RELIABILITY-BASED INITIAL PAVEMENT PERFORMANCE DETERIORATION MODELING

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Abstract: This paper presents an approach for incorporating reliability on initial performance prediction models developed from as little as two time series predictors. It employs a novel methodology to provide apparent ages as surrogate of condition and in addition applies multilevel Bayesian regression to calibrate mechanistic empirical models to local conditions. The paper develops an IRI deterministic performance model for the Costa Rica road network and, further shows the procedure for obtaining a probabilistic multilevel Bayesian model which includes distributions of the mechanistic parameters and confidence intervals for the predicted performance. Bayesian statistics are also deployed for calibrating pavement strength coefficients to local observations.

CE Database subject headings: Performance Model, Multilevel Bayesian Regression, Parameters estimation, Pavement Deterioration.

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INTRODUCTION

Strategic and long-term planning for sustainable civil infrastructure, including pavements and other transportation systems, relies on performance prediction models. Investment decisions (such as what budget strategy would sustain the asset value in the long run) require the ability to predict future asset conditions under each investment strategy. However, despite the maturity of pavement management systems in developed countries (such as the US and Canada), good quality data for performance modeling is always the biggest challenge in initial implementations of comprehensive asset management systems that are capable of full optimization and trade-off analyses. On the other hand and, despite the existence of large data depositories and performance models in developed countries, no such model have been able to capture uncertainty associated with its predictions.

The objective of this paper is to demonstrate using a case study a modeling approach that can be used to estimate performance models capable of accounting for uncertainty even in situations where there is very limited historical data available.

REVIEW OF PERFORMANCE MODELING

Selection of Model Formulation

Performance prediction model formulations are generally classified into two categories: deterministic or probabilistic (George et al. 1989, Prozzi and Madanat 2003). Deterministic model forms are those that generate a single value of the response variable (a performance indicator, output of yield, e.g., International Roughness Index (IRI)) for a given set of independent variables (e.g., time, age, traffic loading, usage rate, environmental exposure, preservation activity level, etc.). The most common analysis technique for deterministic models is the statistical regression analysis. On the other hand probabilistic models generate a statistical distribution for the response variable (i.e., performance indicator) of any asset. Most common probabilistic models include: Markov chain (MC), survivor curves and Bayesian regression. Given the current asset condition (state *i*), the MC technique predicts the future condition of the asset (state *j*) as probability distribution. Bayesian regression modeling was proposed at the end of the nineties (C-SHRP 1997, Li and Haas 1996). The key advantage of the Bayesian regression model formulation is the power to incorporate uncertainty – which is a reality in all design and planning processes for transportation infrastructure. The other advantage is the ability to rapidly incorporate expert opinions to supplement historical data where quality data is unavailable. This paper applied the Multilevel Bayesian Regression formulation because of these advantages. The multilevel component of the proposed model becomes natural when dealing with families of pavements in order to capture group-characteristics and regional differences (Pedigo et al. 1981, Butt et al. 1987).

The Bayesian Regression Model

Bayes theorem (Equation 1) is a useful form for combining prior knowledge of certain event probabilities with observed data (likelihood) in order to produce an adjusted expression of the event probabilistic distribution, called the posterior. According to Hong and Prozzi (2006) the denominator (known as the normalization constant) ensures that the sum of the probabilities reaches one (100%). Equation 1 is composed of three terms: the posterior $P(\theta/data)$ which is given in terms of the likelihood of the *data given a vector of parameters* θ, times the prior knowledge $P(\theta)$. Choosing the right prior has been a matter of debate (Spienhalter and Lunn 2009, Bishop 2006). In general the likelihood is given by the available data, and the prior should come from either previous investigations or expert criteria. Priors can be informative or non-informative. Non-informative priors are preferred whenever little is known about the phenomena under study, although the posterior will tend to mimic the likelihood. Informative priors –whenever there is sufficient knowledge- will get mixed with the likelihood and most likely produce an enhanced posterior distribution.

$$P(\theta / Data) = \frac{P(data/\theta) \cdot P(\theta)}{\int P(data/\theta) \cdot P(\theta) \cdot d\theta} \qquad [1]$$

Simulation for Bayesian Inference

As explained by Freitas (1999), sampling can be used as a manner of approaching the true value of complex integrals (areas under certain probabilistic distribution *p(x)*) by generating random values and counting their frequency within the limits of *p(x)*.

