Effect of Traffic and Environmental Factors on Roughness Progression Rate of Sealed Low Volume Arterials

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ABSTRACT

A high proportion of the rural arterial network in Victoria /Australia are low volume roads built of sealed granular pavements, which are important routes for freight movement between rural centres. Investigation into rehabilitation of these arterials is triggered when roughness reaches a certain threshold level. To assist road agencies in their long term planning, a project has been initiated to develop absolute deterministic deterioration models for these roads. A representative sample network of low volume arterial roads has been selected and all relevant data including pavement condition are collected. The network covers a representative range of traffic loading, subgrade reactivity level and environmental factors. For each highway section, raw longitudinal profile data from at least four years was used to determine roughness progression over time. All profile data was aligned and then cleaned and filtered to ensure that the same length of road profile was compared over time. To remove the influence of maintenance activities, only sections with positive progression was included. Multiple linear regression analysis was used to develop models for these sections to predict pavement roughness over time as a function of a number of contributing variables. The output of the analyses was used to evaluate the significance and contribution of the different factors including traffic and environmental conditions. This paper provides a description of data preparation and analysis. It was observed that higher traffic loading and soil reactivity, poor drainage and climates with high seasonal variation increase roughness progression rate.

INTRODUCTION

As Australia's road network consists of approximately 48 km per 1000 head of population, road infrastructure contributes to a significant portion of all public infrastructures. This equates to around 50% of overall government capital investment in many other fields together (1, 2). In the State of Victoria, the efficient and effective management of roads accounts for much of the \$AUS270 billion of its economy (3). The road agencies are responsible for management of the road network in order to achieve an affordable, acceptable and sustainable level of performance (4). So, one of the primary components of a pavement management system is the method of evaluating the rate of pavement deterioration over time i.e. pavement deterioration models. Once accurate prediction models are identified, and then the implications of optimum maintenance and rehabilitation strategies can be assessed and practical decisions made. In addition, accurate deterioration models based on a comprehensive data set may be used by road agencies for several fundamental applications in pavement management system such as evaluation of the economic strategies, assessment of current and future financial decisions and overall network condition and how it is affected by budget constraints.

SCOPE AND OBJECTIVES

The main objective of this study is to develop an empirical absolute deterministic deterioration model for pavement roughness, in terms of the International Roughness Index (IRI), for sealed low volume rural arterial roads in Victoria. As this model is expected to be used in pavement asset management, this paper focused on:

Alaswadko, Hassan and Evans

- 1. Developing a representative network of low volume roads (Class C) with a wide range of traffic volumes, subgrade soil types and environmental conditions.
- 2. Applying suitable adjustment to the longitudinal road surface profile data to ensure that the same sections were being compared over time.
- 3. Applying appropriate data cleaning and filtering techniques to remove irrelevant data and the influence of maintenance activities.
- 4. Developing aggregate/absolute deterioration model as a function of traffic loading, soil type, climate, drainage and terrain, and studying the effect of each of these factors.
- 5. Studying the influence of soil type and climate and their interaction on the progression rates of pavement roughness.
- 6. Verifying the developed model to ensure its ability to predict future conditions accurately.

BACKGROUND

A large proportion of Victoria's rural highway network is built of locally available unbound material with a chip (sprayed) seal surface (5). The chip sealing technique is common in rural areas because of its low cost and speeds of construction, compared with other types of road pavement surfacing (6). Such low volume roads within this rural network were selected for this study. Typically, they comprise of single carriageways with two lane roads with unsealed shoulders. Class C type roads are primarily responsible for connecting population centres and linking these centres with other parts of the primary transport network (7). The general condition of road pavement is objectively measured by its surface roughness, and is the most popular condition variable in pavement deterioration models (8). In Victoria, once every two years, longitudinal road surface profile data is collected using a multi-laser profilometer. This is converted into roughness data, which is reported in terms of the IRI in m/km and/or NAASRA Roughness Meter (NRM) in counts/km.

A wide range of factors can contribute to the structural and surface deterioration of pavements, such as traffic loading and environmental conditions. This results in a reduced functional performance by increasing surface roughness in its longitudinal profile along the two wheel paths. These factors influence the modelling of performance prediction at different rates through their effects on the initiation and progression phases of various pavement distress modes (9). In this study, a number of these factors are used as independent variables in developing pavement deterioration models and include traffic loading, climate, subgrade soil type, drainage condition and terrain.

