Empirical Roughness Progression Models of Heavy Duty Rural Pavements

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***Abstract*—**Empirical deterministic models have been developed to predict roughness progression of heavy duty spray sealed pavements for a dataset representing rural arterial roads. The dataset provides a good representation of the relevant network and covers a wide range of operating and environmental conditions. A sample with a large size of historical time series data for many pavement sections has been collected and prepared for use in multilevel regression analysis. The modelling parameters include road roughness as performance parameter and traffic loading, time, initial pavement strength, reactivity level of subgrade soil, climate condition, and condition of drainage system as predictor parameters. The purpose of this paper is to report the approaches adopted for models development and validation. The study presents multilevel models that can account for the correlation among time series data of the same section and to capture the effect of unobserved variables. Study results show that the models fit the data very well. The contribution and significance of relevant influencing factors in predicting roughness progression are presented and explained. The paper concludes that the analysis approach used for developing the models confirmed their accuracy and reliability by well-fitting to the validation data.

***Keywords*—**Roughness progression, empirical model, pavement performance, heavy duty pavement.

I. Introduction

SURFACE roughness is a very important pavement condition parameter that is used in triggering investigation into rehabilitation works. The importance of roughness stems from its effects on level of service (users' comfort and safety), users' costs (travel time and vehicle operating cost) and pavement sustainability (dynamic wheel loads). To keep a road network in service at an acceptable condition and preserve the network performance, the management system can be strongly enhanced by models for predicting pavement distress or condition such as road roughness. Moreover, pavement management system (PMS) at a network level is impossible without performance prediction models [1]. Such models help asset managers to predict when the pavement needs to be repaired and to apply the required maintenance works in a timely manner. Identifying the causes and rates of pavement deterioration can help in the adoption of accurate remedies and appropriate techniques. Doing the right work at the right time and using the most efficient options will lead to maintaining suitable road conditions at minimum funds [2]. Hence, a more effective management relies on models which reliably predict the impact of different variables on pavement deterioration including variables such as traffic loading increases and environmental effect changes.

The dataset that has been used in this study is selected from the rural arterial network of the State of Victoria, Australia. It includes a sample of heavy duty pavement sections from a number of freeway roads. The bulk of Victoria's traffic (including freight) is carried on these roads which connect activity centers to provide an integrated road transport system for the social activities and economic life of the community. Further, efficient and effective management of freight routes is crucial to reduce the costs of transport to local and overseas markets. Hence, the development of accurate pavement deterioration models for these highways is of high importance to preserve their high levels of service. The purpose of this study is to develop multilevel roughness progression models for heavy duty sealed granular pavements using historical time series data for many different pavement sections with a wide coverage of relevant available data. The proposed roughness models efficiently incorporate the effect of random variations between panel dataset at network level. Another purpose is to better understand how relevant factors affect performance of these heavy duty pavements under different combinations of operating and environmental conditions.

II. Network Selection

A representative network was selected from rural highway network of the State of Victoria/Australia. The sample network includes heavy duty pavement sections from seven highways of class M roads with a total length around 170 km (170 of 100 m-sections). This class refers to roads that have a high standard of driving conditions, including four traffic lanes, sealed shoulders, divided carriageways and visible line marking. Road of this class connects Melbourne (the capital of Victoria) with other capital cities and major provincial centers [3]. In Victoria, the rural network is essentially spray sealed surface over natural gravels. Road agencies practice for almost all rural roads is to prime or prime seal, then a single or double coat seal of bitumen with one sized aggregate (size 10 or 14 mm).

The selected sample has a reasonable coverage of network characteristics and conditions. It covers wide ranges of all major parameters that contribute to pavement roughness progression including traffic loading, initial pavement strength, subgrade soil, climate condition and drainage condition. The pavements of all these highway sections have granular bases and sub-bases with single or double coat

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spray/chip seal.

