded through an agreement signed in January, 1975 by the Brazilian Government and the United Nations Development Programme (UNDP). The Ministry of Transportation, acting through the Brazilian Transportation Planning Agency (GEIPOT), assumed the responsibility for the project on behalf of the Brazilian Government and the International Bank for Reconstruction and Development (IBRD) acted as the executing agency for UNDP.

The research was carried out by GEIPOT and the National Highway Department (DNER), acting through its Road Research Institute (IPR). Funding from the Brazilian Government was channeled through the Institute for Economic and Social Planning (IPEA) and the Secretariat for International Economic and Technical Cooperation (SUBIN), along with the Ministry of Transportation.

The World Bank contracted the Texas Research and Development Foundation (TRDF) to organize the international technical staff and to select and purchase the imported equipment needed for the research. The participation of the TRDF continued until December of 1979.

This report is comprised of twelve volumes (each edited in both English and Portuguese) which summarize the concepts, methods and results obtained by December, 1981 by the project entitled "Research on the Interrelationships Between Costs of Highway Construction, Maintenance and Utilization (PICR)". It includes a documentary index volume which will aid researchers in locating topics discussed in this report and in numerous other documents of the PICR. This report contains much detailed analysis which is being presented for the first time, and also incorporates relevant parts of earlier reports and documents produced under the 1975 Agreement, updating them through the inclusion of new results and findings.

A special mention is due the Highway Departments of the States of Minas Gerais and Goiás, the Universities of Aston, Birmingham and Texas, and the Western Australia Main Roads Department which placed some of their best and most experienced personnel at the service of this project to fill many key positions on the research staff.

Finally, thanks are due to the Transport and Road Research Laboratory for its assistance during the initial stages of the project, along with specialists from various countries who periodically visited Brazil to discuss the work being done in the PICR and to assist the permanent research staff in conducting analyses.

JOSÉ MENEZES SENNA
President

VOLUMES IN THIS REPORT

VOLUME 1 - SUMMARY OF THE ICR RESEARCH

VOLUME 2 - METHODS AND ORGANIZATION

VOLUME 3 - INSTRUMENTATION

VOLUME 4 - STATISTICAL GUIDE

VOLUME 5 - STUDY OF ROAD USER COSTS

VOLUME 6 - STUDY OF VEHICLE BEHAVIOR AND PERFORMANCE

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* Volume 1 contains a brief description of the contents of each volume, while Volume 12 provides a subject index to this report and all other PICR documents, including technical memoranda and working documents.

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SUMMARY

The primary objective of the Pavement and Maintenance Studies was to develop models to describe pavement performance and behavior for Brazilian paved and unpaved roads. The models are needed to relate road user costs and road maintenance costs to roadway conditions in order to predict total highway transport costs.

The experimental design sampling matrix addresses the major factors considered to influence pavement performance and behavior. Existing road sections were selected and used to satisfy the requirements of the sampling matrix. Detailed information on traffic, vehicle weights and material characteristics was collected for each section. The same data were collected on unpaved roads as well as information related to blading and regravelling. On paved roads, the dependent variables measured were roughness, rut depth, cracking and patching. The dependent variables studied on unpaved roads included roughness, rut depth, and gravel loss.

The results presented in this report are based on data files that were closed in 1981. The data collection effort will continue and future analyses of the expanded data base are expected to change some of the equations. Because of the preliminary nature of the relationships presented, no consideration was given to modifying the equations so that they could be directly implemented. Therefore, engineering judgement and experience should be used in any application of the equations. Finally, the application of the models is defined by factor ranges and the study environment. Extreme care should be taken in extrapolating the models beyond these limits.

CHAPTER 1 - INTRODUCTION

For many years highway engineers and administrators in Brazil have relied on pavement performance models developed mainly in North America and Europe for planning, designing, building and rehabilitating pavements. This is largely a result of the extensive general transportation development and paved highway networks built on those two continents, along with a number of outstanding pavement research projects conducted in those regions.

However, such models have some inherent limitations and are not necessarily directly transferable. Performance prediction models must reflect the conditions to which they are applied and must either be developed from local data or modified and verified based on such data. Brazil represents an excellent example of this need. It has different climatic conditions than the Northern Hemisphere, different subgrade soils and other distinctive factors which affect pavement performance and must therefore be reflected in any useful performance prediction models.

Pavement surface condition, as measured by its roughness, is a major factor influencing road user costs. It is thus important to predict pavement roughness from alternative construction and maintenance standards, so that user costs can be evaluated for each alternative. Maintenance is primarily performed as a response to excessive pavement roughness, cracking and rutting. The latter is related to roughness and has been assigned limiting levels by highway agencies because of the safety hazard it represents to vehicles, especially under wet conditions. Pavement cracking is a risk to the capital invested and, if high levels of cracking are allowed to develop, pavement reconstruction may be required, in lieu of routine maintenance. Therefore, the amount and consequently the cost of timely maintenance will depend on the potential evolution of pavement roughness, cracking and rutting. On the other hand, this potential evolution of pavement attributes depends on the pavement structure, which, in turn, is related to construction costs. Therefore, pavement performance prediction models are an essential technological tool for economic analysis of highways.

The lack of models to predict the performance and behavior of unpaved roads is also apparent (Visser, 1981). A need therefore exists to develop models that predict the deterioration of unpaved roads. These roads are highly susceptible to environmental influences such as rainfall, and different material types perform differently under these influences. Furthermore, performance is also dependent on the strength of the materials.

This volume describes the analysis conducted to develop deterioration prediction models for both paved and unpaved roads. The dependent variables in the paved road analysis are roughness, cracking and rutting, whereas in the unpaved road analysis predictive models were developed for roughness, rut depth, and gravel loss.

A number of details regarding methods and organization of the experiments are described in Chapter 5 of Volume 2 of these 1981 Reports and are therefore not repeated in the present volume.

CHAPTER 2 - PAVED ROAD ROUGHNESS ANALYSIS

2.1 INTRODUCTION

Since the AASHO Road Test, where the concept of pavement serviceability was developed by Carey and Irick (1960), increasing importance has been given to user-related pavement evaluation. This type of evaluation is concerned primarily with the overall function of the pavement, that is, how well it serves traffic or the riding public.

The serviceability of a pavement is largely a function of its roughness (Haas and Hudson, 1978), and several models can be found in the literature to estimate serviceability as a function of roughness (HRB, 1964; Walker and Hudson, 1973). Moreover, it has been demonstrated that roughness is the principal measurement of pavement condition directly related to vehicle operating costs (Hide *et al.*, 1975; Wyatt *et al.*, 1979). Consequently, a major effort is devoted in this study to develop (1) pavement roughness prediction models and (2) a procedure through which the roughness standard used can be transferred among different regions or countries, based on rod and level measurements of roadway profiles. The latter subject is discussed by Queiroz (1981a, 1981b). This chapter presents an empirical analysis of roughness data collected in order to develop roughness predictive models for asphaltic pavements.

2.2 ROUGHNESS PREDICTION MODELS

Roughness was expected to be a function of pavement structural variables, traffic loads and volumes, and environment. The pavement test sections in our study were located in a relatively narrow geographic area. There was very little variation in the environmental parameters, rainfall and temperature, and consequently these factors were not considered in the analysis. However, the implicit influence of the environment over time was considered since the pavement age was included and found to significantly affect roughness.

Traffic loads and volumes were combined to give the number of cumulative equivalent 80 kN axles. Seven groups of variables describing pavement strength were included in the analysis. These variables are: (a) pavement structural variables, consisting of the structural number, structural number corrected for the subgrade resistance; and subgrade, sub-base and base CBR; (b) Benkelman beam deflection; (c) Dynaflect deflection and curvature indexes; (d) a combination of (a) and (b); (e) a combination of (a) and (c); (f) a combination of (b) and (c); and (g) a combination of (a), (b), and (c).

The inference space for this analysis is governed by the ranges of the dependent and independent variables which are listed in Table 2.1. The definition of symbols used in this part of the study is given in Table 2.2. Table 2.3 shows the correlation matrix of variables included in the analysis.

The roughness prediction models which best fits the data are presented next, according to the group of independent variables used.

1. <u>Equation including structural number</u>

$$LQI = 1.487 - 0.1383\ RH + 0.00795\ AGE + 0.0224\ (LN/SNC)^2 \tag{2.1}$$

R squared : 0.259

Standard error for residuals : 0.135

where

LQI = decimal logarithm of quarter-car index, i. e., $\log_{10} QI$*;

RH = state of rehabilitation indicator:
= 0 as constructed,
= 1 overlayed;

AGE = number of years since construction or overlay;

LN = logarithm to the base 10 of the number (N) of cumulative equivalent axles; and

SNC = structural number corrected for the subgrade strength.

TABLE 2.1 - SUMMARY STATISTICS OF VARIABLES USED IN THE ANALYSIS OF ROUGHNESS DATA

Variable	Mean	Standard Deviation	Minimum	Maximum
QI*	39.0	15.2	18.0	95.0
SN	2.8	1.0	1.0	6.5
SNC	4.6	1.1	1.8	7.5
LN	5.5	0.7	2.7	7.2
B (0.01 mm)	64.5	24.3	32.0	128.0
D (0.001 in.)	0.91	0.28	0.40	1.56
SCI (0.001 in.)	0.33	0.13	0.11	0.77
BCI (0.001 in.)	0.12	0.04	0.05	0.20
AGE (years)	7.1	4.6	1.1	20.3
P (%)	0.08	0.50	0.00	4.60

NOTE: Variable symbols are defined in Table 2.2.

TABLE 2.2 - DEFINITION OF SYMBOLS USED IN THE ANALYSIS OF ROUGHNESS DATA

Symbol	Variable
QI*	Roughness measured with a Maysmeter and converted into quarter-car index through a calibration equation (counts/km).
SN	Pavement structural number.
SNC	Structural number corrected for the subgrade resistance.
LN	Logarithm to the base 10 of the number of 80 KN cumulative equivalent axles.
B	Benkelman beam mean deflection (0.01mm).
D, SCI, BCI	Dynaflect maximum deflection, surface curvature index, and base curvature index (0.001 in.).
AGE	Surface age since construction or overlay (years).
P	Percent area of the pavement which received repairs in the form of deep patches (%).
ST	Surface type dummy variable: ST = 0 asphaltic concrete; ST = 1 double surface treatment.
RH	State of rehabilitation dummy variable: RH = 0 as constructed; RH = 1 overlayed.

TABLE 2.3 - CORRELATION MATRIX OF VARIABLES USED IN THE ANALYSIS OF ROUGHNESS DATA

Variable	QI*	SN	SNC	LN	B	D	AGE	P
QI*	1.00	-.32	-.32	.00	.48	.28	.24	.26
SN		1.00	.97	.29	-.17	-.36	.05	-.06
SNC			1.00	.28	-.14	-.32	-.01	-.07
LN				1.00	-.03	-.06	.44	.05
B					1.00	.60	.03	.33
D						1.00	-.01	.12
AGE							1.00	.15
P								1.00

NOTE: Variable symbols are defined in Table 2.2.

Detailed statistical results pertaining to Equation 2.1 are given in Table 2.4. The ridge trace, in Figure 2.1, shows the high stability of the regression coefficients (Chatterjee and Price, 1977). Included in this figure is the coefficient for ST, a surface type indicator variable, which was subsequently deleted. This coefficient value is very close to zero, as can be observed in Figure 2.1, and is not significant even at the 25 percent level, as demonstrated by its F-value.

Assuming normality of residuals, an approximation to the 95 percent confidence interval about the mean roughness predicted by Equation 2.1 is:

$$CI = LQI \pm 0.27 \text{ or } 0.54QI^* \text{ to } 1.86\ QI^*$$

As an example, if the roughness value estimated from Equation 2.1 is 60, the corresponding 95 percent confidence interval lies between QI* values of 32 and 112 counts/km.

2. Equation including Benkelman beam deflection

$$QI^* = 21.8 - 7.52\ RH + 5.16\ ST + 0.515\ AGE + 7.22 \times 10^{-5}(B \times LN)^2 \qquad (2.2)$$

R squared : 0.484

Standard error for residuals : 10.584

where

QI* = quarter-car index (counts/km);

ST = surface type dummy variable:

= 0 asphaltic concrete;

= 1 surface treatment; and

B = Benkelman beam deflection (0.01 mm).

Other symbols were defined previously. Detailed statistical results for Equation 2.2 are given in Table 2.5. All regression coefficients

TABLE 2.4 - REGRESSION ANALYSIS RESULTS FOR EQUATION 2.1

a) Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	3	0.4687	0.1562	8.63
Residual	74	1.3399	0.0181	

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	1.47842		
RH	-0.13827	0.04726	8.56
$(LN/SNC)^2$	0.02244	0.01222	3.37
AGE	0.00795	0.00347	5.24

R squared : 0.259
Standard error for residuals: 0.135

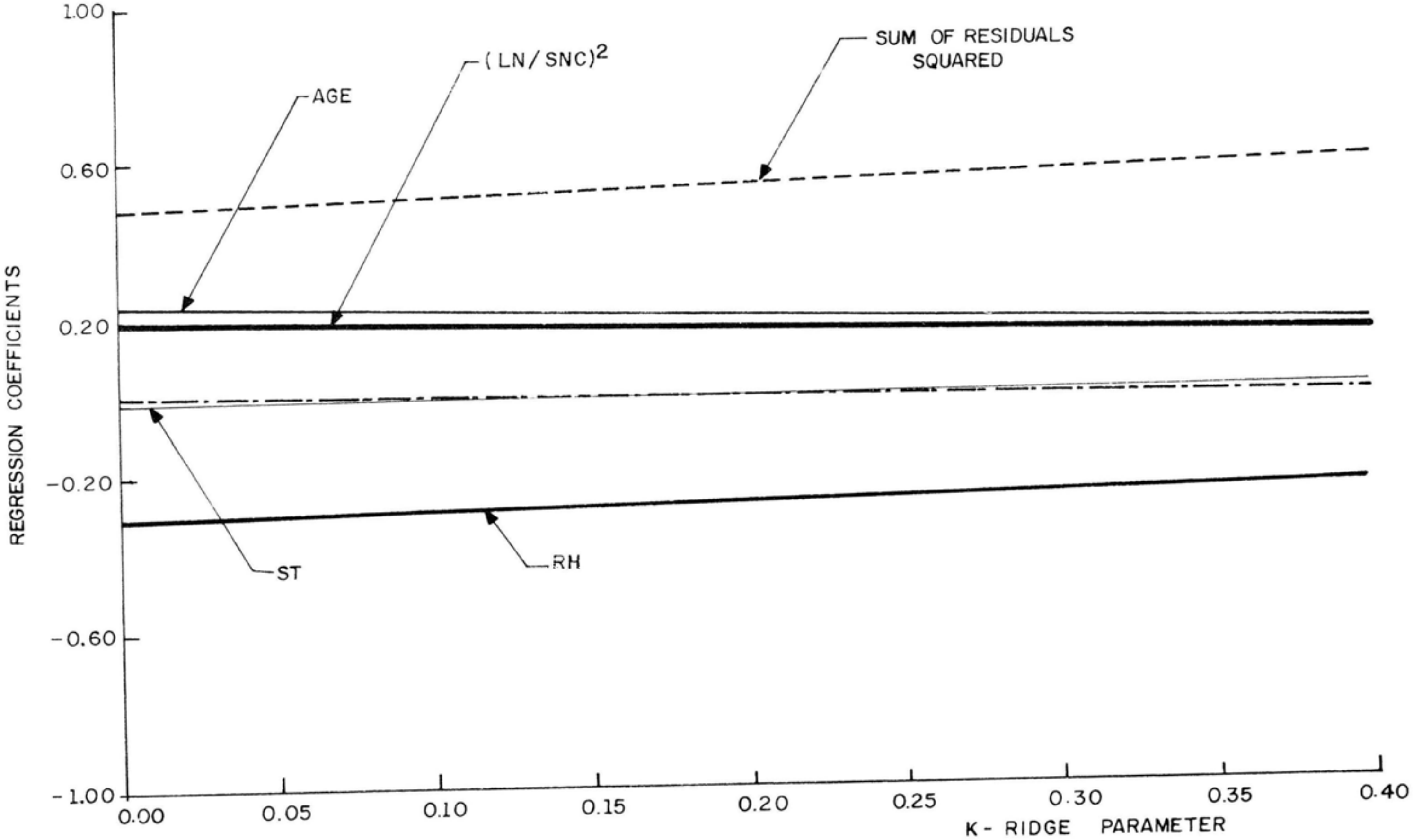

FIGURE 2.1- RIDGE TRACE FOR EQUATION 2.1.

TABLE 2.5 - REGRESSION ANALYSIS RESULTS FOR EQUATION 2.2

a) Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	4	7672.69	1918.17	17.12
Residual	73	8177.77	112.02	

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	21.762	-	
RH	-7.521	3.727	4.07
ST	5.162	2.606	3.92
AGE	0.515	0.271	3.62
$(B \times LN)^2$	7.215×10^{-5}	1.077×10^{-5}	4.49

Multiple correlation coefficient squared: 0.484
Standard error for residuals : 10.584

are very stable. The approximate 95 percent confidence interval for QI* in Equation 2.2 is:

$$CI = QI^* \pm 21.1$$

3. Equation including Dynaflect deflection

$$LQI = 1.391 - 0.1315\ RH + 0.0414\ P + 0.00751\ AGE + 0.0248\ D \times LN \qquad (2.3)$$

R squared : 0.318
Standard error for residuals : 0.130

where

LQI = logarithm to the base 10 of quarter-car index;
P = percent area which received repairs in the form of deep patches; and
D = Dynaflect maximum deflection (0.001 in.).

Other symbols were defined previously. Detailed regression analysis results are given in Table 2.6. All regression coefficients are very stable. The approximate 95 percent confidence interval is:

$$CI = LQI \pm 0.26 \text{ or } 0.55\ QI \text{ to } 1.82\ QI$$

4. Equation including structural number and Benkelman beam deflection

$$QI^* = 12.63 - 5.16\ RH + 3.31\ ST + 0.393\ AGE + 8.66\ (LN/SNC) + 7.17 \times 10^{-5}\ (B \times LN)^2 \qquad (2.4)$$

R squared : 0.525
Standard error for residuals : 10.223

TABLE 2.6 - REGRESSION ANALYSIS RESULTS FOR EQUATION 2.3

a) Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	4	0.575	0.1439	8.52
Residual	73	1.233	0.0169	

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	1.39137	-	
RH	-0.13153	0.04547	8.37
P	0.04142	0.02989	1.92
AGE	0.00751	0.00334	5.06
DLN	0.02482	0.00932	7.09

Multiple correlation coefficient squared: 0.318

Standard error for residuals : 0.130

where

QI* = quarter-car index (counts/km);
RH = state of rehabilitation indicator:
= 0 as constructed,
= 1 overlayed;
ST = surface type indicator:
= 0 asphaltic concrete,
= 1 surface treatment;
AGE = number of years since construction or overlay;
LN = logarithm to the base 10 of the number of cumulative equivalent axles;
SNC = corrected structural number; and
B = Benkelman beam deflection (0.01 mm).

Detailed statistical results pertaining to Equation 2.4 are presented in Table 2.7. The approximate 95 percent confidence interval is CI = QI* ± 20.5.