Traffic Loading

The State of Victoria (Australia) has approximately 150,000 kilometres of roads, which are used by general traffic and the majority carry freight to some extent (10). Existing high volumes of heavy trucks cause accelerated deterioration of the pavement conditions (11), largely due to increased static and dynamic loads (12). This has been shown to be a major contributor to deterioration progression in all types of pavements and explains a sizeable proportion of roughness trends; such as traffic loading being an imperative factor when estimating reliable and applicable models of a road network (13).

Climate

Climate conditions have a significant effect on road pavement performance. According to Paterson (13), when the moisture content of bases and sub-base layers increase, their bearing capacity decreased. This leads to an obvious increase in the deterioration rate and reduces the pavement service life. Therefore, an accurate knowledge of climatic trends plays an important role in developing road performance models (14). Road roughness can be influenced by environmental factors through humidity or moisture regimes in terms of the Thornthwaite moisture index (TMI). TMI is defined as the combination of annual effects of precipitation, moisture deficit, evapotranspiration, soil water storage and runoff (15). The variety of climatic conditions (based on the TMI) in Victoria covers five zones, ranging from wet to arid.

Subgrade Soil

The subgrade soil is a structural layer within the road pavement and needs to support the stresses applied to it under traffic load (16). However, when the subgrade comprises of expansive materials, seasonal moisture variation can lead to an accelerated rate of surface deterioration (17, 18). Areas with highly reactive soils tend to develop higher roughness contents and progress at high rates (19, 20). In Victoria, more than half of the classified road network is built on expansive subgrade soils with varying degrees of reactivity (21).

Drainage

Drainage has been identified as an important factor for both the functional and structural performance of road pavement (22). Drainage systems have a considerable influence on subgrade moisture conditions and bearing strength of pavement materials (17, 23). Pavement permeability contributes to several kinds of surface distresses by stripping the binder from the aggregate and causing loss of bond between pavement layers, which leads to fretting, ravelling and delimitation of pavement (22). To that extent, pavement and subgrade drainage systems are installed for different purposes; such as decreasing the water table level, cutting off water entry from water bearing layer to the pavement or subgrade, and draining specific pavement layers (24, 25).

Terrain

Roads are constructed over a variety of terrain types or vertical grades, which have a varied effect on pavement deterioration. Mann (18) performed an investigation to establish whether terrain produced a significant effect on pavement roughness of rural highways in Victoria. It was found that terrain had a negligible impact on roughness progression for very dry climates and but had a very small effect on roads located in regions within TMI range of +5 to -20. Also, road roughness in valley or pond conditions increase with dry temperate to very wet climates, while sloping roads in wetter climates produce higher levels of long wavelength roughness (18).

NETWORK SELECTION AND DATA COLLECTION

A representative network was selected to reflect Victoria's low volume arterial rural network conditions by covering different types of soils (reactive and non-reactive) and all possible climate conditions. A map of Victoria is shown in Figure (1) that illustrates the extent of expansive soil deposits and locates the selected low volume pavements used in this study. Overall, 13 highway sections with a total length of 653 km (6,536 100m-segments) was selected. A comprehensive time series dataset has been extracted from several databases to address the study objectives. These databases are related to road roughness data (dependent variables), and all possible factors that affect pavement performance (independent variables) as described in the following sections.



FIGURE 1 Map of Victoria vs. expansive soil deposits and selected road sites (18)

Road Roughness Data

Road roughness data in terms of the IRI was calculated from longitudinal surface profile data for the selected highway sections between 1998 and 2010. The profiles from different years were first aligned to ensure that the same sections were assessed over time.

Factors that Affect Pavement Performance

For all the selected sites in this study, major parameter data was extracted from the existing State's Road Asset System (RAS) database. This database is administered by VicRoads, who is the agency responsible for managing Victoria's arterials.