An alternative to solve complex functions such as the (sometimes intractable) integral on the Bayesian theorem denominator is that of sampling. Several techniques for sampling have been tested through history, being the most important: rejection sampling, importance sampling, sampling importance re-sampling, and Markov Chain Monte Carlo (MCMC). The most comprehensive among MCMC is the Metropolis-Hasting and others derived from it, such as the particular case of Gibbs sampling (Andrieu et al. 2003).

According to Gamerman and Lopez (2006), Gibbs sampling is a particular case of Metropolis-Hasting for acceptance (A) either 1 or 0. Gibbs sampling is a very attractive method of setting up a MCMC algorithm for getting the joint posterior distribution of all parameters (causal factors). "*The idea behind Gibbs sampling is that we can set up a Markov chain simulation algorithm from the joint posterior distribution by successfully simulating individual parameters from the set of p conditional distributions*" (Albert 2007). The procedure goes by simulating in turn one value of each individual parameter which is called one cycle of Gibbs sampling.

Multilevel Regression Modeling

Traditional regression models treat all data as individuals belonging to the same population and sharing the same characteristics, therefore, they are said to pool all data and obtain values for the regression parameters to produce the best fit to the completed pooled model. The most popular approaches for fitting such models are: minimum least square distances and maximum likelihood (Bishop 2006). According to Gelman and Hill (2007) approaches such as maximum likelihood can work well with "models with few predictors" and large datasets. However, perfect separation and/or co-linearity issues may arise; producing bad estimation of the regression coefficients because of interactions between predictors, hence a non linear transformation (i.e., exponential) is typically used to provide such a required separation.

The use of regression models containing fixed parameters often produce bad fit (with high dispersion) translated into unreliable predictions. Rather, the recognition of multiple-levels (or hierarchies) allows the experimenter to improve the calibration of the regression coefficients. It is equivalent to accept different intercepts and slopes for a linear fit. According to Gelman and Hill (2007) multilevel regression models recognize such nature by considering that the data is structured within different levels. Bayesian multilevel regression models go beyond by returning probabilistic distributions of the parameters instead of presuming them being fixed values (Bishop 2006).

Multilevel Bayesian models not only produce a more efficient inference of the regression parameters, but also enhance the overall prediction by borrowing information across the groups to improve predictions for those clusters with few data (Spiegelhalter et al. 1994, 2002). Figure 1 illustrates four cases of groups with different levels of data and how partially pooled regression lines perform better as compared to complete and no-pooled models. Only observations for the no-pooled model are shown.

The Bayesian model proposed here assumes model coefficients to be stochastic variables and estimates a posterior probabilistic distribution from a combination of expert criteria and the observed data. Any Bayesian Regression modeling requires prior information for the stochastic nodes (variables). A functional form is used to represent the mean, $E\{*\}$ accompanied by a variance term, $VAR\{*\}$. Finally, both elements are embedded in a probabilistic distribution (normal in this paper) and a few thousand iterations are performed employing a MCMC simulation, which is divided in two steps: the first part (known as the "burn-in") consisted of a few thousand iterations conducted until the convergence of the model. The second part consisted of some extra few thousand more iterations and its results produce the posterior distributions of the parameters and the predictive model for pavement deterioration.