III. Description of Study Variables

Provided in the following subsections are brief descriptions of the study variables:

A. Roughness (IRI)

Time series roughness data, measured in terms of the International Roughness Index (IRI, m/km), were determined by processing the longitudinal surface profile data of the selected sections for all available years. For network monitoring, in Victoria, longitudinal road surface profile measurements are collected every two years with half of the network being surveyed each year. IRI is calculated by processing the raw profile measurements through a mathematical model of a quarter car. The repeatability of profiles measurements are normally conducted during each condition survey to ensure the reliability of outputs. At time of study, the profile data was available from 1998 to 2010 hence some sections of the network have 7 years (1998-2010) of condition data and the others have only 6 years (1999-2009). This type of dataset is called panel data because it consists of time series observations for many sections. Due to uneven spacing of time series observations, this type of data is called unbalanced panel data.

B. Traffic Loading

Traffic volume in terms of number of Heavy Vehicles (HV) for the selected sections was extracted for the relevant years. Estimates of traffic data for missing years were obtained for each highway by using the average growth factor for all its segments over the period for which data was available. HV numbers at the time of construction for each section were estimated using current HV numbers, section's age and average growth rate of relevant highway (see (1)). Cumulative traffic loading in terms of million equivalent standard axles (MESA), for each year condition data was available, was determined using (2) [4] and relevant cumulative growth factor (CGF) was determined using (3).

$$HV_{at\ const} = HV_{current} / [(1+ GF) ^\wedge (Age_{\ at\ current\ HV\ year})]. \quad (1)$$

where: $HV_{at\ const}$ = number of heavy vehicles at time of construction. $HV_{current}$ = number of heavy vehicles in any year where actual traffic data is available. GF = average annual growth rate of heavy vehicles. Age = pavement age.

$$MESA = [365 * HV_{at\ const} * DF * LDF * CGF * NHVAG * (ESA/HVAG)]/10^6. \quad (2)$$

where: MESA= cumulative ESAs from construction time to any year of condition data. DF= direction factor, (proportion of HV travelling in the direction of design lane) =1 for two-way road [5]. LDF= lane distribution factor, (proportion of heavy vehicles in design lane) =1 [5]. According to VicRoads' code of practice document [5]; the LDF value is considered as 1 when the number of road lanes is less than 3 in one direction (Class M roads have two lanes in each direction).

$$CGF = [((1+0.01*GF) ^\wedge Age) -1] / (0.01*GF). \quad (3)$$

NHVAG= average number of axle groups per heavy vehicle = 3.1 [5]. ESA/HVAG= average ESA per heavy vehicle axle group = 0.82 [5].

C. Initial Pavement Strength

The pavement consists of different layers of materials that typically have different properties and behave differently under load. Insufficient pavement strength or deformation and displacement in the upper layers of pavement can contribute to pavement deterioration [6], [7]. It is expected that initial pavement strength in terms of the modified structural number (SNC) has a significant contribution to roughness progression and it has been included as a variable in many studies, such as Paterson [6] and Martin and Choummanivong [8]. As pavement deflection data for the selected sections were not available to calculate pavement structural number, the following approach was used to estimate the initial pavement strength in terms of (SNC_0):

1. Number of commercial vehicles at time of construction ($CV_{at\ const}$) was calculated using (1).
2. Cumulative Growth Factor over the design life (CGF_{DL}) was estimated using (3).
3. Cumulative traffic loading data at design life ($MESA_{DL}$) was calculated using (2) with CGF_{DL} from previous step.
4. Initial value of structural number (SNC_0) at time of pavement construction (Age = 0) was calculated using (4) [9], this expression is based on the cumulative traffic loading ($MESA_{DL}$) that was expected over pavement design life.

$$SNC_0 = [0.55 * Log_{10} (MESA_{DL} / 120 * 10^6)] + 0.6. \quad (4)$$

All above equations have been adapted for use by Australian State Road Agencies. These empirical models were developed for Australian road conditions, including Victoria.