Traffic Loading

Traffic volume data in terms of annual average daily traffic (AADT) and the number of Commercial Vehicles (CV) for different road classes was extracted from the RAS database for 2002, 2009, 2010,

2011, and 2012. Estimation of traffic data for missing years was done for each highway by using the average growth factor for all its segments. CV numbers at the time of construction of different sections along each highway were estimated using current CV, section age and relevant growth rate. This data was then used to determine cumulative traffic loading in terms of million equivalent standard axles (MESA) using Equation 1 (17) in conjunction with relevant parameters from VicRoads' code of practice (26). Based on this document for Victorian class C type roads, the following typical values were adopted in the estimation of cumulative traffic loading (i.e. DF = 1, LDF = 1, $N_{HVAG} = 3.1$ and ESA/HVAG = 0.66). As a result, cumulative traffic loading data was calculated in each year for which condition data was available.

 $MESA = 365 * CV * DF * LDF * CGF * N_{HVAG} * (ESA/HVAG)/1,000,000....(1)$

Where:

CV= number of commercial vehicles at time of construction.

DF= direction factor, (proportion of the two-way AADT travelling in the direction of the design lane)

LDF= lane distribution factor, (proportion of heavy vehicles in design lane)

CGF= cumulative growth factor

N_{HVAG}= average number of axle groups per heavy vehicle

ESA/HVAG= average ESA per heavy vehicle axle group

Climate Condition

A climate data extraction tool developed by Byrne and Aguiar (14) was used to extract climate time series data in terms of TMI. This tool allows easy access to a wide range of historical climate data from 1960 to 2007, and a range of simulated climate data between 2008 and 2099. It is provided as an Excel database and is based on Global Positioning Satellites (GPS) (i.e. latitude and longitude) to access relevant data. TMI values were extracted along all highway sections from 1998 to 2010, which are located within four climate zones. Different TMI ranges and their moisture classification for each climate zone are presented below (27).

- 1) Zone 1: wet : TMI \geq 10
- 2) Zone 2: humid : $10 > TMI \ge -5$
- 3) Zone 3: sub arid : $-5 > TMI \ge -15$
- 4) Zone 4: semi arid : $-15 > TMI \ge -25$
- 5) Zone 5: arid : $-25 > TMI \ge -40$

Subgrade Soil

Expansive soils (i.e. reactive soils which are sensitive to moisture changes during seasonal variation cycles) cover a large area of the State of Victoria which coincides with a significant portion of the

Alaswadko, Hassan and Evans

State's rural highway network. The integrated map of expansive soil regions in Victoria is shown in Figure 1 (18). This map is used in conjunction with AutoCAD software to establish the type of subgrade soils for all selected sites with reference to their start and end chainages. The different colors in the map represent different soil types with different reactivity levels. As can be seen in Figure 1, the sample road sections are located in seven regions. The colors brown, burgundy, orange and pink represents moderate to highly reactive soils and the colors yellow, light brown and white represent low levels soils reactivity. For the purpose of this study, only two groups of subgrade reactivity were considered. The first group was considered as moderate to highly expansive and the second was considered as non-expansive.

Drainage

The conditions of drainage systems of the selected sections were extracted from the RAS database between 1996 and 2011. Drainage condition was rated as good, fair or poor and was coded as 0 for good and fair and 1 for poor.

Terrain

Terrain condition information obtained from the RAS database between 1996 and 2011 was evaluated as flat, hilly and undulating. In this study, flat terrain was coded as 0 and non-flat (hilly and undulating) terrain was coded as 1.

PREPARATION OF ROUGHNESS DATA

All longitudinal road profile data was aligned before being processed into roughness data. Then, the roughness data was filtered and cleaned. These procedures have been described below:

Data Alignment

The main purpose of this step is to ensure that the same length of road profile data is being compared over time. For each selected highway, longitudinal surface profiles of available years were viewed and compared, using Profile Viewing and Analysis (ProVal) software (28). It was observed that the start and end chainages of the profile do not match as can be seen from the example presented in Figure 2(a). Accordingly, an alignment of profile data was required using two processes, namely: offset and shifting. The offset process was done by making the profile chainages start from the same point for all selected years. Then, an In-house Excel-based tool developed by Evans and Arulrajah (29) was used to apply the shifting to align profile data from different years. This was achieved through a number of trials for inputting the required shifting value and changing the sample interval value of profile from different years. The results of these processes to the profiles in Figure 2a can be clearly noticed in Figure 2(b). Adjusted profiles of all selected sections are then processed in ProVal to determined IRI values at 100m intervals.