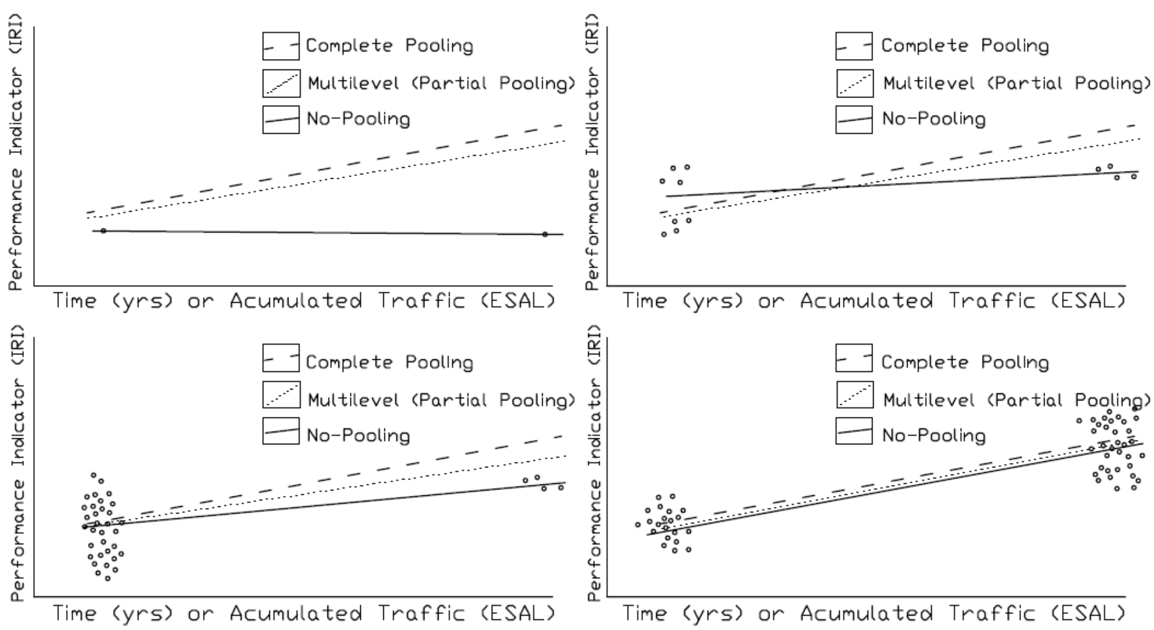

Figure 1 **Comparison of homogeneous groups with different availability of data**

In summary, the use of Multi-level Bayesian regression modeling has several advantages: (1) it provides a probabilistic estimation of expected responses (condition) at any point in time; (2) it is capable of estimating parameters from observed data (hence the ability to re-calibrate the model to local conditions); (3) it is possible to incorporate expert criteria; (4) it weighs the expert opinions, knowledge and reasonable expectations with observed data to produce a better prediction; and (5) it borrows strength across groups in order to improve predictions on those with few observations.

DATA ANALYSIS PROCESS

Construction of a Database for the Costa Rica Road Network

The available information for the Costa Rica road network consisted of linearly referenced International Roughness Index (IRI) data and point-data Falling Weight Deflectometer (FWD) measurements. Both data sets were collected by the University of Costa Rica's National Laboratory of Materials and Structural Models (LANAMME).

Traffic volume data was also available but in non spatial format. Traffic data was mostly available in Excel files with values given for some control points along the major routes. Traffic data was transformed into single axle loads (ESAL) employing the load equivalency factors proposed by the Road Transportation Association of Canada (RTAC 1986) as exemplified by the Transportation Association of Canada (TAC 1997). Manual location of the traffic load (ESALs) across the network was required in this case. Data for the international roughness index (IRI) for both 2004 and 2006 was available in geospatial format with line segments every 100 m. Data for the pavement structure thickness (from coring data) was available every 500 meters. A linearly referenced base map was created with segments of pavement every 100 meters containing all data merged.

Characterization of Traffic Loading

The truck traffic in Costa Rica consists mainly of 3 to 5 axle trucks and a small percentage of buses. The trucking industry in Costa Rica has predominantly relied on pre-owned trucks imported from North America, mainly the US and Canada. The legal axle load limits are also comparable to those in North America although the level of enforcement may be much lower. It was therefore justified to use truck factors from North America. The truck factors were estimated based on the Transportation Association of Canada (TAC) 1986 data. The truck factors adopted were 2.652, 3.027, 4.385 and 4.445 for 2-, 3-, 4- and 5-axles truck, respectively. The buses were given a truck factor of 2.5 (Hajek 1995). The average daily truck traffic data were converted into ESALs per lane per year by multiplying the truck counts in each lane by the corresponding truck factor by class.