5. <u>Equation including structural number and Dynaflect deflection</u>

$$LQI = 1.299 - 0.1072\ RH + 0.0415\ P + 0.00623\ AGE + 0.0856\ (LN/SNC) + 0.0230\ D \times LN \qquad (2.5)$$

R squared : 0.356
Standard error for residuals : 0.127

All symbols are as previously defined. Other statistical results are shown in Table 2.8. The approximate 95 percent confidence interval for QI* in Equation 2.5 is CI = LQI ± 0.25, or 0.56 QI* to 1.78 QI*.

TABLE 2.7 - REGRESSION ANALYSIS RESULTS FOR EQUATION 2.4

a) Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	5	8318.8	1663.76	15.90
Residual	72	7531.7	104.61	

b) Regression Analysis

Parameter	Estimate	Standard Error	F-Value
Intercept	12.631	-	
RH	-5.160	3.725	1.92
ST	3.307	2.626	1.59
LN/SNC	8.663	3.486	6.18
AGE	0.393	0.266	2.18
$(B \times LN)^2$	7.17×10^{-5}	1.041×10^{-5}	4.74

R squared : 0.523

Standard error for residuals: 10.228

TABLE 2.8 - REGRESSION ANALYSIS RESULTS FOR EQUATION 2.5

a) Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	5	0.6436	0.1287	7.96
Residual	72	1.1650	0.0162	

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	1.29857	-	
RH	0.10718	0.0461	5.42
P	0.04151	0.0293	2.01
LN/SNC	0.08556	0.0417	4.21
AGE	0.00623	0.0033	3.50
D x LN	0.02300	0.0092	6.29

R squared : 0.356

Standard error for residuals: 0.127

6. <u>Equation including structural number, Benkelman beam deflection and initial roughness</u>

$$QI^* = QI^*_o + (155.5 + 2.07G - 163.8\frac{B}{B_o} - 165.9\frac{SNC_o}{SNC} + 172.9\frac{B}{B_o} \times \frac{SNC_o}{SNC}) \times N/10^6 \quad (2.6)$$

R squared : 0.565
Standard error for residuals : 9.373

where

QI^*_o = an estimate of the pavement's initial roughness, *i.e.*, QI* value at AGE = 0;
SNC_o = 5;
B_o = 55.

The values of B/B_o and SNC_o/SNC are held to not less than 1. G is a function of the road gradient given by:

$$G = 1 - \frac{1}{1 + 10^{GR-4}} \quad (2.7)$$

where GR is the uphill gradient in percent. On the downhill GR = 0.

2.3 DISCUSSION OF ROUGHNESS PREDICTION MODELS

Six roughness prediction models were developed. The independent variables included represent various degrees of sophistication in the data required for analysis. As an example, Equation 2.3 may be used when only Dynaflect deflections are available, while the use of Equation 2.4 requires that the Benkelman beam deflection and structural number be known.

The latter is considered more appropriate for analysis at the project level (*e.g.*, designing an individual overlay), whereas Equation 2.3 may be suitable for analysis at the network level (*e.g.*, maintenance planning for a number of sections). Equation 2.6 may be used when an estimate of the pavement's initial roughness is available.

Efforts were made to improve the equations by including more information in the regression models, but the result was less significant and produced more unstable coefficients.

Forcing other transformed variables, such as logarithms or squares, into the equations caused similar problems. For instance, if $(D \times LN)^2$ enters Equation 2.3, both its coefficient and the coefficient of $D \times LN$ become very unstable. Concurrently, no significant improvement to R squared was obtained from the inclusion of $(D \times LN)^2$ in the equation.

From the foregoing, it seems reasonable to conclude that the data available on pavement roughness probably do not permit better models to be developed. It is expected that field data collection will continue until all of the sections exhibit high levels of roughness, so that more precise prediction models can be obtained. However, it is felt that the models derived have sound engineering basis, since pavement and subgrade strength, as well as traffic loads are adequately considered.

CHAPTER 3 - PAVED ROAD CRACKING AND RUT DEPTH ANALYSIS

3.1 INTRODUCTION

A considerable amount of public money is spent on pavement maintenance every year, as pavements deteriorate over time due to traffic loading and climatic factors. For efficient use of maintenance resources, it is necessary to estimate the future condition or serviceability level of the different pavement sections in a specific network. Such an estimate is only possible if the pavement engineer or planner has reliable predictive models available. Moreover, distress prediction models are essential technological tools in the analysis of alternative pavement design strategies.

This chapter presents the results of analysis performed on data collected on pavement cracking and rutting, with the objective of developing empirical prediction models for these two types of distress manifestations. Quantitative information on pavement cracking and rutting is obtained from condition surveys, which are mechanistic measurements of distress. It should be clear that the prediction models developed can be only used for estimating pavement distress in a way compatible with the measurement system used in the field.

3.2 ANALYSIS OF PAVEMENT CRACKING

The approach for studying pavement cracking was to monitor the percent area cracked at selected test locations on existing roads. Detailed information developed to characterize each test location included traffic loads and volumes, pavement structural number, Benkelman beam and Dynaflect deflections.

The cracking variable used in this analysis is defined as the percent of the pavement's total area which shows Class 2 to 4 cracks or potholes. Class 1 cracks, which have widths of less than 1 mm and are normally called hairline cracks, were not included in the percent calculation because they are not readily identifiable in the field, and their measurement depends, to a great extent, on the observer's judgement and weather conditions. Additionally, hairline cracks can result from poor rolling of asphalt mixtures during construction and, in this case, their prediction as a function of pavement strength and traffic loadings is meaningless.

Another reason for not including hairline cracks in the computation of the cracking variable is that this type of cracking would hardly ever warrant any pavement maintenance response. Moreover, Class 1 cracks were not included in the cracking term used to estimate serviceability at the AASHO Road Test (HRB, 1962). Therefore, it seems appropriate to quantify a cracking variable as previously defined.

Very few of the surface treatment sections exhibited cracks. Consequently, test sections with this type of surfacing were not included in the analysis of pavement cracking.

3.2.1 *Approach for Cracking Analysis*

Observation of the data indicated that it may take a pavement several years to show the first crack, but after the initial cracks appear, the deterioration process is relatively fast. Therefore, it was considered necessary to develop two types of models: one to predict when cracks first appear and the other to predict how fast cracks progress in a specified pavement. The analyses corresponding to these models are called, respectively, crack initiation and crack progression analysis.

The need for these two types of models was identified by Finn (1973) who stated that, to be helpful to the highway engineer, the output variable of cracking as predicted from research should include not only some estimate of initial cracking, but also the rate of progression of cracking with time.

3.2.2 *Crack Initiation*

The dependent variable used in this part of the analysis is the number of equivalent axles supported by the pavement to first crack. The inference space is governed by the ranges of the dependent and independent variables which are listed in Table 3.1. As the objective of this part of the study was to predict when cracks first appear, only test sections which showed their first crack during the

TABLE 3.1 - MEAN, STANDARD DEVIATION AND RANGE OF THE VARIABLES USED IN THE CRACK PROGRESSION ANALYSIS

DESCRIPTION	MEAN	STANDARD DEVIATION	RANGE	
			MINIMUM	MAXIMUM
Number of Sections	19	-	-	-
- As constructed	12	-	-	-
- Overlayed	7	-	-	-
Age During Observation Period (Years)	5.3	3.5	1.2	15.8
Benkelman Beam Deflection (0.01 mm)	58.7	21.6	34.0	102.0
Dynaflect Deflection (Sensor 1) (0.001 in.)	0.817	0.288	0.400	1.460
Surface Curvature Index (0.001 in.)	0.277	0.104	0.120	0.460
Base Curvature Index (0.001 in.)	0.108	0.042	0.050	0.200
Structural Number	3.49	0.86	1.90	4.30
Corrected Structural Number	5.30	8.60	3.70	6.70
Log_{10} Cumulative Equivalent Axles	5.49	0.61	4.30	6.28
Subgrade CBR	33.6	14.4	13.0	64.0

study period were used. The correlation matrix of variables included in the analysis is given in Table 3.2.

A number of functional relationships were investigated through regression analysis. The model found to best fit the data is:

$$LN = 1.205 + 5.96 \log SNC \tag{3.1}$$

where

LN = logarithm to the base 10 of the number of equivalent axles to first crack;
SNC = corrected structural number; and
log = logarithm to base 10.

Equation 3.1 has a correlation coefficient squared of 0.52, a standard error for residuals of 0.44, and is based on a sample size of 19. Other statistical results pertaining to this equation are given in Table 3.3. The approximate 95 percent confidence interval is:

$$CI = LN \pm 0.95 \text{ or } 0.11N \text{ to } 8.9N$$

As described in Chapter 2, several groups of independent variables were used in the analysis. However, no acceptable regression equation could be developed with independent variables other than corrected structural number. It is expected that test sections which have not shown any cracking - and therefore not included in this analysis - will enhance the inference space for future analyses. This may make it possible to obtain reasonable models for the other combinations of independent variables.

3.2.3 *Crack Progression*

Two different dependent variables were used in this part of the analysis:

TABLE 3.2 - CORRELATION MATRIX OF VARIABLES INCLUDED IN THE CRACK INITIATION ANALYSIS

Variable	SNC	B	D	AGE	LN
SNC	1.00	-.64	-.65	.18	.72
B		1.00	.78	-.24	-.26
D			1.00	-.27	-.26
AGE				1.00	.44
LN					1.00

TABLE 3.3 - REGRESSION ANALYSIS RESULTS FOR EQUATION 3.1

a) Analysis of Variance

	Degrees of Freedom	Sum of Square	Mean Square	F Ratio
Regression	1	3.474	3.474	18.29
Residual	17	3.229	0.190	-

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	1.205	-	-
LSNC	5.963	1.394	18.29

Correlation coefficient squared : 0.518

Standard error for residuals : 0.436

a) the percentage area cracked at a specified pavement age; and
b) the age when the percent of area cracked reaches a specified value.

Models developed for the first dependent variable are useful, for example, when the engineer wants to predict the cracking condition of a pavement t years from now, if no maintenance is applied to the pavement. The resulting numbers could indicate the need to request additional funds for certain projects in the road network.

An example of application of models developed for the second dependent variable is the estimation of the time at which a pavement cracking condition will reach a limiting value, at which rehabilitation is necessary. Limiting values for this condition depend on a number of factors, including the highway function, resources available and local practice. Limiting values suggested by diferent researchers fall in a wide range of 5 to 35 percent, the average approaching 15 percent (Queiroz,1981a, p. 119).

The inference space in the crack progression analysis is governed by the ranges of the dependent and independent variables which are listed in Table 3.4. The correlation matrix of a select subset of variables included in the analysis is given in Table 3.5.

A number of functional relationships were investigated in order to develop models to predict the amount of pavement cracking. The three models which to best fit the data are:

1. <u>Independent variables include Benkelman beam deflections</u>

$$CR = - 18.53 + 0.0456\ B \times LN + 0.00501\ B \times AGE \times LN \qquad (3.2)$$

R squared : 0.644
Standard error : 12.616
CI = CR $\pm$ 25.28

TABLE 3.4 - MEAN, STANDARD DEVIATION AND RANGE OF THE VARIABLES USED IN THE CRACK PROGRESSION ANALYSIS

DESCRIPTION	MEAN	STANDARD DEVIATION	RANGE	
			MINIMUM	MAXIMUM
Number of Sections	28	-	-	-
- As Constructed	18	-	-	-
- Overlayed	10	-	-	-
Age During Observation Period (Years)	7.63	4.82	1.2	20.7
Benkelman Beam Deflection (0.01 mm)	63.8	27.0	34.0	132.0
Dynaflect Deflection (Sensor 1) (0.001 in.)	0.780	0.236	0.40	1.46
Surface Curvature Index (0.001 in.)	0.269	0.094	0.11	0.46
Base Curvature Index (0.001 in.)	0.108	0.034	0.05	0.20
Structural Number	3.76	0.91	1.90	6.50
Corrected Structural Number	5.55	0.79	3.70	7.50
Log_{10} Cumulative Equivalent Axles	5.75	0.64	4.30	7.27
Subgrade CBR	33.2	12.8	13.0	64.0
Percentage of Area Cracked	12.50	20.86	0.00	83.75

TABLE 3.5 - CORRELATION MATRIX OF VARIABLES INCLUDED IN THE CRACK PROGRESSION ANALYSIS

Variable	SNC	CBR	B	D	AGE	LN	CR
SNC	1.00	-.02	-.41	-.42	.35	.62	.04
CBR		1.00	-.13	-.11	-.30	-.31	-.18
B			1.00	.67	-.06	.01	.55
D				1.00	-.12	.16	.34
AGE					1.00	.49	.47
LN						1.00	.38
CR							1.00

Definition of symbols:

SNC = corrected structural number;
CBR = subgrade CBR;
B = mean Benkelman beam deflection (0.01 mm);
D = mean Dynaflect deflection (0.001 in.);
AGE = pavement age in years;
LN = $\log_{10}$ cumulative equivalent axles;
CR = percentage area cracked (%).

2. <u>Independent variables include Dynaflect deflections</u>

$$CR = -14.10 + 2.84\ D \times LN + 0.395\ D \times AGE \times LN \qquad (3.3)$$

R squared	:	0.439
Standard error	:	15.843

CI = CR ± 31.74

3. <u>Independent variables include corrected structural number</u>

$$CR = -57.7 + 53.5\ LN/SNC + 0.313\ AGE \times LN \qquad (3.4)$$

R squared	:	0.345
Standard error	:	17.120

CI = CR ± 34.31

where

CR = percentage area cracked;
B = mean Benkelman deflection (0.01 mm);
LN = logarithm to the base 10 of the number of cumulative equivalent axles;
AGE = pavement age since construction or overlay (years);
D = mean Dynaflect deflection (0.001 in.);
SNC = corrected structural number; and
CI = approximate 95 percent confidence interval.

Detailed regression results pertaining to Equation 3.2 to 3.4 are given in Tables 3.6 to 3.8, respectively. Stability of the regression coefficients was examined through ridge analysis. The corresponding ridge traces showed that the three equations developed have very high stability. It was not possible to obtain acceptable regression equations (in terms of statistical significance and stability of coefficients) involving other groups of independent variables.

TABLE 3.6 - REGRESSION ANALYSIS RESULTS FOR EQUATION 3.2

a) Analysis of Variance

	Degree of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	2	21031	10515.7	66.07
Residual	73	11613	159.2	-

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	-18.530	-	-
B x LN	4.564×10^{-2}	1.089×10^{-2}	17.55
B x AGE X LN	5.011×10^{-3}	7.226×10^{-4}	48.08

Multiple correlation coefficient squared : 0.644
Standard error for residuals : 12.616

TABLE 3.7 - REGRESSION ANALYSIS RESULTS FOR EQUATION 3.3

a) Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	2	14328	7164.2	28.54
Residual	73	18322	251.0	-

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	-14.105	-	-
D x LN	2.843	1.278	4.95
D x AGE x LN	0.3948	0.0684	33.28

Multiple correlation coefficient squared : 0.439

Standard error for residuals : 15.843

TABLE 3.8 - REGRESSION ANALYSIS RESULTS FOR EQUATION 3.4

a) Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	2	11254	5626.9	19.20
Residual	73	21397	293.1	

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	-57.66	-	-
LN/SNC	53.47	16.96	9.94
AGE x LN	0.3126	0.0610	26.23

Multiple correlation coefficient squared : 0.345
Standard error for residuals : 17.120

As mentioned previously, an effort was also made to develop equations to predict the age when the percent of area cracked reaches a specified value. Only one statistically acceptable model could be derived from this part of the analysis:

$$AGE = 11.46 - 0.0974\ B + 0.1454\ CR + 2.51 \times 10^{5}\ CR/(RLA \times B) \qquad (3.5)$$

R squared : 0.418
Standard error : 3.751
CI = AGE ± 7.51

where

RLA = rate of load applications, *i.e.*, average number of equivalent axles per year;
AGE = number of years since construction or overlay it will take a pavement to have a percent area cracked CR;
B = Benkelman beam deflection (0.01 mm); and
CI = approximate 95 percent confidence interval.

Detailed statistical results for Equation 3.5 are listed in Table 3.9.

3.3 *INTERPRETATION OF CRACKING MODELS*

3.3.1 *Crack Initiation*

Equation 3.1 predicts the number of equivalent 80 kN single axle loads to first crack, as a function of corrected structural number. The equation is graphically shown in Figure 3.1, along with the data points obtained from 19 test sections which first cracked during the study period.

As in other parts of the analysis conducted in this investigation, an effort was made to develop crack initiation models involving different groups of independent variables. However, no

TABLE 3.9 - REGRESSION ANALYSIS RESULTS FOR EQUATION 3.5

a) Analysis of Variance

	Degrees of Freedom	Sum of Squares	Mean Square	F Ratio
Regression	3	728.76	242.92	17.27
Residual	72	1012.94	14.07	-

b) Regression Equation

Parameter	Estimate	Standard Error	F-Value
Intercept	11.457	-	-
B	-9.74×10^{-2}	2.01×10^{-2}	23.38
CR	14.54×10^{-2}	2.62×10^{-2}	30.89
CR/(RLA x B)	2.51×10^{-5}	9.62×10^{4}	6.83

Multiple correlation coefficient squared : 0.4184
Standard error for residuals : 3.7508

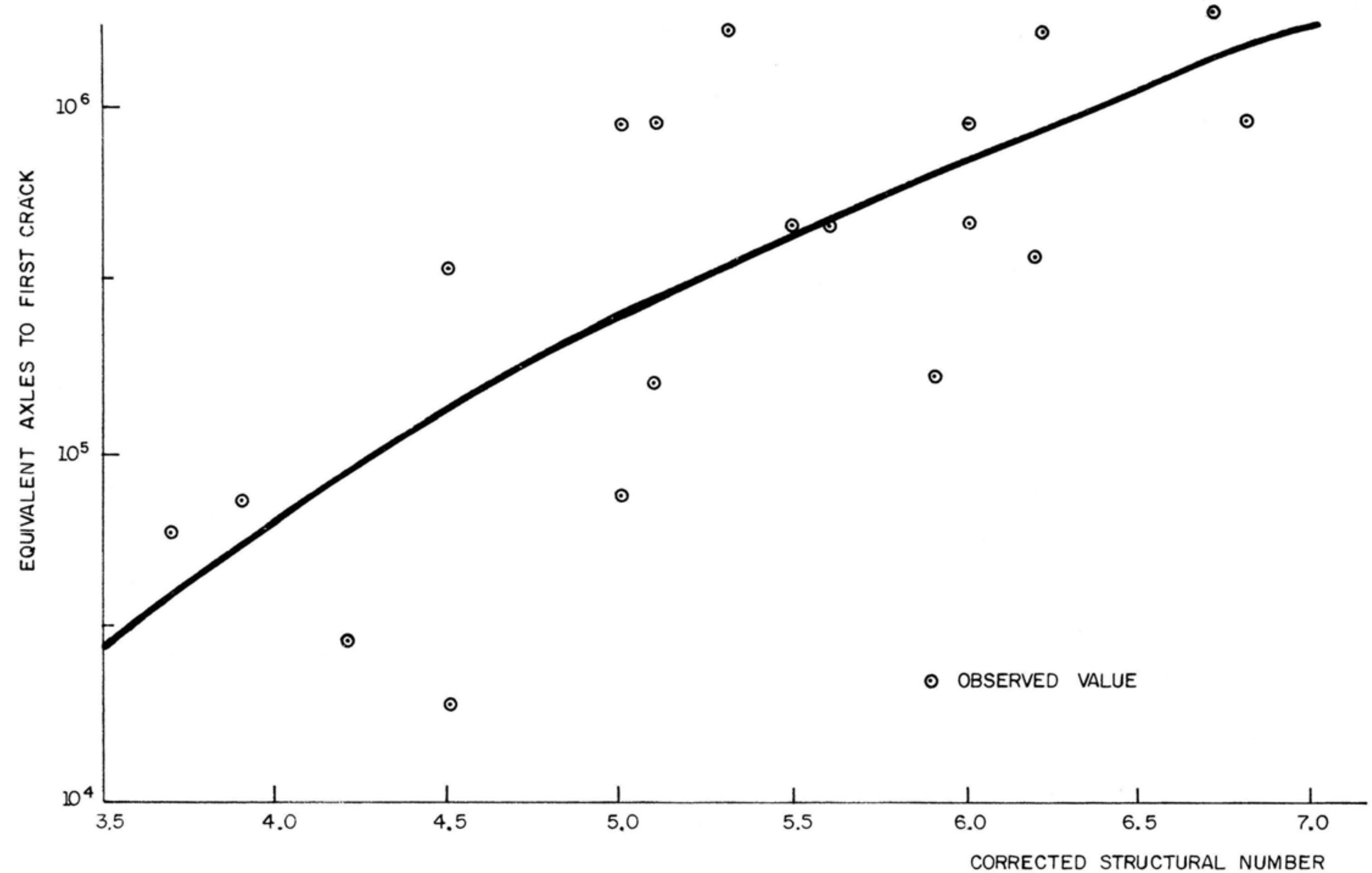

FIGURE 3.1 - NUMBER OF EQUIVALENT AXLES TO FIRST CRACK FOR ASPHALTIC CONCRETE PAVEMENTS, AS A FUNCTION OF CORRECTED STRUCTURAL NUMBER (EQUATION 5.1).

structural variable, other than corrected structural number, was able to explain the phenomenon of crack initiation in pavements. This fact could, to some extent be anticipated from inspection of the correlation matrix shown in Table 3.2, where very low correlation between deflection and cumulative number of equivalent axles (or age) to first crack is presented.