D. Climate Condition

Thornthwaite Moisture Index (TMI) deals with engineering applications that lie on or beneath the ground surface, such as road pavements [10]. It is defined as the combination of annual effects of precipitation, moisture deficit, evapotranspiration, soil water storage and runoff [11]. Historical climate time series data in terms of TMI was extracted from the climate extraction tool developed by Byrne and Aguiar [10]. It is provided as an Excel database which uses latitude and longitude values to access relevant data over time for each 100m road section. TMI values were extracted along all highway sections for all relevant years. Generally, a positive sign of TMI refers to a wet area, while a negative sign of TMI refers to a dry area.

E. Subgrade Soil Type

Subgrade soil provides support to the upper layers of road pavement and withstands the stresses applied to it under load. Roads are constructed on different types of soils and seasonal moisture variations affect their strength and/or volume differently. Though, all these roads are expected to deteriorate over time. Yet, if roads are constructed on expansive subgrade soils, they can deteriorate at a faster rate than those with stable subgrade [12]. A large area of the State of Victoria covers with expansive subgrade soils which are sensitive to moisture changes during seasonal variation cycles. More than half of Victorian road pavements are built on expansive subgrade soils with varying levels of expansion potential.

The integrated color coded map of expansive soil regions in Victoria [12] was coincide in AutoCAD software to determine the subgrade soil types for all selected road sections by using their start and end chainages as reference points. Different soil types were presented by different colors in the map. For this study, two levels of expansion potential of subgrade soils were identified; namely, moderate to highly expansive soils and the non-expansive soils.

F. Drainage

An essential aspect for both the functional and structural performance of highway pavement is drainage system [13]. The condition of drainage for the selected highway sections was extracted from relevant database between 1998 and 2010; rated as good or poor.

IV. Boundary of Deterioration Phase

The three phases of roughness development are initial, gradual and rapid deterioration phases [14]. In this study, roughness progression is modelled during the gradual phase only. The initial phase considers the first deterioration in road pavement after construction. Based on typical construction standards, the initial surface condition of a new pavement can be assumed [15]. For Victoria's class M rural roads, the initial conditions can be assumed to be 1.2 m/km [16]. Predicting pavement deterioration during the rapid phase is considered unreliable because the pavement condition would not be acceptable to road users beyond the gradual phase and the pavement needs to be maintained or rehabilitated before reaching the rapid deterioration phase [17]. For this reason and lack of observational data within the rapid phase, this phase was not modelled in this study. According to Austroads [18], the transition from gradual deterioration phase to the rapid deterioration phase is limited by the road terminal roughness values. The terminal roughness value is considered to be 4.2 m/km for class M heavy duty roads [18]. In the current study, the initial and terminal condition values mentioned above were used to establish boundary limits for the gradual deterioration phase. Hence, all sections with roughness values within the initial phase (below or at the values above) were removed to ensure pavement deterioration had passed the initial phase and entered the gradual phase. Also sections with roughness data that had passed the terminal condition values (above or at the values above) were removed to ensure pavement deterioration did not enter the rapid phase.

V. Splitting the Dataset

After the data boundary limits process, a significant number of sections were excluded. Data for the available variables were extracted from different databases. Hence for each 100m segment, the chainages of roughness data were treated as the base and chainages of data related to contributing factors were matched to them for all relevant years. Good and Hardin [19] recommended that one-fourth to one-third of the data should be set aside for validation purposes. Random dataset split was utilized to divide the dataset into two parts where approximately 70% of the data were used for model development and the remaining 30% of the data were used for model validation. The statistics of continuous independent variables that were used for roughness model development are presented in Table I.

TABLE I
Statistics for Independent Variables Used for Developing Roughness Models

Statistics	Roughness (IRI)	Traffic loading (MESA)	Initial pavement strength (SNC_0)	Climate (TMI)
Mean	1.94	8.14	3.62	6
Standard Deviation	0.56	5.21	0.12	18.92
Minimum	1.21	1.34	3.42	-13
Maximum	4.20	34.78	4.14	94

VI. Study Methodology

One of the most useful nested data analysis techniques is hierarchical linear modelling (HLM) which can be used to develop pavement deterioration models [20]. It is a statistical modelling approach that captures the effects of variation at multiple levels [21], [22]. HLM explicitly models the dependency between observation data, producing more stable intercept and slope estimates with unbiased standard errors.