Pavement Families

The first step in developing performance models for network-level long-term planning is to separate the road network into homogeneous groups of similar characteristics. The characteristics of interest here are those that have an effect on the causal variables for the performance model such as initial structure, as-built quality, environmental exposure, traffic loading and maintenance practice. The concept of similar families of pavements is not new; it has been extensively used by others (Pedigo et al. 1981, Li and Haas 1996, Mauch and Madanat 2001) to analyze large databases and enhance reliability of the performance models.

The next step is to decide on the causal factors that affect the deterioration process that can realistically be included in the performance model. Traffic load intensity has been as recognized as the most significant factor affecting pavements deterioration

(Watanatada 1987). This is especially the case when traffic loads are moderate to high as noted in the national road network in Costa Rica. For the purposes of developing initial estimates of performance models, availability of network condition data is a critical constraint. This is certainly the situation in Costa Rica. In such situations, the decision of which causal variable to include or not to include in the model is largely driven by the availability of data. This research employs traffic loading and pavement structure as the primary causal variables in the performance model.

Data on material types, soil strength, etc. as well as the region specific environmental exposure was not available. The estimated initial performance model used only the traffic loading (ESALs) as the key causal factor. In the absence of data on the absolute age of assets, the current condition of the asset element (i.e., pavement) was used to group the pavements into apparent age groups. The condition classes based on IRI were broken at four levels: good, fair, poor and very poor, while traffic load intensity was divided into three levels: high, medium and low traffic. With this classification we established 12 groups of pavements corresponding to each pair of traffic-apparent age level as shown in Table 1.

Table 1. Summaries of Pavement Groups Assumed Untreated over the Period 2004 – 2006

Group	IRI 2006 Range (m/km)	Rut depth Range (mm)	Condition Class	ESAL / year (thousands)	Traffic Class
1	1.0 - 2.8	< 5	Good	> 308	3
2	2.8 – 5.0	5-10	Fair	> 308	3
3	5.0 – 7.0	10- 20	Poor	> 308	3
4	7.0 - 20	> 20	Very Poor	> 308	3
5	1.0 - 2.8	< 5	Good	131 – 308	2
6	2.8 – 5.0	5-10	Fair	131 – 308	2
7	5.0 – 7.0	10- 20	Poor	131 – 308	2
8	7.0 - 20	> 20	Very Poor	131 – 308	2
9	1.0 - 2.8	< 5	Good	< 131	1
10	2.8 – 5.0	5-10	Fair	< 131	1

11	5.0 – 7.0	10- 20	Poor	< 131	1
12	7.0 - 20	> 20	Very Poor	< 131	1

Key: Traffic classes: 3 = high, 2=medium, 1 = low

MODEL SPECIFICATION

Mechanistic Model for International Roughness Index

A deterioration performance model for roughness was constructed employing the first term of the incremental roughness model as proposed by Watanatada (1987), Equation 2 shows such term which was then incorporated as the rate of a linear, exponential functional form. A conversion from the old roughness scale of quarter-car (QI) into the International roughness index (IRI) was necessary to fit the format of the available data (Equation 2). Equation 3 shows the deterministic IRI prediction model in the exponential form that (after several trials) was found to better capture the observed data.

$$\Delta QI = 13\left[\frac{134e^{0.023 \cdot Age} ESAL}{(SNCK+1)^5}\right] \qquad [2]$$