A number of test sections, including most of the surface treatment sections, did not show any sign of cracking during the study period. Therefore, these sections were not used in the crack initiation (nor crack progression) analysis. As data collection in the field is anticipated to continue, it is expected that crack initiation models, in terms of other structural variables, can be developed in future analysis. Then, the data base may be significantly augmented.

3.3.2. *Crack Progression*

Three models to predict the amount of cracking have been developed in terms of pavement age and traffic and one of the following: Benkelman beam deflection, Dynaflect deflection, or corrected strutural number. Simultaneous inclusion of two structural variables into the equation, *e.g.*, Dynaflect deflection and structural number, did not improve the equation significantly. In fact, this simultaneous inclusion caused high instability of the regression coefficients, as verified in the ridge analysis.

Equations 3.2 to 3.4 are relatively similar in form. Equation 3.2 is graphically shown in Figure 3.2, which demonstrates the effect of Benkelman beam deflection on the estimated amount of cracking over time. The figure was constructed assuming an average of 50,000 equivalent axle load applications per year.

It is clear that empirical models should be used at the bounds of the inference space only with extreme caution. It is evident, from Figure 3.2, that Equation 3.2 does not give accurate predictions at very low pavement ages and very high deflections. However, the equation does give suitable prediction accuracy in those applications where it is most needed; the region corresponding to the average limiting criterion of 15 percent cracking (as discussed

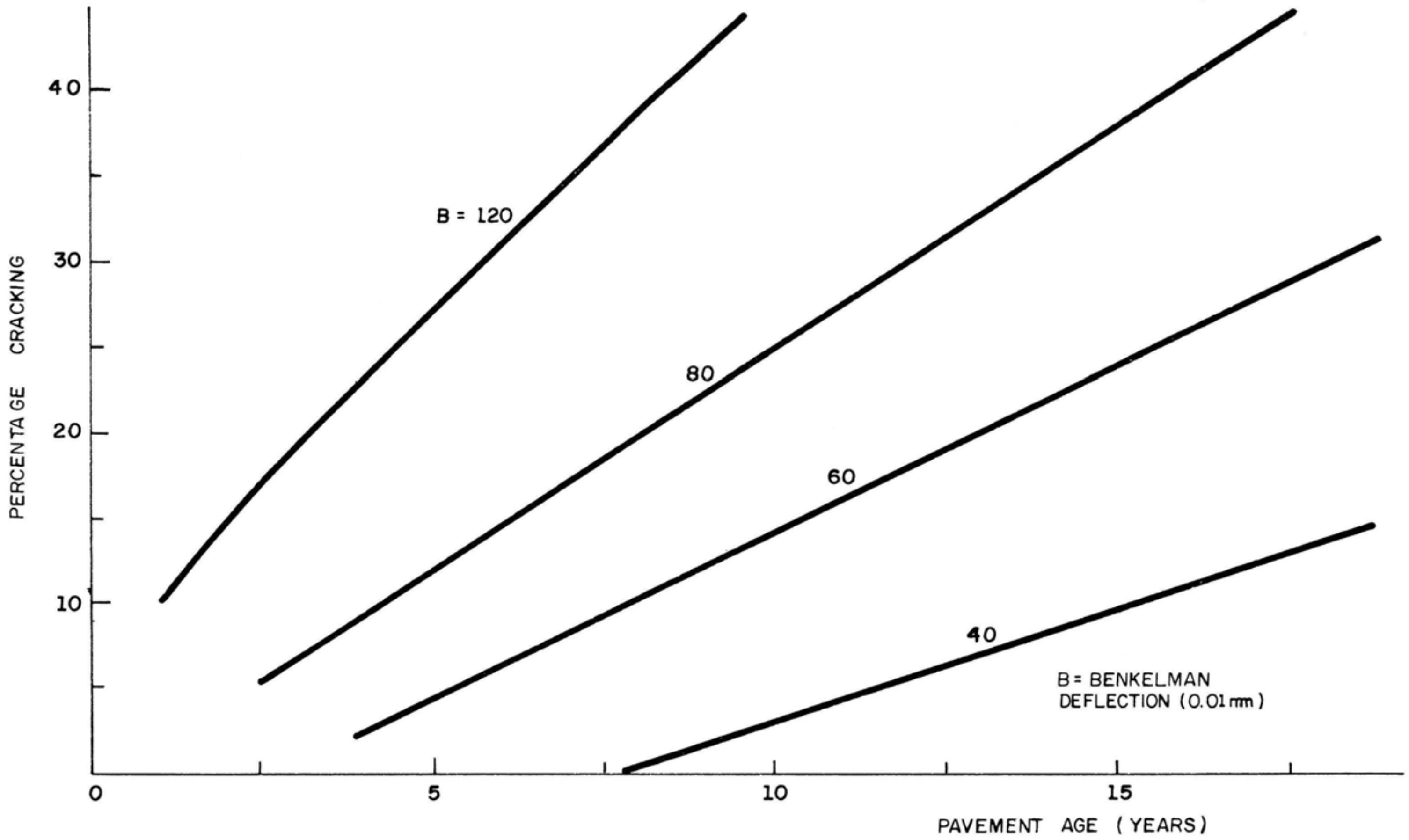

FIGURE 3.2- EXAMPLE OF PAVEMENT CRACKING ESTIMATED FROM EQUATION 3.2.

earlier) is close to the mean cracking value of 12.50 percent encountered in the inference space (see Table 3.4).

A model has also been developed to predict the age when the percent of area cracked reaches a specified value, *i.e.*, Equation 3.5. This equation is illustrated in two different examples presented in Figures 3.3 and 3.4. Figure 3.3 shows the influence of Benkelman beam deflection on the number of years it takes a pavement to develop different cracking levels. The figure was constructed assuming an average of 50,000 equivalent axle load applications per year.

The number of years it takes a pavement to develop 15 percent cracking, which is the cracking level corresponding to an average limiting criterion, is graphically shown in Figure 3.4, for different levels of the rate of load applications, as a function of Benkelman beam deflections. As expected, the age decreases as deflection or loading rate increases.

Because of the vicinity of the inference space bounds, Equation 3.5 does not give accurate predictions at very high deflections and very low cracking levels. However, the model is considered to have very good accuracy at the important level of 15 percent cracking, which is close to the mean of 12.50 percent cracking of the inference space.

3.4 EFFECT OF SLURRY SEAL

The cracking variable previously defined, CR, was the dependent variable studied to evaluate the effect of slurry sealing on pavement cracking. Class 4 cracks and potholes were, in general, patched before slurry seal applications. Therefore, they are not included in the slurry seal effect analysis.

Plots of the data were examined and the following observations made:

1) After a slurry seal there always existed a period of time when no cracks reappeared.
2) The length of time before the first appearance of crack was related to the amount of cracking on the subsection when it was sealed.

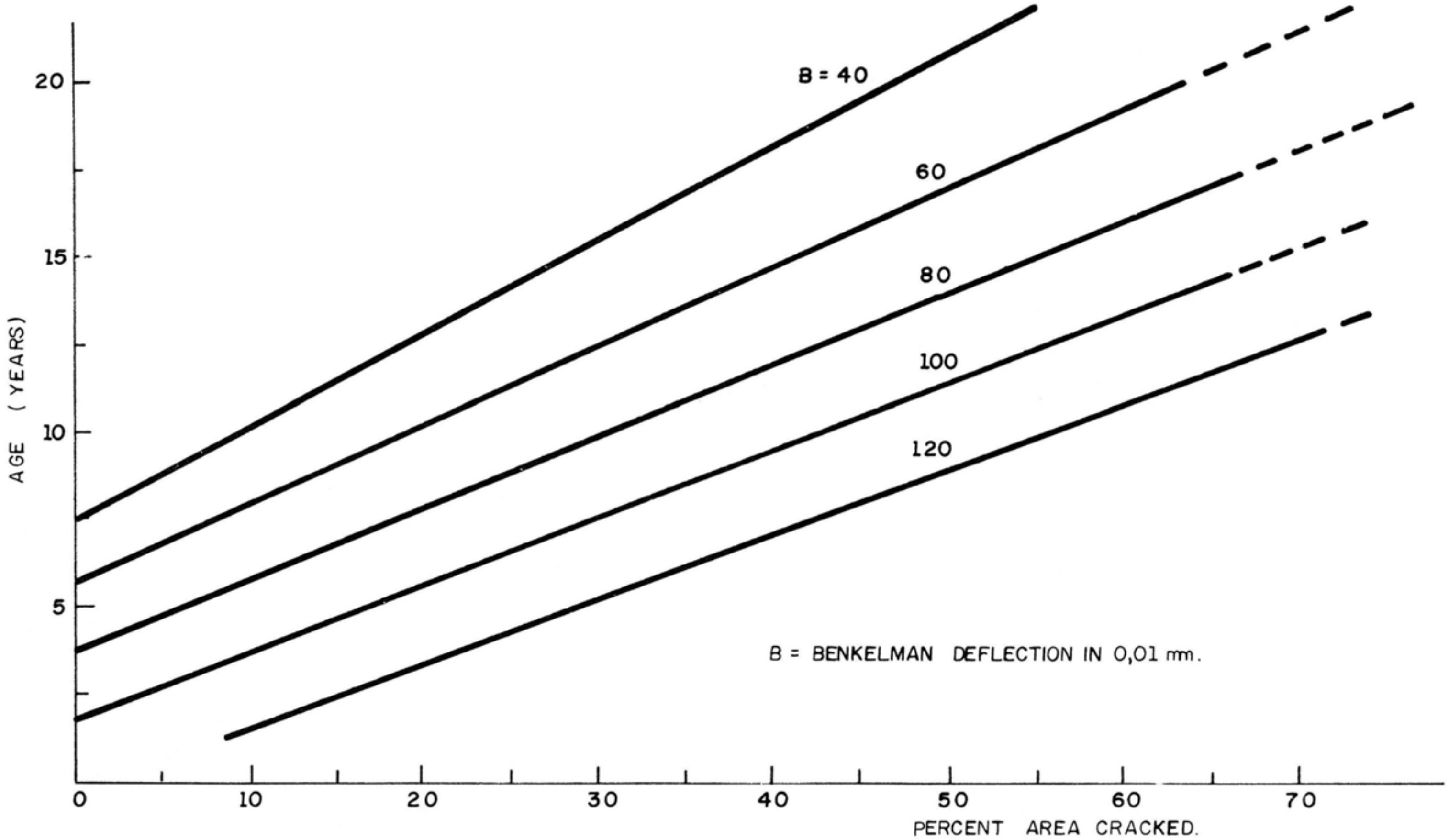

FIGURE 3.3 - EXAMPLE OF AGES TO DIFFERENT LEVELS OF CRACKING PREDICTED BY EQUATION 3.5.

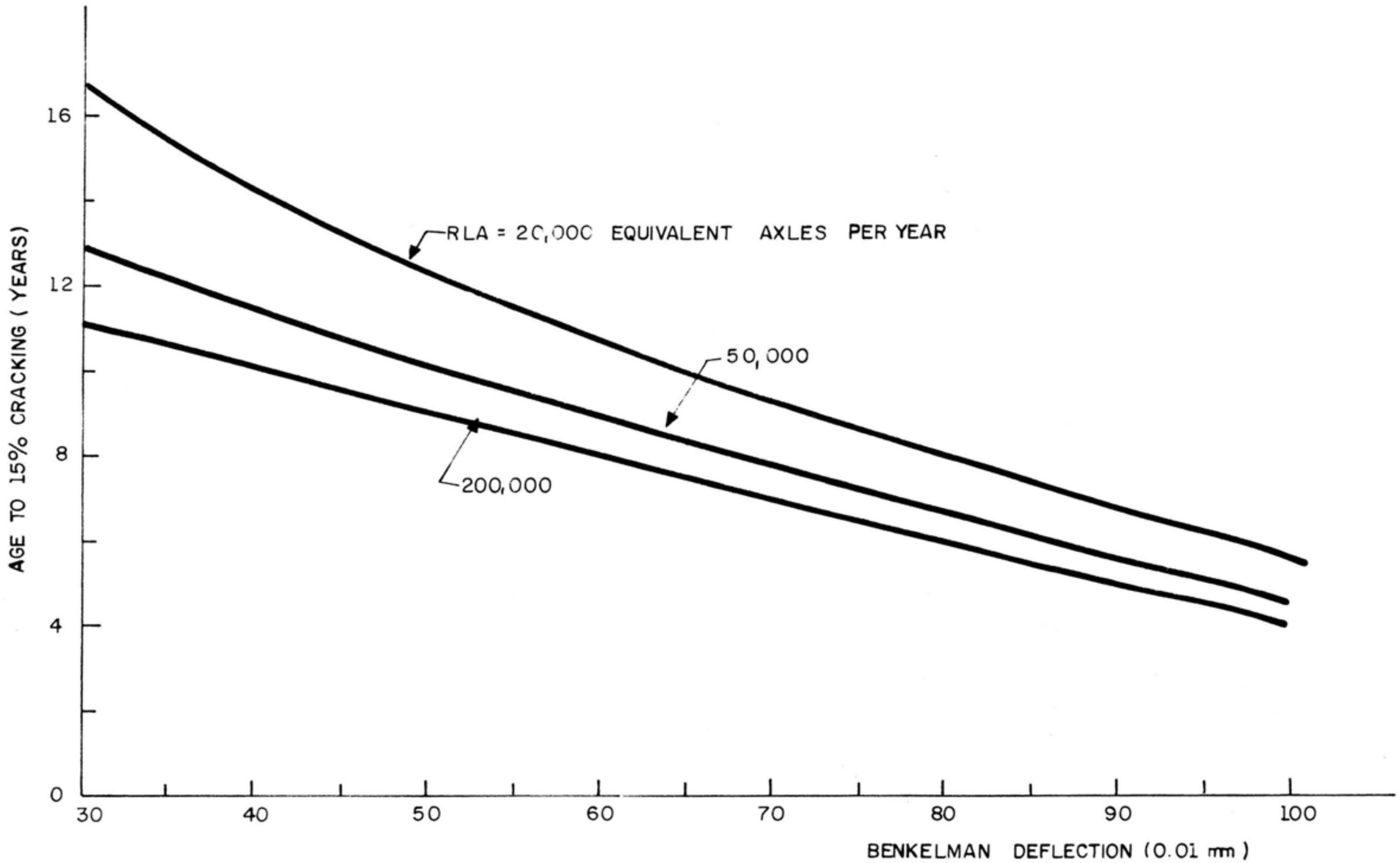

FIGURE 3.4 - PAVEMENT AGE AT 15 PERCENT CRACKING AS PREDICTED BY EQUATION 3.5.

The effects of grade, overlay, base type, number of equivalent axles per year, structural number, and CBR of the subgrade were investigated and found to be nonsignificant at $\alpha = 0.1$. The development of more realistic models to predict the effect of slurry sealing on pavement cracking will require data collection over longer time periods and further analysis.

The model found to best describe the progression of cracking after a slurry seal was applied is:

$$CR = T\,(0.219\,B + 1.43\,CR_o) \qquad (3.6)$$

R squared : 0,770
Standard error for residuals : 0,130

where

CR = percentage area cracked;
B = Benkelman beam deflection (0.01 mm);
CR_o = the last observed value of CR before slurry sealing;
$T = 0$ if $A_o - (A_s + 10/CR_o) \leq 0$,
$T = A_o - (A_s + 10/CR_o)$ otherwise;
A_o = pavement age when it is being observed;
A_s = pavement age when it is slurry sealed ($A_o > A_s$).

The t-values in Equation 3.6 are 2.80 and 6.34 for B and CR_o respectively.

The equation shows that once cracks appear after slurry sealing, their rate of increase is relatively high.

3.5 *RUT DEPTH STUDY*

The objective of this part of the study was to develop models to predict rut depth as a function of age and structural and traffic variables. The mean, standard deviation and range of variables studied is presented in Table 3.10. The observed rut depths on the test sections were very low (maximum of 7.4 mm).

Haas and Hudson (1978) indicated that the major possible effects of excessive rutting on the road user are:

1. hydroplaning;
2. loss of vehicle control; and
3. freezing of ponded water resulting in icy conditions.

Of course, the last effect is not a factor of importance for Brazilian conditions. There are no absolute limiting values to avoid the foregoing safety hazards, nor can researchers and practicing engineers generally agree as to a limiting criterion for maximum allowable rut depth, as discussed by Queiroz (1981).

Although the limiting criterion for pavement rut depth varies among authors, it falls within the range of 10 to 25 mm. As mentioned earlier, rutting was found to be very slight in the study area, with an average of 2.5 mm. This means that rut depth probably will not act as a trigger to initiate maintenance on the pavements studied in this investigation.

Empirical models apply to the inference space governed by the observed variables. Thus, any rut depth prediction model developed from the data currently available will apply for rut depths below 7.4 mm, as shown in Table 3.10. However, as previously demonstrated, it is important to predict rut depths of at least 10 mm, in order that the prediction models find practical application. Therefore, no attempt has been made in this investigation to develop equations to predict pavement rutting.