(a)



(b)

FIGURE 2 Longitudinal profile data for a typical section of road over five consecutive surveys. (a) before alignment (b) after alignment

Data Filtering

The main objective of pavement maintenance activities is to keep pavement condition at or above the minimum acceptable serviceability level. Generally, maintenance has two significant effects on improving the condition and performance of road pavement, represented by (13):

- An immediate impact on pavement condition, and
- An impact on the future rate of pavement deterioration.

The prediction model should account for the maintenance activities which affect the condition and the rate of deterioration, which could be in a positive or a negative way. However, this influence should be removed from the model, if information on maintenance activities is not available or not accurate (30). In this study, the effects of periodic and rehabilitation maintenance works were removed for this reason.

To remove the effects of major maintenance works, only segments with positive progression rates were included in the analysis. This was achieved by using the Linear Rate of Progression (LRP) tool (31) to determine roughness progression rates of 100m segments from available years. The output of LRP tool is based on the 'latest' linear trend of deterioration that is not immediately influenced by the impact of maintenance (31). Sections that were subject to periodic maintenance and rehabilitation activities are excluded with this process. However, the effects of routine maintenance, such as crack sealing, are already taken into account in the progression rates of roughness. Details of the LRP tool and its application can be found in Martin and Hoque (31).

Data Cleaning

Using box plots, all outlier values and influential observations were identified and removed from the data set. Road roughness develops progressively throughout the depth of road pavement; the three phases of roughness development are initial roughness, gradual deterioration and rapid deterioration. In this study, only sections in the gradual deterioration phase were included in the data set and include those with roughness values below 6.7 m/km IRI. The latter is the terminal roughness value considered by Australian road agencies for in-service pavements of arterial roads (all classes) (1). Only a small number of the sections have IRI values greater than 6.7 m/km. Additionally, estimate pavement ages of the sections range between 2 and 42 years i.e. are past the initial phase, where roughness might decrease or remains steady due to embedment of aggregate into the binder before it starts increasing.

DATA ANALYSIS AND MODELS DEVELOPMENT

Family modelling was used where the sample network was divided into groups of pavements with similar combinations of climate and subgrade soil type. This resulted in 8 groups covering 2 types of soil types (expansive and non-expansive) and 4 climate zones (wet, humid, sub-arid and semi-arid). The prepared data set included time series data for all relevant parameters for each segment of selected highways was divided in half; one half (sample size (N) of 8,971) was used for model development and the other half (N = 8,263) was used for model validation and verification. Multiple regression analysis (MRA) was used (using Statistical Package for Social Sciences

(SPSS)) to develop models that include more than one independent variable. Firstly, the descriptive statistics of roughness (dependent variable, DV) and the contributing factors (independent variables, IVs) were explored by producing their summary statistics, frequency distribution histograms and normal probability plots. Some of these plots have been included as Figure 3. It was observed that roughness data in terms of average IRI and traffic loading (MESA) data were not normally distributed and positively skewed as shown in Figures 3(a) and 3(c), respectively. Accordingly, these data sets were transformed using different functions and were examined by comparing skewness, variance and standard deviation values. The logarithm of IRI and square root of MESA were found to be the most appropriate transformation functions as shown in Figures 3(b) and 3(d), respectively. Secondly, linear regression assumptions were investigated, which include: (1) Linearity (the relationship between DV and IVs is linear), (2) Equal variance (the distribution of residuals has the same spread), and (3) Normality (the DV is normally distributed). The outliers and out of range values were then detected and removed using standardized residuals range and Mahalanobis distance.

Model for All Groups

Linear MRA was performed to assess the relative importance of each of the predictor variables and their contributions to explaining the variation in road roughness values. A multiple regression model was developed for the whole data set (for model development) with roughness as the DV and traffic loading and environmental factors (including subgrade reactivity, climate, and terrain and drainage conditions) as the IVs. The model form is shown in Equation 2.