Where; SNCK = 0.0394 ($a_1H_1+a_2H_2+a_3H_3$) + SG, with a_1 to a_3 pavement strength coefficients, H_1 to H_3 pavement layer thickness and SG = 3.51 log CBR — 0.85 (log CBR)^2 - 1.43, in which CBR = California Bearing Ratio. ESAL = Equivalent Single Axle Loads, Age = number of years since last major rehabilitation, t = time in years

$$IRI = 1.8e^{\left\{\frac{134e^{0.023 \cdot Age} ESAL}{(SNCK+1)^5}\right\} t} \qquad [3]$$

The effect of the term $e^{0.023 \cdot Age}$ (which accounts for the elapsed time since the roads last rehabilitation, reconstruction, or construction) was left variable under a normal distribution ranging from 1 to 2, which corresponds to ages from new to thirty years old.

As observed in Figure 2 no ages above 20 years old are expected for local pavements in the Costa Rica road network.

Equation 3 was used as the mean expectation of IRI for predicting the performance progression of IRI across time. The term in brackets in Equation 3 was embedded in a normal distribution for a multilevel Bayesian regression model in order to obtain probabilistic distributions of the pavement strength coefficients. The multilevel Bayesian model carries computations across groups and returns probabilistic distributions of every parameter per group.

Generating Apparent Ages

The Costa Rica data consist of only two data points along the time axis. In other words, the starting model would only have two ordinates making it impossible to establish the curvature of performance progression. However, one knows that in any network of assets, the condition survey of a given year provides assets in almost all age classes – from very young to very old. One also intuitively knows that the age of the asset relates to its condition in some fashion. In the absence of the asset age, the condition of the untreated asset can be used as a surrogate for its age. The first step in the analysis is to separate out those assets that were treated in the 2004 – 2006 time window.

The remainder of the sections showing an increase in IRI (or rut depth) from 2004 to 2006 were used to estimate apparent ages for the performance models. The mean 2004 and 2006 IRI values presented in Table 2 are based on this later subset of the network utilized for performance modeling. As expected, the averages of IRI for 2006 were higher than those for 2004 for each pavement group. It is worth noting that the starting IRI breakpoints between good – fair, fair – poor and, and poor – very poor (i.e., 2.8, 5 and 7, respectively) were arbitrarily selected.

Table 2. Summary of Pavement Groups Mean Condition, 2004 – 2006

Group	Traffic Class	Condition Class	Mean 2004 IRI (m/km)	Mean 2006 IRI (m/km)	Mean 2004 Rut depth (mm)	Mean 2006 Rut depth (mm)
1	3	Good	1.93	2.27	2.73	3.43
2	3	Fair	2.95	3.75	4.39	7.28
3	3	Poor	4.20	5.97	7.00	14.39
4	3	Very Poor	5.54	8.76	13.59	20.94
5	2	Good	1.95	2.25	2.51	3.29
6	2	Fair	2.98	3.76	4.61	7.21
7	2	Poor	4.44	5.94	7.59	14.09
8	2	Very Poor	5.92	9.30	14.06	41.44
9	1	Good	1.96	2.29	2.05	3.13
10	1	Fair	3.21	3.89	4.01	7.20
11	1	Poor	4.61	5.94	6.66	13.91
12	1	Very Poor	6.53	9.62	15.91	43.65

***Key**: Traffic classes: 3 = high; 2=medium; and 1 = low.*

According to TAC (1997) minimum values of IRI for new pavements may be as low as 1 m/km, while maximum values for damaged pavements can be expected to approach 12 m/km. Hence, an IRI apparent age scale with new pavements starting at 1.5 m/km was established (this assumed intercept will be later adjusted by the Bayesian regression model). Maximum apparent age was determined by the fitting technique subsequently explained.