3.6 *SUMMARY AND CONCLUSIONS*

Models were developed to predict asphaltic concrete pavement cracking. Two separate analyses were carried out to yield crack initiation and crack progression models. The resulting regression equations are useful to predict:

TABLE 3.10 - MEAN, STANDARD DEVIATION AND RANGE OF VARIABLES STUDIED TO EVALUATE RUT DEPTH

Variable	Mean	Standard Deviation	Minimum	Maximum
Number of sections	45	-	-	-
Age (years)	7.71	4.80	1.5	20.5
Benkelman beam deflection (mm)	0.78	0.43	0.17	2.13
Corrected structural number	5.00	0.88	3.40	7.50
Log_{10} cumulative equivalent axles	5.56	0.74	3.20	7.23
Rut depth (mm)	2.53	0.90	0.40	7.40

1. the number of cumulative equivalent 80 kN single axle loads to first crack, as a function of corrected structural number;
2. the degree of cracking as a function of Benkelman beam deflection, traffic, and age;
3. the degree of cracking as a function of Dynaflect deflection, traffic, and age;
4. the degree of cracking as a function of corrected structural number, traffic, and age;
5. the pavement age at a specified percentage cracking as a function of Benkelman beam deflection, rate of axle load applications, and the degree of cracking, and
6. the effect of slurry sealing on pavement cracking.

The models developed are acceptable with respect to the traditional statistical criteria of levels of significance, and have highly stable regression coefficients, as evaluated through ridge analysis.

Rutting was found to be very slight in the study area. This means that rut depth probably will not act as a trigger to initiate maintenance on the pavements studied in this investigation. Any rut depth prediction model derived from the data base currently available would not apply to the range of interest in practical applications. Thus, no equation was developed to predict rut depth.

CHAPTER 4 - UNPAVED ROAD ROUGHNESS ANALYSIS

4.1 INTRODUCTION

Road maintenance in the form of blading has the greatest influence on the roughness-time curve; consequently, two blading strategies were evaluated. The first consisted of withholding blading for as long as possible on all 48 unpaved study sections because of difficulties in the control of blading operations. The second strategy consisted of selecting ten study sections in the vicinity of Brasília, each of which was divided into two subsections. Under this strategy one subsection was bladed every two weeks, whereas the other subsection was bladed every six weeks. Table 4.1 contains the dependent and independent variable statistics for the roughness studies, and these statistics aid in placing in perspective the inference space within which the models were developed.

4.2 APPROACH FOR UNPAVED ROUGHNESS ANALYSIS

The period between bladings was considered a cycle since every time an unpaved road was bladed, the roughness was generally reduced and the new deterioration during the cycle depended on the length of time between bladings. Consequently, deterioration was considered a function of the number of days since the last blading. In the Kenya study (Hodges, Rolt and Jones, 1975) the same approach was used, but in that study they assumed that blading a road returned its roughness to some standard value. Inspection of the data collected in Brazil showed that the roughness measured after blading varied, so that the assumption of a standard value would not be appropriate. Because roughness after blading was variable, and the number of days between blading varied widely, the analysis was executed in two parts: the first part consisted of predicting the change in roughness with time, while the second part involved predicting the roughness after blading.

The choice of the form of the deterioration model was based on considerations of the interaction of a vehicle with a road. When a road is very smooth with no surficial irregularities, a vehicle imparts forces which are similar to its static loading. Then, as the first irregularities develop from traffic and weathering, increased

TABLE 4.1 - UNPAVED ROAD DATA SUMMARY (Continued)

Variable	Mean	Standard Deviation	Range	
			Minimum	Maximum
Number of sections = 48				
Grade (%)	3.8	2.6	0.0	8.2
Curvature (1/Rad) on curved sections	.0039	.0009	.0025	.0055
Road width (m)	9.8	1.09	7.0	12.0
MATERIAL PROPERTIES				
Percentage passing the 0.42 mm sieve	53	22	24	98
Percentage passing the 0.074 mm sieve	36	24	10	97
Plasticity index (%)	11	6	0	33
Liquid Limit (%)	32	9	20	62
AVERAGE DAILY TRAFFIC (both directions)				
Passenger cars	88	64	11	288
Buses	7	7	0	29
Pickups	37	29	4	115
Two axle trucks	56	93	1	435
Trucks and trailer combinations with more than 2 axles	15	18	0	66
TIME RELATED INFORMATION FOR GRAVEL LOSS				
Number of observations	604			
Time of observation relative to start of observation or regravelling (days)	238	211	0	1099
Number of bladings relative to start of observation or regravelling	2.3	3.3	0	23

TABLE 4.1 - UNPAVED ROAD DATA SUMMARY (Conclusion)

Variable	Mean	Standard Deviation	Range	
			Minimum	Maximum
INFORMATION RELATED TO ROUGHNESS MEASUREMENTS				
Roughness (QI* counts/km)	117	61	15	445
Number of days since blading for the last observation in each blading period	75	70	1	661
Number of vehicle passes since blading for the last observation in each blading period	16080	17880	63	136460
INFORMATION RELATED TO RUT DEPTH MEASUREMENTS				
Rut depth (mm)	11.1	8.6	0	75
Number of days since blading for the last observation in each blading period	61	66	1	661
Number of vehicle passes since blading for the last observation in each blading period	12490	14030	21	86700

dynamic forces are imposed on the road with resultant deterioration and a rapid increase in roughness. At the upper end of the roughness scale it is unlikely that a road will continue to increase in roughness, but rather that at a very high roughness level, the vehicles slow down and there is hardly any change in roughness. In fact, if all conditions of traffic and weather remain constant, virtually the same roughness will be maintained.

In addition to the macro-development of roughness, as described above, there is also the micro-development of roughness associated with the period immediately following a blading. This usually occurs within the first few days after blading, and although no data on this aspect was collected, a possible deterioration mechanism is postulated for completeness. The mechanism is probably different for the dry and rainy seasons. In the dry season the loose material is scraped from the side drains and is pulled over the road filling the depressions and acting as a blanket to retard the abrasive action of tires on the surfacing. However, because the moisture content is generally low, there is nothing to bind the material and consequently within a relatively small number of vehicle passes most of the material will again be displaced into the side drain. This means that there will be a rapid increase in roughness until most of the loose material has been dislocated, and then the rate of roughness development will reduce to the long term rate. Although bringing in loose material from the side drain was accepted practice in the study area, it should be noted that an alternative maintenance philosophy exists, namely all loose material is bladed off the road since it is claimed that loose material acts as a grinding paste and adds to abrasion and gravel loss. It is likely that each philosophy is applicable to specific material types, and this remains an area for further study.

When blading in the wet season, loose material is also brought in from the side drains and sometimes the existing road surface is cut to eliminate high spots and to generate material to fill in the low spots. Usually sufficient moisture is available that the material is not displaced into the side drains and is compacted under traffic. However, an uneven thickness of loose material across the road width results in depressions under traffic compaction. Therefore, initially there is a fairly rapid development of roughness as vehicles seek out the smoothest path through a section, and thereafter, once this path has been developed, the roughness is slightly lower than before and the road deteriorates at the long term deterioration rate.

In selecting a model type that could represent the deterioration curve there were two important restrictions, namely: (1) that the model form could be linearized to accomodate the large number of deterioration cycles studied in a linear regression technique; and (2) that the data would permit the development of the model.

Inspection of the data showed that the rate of increase in roughness with respect to time or traffic is a function of the current roughness level (QI*), not of the initial roughness level after blading (QI^*_o) as some engineers may suggest. This means:

$$\frac{dQI^*}{dt} = f\ (QI^*)$$

Both the logit and exponential models possess the above property, although they are not the only ones.

A first model type is the typical s-shaped or logit curve. This has the general form of:

$$QI^* = QI^*min + (QI^*max - QI^*min)/\{1 + EXP(-t.f)\}$$

where

QI* = roughness;

t = time;

f = regression function which is a linear combination of independent variables.

The major disadvantage of this type of model is the fact that it is symmetrical about (QI*max - QI*min)/2, and that its maximum rate of change of roughness is also at this point rather than at some higher roughness level as is expected.

This model does have the benefit that it can be linearized readily. In addition, QI*max and QI*min are actual limits of roughness, which are respectively 450 and 15 as observed during the study period and were thus used in the development of the prediction model.

Another model type that could readily fit the hypothesized deterioration curve is a piecewise combination of two exponential type curves. However, inspection of the data showed that very little data existed in the range from 300 to 450 QI*, and thus the piecewise combination of two curves became unfeasible. Because of the absence of extensive data in the higher roughness range an exponential curve which would have a similar shape as the logit curve in the low roughness range but would then continue increasing indefinitely, could fit the data adequately. An artificial upper limit at 450 QI* would make the model practical. The general form of the exponential model is:

$$QI^* = EXP\ (f1 + t.f)$$

where f1 = regression function, a linear combination of independent variables and the other variables are as previously defined.

The advantage of both the logit and the exponential model is that since the standard deviation of roughness is related to the magnitude of the roughness a logarithmic transformation results in homogeneous variances for the regression analysis. Both models were selected for evaluation as described below.

For the development of a prediction model for the roughness after blading, a logarithmic transformation of both the roughness before and after blading was deemed necessary to homogenize variances. The greater the measured roughness, the greater was the observed standard deviation of observations. The roughness after blading was then evaluted as a linear combination of the roughness before blading and material property effects and section characteristics.

4.3 *ANALYSIS OF CHANGE OF ROUGHNESS WITH TIME*

Two functional forms of the roughness-time relationship were evaluated, namely, an exponential and a logit relationship. In both these relationships the regression function was assumed to be a linear combination of the independent variables. The following independent variables were evaluated: (1) grade of road; (2) radius of curvature; (3) liquid limit of surfacing material; (4) plasticity index of surfacing material; (5) percentage of surfacing material passing the 0.42 mm sieve; (6) percentage of surfacing material passing the 0.074 mm sieve; (7) average daily traffic of each of five vehicle classes: cars, pickups, buses, two axle trucks and other trucks; (8) uphill or downhill lane; (9) road width; (10) wet or dry season; (11) qualitative surfacing type descriptors, *e.g.* laterite, quartzite or clay; and (12) time in days since the most recent blading.

The generalized linear model (GLM) procedure of the SAS statistical package (SAS Institute, 1979) was used to evaluate the significant effects. Since the objective of this analysis was to determine the rate of change of roughness, the intercept terms were removed by centering the data through the mean time within each cycle between bladings. Then , one two factor interactions of the other independent variables with time were investigated.

The following independent variables were found significant in the exponential model:

$$\begin{aligned} LDQ = D\{&0.4314 - 0.1705T2 + 0.001159\ NC \\ &+ 0.000895\ NT - 0.000227\ NT \times G \\ &+ S\ (-0.1442 - 0.0198\ G + 0.00621\ SV \\ &- 0.0142PI - 0.000617\ NC)\} \end{aligned} \tag{4.1}$$

where

LDQ = change in natural logarithmic value of roughness (QI* counts/km);

D = number of days since last blading in hundreds, *i.e.*, time/100;

T2 = surfacing type dummy variable:

T2 = 1 if surfacing is clay;

T2 = 0 otherwise.

NC = average daily car and pickup traffic in both directions;

NT = average daily bus and truck traffic in both directions;
G = absolute value of grade in percent;
S = season dummy variable:
  S = 0 if dry season,
  S = 1 if wet season;
SV = percentage of surfacing material passing the 0.074 mm sieve;
PI = plasticity index of surfacing material (%)

The t-values of each coefficient are given in Table 4.2. This model has an R-squared value of 0.26, and the sample size was 8276.

The confidence interval (CI) relates to that of predicting one future value, in this case the roughness of a 320 m section, and is as follows for the large sample sizes employed:

$$CI = \hat{y} \pm 2.01\ s\sqrt{1+\frac{1}{n}}$$

where

$\hat{y}$ = predicted value;
s = standard error of the prediction model;
n = number of observations in the sample used to develop the prediction model, which is very large for the models and thus 1/n is approximately zero.

For a standard error of the model of 0.222, approximate 95% confidence intervals are LDQ + or - 0.433 for the logarithmic value of the change in QI*, or from 0.65 to 1.54 per unit change in QI*. Thus, if equation (1) predicts a change in roughness of 100, the true value of the change falls between 65 and 154 with 95% confidence.

Note that although the R-squared value is relatively low, a very large number of observations were taken, so the equations are statistically highly significant. Another contributory factor to the relatively low R-squared value is the large variability in roughness across the road width and within the relatively short road sections

TABLE 4.2 - REGRESSION ANALYSIS OF THE CHANGE IN ROUGHNESS (IN QI*) WITH TIME

Parameter	Estimate	Standard Deviation	t-value
D	0.4314	0.0250	17.26
D x T2	-0.1705	0.0258	-6.60
D x NC	0.001159	0.000155	7.46
D x NT	0.000895	0.000087	10.22
D x NT x G	-0.000227	0.000049	-4.65
D x S	-0.1442	0.0463	-3.11
D x S x G	-0.0198	0.0051	-3.87
D x S x SV	0.00621	0.00073	8.43
D x S x PI	-0.0142	0.0021	-6.75
D x S x NC	-0.000617	0.000199	-3.10

that were studied. This meant that the Mays Meter vehicles, although attempting to follow the same wheelpath through a section, were not always successful. Finally, a high R-squared value means that there is a precise relation between dependent and independent variables. We know that in the unpaved road studies the wheeltracks moved to different lateral positions as the vehicles found more desirable paths in terms of roughness or rut depth than the previously used paths. This means that the roughness could decrease or increase from one time to the next, without maintenance. The regression model thus depicts what happens on the average to the roughness on unpaved roads.

One of the major objectives of the regression analysis was to determine the relative influence of different vehicle types on the development of roughness. Unfortunately, a number of sections had no truck other than two axle or bus traffic, with the result that these vehicle type average daily traffic figures affected the residuals only on a few specific sections. As a consequence, the regression coefficients were either of the wrong sign, or they were disproportionately larger or smaller when compared with the other vehicle types. Cars and pickups were also highly correlated, as would be expected, since the proportions of these two vehicle types were fairly constant. Consequently, only the two vehicle groups, cars and pickups, and buses and trucks, termed cars and trucks respectively, were found to be meaningful.

Another regression model in which the average daily traffic was substituted for the two traffic classifications, was evaluated. This model had an R-squared value which was significantly smaller, at the 0.01 level, than the R-squared of model (4.1). Therefore the hypothesis that the coefficients of the two traffic classifications in model (4.1) are equal is rejected. However, the confidence interval for this new model is not meaningfully larger than that of model (4.1), and therefore care should be taken in the application of equivalency factors between the two vehicle types.

Model (4.1) predicts an increase of roughness with time even in the absence of traffic. This effect is reduced on roads classified as having a clay surface. This is believed to be the result of binding of the surfacing which is not adequately described by liquid limit, plasticity index or percentage of the surfacing material passing the 0.074 mm sieve. Other effects are as follows:

1 - Both the average daily car and truck traffic are positively correlated with the rate of change of roughness on the level road and the effects are very similar, *i.e.*, one truck passage increases the roughness approximately as much as one car pass. On grades, the truck influence is reduced and on a four percent grade, the truck influence is zero. This is possibly attributable to low truck speeds on the grade since the sections were generally 720 m in length, and that the trucks compact the surfacing, and even tend to smooth out unevenness. At the lower truck speeds, abrasion of the surfacing may also be lower than at higher speeds.

2 - In the wet season, the development of roughness is lower than in the dry season. On grades, the rate of roughness development is further reuuced, probably because of better drainage. Transverse erosion was minimal on grades greater than 5%. In these cases where longitudinal erosion occurred vehicles avoided it and there was thus no influence on roughness.

3 - The influence of cars is reduced in the wet season to such an extent that one truck passage is equivalent to 1.7 car passages on the level road. On grades, truck influences are again reduced compared to the level stretches, as occurs during the dry season.

4 - Surfacing material characteristics are important in the wet season. Increasing the material passing the 0.074 mm sieve increases the rate of roughness development, whereas an increase in the plasticity index has an opposite effect. Historically clay has been added to sand to enhance the wearing characteristics, and thus is reflected in the model, since clay has a higher PI than sand. From experience, in the wet season a low percentage of fine material, and consequently a low plasticity index, is beneficial. For the percentage of surfacing material passing the 0.074 mm sieve greater than 2.28 times the plasticity index, the model predicts an increase in roughness in the wet season, all other factors being constant.

Model (4.1) predicts the development of roughness in terms of inter alia wet or dry season. For the central plateau region of Brazil where the study was executed, this type of differentiation may be sufficient, but problems are possible when the model is extrapolated to other regions in Brazil, or to other countries. Consequently a further analysis was run in which actual rainfall data was used. From the logistics involved it was not possible to maintain a rain gauge at every test section. Instead, the rainfall data collected by the Meteorology Department of the Ministry of Agriculture at permanent recording stations were used. In the unpaved study region there were seven recording stations. The distances from the stations to the test sections were less than generally accepted as the influence radius of a station. However, because of the distances from the stations, microclimate influences were undetermined and an averaging of the rainfall data occurred. In addition to the factors evaluated for Model (4.1), the cumulative rainfall since the last blading was considered. The following variables were found to be significant:

$$\begin{aligned} LDQ = {} & D(0.3759 - 0.1010T2 + 0.000320NC + 0.001015NT) \\ & + CRF(-0.00016 - 0.0000354G + 0.00000883SV \\ & - 0.0000218PI) \end{aligned} \tag{4.2}$$

where CRF = cumulative rainfall since the previous blading, in mm, and the other variables are as defined for Model (4.1). Model (4.2) has an R-squared value of 0.31, a standard error of 0.236 and the sample size was 8276. The t-statistics of each coefficient are given in Table 4.3.

The R-squared value of model (4.2) is larger than that for Model (4.1) since a different analysis method was employed to accommodate the cumulative rainfall. On the other hand, the standard error is larger than for Model (4.1), but this difference is not considered to be meaningful.

The inclusion of rainfall substituted adequately for the season dummy variable used in Model (4.1). Furthermore, the coefficients of Model (4.2) excluding rainfall effects are similar to those of Model (4.1) for the dry season. Two traffic terms found significant in Model (4.1) became non-significant when rainfall was

TABLE 4.3 - REGRESSION ANALYSIS OF THE CHANGE IN ROUGHNESS (IN QI*) WITH TIME, INCLUDING RAINFALL

Parameter	Estimate	Standard Deviation	t-value
D	0.3759	0.0156	24.13
D x T2	-0.1910	0.0162	-11.81
D x NC	0.000320	0.000072	4.47
D x NT	0.001015	0.000073	13.98
CRF	-0.000160	0.000045	-3.56
CRF x G	-0.0000354	0.0000052	-6.79
CRF x SV	0.00000883	0.0000008	11.46
CRF x PI	-0.0000218	0.0000022	-10.10

considered, and this suggests that the traffic terms were surrogates for other unexplained variables, possibly rainfall effects. The signs of the coefficients of the remaining terms are the same as for Model (4.1), and therefore the response is as for Model (4.1). Interestingly the change in roughness for a truck is 3.2 times that of a car, but again care should be taken in the application of this type of equivalency factor. Rainfall has a beneficial effect in the development of roughness in that it reduces the rate of change. This finding is in accordance with the wet season effect in Model (4.1).

The consistency between the significant effects found in models (4.1) and (4.2), as well as the similarity of the statistics related to the prediction equations suggest that either model may be used. In the event that rainfall data were available, Model (4.2) would be used, while Model (4.1) would be used in the absence of rainfall data.

In the discussion of the analysis approach a logit model was proposed as an alternative model. By transformation, the logit model reverts to a linear regression. The same linear combination of the independent variables as used for the exponential model were again evaluated. For comparison of the predictive capabilities of the logit with the exponential Model (4.1) the mean squared deviations of the log of the actual QI* values from the log of their respective predicted values were computed. A difference existed only in the fourth significant digit, and there is thus no difference between the predictive capabilities of either the exponential or logit functions for the data set analyzed.