 $Log IRI = 0.38 \sqrt{MESA} - 0.001 TMI + 0.255 SSR + 0.047 DRA + 0.018 TER \dots$ (2)

- Where: IRI = Roughness value in terms International Roughness Index (m/km), range of values in data set between 1.8 and 6.73
 - MESA = Traffic loading in terms of Million Equivalent Standard Axles load /lane, range of values in data set between 0.032 and 2.495
 - TMI = Climate condition in terms of Thornthwaite Moisture Index, range of values in data set between -24 and 54
 - SSR = Subgrade soil reactivity (non-expansive = 0 and expansive = 1)
 - DRA = Drainage condition (good = 0 and poor = 1)
 - TER = Terrain condition (flat = 0 and non- flat = 1)

The above model and all coefficients of the IVs are statistically significant with a correlation coefficient (R) = 0.96, which implies that there is linear relationship of strong strength between road roughness and all predictor variables for a very large sample size (N) of 8971. These variables, in combination, explain 92% of the variation in roughness. From the standardized regression coefficient (Beta), it was observed that traffic loading and soil reactivity type were the most important predictors of pavement roughness progression (Beta = 0.563 and 0.437, respectively).

Alaswadko, Hassan and Evans

Moreover, from the results of an analysis of variance (ANOVA) test, F (5, 8966) = 21163.7 at p < 0.001, the model explains a significant proportion of the variance of the outcome variable. The problem of multicolinearity between IVs was checked by exploring the tolerance value, which was found to be more than 0.3 for all variables. Partial R² values indicated that traffic loading, soil reactivity and drainage and terrain conditions all had positive contributions to roughness progression at approximately 62%, 54%, 1.7% and 0.3% respectively.



FIGURE 3 Frequency histograms and normal probability plot for roughness data (a) before transformation and (b) after transformation and for traffic loading data (c) before transformation and (d) after transformation

Thus, there is evidence that the roughness progression rate increases with an increase in traffic loading and soil reactivity and for when the drainage is poor and the highway terrain is hilly/undulating. However, climate condition produced negative trends and account for 0.9% of roughness variation. The observed negative trend for TMI refers to that dry/arid zones experience higher roughness than wet zones. This is mainly due to the fact that these zone experience higher seasonal moisture variation than the latter.

Model Validation

A method of data splitting was used to validate the effectiveness of the model. The second half of the data set was utilized for the validation process by using the developed model (Equation 2) to predict roughness values from relevant IVs and comparing the outcomes with observed values. The model's fit was evaluated by examining the residual values of the dependent variable (IRI) i.e. the difference between actual (observed) and predicted values. The residual values were normally distributed, with a mean of 0.51 and a standard deviation of 0.28. Figure 4 presents IRI predicted versus observed IRI. It indicates that, within residual values between -0.5 and 0.5, the model is estimating well the rate of deterioration to explain the trends of the factor combinations. As a further verification of the model, the descriptive statistics indicated that the mean and standard deviation are 3.07 and 0.92 respectively for actual data, and 2.56 and 0.73 respectively for predicted data. Also, the ANOVA output showed that the difference between actual and predicted data is significant at 95% confidence level with a *p* value of 0.001.



FIGURE 4 Actual and predicted IRI values

Models for Each Group

Separate multiple regression models were also developed for the 8 groups, group with similar climate condition and soil reactivity, using traffic loading, drainage condition and terrain as the predictor variables of roughness. The developed models for the different families/groups and their detailed regression statistics are summarized in Table 1 (model 1-8). In general, Table 1 shows that when soil reactivity and climate condition are statistically controlled, all models have moderate to strong strength with R values ranging from 0.50 to 0.92 with R² values from 0.25 to 0.84, and are statistically significant with p values < 0.001. Also, partial R^2 values represent the % contribution of the different significant variables to explaining the variation in roughness. For all models, traffic loading explains between 24% and 85% of the variation in IRI followed by drainage or/and terrain conditions which range between 0.3% to 48% for drainage and 3% to 49% for terrain. Models numbers 9 and 10 in Table 1 indicate that when sections are grouped by soil reactivity only (expansive and non-expansive), all predictor variables contribute to roughness progression with 12% (partial R²) of climate contribution for sections of non- expansive subgrade soil. Whereas, sections with expansive subgrade soils, only traffic loading (41%) and climate (8%) contribute significantly to roughness progression model. For all these models, similar trends to the model of whole data are observed in terms of the relationships between the different predictors and roughness.