The procedure starts by assuming an apparent age (AGE_1) of zero for the first IRI breakpoint (BP_1) of 1.5 (m/km). This arbitrary assumption can be changed as needed. Secondly, the apparent age (AGE_1) for the first pair of average good IRI points (μ_{2004}^{Good}, μ_{2006}^{Good}) was determined by finding the value of age of the second break point (AGE_2) that achieve the objective of separating the first pair of average IRI points (μ_{2004}^{Good}, μ_{2006}^{Good}) by a distance of 2 years (because of the time elapsed between condition surveys). The apparent age (AGE_3) for the third breakpoint (BP_3) use the just established apparent-age of the second breakpoint (AGE_2) and find the value of the corresponding age of the third break-point (AGE_3) that achieves a distance of 2 years between the second pair of average fair IRI points (μ_{2004}^{FAIR}, μ_{2006}^{FAIR}). This procedure continues in this fashion using the Poor and Very Poor pairs of average condition until all apparent ages have been established. Equation 4 was used for finding the apparent-age of each brake point and then it was modified to obtain Equation 5, which is an expression to obtain the individual values of age of each pair of average IRI points. Figure 3 shows the deterministic performance model final results.

$$\frac{BP_n - \mu_{2006}}{\left(\dfrac{BP_n - BP_{n+1}}{AGE_{n+1} - AGE_n}\right)} - \frac{BP_n - \mu_{2004}}{\left(\dfrac{BP_n - BP_{n+1}}{AGE_{n+1} - AGE_n}\right)} = 2 \qquad [4]$$

$$\frac{BP_n - \mu_{2006}}{\left(\dfrac{BP_n - BP_{n+1}}{AGE_{n+1} - AGE_n}\right)} + AGE_n = \text{Age of } \mu_{2006} \qquad [5]$$

where, BP_j = break point of group j; AGE_t= apparent age of the group in year t; and μ_{2004} = the mean condition (IRI) of the group in year 2004. Apparent ages for the break points of the traffic intensity groups were used as a basis to assign apparent ages for the entire database of observations. A direct formulation given by Equation 6 facilitates the direct computation of apparent ages for every observation

$$\frac{2(BP_n - BP_{n+1})}{x_{04} - x_{06}} + AGE_n = \mathrm{AGE}_{n+1} \qquad [6]$$

In Equation 6 the variable x represents individual observations of IRI values at certain point in time. Figure 2 shows a scatter plot graph of IRI observations (from the high traffic class) versus apparent ages and, classical best fit exponential line trend; models for the medium and low traffic categories can be developed similarly, rather this research builds a multilevel Bayesian model –as presented below- from the basis of the deterministic case. As demonstrated by Amador and Mrawira (2008) lifespan of roads in Costa Rica are not expected to overpass 20 years (see also Figure 3)