The factors, bar one, found to be significant in the exponential function were also found to be significant for the logit model. Two additional two-factor interactions with time were found to be significant for the logit model. Thus, both models have similar characteristics. This could, however, change for the logit model if sufficient high roughness data were available. Because of this, and the fact that the exponential model is easier to handle computationally, the use of Model (4.1) or (4.2) is recommended rather than the logit model.

4.4 ROUGHNESS AFTER BLADING

Coordinating maintenance activities and the measurement program to coincide on all 48 study sections was impossible, and roughness measurements were usually taken a few days before and after blading. Equation (4.1), together with the measurements obtained, *i.e.*, the last measurement before and the first measurement after blading, were used to estimate the roughness immediately before and immediately after blading. The standard deviation of roughness was related to the magnitude of the measured roughness. Therefore, log transformations of the roughness before and after blading were used to derive the prediction equation. The independent variables that were evaluted were: (1) grade; (2) radius of curve; (3) road width; (4) percentage of surfacing material passing the 0.074 mm sieve; (5) plasticity index of the surfacing material; (6) natural logarithm of roughness before blading; (7) qualitative descriptors of surfacing type, *e.g.*, laterite, quartzite, or clay; (8) average daily car and truck traffic; (9) uphill or downhill lane; (10) time of the previous blading; (11) season during which the blading occurred; (12) interaction of season and variables (4), (5), (6), and (7). The following model was developed:

$$\begin{aligned} LRA = {} & 1.4035 - 0.0239\ W - 0.00480\ SV + 0.01694\ PI \\ & + 0.6307\ LRB + 0.1499\ T1 + 0.3096\ T2 \\ & + 0.00020\ NT + 0.2056\ BS \\ & - 0.01183\ PI \times BS \end{aligned} \tag{4.3}$$

where

LRA = natural logarithm of roughness (QI* counts/km) after blading;

LRB = natural logarithm of roughness (QI* counts/km) before blading;

T1 = surface type dummy variable:
T1 = 1 if surfacing type is quartzite,
T1 = 0 otherwise;

BS = season during which blading occurred:
BS = 0 in dry season,
BS = 1 in wet season.

The t-values associated with each coefficient are shown in Table 4.4.

A total of 1308 observations were used to develop the model which has an R-squared value of 0.61. The standard error of the model is 0.340, which means that the 95 percent confidence interval is LRA + or - 0.663. In untransformed roughness terms, if the predicted roughness after blading is 100, then the confidence interval is 52 to 194.

Roughness after blading is mainly a function of the expertise of the grader operator. The standard deviation of $\log_e$ roughness values after blading, for equal roughness values before blading on the same section was 0.297, which reflects operator variability. This value is similar to the standard error of the model, and thus the model explains the roughness after blading with the same order of accuracy as operator influences.

Roughness after blading is highly dependent on the roughness before blading, as would be expected. As the road width increases, the roughness after blading decreases, probably because of the larger number of lateral position options for a vehicle, and thus, the chance of finding a "smooth" path is increased. An increase in plasticity index increases the roughness after blading in the dry season because if the surface is well compacted, a high plasticity index signifies a high clay content and the surface is very hard from pore water suction in the clay particles. Increasing the percentage of fine material reduces the roughness after blading because of the greater ease in spreading and cutting the surfacing material. However, the surfacing material properties did not fully explain the variation in surfacing type, and the qualitative surfacing type descriptors were found to be significant. Despite this statistical significance it is believed that the differences probably reflect differences in maintenance quality, because the sections with the same surfacing type were frequently located in the same maintenance regions. The average daily truck traffic increases the roughness after blading, probably because of a higher degree of compaction of the upper part of the surfacing, which implies difficulty in cutting this material. If a road section is bladed in the wet season, and if the plasticity index is greater than 17, then the roughness is lower than in the dry season. For a plasticity index less than 17, the roughness is great-

TABLE 4.4 - REGRESSION ANALYSIS OF LOG_e ROUGHNESS AFTER BLADING.

Parameter	Estimate	Standard Deviation	t-value
Intercept	1.4035	0.1434	9.78
W	-0.0239	0.0097	-2.46
SV	-0.00480	0.00105	-4.55
PI	0.01694	0.00366	4.63
LRB	0.6307	0.0189	33.30
T1	0.1499	0.0245	6.11
T2	0.3096	0.0493	6.28
NT	0.00020	0.00007	2.82
BS	0.2056	0.0461	4.46
PI x BS	-0.01183	0.00384	-3.08

er. The wet season effect appears to reflect an adjustment for the very hard upper layer that exists on road sections with a high plasticity index.

4.5 *DISCUSSION OF THE MODELS*

Roughness at any point in time, within the same season, is determined as the exponential of the sum of the logarithm of the change in roughness over time and the logarithm of the roughness at time zero. Thus, the roughness can be determined by using Equation (4.1) or (4.2), together with a known initial roughness, or the roughness after blading can be estimated from Model (4.3). Data from several sections having different surfacing types and maintenance strategies together with the roughness prediction from Model (4.1) are shown in Figures 4.1, 4.2 and 4.3. In each case, the first observed roughness after blading was used as input for RA, the roughness after blading variable. Therefore, the position of the predicted curve is dependent on the first roughness value. If the value is low relative to the other roughness observations, then the prediction is low, and vice versa if the first roughness value is high. This phenomenon is particularly accentuated in Figure 4.1, where errors in roughness prediction are amplified because no blading occurred during the observation period on section 205. The data points shown apply to a specific section, whereas the model was developed on 48 sections and therefore represents an average over all sections. For this reason, the data points shown may not appear to fit the models very well at all data points. Furthermore, the data points do not follow a pattern but rather fluctuate haphazardly over time, thus emphasizing the statement that because of the variations in wheel path positions with time, a high correlation between roughness and time is not expected. This type of roughness development could have been forced by arranging that vehicles always travel within the same wheel paths, but this would not represent what actually occurs in the field.

As was found in the regression analysis, Model (4.1) underpredicts the roughness development on the high frequency maintenance sections, and this is illustrated by Figure 4.3. This figure stands in contrast to Figure 4.2, which also applies to Section 251, where Model (4.1) realistically predicts the roughness development. As was

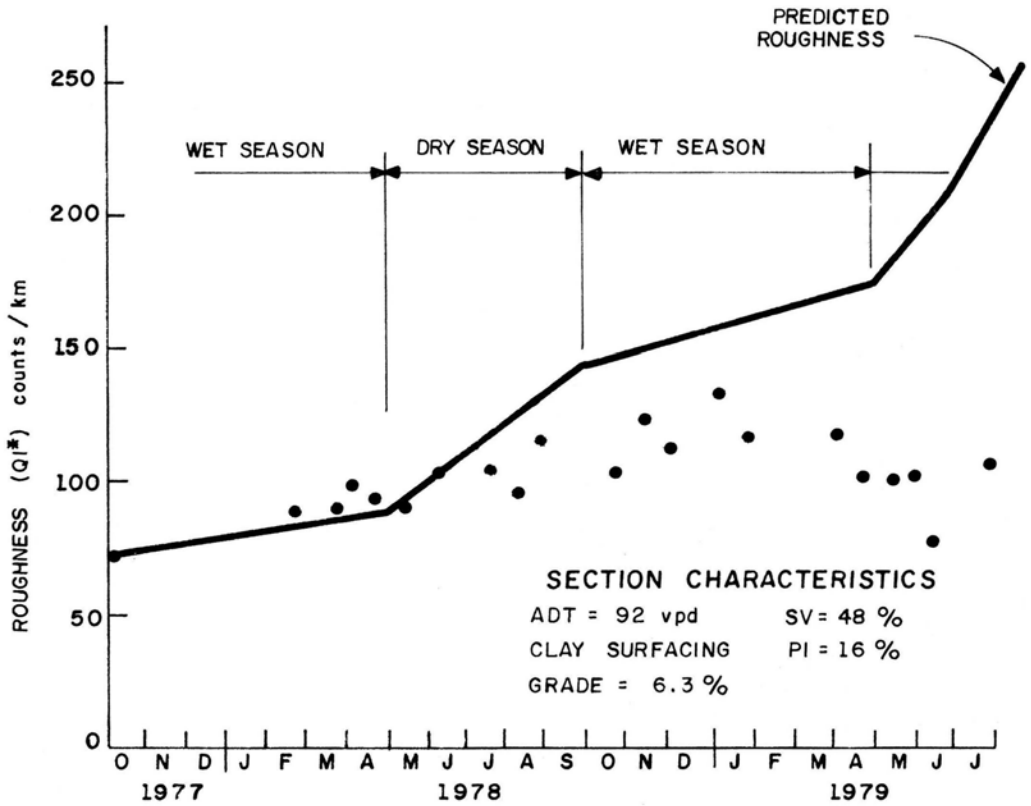

FIGURE 4.1 - MEASURED AND PREDICTED ROUGHNESS ON SECTION 205 WHICH WAS NEVER BLADED DURING THE OBSERVATION PERIOD.

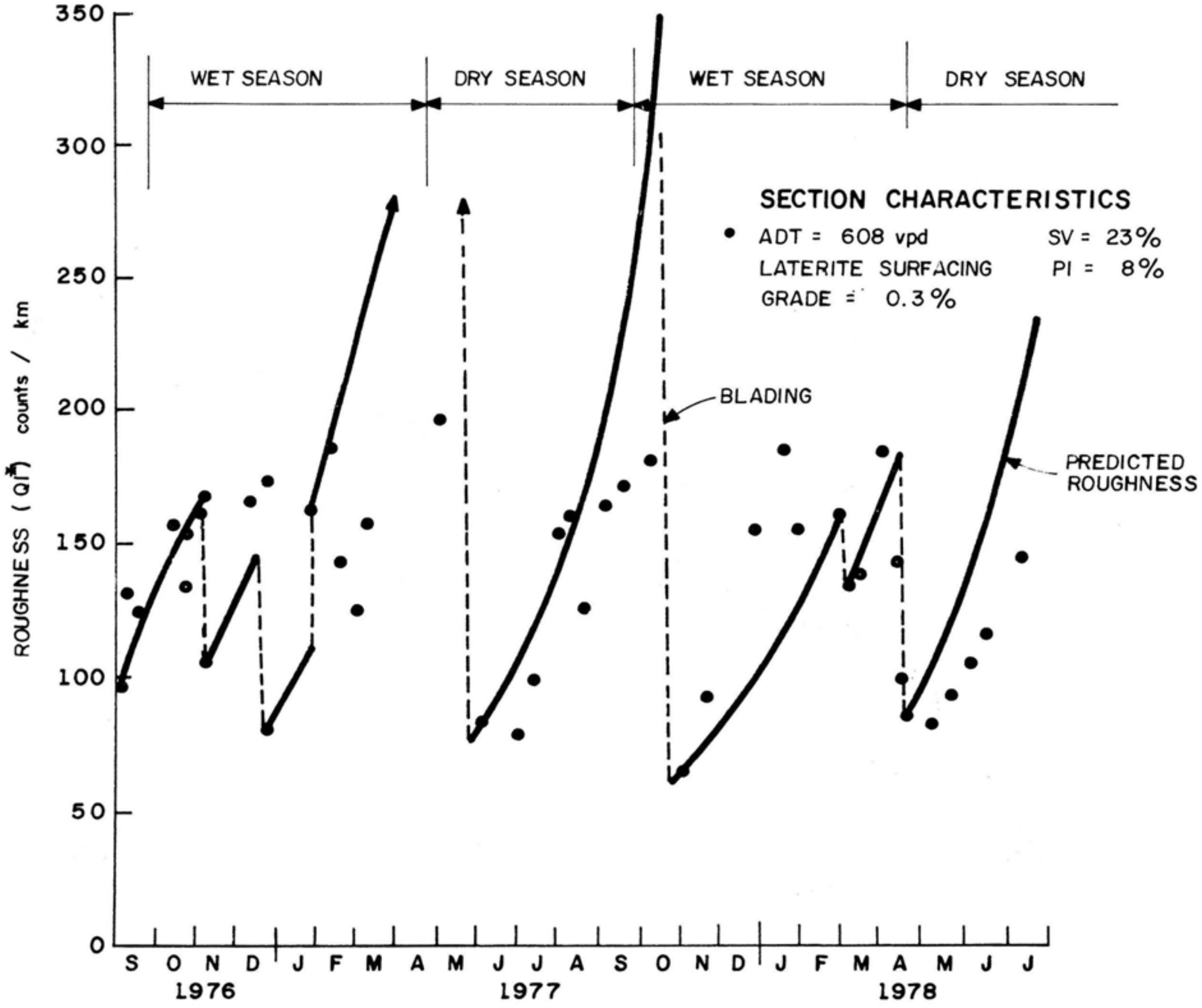

FIGURE 4.2 - MEASURED AND PREDICTED ROUGHNESS ON SECTION 251 UNDER INFREQUENT MAINTENANCE.

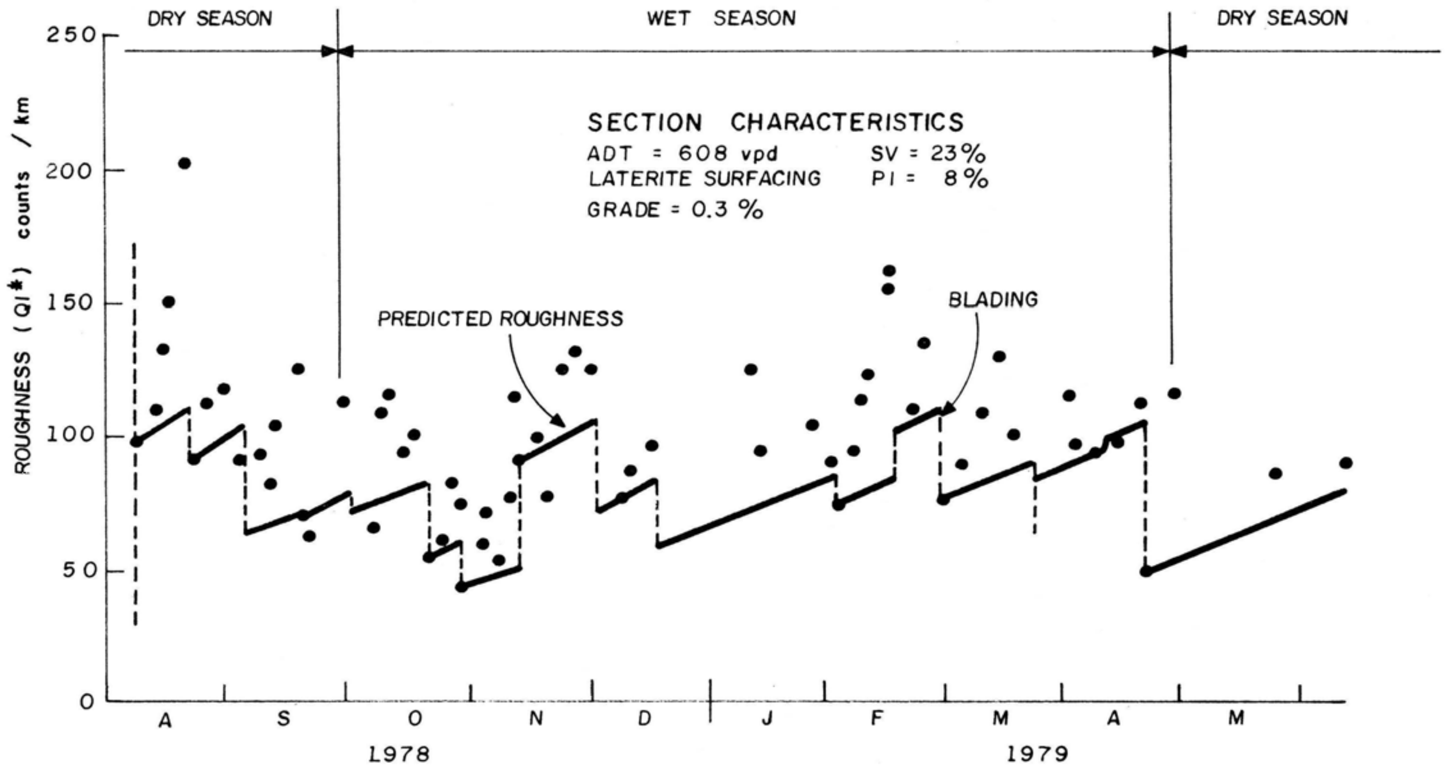

FIGURE 4.3 - MEASURED AND PREDICTED ROUGHNESS ON SECTION 251 WHEN ROAD WAS BLADED EVERY TWO WEEKS.

indicated before, the difference between measured and predicted roughness on the high frequency maintenance section is attributed to the method used in conducting the experiment, When the conditions for blading are non-optimal, water should be added if the road is dry, or if over wet, the road should be left to dry somewhat. Motor-grader operators know from experience which strategy to apply.

As a further comparison of the similarity of the exponential and logit functions, both models were superimposed for Section 205, as shown in Figure 4.4. Very close agreement is apparent, at least at the lower levels of roughness found on this section.

Road closures from the road becoming impassable were not considered in the roughness evaluation. On several occasions during the wet season, clay sections became impassable for several weeks. Roughness before and after these closures were relatively low. Thus, roughness does not seem to adequately characterize road closures. Although high roughness (QI* greater than 400) were measured on some sections, traffic continued to use the road. From an operational point of view, very high roughness will not force a road closure, but may detrimentally affect vehicle operation.

The material properties studied do not fully explain surfacing type differences in the prediction of the change of roughness with time. Clay surfacings exhibit a binding of the surfacing in the dry season, which is attributed to pore water suction in the clay particles. In future studies an evaluation of the clay content of unpaved road surfacing materials may discriminate between the different surfacing types. For evaluating vehicle type influences on roughness it is essential to ensure that all vehicle types be represented on all the study sections, and that a sufficiently wide range exists in the traffic figures to draw meaningful conclusions. In the Brazil study, normal maintenance procedures were applied, and no quantification of the maintenance was attempted. Future work should evaluate this aspect to reduce the large confidence band which applies to Model (4.3).