The basic simple linear regression model is generally represented in the following form:

$$Y = \beta_0 + \beta_1 * X + e \quad (5)$$

where: Y: is the dependent variable, X: is the independent variable (predictor), e: is the error value (random variable), β_0 and β_1: are fixed and unknown coefficients, where β_0 is the intercept and β_1 is the slope.

In (5), there is only one independent variable (X) to explain the dependent variable (Y) and all the other factors that affect Y are jointly captured by the error value (e). In the other words, the error value represents factors other than X that affect Y. However, it is assumed that the variance of the errors (e) is constant.

The HLM modelling approach handles models with datasets that have a three level nested structure [23]. Hence, in this study, the three levels of random variations (heterogeneity) include the following:

- Variation among time series observations within the same sections which is called level-1 random effect (e).
- Variation among pavement sections within the same highways which is called level-2 random effect (r_0).
- Variation among highways within the same road classes which is called level-3 random effect (u_{00}).

Theoretically, the effect of heterogeneity can be captured by allowing randomness over the model parameter(s) [21], [22]. A study conducted by Hong [24] showed that unobserved heterogeneity could potentially be accounted for through the intercept and other regression parameters (i.e. slopes). In the current study, the random parameter approach is utilized by allowing the intercepts to vary at level-2, and level-3, and the slope of X factor to vary at level-2.

The above simple linear model (5) could be extended to the following three-level model (multilevel model):

Level 1. $Y = \beta 0 + \beta 1 * X + e$
Level 2. $\beta 0 = \beta 00 + r0$, $\beta 1 = \beta 10 + r1$
Level 3. $\beta\ 00 = \beta 000 + u00$

The final mixed model is:

$$Y = \beta_{000} + \beta_{10} * X + X * r_1 + e + r_0 + u_{00} \tag{6}$$

where: Y, X, β_0, β_1 and e: are as defined previously, r_0 and r_1: are the level-2 random effect, u_{00}: is the level-3 random effect, β_{00} and β_{10} : are level-2 fixed coefficients, β_{000}: is level-3 fixed coefficient.

In (6), if Y is a measure of pavement roughness in terms of IRI and X is a time factor, the pavement roughness progression in a multilevel model with random intercepts and random slope for the time factor is proposed as:

$$Y = \beta_{000} + \beta_{10} * \text{Time} + \text{Time} * r_1 + e + r_0 + u_{00} \tag{7}$$

By incorporating all available variables that are considered in this study from network information, the above multilevel models can be expressed as:

$$Y = \beta_{000} + \beta_{10} * \text{Time} + \beta_2 * \text{MESA} + \beta_3 * \text{TMI} + \beta_{01} * \text{SNC}_0 + \beta_{02} * \text{SSR} + \beta_{03} * \text{DRA} + \text{Time} * r_1 + e + r_0 + u_{00} \tag{8}$$

where: Y: Predicted roughness value in terms of IRI (m/km), Time: is time variable in years, MESA: is traffic loading variable in terms of MESA load /lane, TMI: is climate condition variable in terms of Thornthwaite Moisture Index, SNC_0: is initial pavement strength variable at time of pavement construction, in terms of modified structural number, SSR: is subgrade soil expansion potential variable (non-expansive = 0 and expansive = 1), DRA: is drainage condition variable (good = 0 and poor = 1), All other variables are as defined previously.