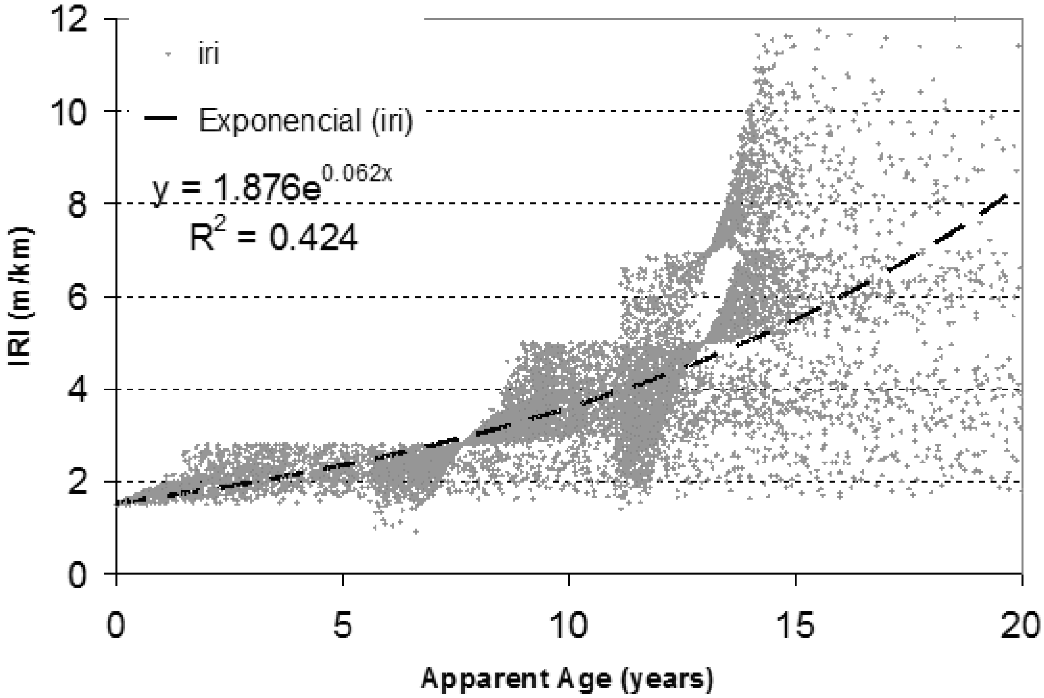

Figure 2 **Progression of IRI versus apparent ages for high intensity of traffic loading**

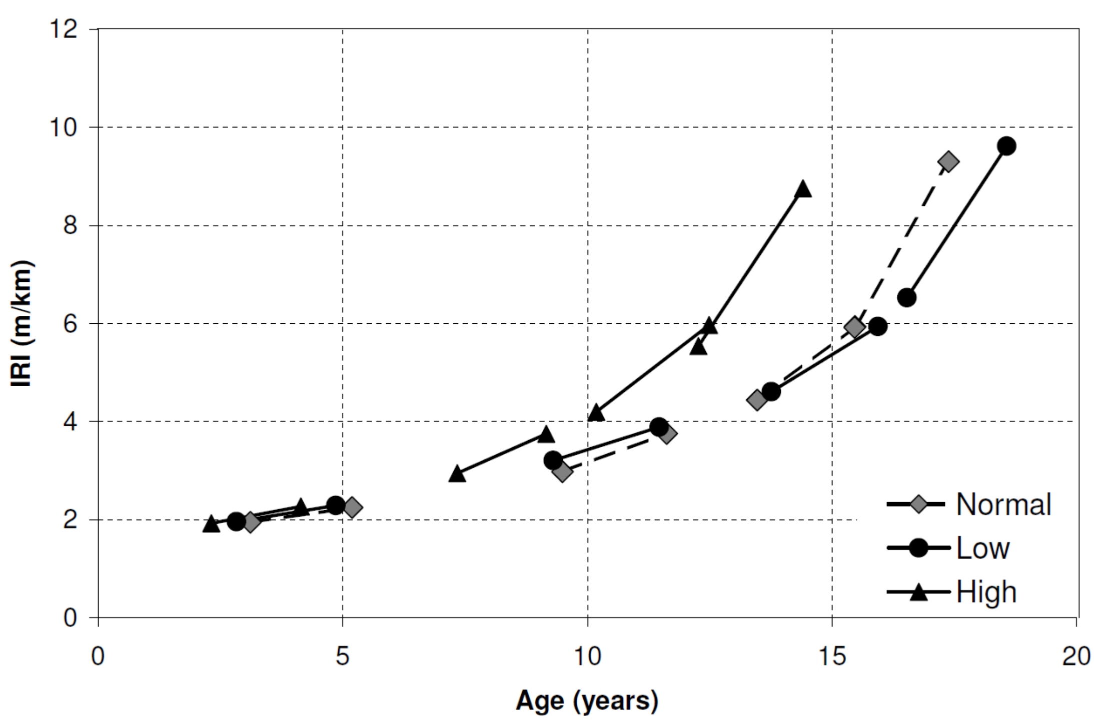

Figure 3 **Deterministic IRI versus apparent age by traffic intensity**

Multilevel Bayesian Regression Modeling for Costa Rica

Regular Bayesian models contain several terms; (1) the mean expectation of the response and (2) the variability represented by the standard deviation or the precision (square inverse of the standard deviation), (3) the prior believes, (4) probabilistic distributions of the parameters and some initial guess or starting point for the parameter values and (5) the observed data

A multilevel probabilistic model contains –on top of the aforementioned- the assumption of probabilistic distributions for every parameter per class or group of which it depends. Two separate multilevel models were analyzed: (a) one for estimating the pavement layer strength coefficients and (b) another one for producing the probabilistic performance deterioration. Both for the international roughness index (IRI). Models as the herein presented can be extended to rut depth or other condition indicators.