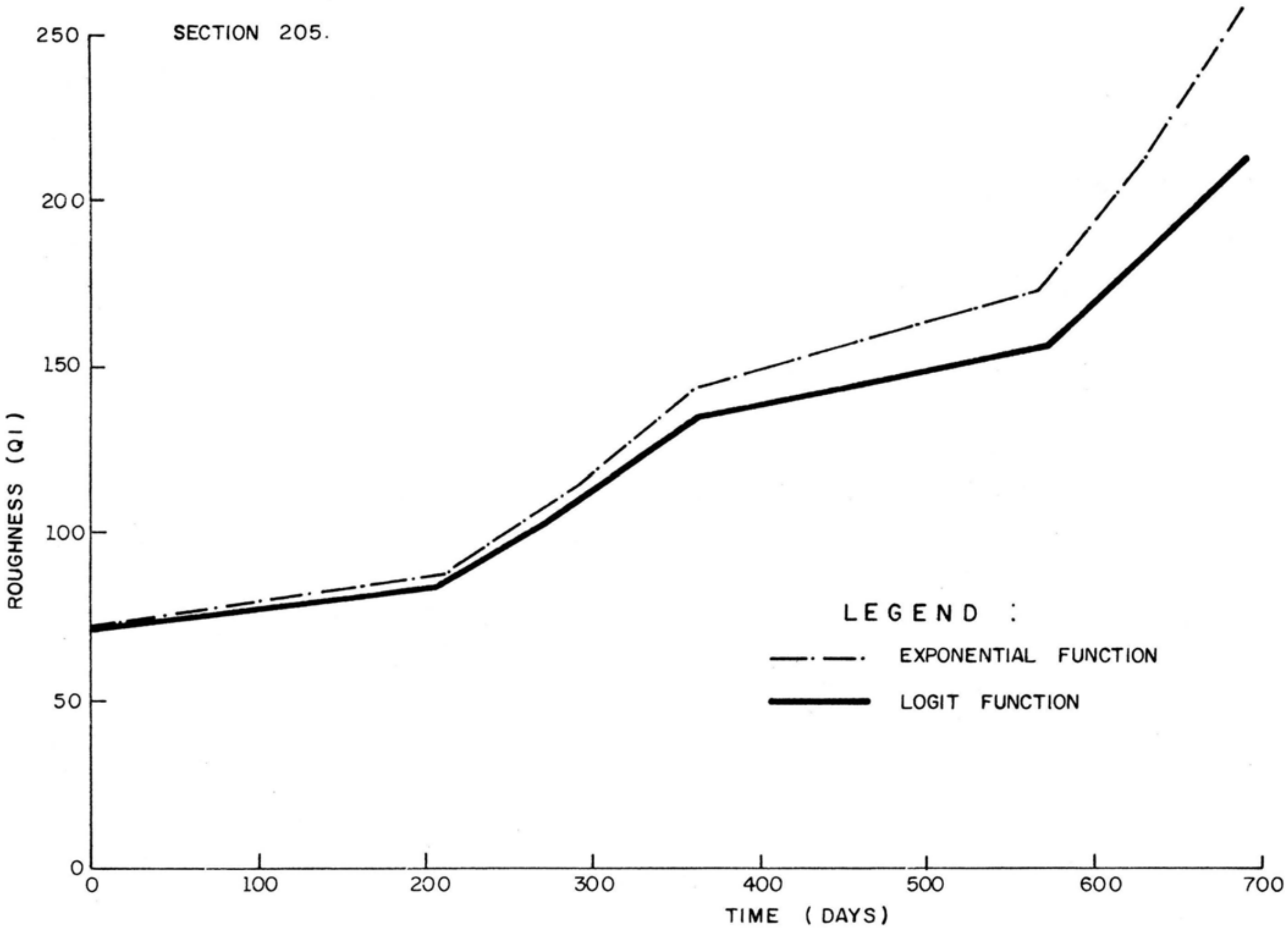

FIGURE 4.4 - COMPARISON OF PREDICTED ROUGHNESS BY THE EXPONENTIAL AND LOGIT FUNCTIONS.

4.6 CORRUGATIONS

One of the road conditions that has a major impact on road roughness is the existence of corrugations. A number of theories and hypotheses were developed since the phenomenon of corrugations was first observed to influence the comfort of the unpaved road user. The majority of these theories were laboratory developed, are oriented towards one wheel and require detailed soil parameter information. During the research study the Maysmeter personnel were required to note whether corrugations existed. Thus the conditions under which many of the theories were developed are not applicable to the conditions that existed in the research project.

Consequently the investigation into the development of corrugations was restricted to an empirical one. Of the 42 study sections, 11 were found to corrugate, where the definition of corrugation related to the observation of this phenomenon on at least three ocasions during the 12-month period in which this information was recorded.

Since two distinct populations of sections exist, those that corrugate and those that do not corrugate, discriminant analysis was attempted. Discriminant analysis relates to deciding on the membership of an observed section in one of a given set of populations to which it may belong (Rao, 1973). The SAS discriminant analysis procedure was used to perform the analysis. Factors such as road geometry, traffic and material properties were included as discriminatory variables.

The analysis showed that the variances of the two populations were significantly different, and that the variance of the sections that corrugate was smaller than that of the other population. This is an expected result since corrugation is a specific road condition, whereas the other population may contain a number of conditions which were not quantified. Because of the non-homogeneous variances, the variances cannot be pooled, and a quadratic discriminant function is used in the program (Rao, 1973). The use of this procedure results in the misclassification of two of the 42 sections. However, the discriminant fucntion is not explicitly stated, as would be for the case if the variances were homogeneous and could be pooled. The SAS procedure also does not have the computational capability to indicate which factors have the most significant effect, and which may be deleted from the analysis.

A further investigation was performed by pooling the variances although it was known that they were non-homogeneous. A total of seven of the 11 sections that corrugated were misclassified as not corrugating, and this is an unacceptable result.

4.7 *CONCLUSIONS AND RECOMMENDATIONS*

The quadratic discriminant function is able to satisfactorily discriminate between sections that corrugate and those that do not. Assuming that the variances of the two populations were homogeneous, while it was proven that they were not, resulted in a very poor discrimination. Since the SAS package is not able to give the quadratic discriminant function explicitly, the recommended procedure to evaluate whether any new section will corrugate is to add the characteristics of the section to the computer file of existing sections, assuming whether the section will corrugate or not, and to rerun the discriminant analysis program and test the assumption.

4.8 *SUMMARY*

Based on a hypothesized model for the development of roughness on an unpaved road, an exponential and logit function were evaluated. These models provided similar predictive qualities and because of simpler application the exponential model is recommended for general use. Two forms of the exponential model are available for use. The one uses a wet/dry season differentiation whereas for the other the cumulative rainfall profile is necessary. Maintenance influences on the exponential model were studied and it was found that blading every two weeks resulted in a larger rate of increase of roughness than when bladings occurred when the road surfacing conditions were optimal. This conclusion is believed to be the result of the experiment rather than a condition that would occur in pratice. A model for predicting the roughness after blading was developed which predicted roughness with the same variance as that of operator variability in blading a section. A comparison with other data sources was not possible because of a lack of a standard roughness scale and a lack of correlations between different roughness measuring instruments. An attempt was also made to separate those factors that would have a major impact on the formation of corrugations, but unfortunately the computational ability was insufficient to draw any conclusions.

CHAPTER 5 - UNPAVED ROAD GRAVEL LOSS ANALYSIS

5.1 SCOPE OF THE GRAVEL LOSS STUDIES

Regravelling is the major maintenance operation on unpaved roads, and it is analogous in importance to overlaying a paved road with asphaltic concrete. It is therefore important that the agency responsible for regravelling know when it should be programmed. The gravel loss studies were aimed at predicting the loss of surfacing material on sections with laterite and quartzite gravel and sections without gravel, *i.e.*, clay. The surfacing material of these latter sections contained more than 35 percent material passing the 0.074 mm sieve. A data summary of the dependent and independent variables studied is given in Table 5.1. These statistics aid in putting the model inference space into perspective. Original data are contained in Working Documents 9, 13, 14, and 15 of this project (Visser and Queiroz, 1979).

5.2 APPROACH FOR GRAVEL LOSS ANALYSIS

Gravel loss is defined as the change in gravel thickness over a period of time. On a well compacted subgrade the change in gravel level or gravel height is the change in gravel thickness. Although gravel thickness is not necessarily equivalent to gravel level or gravel height under all conditions, gravel thickness is used in this report as a synonym for gravel level or height. Since gravel loss is a change of gravel thickness over time, it was not necessary to determine an absolute value at some initial point in time as was done for unpaved roughness and rut depth. Gravel loss was evaluated for the interval between regravellings, which initiated a new analysis cycle, or from the time of the first observation until a regravelling occurred.

Three major influences were identified as affecting gravel loss. These are weathering, traffic, and the influence of maintenance in the form of blading. Material properties and road alignment and width then influence the gravel loss generated by each of these influences. The general model is then:

$$\text{gravel loss} = (\text{time})f_1 + (\text{time})(\text{average daily traffic})f_2 + (\text{bladings})f_3$$

TABLE 5.1 - UNPAVED ROAD DATA SUMMARY (Continued)

Variable	Mean	Standard Deviation	Range	
			Minimum	Maximum
Number of sections = 48				
Grade (%)	3.8	2.6	0.0	8.2
Curvature (1/Rad) on curved sections	.0039	.0009	.0025	.0055
Road width (m)	9.8	1.09	7.0	12.0
MATERIAL PROPERTIES				
Percentage passing the 0.42 mm sieve	53	22	24	98
Percentage passing the 0.074 mm sieve	36	24	10	97
Plasticity index (%)	11	6	0	33
Liquid limit (%)	32	9	20	62
AVERAGE DAILY TRAFFIC (both directions)				
Passenger cars	88	64	11	288
Buses	7	7	0	29
Pickups	37	29	4	115
Two axle trucks	56	93	1	435
Trucks and trailer combinations with more than 2 axles	15	18	0	66
TIME RELATED INFORMATION FOR GRAVEL LOSS				
Number of observations	604			
Time of observation relative to start of observation or regravelling (days)	238	211	0	1099
Number of bladings relative to start of observation or regravelling	2.3	3.3	0	23

TABLE 5.1 - UNPAVED ROAD DATA SUMMARY

(Conclusion)

Variable	Mean	Standard Deviation	Range	
			Minimum	Maximum
INFORMATION RELATED TO ROUGHNESS MEASUREMENTS				
Roughness (QI* counts/km)	117	61	15	445
Number of days since blading for the last observation in each blading period	75	70	1	661
Number of vehicle passes since blading for the last observation in each blading period	16080	17880	63	136460
INFORMATION RELATED TO RUT DEPTH MEASUREMENTS				
Rut Depth (mm)	11.1	8.6	0	75
Number of days since blading for the last observation in each blading period	61	66	1	661
Number of vehicle passes since blading for the last observation in each blading period	12490	14030	21	86700

where f_1, f_2, and f_3 are linear combinations of material properties and road alignment and width.

The average elevation of a subsection relative to the bench mark was used to evaluate gravel loss. These elevations were obtained at about three monthly intervals, and it was not possible to separate seasonal influences. In the Kenya study (Hodges, Rolt and Jones, 1975) it was shown that no seasonal pattern existed in the data, and this also appeared to be the case for the Brazil data. Furthermore, seasonal influences do not have any practical implications since the agency responsible for regravelling wishes to know its frequency in terms of years, and has little interest in the influences of each particular season.

5.3 *ANALYSIS OF GRAVEL LOSS*

The analysis of gravel loss considered the following independent variables: (1) time in days since observations started or since regravelling; (2) grade; (3) horizontal curvature; (4) liquid limit and (5) plasticity index of surfacing material; (6) the percentage of surfacing material passing the 0.42 mm sieve and (7) the 0.074 mm sieve; (8) qualitative description of the surfacing type, *e.g.*, laterite and quartzite; (9) numbers of vehicles per day of each of cars, buses, pickups, two-axle trucks and other trucks and truck-trailer combinations; (10) road width; and (11) the number of bladings since observations started or since regravelling. Three factor interactions were also investigated, *i.e.*, time and bladings times two factor interactions of the other independent variables.

The GLM procedure of the SAS statistical package (SAS Institute, 1979) was used to determine the significant factors. This procedure permitted evaluation of different combinations of factors, unlike stepwise regression where it is difficult to determine significant effects in cases of high correlation among factors.

Two models containing terms multiplied by the number of bladings were developed within experimental conditions, where the maximum number of bladings was 23. Some organizations, such as the U.S. Forest Service (Lund, 1973), blade a road at very frequent intervals - some times daily - and this gives a value of B far in excess of that used to develop the model. This leads to unrealistically high gravel loss predictions. To overcome this limitation a model containing only interactions with time was investigated. The significant factors are the following:

$$GL = D(-1.58 + 0.366\ G + 0.083\ SV - 0.210\ PI + 0.0132\ NC + 0.0081\ NT + 420.45/R) \quad (5.1)$$

where

GL = gravel thickness loss in mm;
D = time period considered, in hundred days, *i.e.*, days/100;
G = absolute value of grade in percent
SV = percentage of surfacing material passing the 0.074 mm sieve;
PI = plasticity index (PI)
NC = average daily car and pickup traffic, both directions;
NT = average daily truck traffic, both directions;
R = radius of horizontal curvature, in m.

The t-values of each coefficient are given in Table 5.2. The R-squared of this model is 0.60, the sample size 604, and the standard error of the model 11.43. Assuming normality of the residuals, the approximate 95 percent confidence interval is GL + or - 22.8 mm.

Several observations relate to this model.

1. Increasing the grade, the percentage of material passing the 0.074 mm sieve, the average daily car and truck traffic, or decreasing the radius of curvature increases gravel loss.
2. Increasing the plasticity index decreases the gravel loss, *i.e.*, the plasticity index represents the cementing or binding ability of the fine material.
3. Gravel loss associated with the passage of one passenger car is twice that of one truck passage. Care should be taken in attaching too much weight to the vehicle equiv-

TABLE 5.2 - GRAVEL LOSS REGRESSION ANALYSIS (MODEL 5.1)

Parameter	Estimate*	Standard Deviation	t-value
D	1.58	0.96	1.64
D x G	0.366	0.103	3.56
D x SV	0.083	0.016	5.01
D x PI	-0.210	0.054	-3.88
D x NC	0.0132	0.0030	4.40
D x NT	0.0081	0.0027	3.01
D/R	420.45	116.07	3.62

* Negative sign denotes gravel loss.

alency factors, as demonstrated below.

4. Attempts were made to evaluate the effects of each of the different vehicle types, but the relatively small numbers of buses, pickups and trucks other than two-axle resulted in insignificant influences, or these vehicle influences resulted in illogical signs on the coefficients which were incompatible with field experience. Consequently only two vehicle types were used.
5. Surfacing material properties explained the influence of surfacing type sufficiently well such that the qualitative surfacing type descriptors were not found to be significant.

Model (5.1) also contains blading influences although not explicitly defined. When using this model it is assumed that the importance of blading influences decreases as the frequency of blading increases. For example, the effect of a blading every day on gravel loss is not the same as a blading every three months. On the average, it is assumed for Model (5.1) that blading influences are constant irrespective of the number of bladings that occur.

5.4 DISCUSSION OF THE MODELS

Despite of the dangers of developing vehicle equivalency factors, Model (5.1) has a wide applicability and is suggested as the model for general use. The effects of the factors that were found to be significant are in general agreement with field experience. A comparison of gravel loss measurements and the predicted gravel loss for two sections are given in Figures 5.1 and 5.2. Figure 5.1 shows the information for Section 205, which,according to the records, was never bladed in an 18 month period. The predicted gravel loss was centered through the mean date and mean gravel thickness. Section 251, on the other hand, was heavily trafficked, received frequent bladings and is one of the sections on which almost three years of data were collected. The predicted curves were again centered through the mean gravel thickness and mean time for each period between re-gravellings. Both figures demonstrate good concordance between measurements and predictions. In some cases the gravel thickness mea-

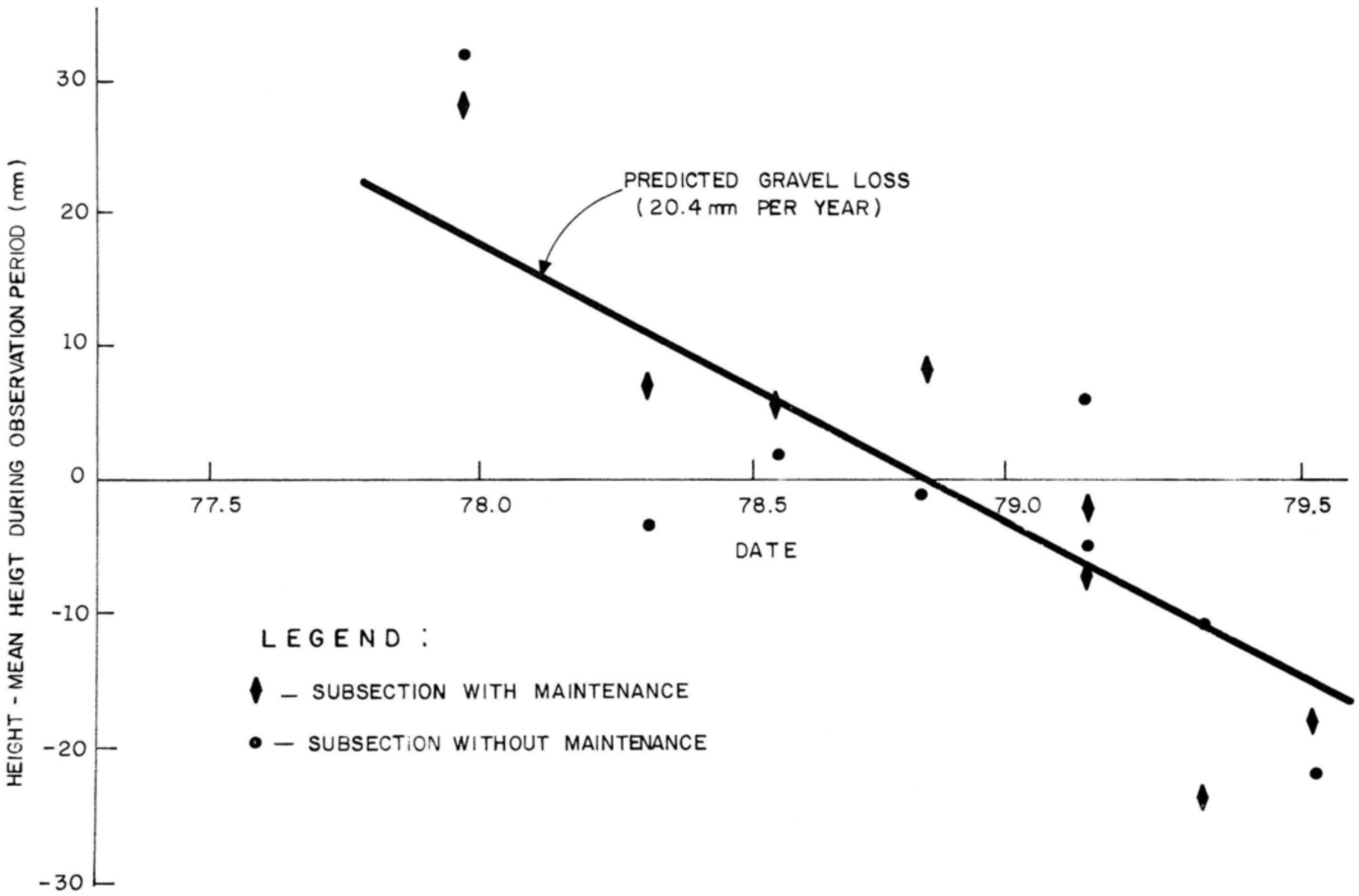

FIGURE 5.1 - PREDICTED AND MEASURED GRAVEL LOSS ON SECTION 205.