VII. Data Analysis Using HLM

HLM approach (or called multilevel analysis) was used to develop empirical deterministic models to predict pavement roughness progression over time as a function of a number of contributing variables using full maximum likelihood estimation. The analysis was performed using Hierarchical Linear Modelling (HLM7) software [25] and Statistical Package for Social Sciences software [26]. To develop the roughness progression model for the heavy duty sample, three types of models were fitted: null, growth and conditional models; details of these models are presented below:

G. Development of Null Model

This model predicts the outcome variable with no specified predictors (only intercept). The null model should be created first as a primary step in a hierarchical data analysis for the following purposes [21], [22]:

- To provide an estimate of the grand mean of roughness value within gradual deterioration phase for the selected network.
- To use as a baseline model for model comparisons when adding predictors to the model, based on a deviance statistic test.
- To estimate the proportion of variance at each level in the dataset used to predict roughness progression and to test whether multilevel modelling is needed. The proportion of variance could be estimated using the following formulas [21]:

o Proportion of variance within level-1:

$$PVO = Ve / (Ve + Vr_0 + Vu_{00}). \tag{9}$$

o Proportion of variance within level-2:

$$PVS = Vr_0 / (Ve + Vr_0 + Vu_{00}). \tag{10}$$

o Proportion of variance within level-3:

$$PVH = Vu_{00} / (Ve + Vr_0 + Vu_{00}). \tag{11}$$

where: V*e*: is the variance of level-1 random variable. Vr_0: is the variance of level-2 random variable. Vu_{00}: is the variance of level-3 random variable.

The fixed and random effect parameters for the regression statistics of the developed null model are presented in Table II. The final estimated roughness null model is:

$$LN\ (IRI) = 0.5772. \tag{12}$$

where: LN (IRI): is the natural logarithm of roughness variable in terms of IRI.

TABLE II
Estimation of the Fixed Effect Variable and Variance Components (Random Effect Variables) for Roughness Null Model

Fixed effect variable	Coefficient	Standard error	*t-ratio*	Degree of freedom (*df*)	*p-value**
Intercept	0.5772	0.0296	19.52	6	<0.001
Random effect variable	Standard deviation	Variance component (V)	Degree of freedom (*df*)	Chi-Statistic (χ^2)	*p-value*
e	0.0788	0.0062			
r_0	0.2463	0.0607	717	25779.66	<0.001
u_{00}	0.0698	0.0049	6	70.66	<0.001

* All predictors are statistically significant ($p < 0.001$) with 95% level of confidence.

Based on V*e* (0.0062) for the above null model, the correction factor (CF) is 1.003 (Exp (0.0062/2)). The null model results indicate that the roughness grand mean value is 1.79 m/km (Exp (0.5772)* 1.003). The three variance components (Ve, Vr_0 and Vu_{00}) are highly significant (p< 0.001) and indicate that there is significant variance between observations, segments, and highways for the roughness condition variable. Using (9)-(11), the proportion of variance results indicates that there is a high variance between segments within highways (PVS = 84%). Also, 9% of the variance is found within time series observations (PVO), and around 7% between highways (PVH).

H. Development of Growth Model

This model predicts roughness progression as a function of time variable to study the progression rate over time. As time is the most important factor in time series data, the growth model is estimated with only time as a predictor with the intercept and slope regarded as random. The model estimates the average growth of roughness per year on heavy duty pavements. The results of roughness growth model for heavy duty roads are shown in Table III. Allowing only for the time predictor, the final estimated model is:

$$\text{LN (IRI)} = 0.5181 + 0.0183 \text{ Time.} \tag{13}$$

where: Time: is time variable in years.

The roughness growth model estimates that, for each additional year, the log IRI increases by 0.0183 m/km. On average, the IRI value increases by 1.85% [(EXP (0.0183) -1) * 100%] for every additional year. Chi-square (χ^2) results also indicate that highway segments differ significantly in their intercepts and slopes. Based on Ve (0.0028) for the growth model, the CF is 1.001 (Exp (0.0028/2)). This CF must be applied to IRI predictions from the growth model in (13).