CONCLUSIONS

Reported in this paper is the process for developing and validating an absolute aggregate model for roughness progression of low volume roads, using multiple regression analysis. A large sample size is used and preparation of roughness data include alignment of profiles for each section over a number of years to ensure that time series data of the same section is being used. Further, the data set is divided into eight groups with similar combinations of climate and soil reactivity level, for which separate regression models are developed. Provided below is a list of the conclusions that could be drawn from study findings regarding the effects of traffic and environmental conditions on roughness progression of low volume roads.

- (1) The multiple regression model of all groups combined provides evidence that higher traffic loading and soil reactivity, poor drainage, non-flat terrain and climates with high seasonal variation increase roughness progression rate. These factors explain 62%, 54%, 1.7% and 0.3% and 0.9%, respectively to the variation in roughness.
- (2) For groups of sections located in expansive or non-expansive soil areas and within different climate zones, traffic loading plays a pivotal role with 24% to 85% contribution to roughness variation. Drainage and terrain conditions however, are not significant in all models.
- (3) When the groups are combined into two groups by soil reactivity only (expansive and nonexpansive) and each covering all four climate zones, the developed models indicate the following:
 - a. For non-expansive soils all predictors (traffic loading, drainage, terrain and climate) have significant contribution to roughness progression.
 - b. For expansive soils the predictors, traffic loading and climate only are significant.

Model No.	Soil reactivity	Climate Zone	Sample size	Predicted model	Standard deviation	Correlation coefficient, R	Coefficient of determination,R ²	Partial correlation coefficient			t- test			Tolerance		
								MESA	DRA	TER	MESA	DRA	TER	MESA	DRA	TER
1	Non Expansive	Zone 1	489	IRI = 2.189 + 1.635 MESA – 1.232 TER	0.998	0.73	0.53	0.66	-	0.69	18.4	-	20.0	.72	-	0.72
2		Zone 2	732	IRI = 2.1 + 0.831 MESA – 0.784 TER	0.998	0.68	0.46	0.67	-	0.46	21.5	-	12.4	.87	-	.87
3		Zone 3	904	IRI = 2.018 + 1.028 MESA + 0.779 DRA - 1.189 TER	0.998	0.86	0.74	0.76	0.34	0.70	33.9	10.4	28.6	.91	.34	.70
4		Zone 4	574	IRI = 0.939 + 1.774 MESA + 1.065 DRA	0.998	0.84	0.71	0.84	0.69	-	35.2	21.9	-	.75	.75	-
5	Expansive	Zone 1	1627	IRI = 0.85 + 4.717 MESA + 0.573DRA	0.999	0.92	0.84	0.92	0.44	-	83.1	17.8	-	.91	.91	-
6		Zone 2	2251	IRI = 1.885 + 1.314 MESA + 0.114 DRA + 0.541 TER	0.999	0.50	0.25	0.49	0.05	0.28	25.9	2.3	13.4	.83	.91	.76
7		Zone 3	958	IRI = 1.187 + 6.109 MESA - 0.28 TER	0.999	0.77	0.59	0.70	-	0.18	26.5	-	4.8	.53	-	.53
8		Zone 4	3512	IRI = 2.679 + 1.955 MESA – 0.416DRA	1.0	0.55	0.31	0.54	0.23	-	35.2	12.8	-	.99	.99	-
9	Non Exp	All Zones	2699	IRI = 2.338 + 1.117 MESA – 0.477 TMI + 0.577 DRA – 1.128 TER	0.999	0.78	0.61	0.67	0.28	0.64	45.0	15.0	41.7	.75	.73	.72
10	Exp	All Zones	8348	IRI = 1.867 + 2.817 MESA - 0.014 TMI	0.999	0.69	0.48	0.64	-	-	70.8	-	-	0.95	-	-

TABLE 1 Developed Model Considering Different Climate Zones and Soil Reactivity

(-): refers that there is no correlation or no contribution of the variable on roughness progression rate

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