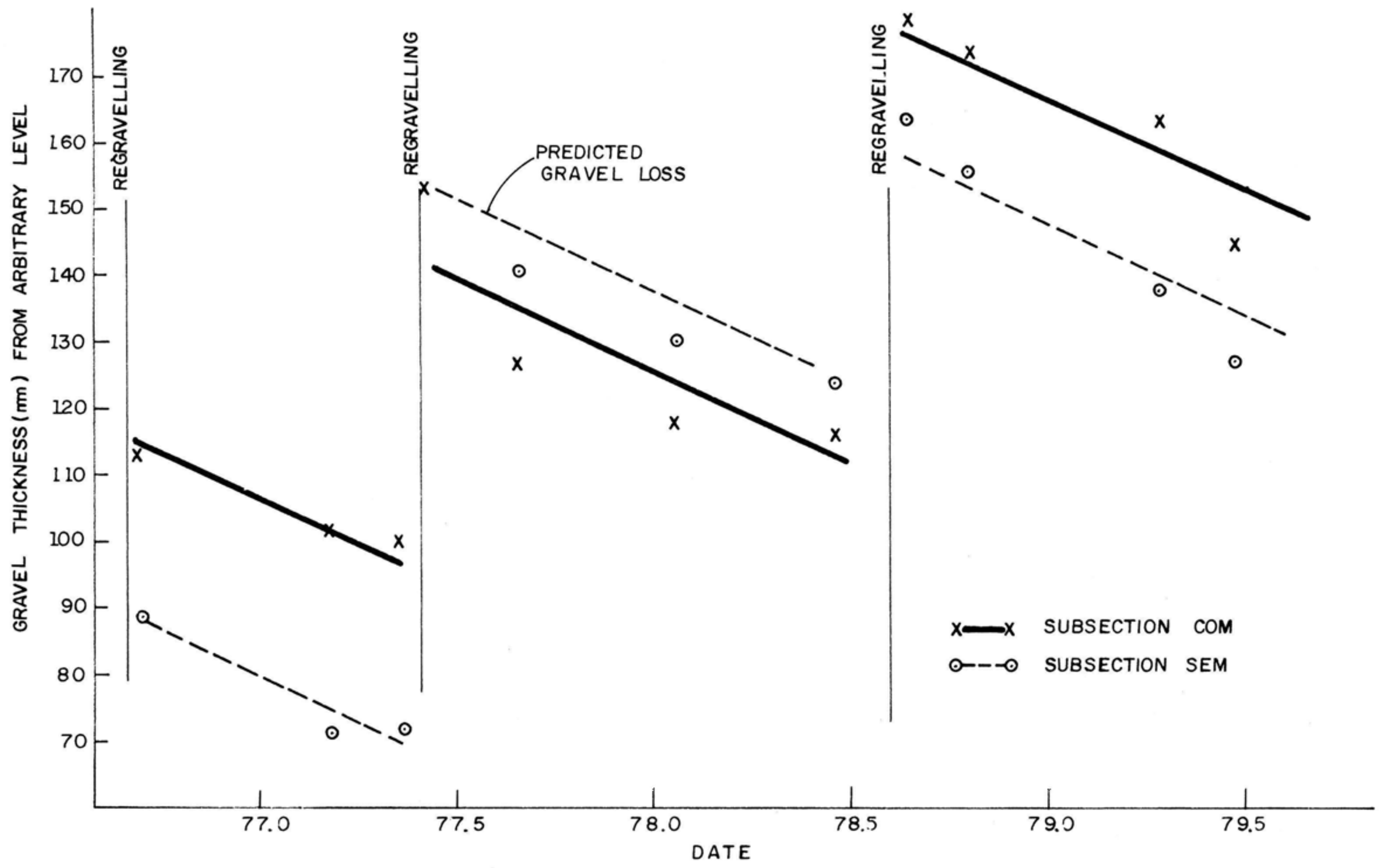

FIGURE 5.2 - PREDICTED AND MEASURED GRAVEL LOSS ON SECTION 251.

sured after regravelling on, for example, Section 251, was much higher than that predicted. This is attributed to the material being relatively uncompacted. In other cases, the material was relatively well-compacted as shown by the predicted and measured gravel thickness, although to the best knowledge only traffic compaction was used in all cases. It could be argued that it would be necessary to predict initial compaction effects, but since this is extremely variable and little information on the degrees of compaction is usually available, this will have little benefit. When calculating gravel quantities, engineers take bulking and compaction effects into account to achieve a final compacted thickness. In repeating this type of study it may be worthwhile to initiate measurements, say, one month after regravelling, to overcome initial compaction effects.

Table 5.3 was generated from Model (5.1) to assist in obtaining some feel for the behavior of the model. Values covering the extremes of the independent variables were selected. This resulted in combinations which normally do not exist in practice, such as a surfacing material containing 10 percent of the material passing the 0.074 mm sieve which has a plasticity index of 30. For this case the model predicts a gravel gain, which is unrealistic. To avoid the prediction of unrealistic values for cases such as these, it is necessary to use a nominal annual gravel loss of, say, 5 mm whenever the gravel loss is less than this value.

An attempt to include cumulative rainfall in the model was unsuccessful since it resulted in a model that predicted contrary to held experience, and also resulted in a change-over of effects within the data range studied.

5.5 *SUMMARY*

Model (5.1) is recommended for general use and comparison of the predictions from this model with data collected in Kenya show good agreement. From a very limited comparison it appears that although the Brazil data was collected in a region of about 1600 mm annual rainfall, the model is valid for predicting gravel loss in low rainfall regions, *e.g.*, below 750 mm per year. An attempt to include rainfall in the Brazil gravel loss prediction model was un-

GRADE (%)	PLASTICITY INDEX	% PASSING THE 0.074 mm SIEVE								
CURVATURE RADIUS (m)			TANGENT				180			
TRUCK ADT			0		400		0		400	
CARS ADT			15	400	15	400	15	400	15	400
0	0	10	9.5*	28.1	21.3	39.9	18.1	36.6	29.9	48.4
		90	33.8	52.3	45.6	64.1	42.3	60.8	54.1	72.7
	30	10	-13.5	5.1	-1.6	16.9	-4.9	13.6	6.9	25.4
		90	10.1	29.3	22.6	41.1	19.3	37.8	31.1	49.7
8	0	10	20.2	38.8	32.0	50.6	28.7	47.3	40.6	59.1
		90	44.4	63.0	56.3	74.8	53.0	71.5	64.8	83.4
	30	10	-2.8	15.8	9.0	27.6	5.7	24.3	17.6	36.1
		90	21.4	40.0	33.3	51.8	30.0	48.5	41.8	60.4

* OBS: POSITIVE VALUES DENOTE GRAVEL LOSS

TABLE 5.3 - ANNUAL GRAVEL LOSS GENERATED FROM MODEL 5.1.

successful.

Under certain combinations of factors outside the range in which the model was developed, gravel gains or unrealistically low gravel loss can occur. To overcome this problem a minimum annual gravel loss of 5 mm should be used, irrespective of the model predictions. Very short radius curves result in unrealistically high gravel loss predictions, and from a comparison with the Forest Service Study a substitution of a 100 m radius for smaller radius curves in Model (5.1) is recommended.

CHAPTER 6 - UNPAVED ROAD RUT DEPTH ANALYSIS

6.1 INTRODUCTION

Users of unpaved roads claim that deep ruts affect the safe operation of vehicles, and can lead to accidents. In addition, prominent ruts act as drainage channels and prevent water from running off the roadway, thus causing drainage problems which could lead to rapid deterioration of the riding quality or the road becoming impassable. The responsible agency therefore needs to know when to program maintenance in terms of the developed rut depth. The rut depth studies were aimed at predicting rut depth at any point in time, in both the wet and dry seasons. A data summary of the dependent and independent variables studied are given in Table 6.1. These statistics aid in defining the inference space in which the models were developed.

6.2 APPROACH FOR RUT DEPTH ANALYSIS

A deterioration cycle for rutting starts following a given blading and continues until the next blading. Thus a deterioration cycle is a short term phenomenon, and it was possible to make observations during a number of cycles during the study period. The amount of deterioration was a function of the length of time between bladings. Inspection of the data showed that, contrary to general belief, rut depth after blading was not zero. This agreed with the Kenya study (Hodges, Rolt and Jones, 1975) where models predicted a non-zero rut depth after blading. Because the rut depth after blading was variable, and the number of days between bladings varied widely, the analysis was executed in two parts: the first part consisted of predicting the change in rut depth over time, while the second part addressed predicting the rut depth after blading. A combination of the two parts predicts the rut depth as a function of time since blading and other independent variables.

6.3 ANALYSIS OF THE CHANGE IN RUT DEPTH WITH TIME

The rate of change in rut depth was hypothesized to be a function of a linear combination of the independent variables. This model form was selected since the development of rut depth appeared

TABLE 6.1 - UNPAVED ROAD DATA SUMMARY

(Continued)

Variable	Mean	Standard Deviation	Range	
			Minimum	Maximum
Number of sections = 48				
Grade (%)	3.8	2.6	0.0	8.2
Curvature (1/Rad) on curved sections	.0039	.0009	.0025	.0055
Road width (m)	9.8	1.09	7.0	12.0
MATERIAL PROPERTIES				
Percentage passing the 0.42 mm sieve	53	22	24	98
Percentage passing the 0.074 mm sieve	36	24	10	97
Plasticity index (%)	11	6	0	33
Liquid limit (%)	32	9	20	62
AVERAGE DAILY TRAFFIC (both directions)				
Passenger cars	88	64	11	288
Buses	7	7	0	29
Pickups	37	29	4	115
Two axle trucks	56	93	1	435
Trucks and trailer combinations with more than 2 axles	15	18	0	66
TIME RELATED INFORMATION FOR GRAVEL LOSS				
Number of observations	604			
Time of observation relative to start of observation or regravelling (days)	238	211	0	1099
Number of bladings relative to start of observation or regravelling	2.3	3.3	0	23

TABLE 6.1 - UNPAVED ROAD DATA SUMMARY

(Conclusion)

Variable	Mean	Standard Deviation	Range	
			Minimum	Maximum
INFORMATION RELATED TO ROUGHNESS MEASUREMENTS				
Roughness (QI* counts/km)	117	61	15	445
Number of days since blading for the last observation in each blading period	75	70	1	661
Number of vehicle passes since blading for the last observation in each blading period	16080	17880	63	136460
INFORMATION RELATED TO RUT DEPTH MEASUREMENTS				
Rut depth (mm)	11.1	8.6	0	75
Number of days since blading for the last observation in each blading period	61	66	1	661
Number of vehicle passes since blading for the last observation in each blading period	12490	14030	21	86700

to be independent of the existing rut depth for the available data. The following independent variables were investigated: (1) horizontal alignment; (2) grade; (3) liquid limit and (4) plasticity index of surfacing material; (5) the percentage of the surfacing material passing the 0.42 mm and (6) the 0.074 mm sieve; (7) qualitative surfacing type descriptors, *e.g.*, laterite, quartzite and clay; (8) average daily traffic in both directions for five vehicle classes: cars, pickups, buses, two-axle trucks and other trucks; (9) internal and external wheelpath; (10) uphill or downhill lane; (11) road width; and (12) seasonal effects. Two factor interactions of these independent variables and time were also studied. The dependent variable investigated was the change in rut depth in mm. Because of variations in periods between bladings, and also in the rut depths after bladings, the analysis was conducted by centering the data within each blading period through the origin. This procedure allows the determination of the change of rut depth without the influence of the rut depth after blading. The GLM procedure of the SAS package (SAS Institute, 1979) was again used to perform the regression analysis.

Initially, two season parameters, representing wet and dry seasons, were used. A preliminary model predicted decreases in rut depth over time on most sections during the wet season. Inspection of the data showed that at the start of the wet season a rapid decrease in rut depth occurred. This continued for the first two months of the season, or until the section was bladed. It was postulated that this phenomenon was a result of drivers avoiding the ruts where water was ponding, and thus the ruts decreased. Therefore, a third season descriptor, transition season, was introduced. The significant variables for the change in rut depth (DRD in mm) with time are shown in the models for the three seasonal conditions:

Dry season (S1 = 0, S2 = 0)

$$\begin{aligned} DRD = D(&9.78 - 1.033G - 0.192PI - 3.63T2 + 0.0302NC \\ &+ 0.0198NT - 3.27RO - 3.04NT/R \\ &+ 0.46G \times RO - 325.0L/R + 0.0364L \times SV) \end{aligned} \qquad (6.1\ a)$$

Transition season ($S1 = 1$, $S2 = 0$)

$$DRD = D(-83.76 + 3.658G - 0.192PI - 3.63T2 - 0.1147NC + 0.1249NT - 3.27RO - 3.04NT/R + 0.46G \times RO - 325.0L/R + 0.0364L \times SV + 6.874W) \quad (6.1\ b)$$

Wet season ($S1 = 0$, $S2 = 1$)

$$DRD = D(9.78 - 1.033G - 0.192PI - 3.63T2 - 0.0109NC + 0.0198NT - 3.27RO - 3.04NT/R + 0.46G \times RO - 325.0L/R + 0.0364L \times SV) \quad (6.1\ c)$$

where

D = time since last blading, in days/100;
G = absolute value of grade, in percent;
PI = plasticity index, in percent;
T2 = surfacing type dummy variable:
  T2 = 1 if surfacing is clay,
  T2 = 0 otherwise;
NC = average daily number of cars and pickups in both directions;
NT = average daily number of buses and trucks in both directions;
RO = wheelpath dummy variable:
  RO = 0 for external wheelpath,
  RO = 1 for internal wheelpath;
R = radius of curve, in m;
L = lane dummy variable:
  L = 0 for uphill lane,
  L = 1 for downhill lane.

S1 = transition from dry to wet season dummy variable: first two months of wet season or until first blading in this period, S1 = 1, otherwise S1 = 0;

S2 = wet season dummy variable: after first blading in first two months of wet season, or after two months in wet season, S2 = 1, otherwise, S2 = 0;

W = road width, in m.

The t-values of each coefficient are given in Table 6.2. This model has an R-squared value of 0.14, a standard error of 4.87 and 7957 observations were used in the regression analysis. The 95 percent confidence intervals are DRD + or - 9.50. The R-squared value is low because of the variations in the position of the ruts resulting in measured rut depths which are variable and thus do not correlate highly over time. The model depicts an average condition of the ruts. In addition, a very large data base was used and the model is statistically highly significant.

As a check for the robustness of the coefficients of the traffic terms, a further analysis was run using the average daily traffic as the only traffic term. The resultant model had an R-squared of 0.12, which is significantly lower than for model (6.1) at the 0.01 level. Therefore, the hypothesis that the coefficients of the two traffic classifications are equal is rejected.

Equation (6.1) predicts an increase in rut depth with time for both cars and trucks in the dry season, and the influence of one car passage is equivalent to 1.5 truck passages. On curves one car passage is equivalent to more than two truck passages, depending on the radius of curvature. These phenomena are attributed to a wider influence area of especially dual truck wheels compared to car wheels, and also since trucks do not necessarily travel with their wheels completely in the ruts,thus compacting and displacing material into the wheeltracks. In the wet and transition seasons the relative influences of cars and trucks change. Car traffic results in a decrease in rut depth, probably because they avoid the existing ruts, whereas truck traffic has a significant positive effect, probably because of their compaction and movement of the surfacing material. In the transition season the coefficient of time is large and negative, signifying a large rate of reduction in rut depth, but this effect should be considered in conjunction with the term containing

TABLE 6.2 - REGRESSION ANALYSIS OF THE CHANGE IN RUT DEPTH (IN mm) WITH TIME

Parameter	Estimate	Standard Deviation	t-value
D	9.78	1.52	6.42
D x G	-1.033	0.292	-3.54
D x PI	-0.192	0.049	-3.94
D x T2	-3.63	0.92	-3.93
D x NC	0.0302	0.0027	11.33
D x NT	0.0198	0.0034	5.86
D x RO	-3.27	0.83	-3.95
D x NT/R	-3.04	0.99	-3.07
D x G x RO	0.46	0.18	2.57
D x L/R	-325.0	93.1	-3.49
D x L x SV	0.0364	0.0093	3.90
D x S1	-93.54	13.59	-6.88
D x G x S1	4.691	0.601	7.80
D x NC x S1	-0.1449	0.0159	-9.10
D x NT x S1	0.1051	0.0138	7.62
D x W x S1	6.874	1.181	5.82
D x NC x S2	-0.0411	0.0032	-12.80

road width, which has a fairly large and positive coefficient. Clay surfaced roads rut at a slower rate than laterite or quartzite surfaced roads.

In the dry and wet seasons an increase in grade leads to a reduction in the predicted change in rut depth. This is attributed to improved surface and subsurface drainage of sections on grade compared to those on the level. An increase in plasticity index results in a decrease in the predicted change in rut depth, because of the better binding or cohesion of the higher plasticity index material.

As would be expected, the rut in the internal wheelpath develops more slowly than in the external wheelpath, but on grades this effect is changed such that on a 7.1 per cent grade ruts in both wheelpaths develop at the same rate. The downhill lane develops ruts faster than the uphill lane, and this is predicted to be dependent on the percentage of fine material in the surfacing passing the 0.074 mm sieve. This influence on the downhill lane is, however, reduced on curves. It is believed that this phenomenon occurs because vehicles pay more attention to driving in the existing ruts to ensure braking capability in the region devoid of loose material. Outside the wheeltracks the loose material could act as a lubricant.

6.4 *RUT DEPTH AFTER BLADING*

To develop a model for predicting the rut depth immediately after blading, this rut depth would be required. It was impossible to coordinate measurements on all 48 study sections to coincide with applied maintenance, and rut depth measurements were made as soon as possible after blading, usually within a few days. Consequently, rut depths immediately after blading had to be computed. Using the change of rut depth with time model (Equations 6.1a to 6.1c), the rut depth after blading was computed from the average rut depth and average observation time within each blading period. This procedure gives a more realistic estimate of the rut depth after blading than if only the first measurement had been used. The analysis was performed with rut depth after blading as the dependent variable, and the following independent variables: (1) grade; (2) horizontal alignment; (3) surfacing material characteristics; (4) qualitative surfacing type descriptor; (5) uphill or downhill lane; (6) external or internal wheelpath; (7) average daily number of cars and trucks; and (8) the interaction of wet season with these aforementioned independent variables. In this analysis, those measurements taken during the transition portion of the wet season were removed from the analysis, since by definition, no bladings occur during this time.

The significant variables are shown in the model for the rut depth immediately after blading:

$$\begin{aligned} FRD = {} & 5.46 + 3.80T1 + 4.74T2 + 0.0158\ NT \\ & + S2(0.178G - 587.4/R - 0.118\ PI + 3.00T1 \\ & + 0.0226\ NC - 0.0134\ NT) \end{aligned} \tag{6.2}$$

where

FRD = rut depth after blading in mm;

T1 = surfacing type dummy variable:
T1 = 1, if surfacing is quartzite,
T1 = 0, otherwise;

T2 = surfacing type dummy variable:
T2 = 1, if surfacing is clay,
T2 = 0, otherwise;

NT = average daily truck traffic in both directions;

S2 = wet season dummy variable after first blading in first two months of wet season or after two months in wet season S2 = 1 otherwise, S2 = 0;

G = absolute value of grade in percent;

R = radius of curve in m;

PI = plasticity index, in percent;

NC = average daily car traffic in both directions.

The t-values for the coefficients are given in Table 6.3. This model has an R-squared of 0.24, a standard error of 6.25 and the sample size was 2364. The 95 percent confidence interval for this model is FRD + or - 12.2.