TABLE III
ESTIMATION OF THE FIXED EFFECT VARIABLES AND VARIANCE COMPONENTS FOR ROUGHNESS GROWTH MODEL

Fixed effect variable	Coefficient	Standard error	*t-ratio*	Degree of freedom (*df*)	*p-value**
Intercept	0.5181	0.0300	17.25	6	<0.001
Time	0.0183	0.0008	23.86	716	<0.001
Random effect variable	Standard deviation	Variance component (V)	Degree of freedom (*df*)	Chi-Statistic (χ^2)	*p-value*
e	0.0528	0.0028			
r_0	0.2478	0.0614	717	18655.58	<0.001
r_1	0.0153	0.0002	723	1669.15	<0.001
u_{00}	0.0710	0.0050	6	76.33	<0.001

* All predictors are statistically significant (p < 0.001) with 95% level of confidence

I. Development of Conditional Model

In this model, available independent variables are added to the growth model as predictors. A backward variable selection procedure has been followed, in which all predictors are added to the model simultaneously and evaluated together. Then, any non-significant fixed effects are removed one at a time to determine which variables to include in the final model. The results of the fixed and random effects parameters of predicted roughness conditional model are shown in Table IV. The final developed model for heavy duty roads as a function of the available contributing variables is presented below:

$$\text{LN (IRI)} = 3.3552 + 0.0067 \text{ Time} + 0.0115 \text{ MESA} - 0.786 \text{ SNC}_0 \tag{14}$$

where: MESA: is traffic loading variable in terms of MESA load /lane. SNC_0: is initial pavement strength variable at time of pavement construction, in terms of modified structural number. All other variables are as defined previously.

TABLE IV
ESTIMATION OF THE FIXED EFFECT VARIABLES AND VARIANCE COMPONENTS FOR ROUGHNESS CONDITIONAL MODEL

Fixed effect variable	Coefficient	Standard error	*t-ratio*	Degree of freedom (*df*)	*p-value**
Intercept	3.3552	0.3983	8.42	6	<0.001
Time	0.0067	0.0015	4.57	715	<0.001
MESA	0.0115	0.0012	9.29	1167	<0.001
SNC_0	-0.7860	0.1076	-7.30	715	<0.001
Random effect variable	Standard deviation	Variance component (V)	Degree of freedom (*df*)	Chi-Statistic (χ^2)	*p-value*
e	0.0527	0.0027			
r_0	0.2269	0.0515	716	16000.74	<0.001
r_1	0.0154	0.0002	723	1696.07	<0.001
u_{00}	0.0415	0.0017	6	19.22	<0.05

* All predictors are statistically significant (p < 0.05) with 95% level of confidence

From the developed conditional model, the significant p-values < 0.001 for the Likelihood Ratio test show that the variables Time, MESA and SNC_0 significantly influence pavement roughness progression with significant variance components within random effects variables. However, TMI, SST and DRA are not significant and are excluded from the model. The model indicates that MESA and Time are positively related to roughness progression, whereas SNC_0 is negatively related to roughness progression.

The following results are observed from the heavy duty road (class M) roughness conditional model:

- On average, IRI value increases by 0.67% [(EXP (0.0067) -1) * 100%] for every additional year, when all other variables in the model are held constant.
- For a one MESA increase in traffic loading, about a 1.16% [(EXP (0.0115) -1)* 100%] increase in roughness value is expected, when all other variables in the model are held constant.
- For a one SNC_0 unit decrease in pavement strength, about a 54.43% [(1- EXP (- 0.786)) * 100%] increase in roughness value is expected, when all other variables in the model are held constant.

The t-ratios suggest that the effect of MESA is stronger than SNC_0 and Time on roughness progression due to the high volume of heavy trucks which cause accelerated deterioration of pavement. Based on Ve (0.0027) for the conditional model, the CF is 1.001 (Exp (0.0027/2)). This CF must be applied to IRI predictions from the conditional model in (14).

VIII. Validation of Developed Models

Using internal validation method, the developed models were tested to ensure their ability to predict future conditions accurately. As mentioned before in this paper, approximately one-third of the data (30%) are set aside to use for model validation. This dataset is used to develop a validation model with the same variables that are used for the developed models. Multiple statistical testing using a Bonferroni correction is applied when checking whether the coefficients of the validation model fall within the 99% confidence intervals for the coefficients of the developed model, or not. The confidence interval (CI) estimate provides a range of likely values for each of the model parameters. Based on the general form of a confidence interval, the lower and upper bounds of the 99% confidence intervals are calculated using the following formula [22]:

$$99\%\ \text{confidence interval} = \text{estimated parameter} \pm 2.576 * \text{standard error} \quad (15)$$

The internal validation results for the growth and conditional roughness progression models are presented in Table V. The results of validation models indicate that all parameters of the models based on the validation datasets fall within the upper and lower bound intervals for the parameters of the developed models. This means that both models (growth and conditional) exhibit internal validity.

TABLE V
Validation Results for Growth and Conditional Roughness Progression Models

Model fit	Variables	Coefficient of developed model	*p*-value for developed model	Standard Error	99% CI Lower Bound	99% CI Upper Bound	Coefficient of validated model	*p*-value for validated model
Growth model	Intercept	0.518	<0.001	0.030	0.441	0.595	0.520	<0.001
	Time	0.018	<0.001	0.001	0.016	0.020	0.019	<0.001
Conditional model	Intercept	3.365	<0.001	0.398	2.329	4.381	2.646	<0.05
	Time	0.007	<0.001	0.001	0.003	0.011	0.007	<0.05
	MESA	0.011	<0.001	0.001	0.008	0.015	0.011	<0.001
	SNC_0	-0.788	<0.001	0.108	-1.063	-0.509	-0.598	<0.001

IX. Conclusions

The reported study was undertaken to apply multilevel regression approach to develop roughness prediction models for heavy duty sealed granular roads at network level. Particularly, the study presents hierarchical multilevel models that can account for the correlation among time series data of the same section and capture the effect of unobserved factors. Also, the objectives were to study the effect of different factors that contribute to pavement roughness progression within the gradual deterioration phase. The results indicate that unobserved heterogeneity is a critical aspect that should be considered not only among sections but among highways as well. For the heavy duty sets of network road sections used herein, the following results and outcomes can be drawn from the analysis approach performed:

- Developed models were statistically significant and the parameter estimates are highly significant with *p*-values <0.05 (at the 95% confidence level) with expected directions (signs).
- Significant variation among road highways, sections and observations were available in the heavy duty network roughness panel dataset.
- Developed growth model indicated that time variable made a significant contribution to roughness progression. However, the growth model could be improved by adding additional independent variables. The conditional model showed that other factors also have a significant effect on roughness progression.
- Developed conditional model indicated that time and traffic loading had positive contributions to roughness progression; however, initial pavement strength had negative contributions to roughness progression. Also, expansive soils, climate and drainage condition have no significant contribution to roughness progression in the selected network. The reason behind that is the heavy duty roads have high standards of design and construction, well maintained, and generally exhibit high levels of smoothness. Also, road cross sections' crowns are generally high, with deep table drain inverts and sub-soil drains may also be present, and therefore there is a little opportunity for water to gain access to the pavement.
- The most important predictor of pavement roughness progression was traffic loading, followed by initial pavement strength then time. This is due to the high volume of heavy trucks which cause accelerated deterioration of pavement.
- On average, the roughness (IRI) grand mean value for the network sample was 1.79 m/km (from null model) and the rate of roughness progression was 0.0185 IRI per year (from growth model).

The developed models in this research study are statistical empirical regression models. The main limitation of regression models is that they can be used only within the range of independent variables used in their development. Therefore, it is recommended that the developed models should be used only within the data limits (see Table I) and only for heavy duty sprays sealed pavements. In addition, it is anticipated that more sound deterioration model could be estimated by including more independent variables such as pavement thickness, material quality and road geometry.

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