In the dry season (S2 = 0), the coefficients of the surfacing type dummy variables signify different rut depths for the different surfacing types. This is believed to be attributable to dif-

TABLE 6.3 - REGRESSION ANALYSIS OF THE RUT DEPTH (IN mm) AFTER BLADING

Parameter	Estimate	Standard Deviation	t-value
Intercept	5.46	0.29	19.09
T1	3.80	0.38	10.10
T2	4.74	0.39	12.03
NT	0.0158	0.0014	11.54
S2 x G	0.178	0.069	2.57
S2/R	-587.4	88.7	-6.62
S2 x PI	-0.118	0.033	-3.56
S2 x T1	3.00	0.56	5.35
S2 x NC	0.0226	0.0023	9.79
S2 x NT	-0.0134	0.0018	-7.41

ferent maintenance standards, rather than a surfacing type influence. A consistent influence over all three surfacing types is that of the number of trucks. The larger the average daily truck traffic, the greater the rut depth after blading, probably because of compaction of the surfacing which makes blading more difficult. In the wet season several other factors become important, while the truck influence is virtually eliminated. For increasing grade and average number of cars the rut depth after blading is increased, as is the rut depth on quartzite surfaced roads. On curves, the rut depth is less than on tangents, probably because a wider dispersion of lateral positions occur on curves. An increase in the plasticity index results in a decrease in rut depth. This is attributed to the increased cohesion at relatively low moisture contents where the road was passable for the Mays Meter vehicles, but in those cases at high moisture contents where the road became impassable, no measurements were taken.

A further analysis was run to determine whether the average daily traffic could adequately substitute the two traffic classifications of Model (6.2). The resultant model had an R-squared of 0.21, which is significantly lower, at the 0.01 level, than that of Model (6.2). Therefore, the hypothesis that the coefficients of the two traffic classifications are the same is rejected.

6.5 *DISCUSSION OF THE MODELS*

The rut depth at any time is determined using two models. One model predicts the change of rut depth over time, and the second predicts the rut depth after blading. Intuitively, one might expect that immediately after blading, rut depth should be zero. This was not found to be the case, and thus supports the findings of the Kenya study (Hodges, Rolt and Jones, 1975) which showed that the rut depth after blading was, for example, 11 mm on laterite roads. This phenomenon may be attributed to blading techniques. Blading on the study sections in Brazil consisted of pulling loose material from the shoulder and spreading it over the roadway. The riding surface was normally not cut, particularly if the surface was firmly compacted.

Table 6.4 shows the change in rut depth over a 100 day period generated from Model (6.1). The values are for the external

GRADE (%)			0								8							
RADIUS OF CURVE (m)			TANGENT				180				TANGENT				180			
PLASTICITY INDEX (%)			0		30		0		30		0		30		0		30	
UPHILL OR DOWNHILL LANE			U	D	U	D	U	D	U	D	U	D	U	D	U	D	U	D
SEASON	**ADT TRUCKS AND BUSES**	**ADT CARS AND PICKUPS**																
DRY	0	15	10.2	10.6	4.5	4.8	10.2	8.8	4.5	3.0	2.0	2.3	-3.8	-3.4	2.0	0.5	-3.8	-5.2
		400	21.9	22.2	16.1	16.5	21.9	20.4	16.1	14.7	13.6	14.0	7.8	8.2	13.6	12.1	7,8	6.4
	400	15	18.1	18.5	12.4	12.7	11.4	9.9	5.6	4.2	9.9	10.2	4.1	4.5	3.1	1.7	-2.7	-4.1
		400	29.8	30.1	24.0	24.4	23.0	21.5	17.2	15.8	21.5	21.9	15.7	16.1	14.7	13.3	9.0	7.5
WET (S2=1)	0	15	9.6	10.0	3.9	4.2	9.6	8.2	3.9	2.4	1.3	1.7	-4.4	-4.0	1.3	-0.1	-4.4	-5.8
		400	5.4	5.8	-0.3	0.0	5.4	4.0	-0.3	-1.8	-2.8	-2.5	-8.6	-8.2	-2.8	-4.3	-8.6	-10.0
	400	15	17.5	17.9	11.8	12.1	10.7	9.3	5.0	3.6	9.3	9.6	3.5	3.9	2.5	1.0	-3.3	-4.7
		400	13.3	13.7	7.6	7.9	6.6	5.1	0.8	0.6	5.1	5.4	-0.7	-0.3	-1.7	-3.2	-7.5	-8.9

FOR PERCENTAGE PASSING 0,074 mm SIEVE = 10 %

TABLE 6.4 - GENERATED VALUES OF CHANGE IN RUT DEPTH OVER A 100 DAY PERIOD AFTER BLADING FROM MODEL (6.1).

wheelpath and for a surfacing material which has 10 percent passing the 0.074 mm sieve. Substantial ruts develop under heavy traffic, as evidenced by the predicted 30 mm change in rut depth. However, in general, the change in rut depth over a 100 day period is relatively small, suggesting that rutting may not trigger maintenance for the strong pavements studied.

Figures 6.1, 6.2 and 6.3 show the data points and the rut depths predicted from Equations 6.1 and 6.2 for several different sections. The lack of close agreement between data points and predicted values is due in part to using equations that fit the data for all study sections. Also, the vertical scale of the plots is exaggerated for a very small unit of measurement (mm) on an extremely variable property. The figures show that the rut depth is self-restoring during the transition of the dry to wet season, *i.e.*, the rut depth after the transition season is relatively low. This is attributed to drivers who, in avoiding the water in the ruts, generate new wheeltracks which were then measured. According to all acounts, section 205 was never bladed during the observation period and the predicted rut depth represents this situation. There are no data points from November to April because the road was extremely muddy, and at times completely impassable to the Mays Meter vehicles. In addition, the transverse road profile was extremely uneven from material that was squeezed aside making realistic measurements extremely difficult.

The use of Equation 6.1 in the transition season can possibly result in negative rut depths. Inspection of the data showed that during this period the minimum rut depth was about 5 mm, and this value is used as a minimum in those cases where the prediction results in a lower value. Both the prediction equations for rut depth after blading and the change in rut depth over time contain horizontal radius of curvature terms. For very small radius curves, say 20 m, completely unrealistic predictions result. To overcome this problem a minimum radius of curvature of 100 m is proposed, until a more rational limiting value is obtained from future data sources.

6.6 SUMMARY

Models (6.1) and (6.2) are recommended for general use for

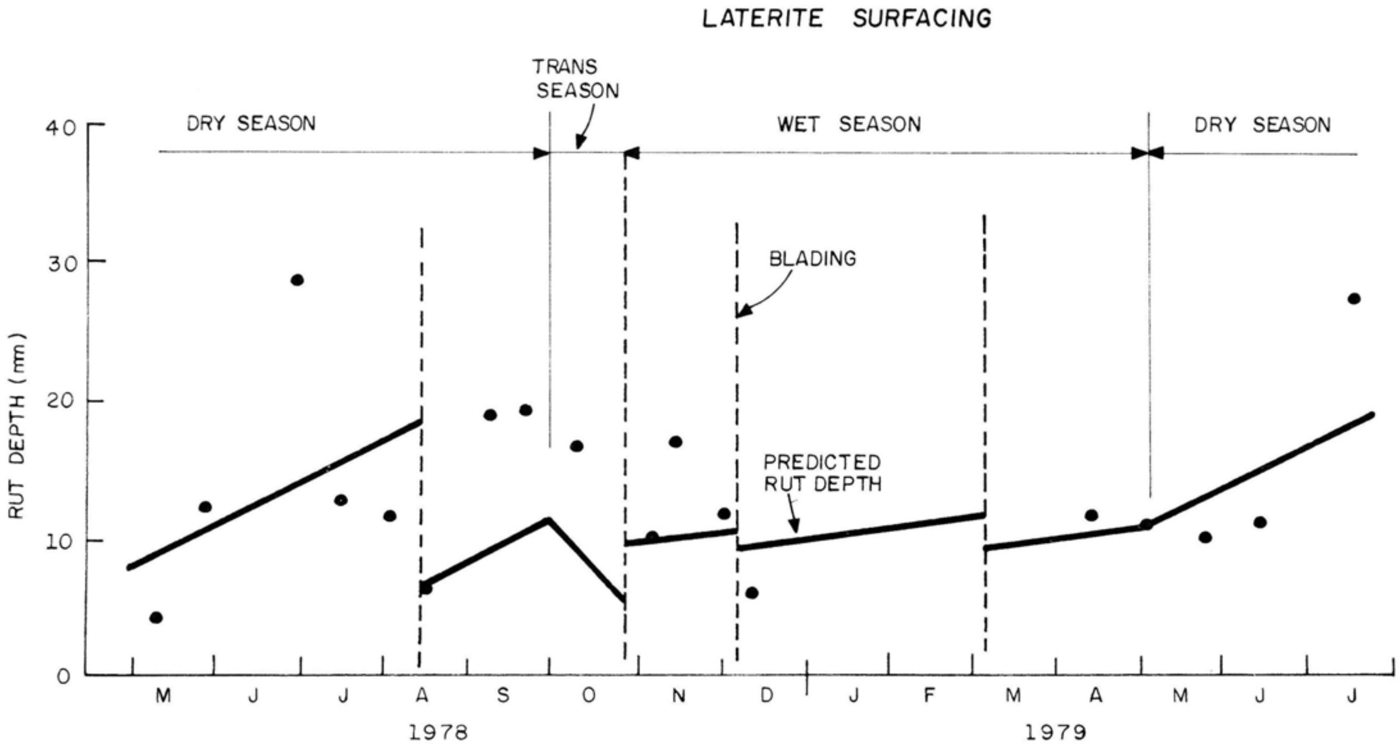

FIGURE 6.1- MEASURED AND PREDICTED RUT DEPTH ON DOWNHILL LANE OF SECTION 256.

QUARTZITE SURFACING

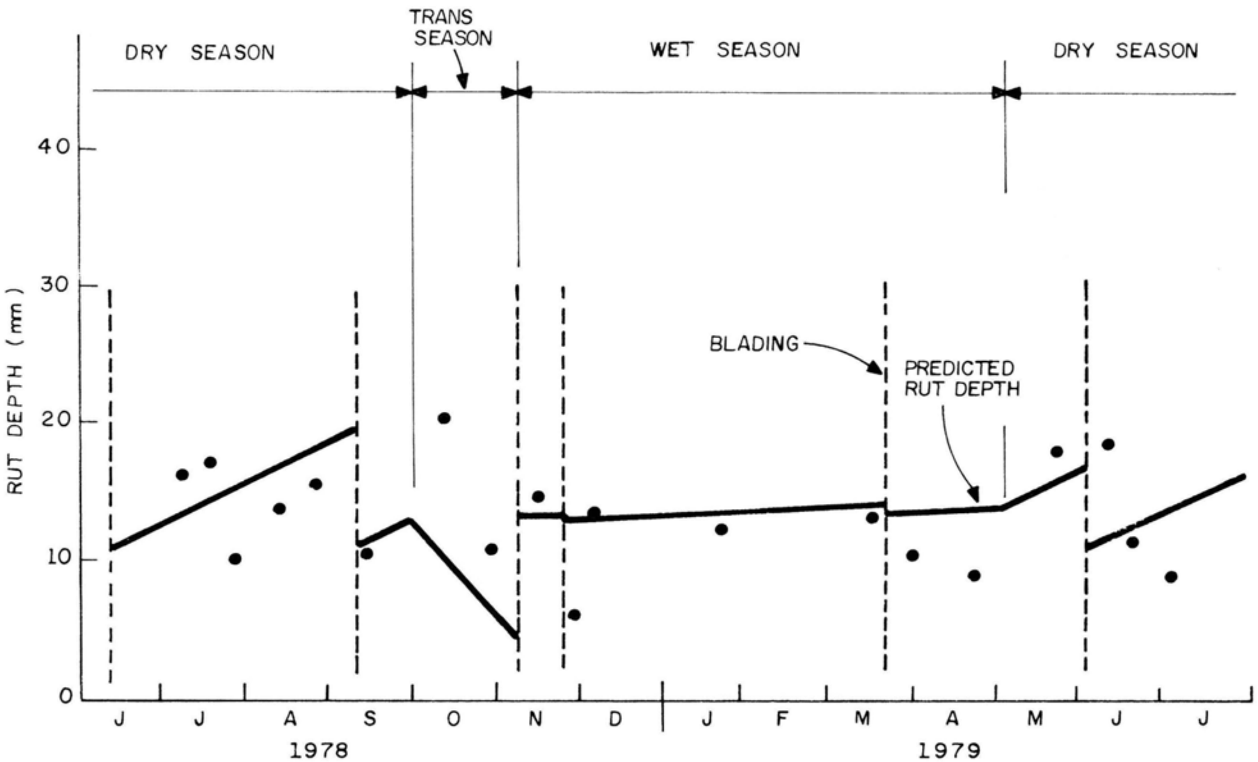

FIGURE 6.2 - MEASURED AND PREDICTED RUT DEPTH ON UPHILL LANE OF SECTION 303.

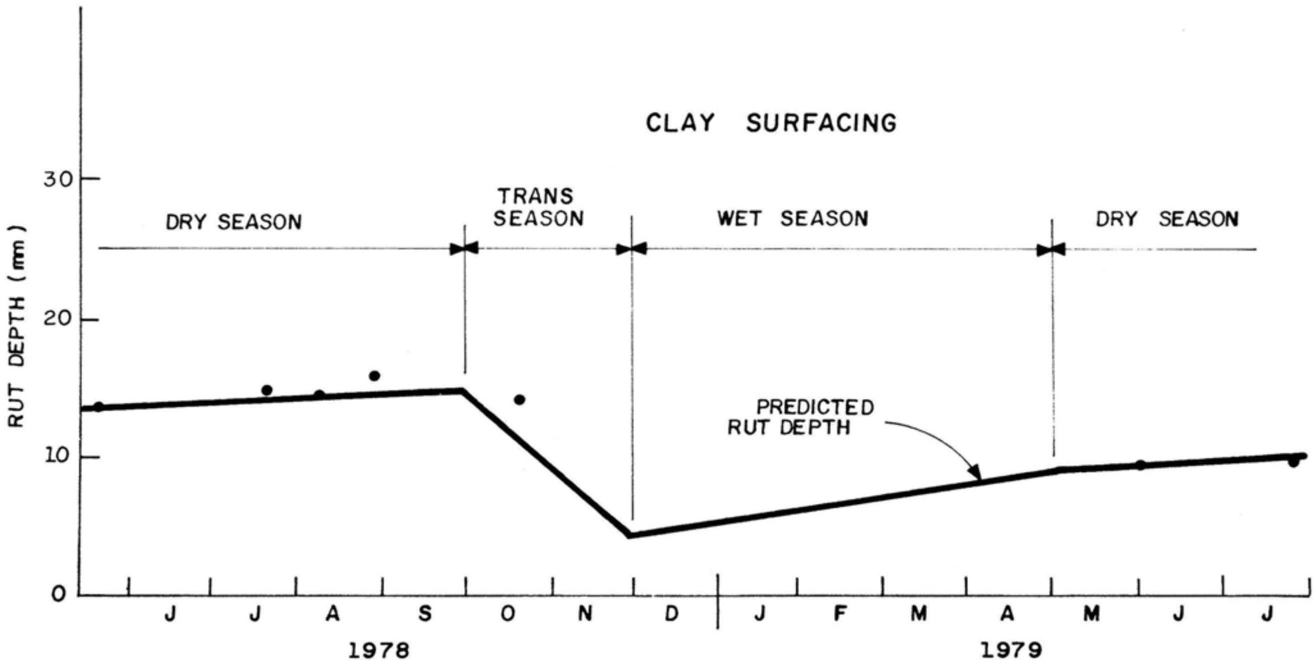

FIGURE 6.3 - MEASURED AND PREDICTED RUT DEPTH ON UPHILL LANE OF SECTION 205.

predicting the rut depth at any time. These models generate reasonable predictions during the wet and dry seasons even outside the inference space in which the models were developed. Although no substantive data are available, it is proposed that a 100 m radius curve be used as a limit even if the radius is smaller, to avoid unrealistic extrapolations. In the transition season from the dry season to wet season there is a sharp reduction in rut depth as drivers avoid ruts where water collects. In certain cases, the reduction could lead to predict negative values of rut depth. To overcome this problem, a threshold of a 5 mm rut depth, which was an average minimum value observed during this period, is recommended when this model is applied.

A comparison of the predicted timewise change in ruth depth with data collected in the Kenya study shows excellent agreement. Furthermore, this good agreement is applicable to both the high and low annual rainfall data. This leads to a tentative conclusion that the models developed are applicable to all rainfall conditions.

CHAPTER 7 - CONCLUSIONS AND RECOMMENDATIONS

7.1 CONCLUSIONS

The models presented in this report predict the performance and behavior of paved and unpavéd roads. These are preliminary models based on limited data. Additional data should be collected to validate these models.

Pavement performance prediction models, in terms of roughness and cracking, were developed in this investigation through empirical analysis. Pavement rut depth measured on the study sections was very low. Consequently, no effort was spent on developing a rut depth prediction equation.

Paved road roughness prediction models were developed as a function of traffic, age, and one of the following independent variables: (a) corrected structural number; (b) Benkelman beam deflection; (c) Dynaflect deflection; (d) corrected structural number and Benkelman beam deflection; or (e) corrected structural number and Dynaflect deflection.

Empirical relationships for predicting asphaltic concrete cracking were developed as a function of traffic, age, and one of the following: (a) Benkelman beam deflection; (b) Dynaflect deflection; (c) corrected structural number. In the prediction of cracking it was shown that if more than 10 percent of the area of the road is cracked, then cracking will reflect through a slurry seal within one year. Further, the rate that reoccurring cracking develops following a slurry seal exceeds the progression rate associated with the original cracking. Therefore, the utility of using a slurry seal for resealing may be questioned.

Unpaved road deterioration relationships were developed for the roughness and rut depth after blading and the change in roughness and rut depth as a function of time. In addition, a prediction for the rate of gravel loss was developed. The major factors influencing these relationships are traffic distribution, road geometric characteristics, and surface material properties. Although a concerted effort was made to consider the widest possible range of road and operating conditions in the development of the deterioration models, it is conceivable that more extreme conditions can be found. For example, heavier trucks, steeper grades or sharper curves than studied. Application of these extreme conditions would mean extrapolating beyond the range in which the models were developed. Since no other information is currently available for these extreme conditions, judgement and care should be exercised when using the predicted results. Additional adjustments and refinements may be needed as experience permits.

7.2 RECOMMENDATIONS

A considerable amount of time and money has been spent on characterizing and measuring the test sections included in this investigation. However, some paved sections have not yet shown any sign of cracking, and most of them still exhibit relatively low levels of roughness. It is therefore recommended that data collection be continued in the field until more sections exhibit higher levels of pavement deterioration. Further data collection can be accomplished at a relatively low marginal cost and will enhance the data base so that future analysis can yield improved prediction models.

The Pavement and Maintenance Studies were executed primarily in the central portion of Brazil where the climate is relatively uniform and the subgrades usually strong. It is recommended that satellite studies be made in regions of differing climate, and for conditions where heavy traffic is associated with poor quality subgrades.

Three experimental sections of road were constructed where alternative maintenance and rehabilitation procedures could be studied. Also, further sections should be constructed to complete the experimental design matrix. Continued monitoring and analysis of these sections should provide answers about the relative efficiencies of surface treatments and asphaltic concrete overlays to seal pavements and influence performance. At the time of analysis, these sections had shown very few distress manifestations, and consequently were not included in the analysis. Further data collection on these experimental sections will be invaluable for developing an overlay design method applicable to Brazil. The data should be associated with observation of the test sections which were overlayed during this project. It is also recommended that the data base from this project be analyzed in conjunction with the information which is being obtained on the IPR (Brazilian Road Research Institute) overlay research project.

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