The IRI model introduced by Equation 3 corresponds to a complete pooled data model which disregards traffic intensity, environmental zones, and any other criteria for creating families of pavements or homogeneous groups. Therefore a multi-level model considering traffic intensity (the only available criteria) was developed. Such a model was expected to produce three IRI performance models.

Hence, the model presented by Equation 3 was used as the mean expectation for IRI which was accompanied by an expression for precision. As aforementioned one can study the complete pooled data model: where no consideration to group level parameters is done, the no-pooled data: where effects amidst groups are neglected, or the partially pooled group where a multilevel structure (nested or not) is set in place.

Results were summarized into 2 parameters for easy comparison: initial IRI was summarized by β, an stochastic node with a normal distribution *N(1.5,1)* which allow it to fluctuate between 1 and 2. The β parameter is thought to be strongly related to the as-built quality. Another parameter α was introduced for capturing the rate of deterioration on the power of the exponential. This model produces part of the results discussed in the next section.

Another model was developed to tackle the issue that the pavement strength coefficients (a_1, a_2, and a_3) were unknown. This model estimates them from local observations. Hence, each layer coefficient was given normal probabilistic distributions. Because these coefficients may respond differently according to the type of material, a non-nested multilevel model was used to estimate coefficients per type of material in both the surface structure a_1 and the base a_2. Table 3 presents the grouping categories. The type of subgrade material was so extent that it would have required an enormous effort to create tens of group categories for a coefficient whose contribution in the overall pavement structure is very limited. It is worth noticing that the information regarding types of subgrade-soil may have been used in other groups for determining the contribution of the subgrade in the modified structural number (SNCK), however it was held constant at a value of 1.6 that corresponds to a CBR of 30% which is typical for soils in Costa Rica (Bogantes 1999). This assumption does not contribute substantially to the final result because this term plays a minor role with a theoretical maximum value of 2.1.

Table 3. Levels for Surface and Base Layer Types

Pavement	surface class	a_1
AC	1	0.2 to 0.45
ST	2	0.2 to 0.40
BASE	Base class	a_2
GRAVEL	1	0.07 to 0.14
Stabilized	2	0.1 to 0.24
AC.MIX	3	0.2 to 0.32

Key: *AC=Asphalt Pavement, ST = Surface Treatment, AC.MIX= Full Depth Asphalt Mix*

RESULTS AND DISCUSSION

The software suite WinBUGS (Lunn et al. 2000) was employed for running multilevel Bayesian regression modeling. Results from two main models are presented below, and as mentioned before, they were intended for: (1) calibration of pavement layer strength coefficients from local observations, (2) production of probabilistic performance models per traffic intensity group.

Calibration of Pavement Layer Strength coefficients

The estimation of pavement layers structural coefficients from the data was equivalent to calibrate the model to local conditions. Equation 2 was used for this purpose. The software used such equation as the mean response of the differential IRI and by processing a sample of 4500 data points (and running 120,000 samples) the model produced the probabilistic distributions of the pavement layer strength coefficients (a_1, a_2, a_3) per type of material shown on Table 4.

Table 4. Probabilistic distributions of pavement strength coefficients

Node	mean	sd	MC error	0.0250	median	0.9750	start	sample
a1[1]	0.3304	0.0604	3.97E-04	0.2123	0.3300	0.4482	20000	120002
a1[2]	0.3298	0.0608	4.06E-04	0.2110	0.3297	0.4484	20000	120002
a2[1]	0.1990	0.0604	3.90E-04	0.0798	0.1996	0.3158	20000	120002
a2[2]	0.1990	0.0598	4.08E-04	0.0818	0.1987	0.3166	20000	120002
a2[3]	0.1999	0.0599	3.79E-04	0.0835	0.2005	0.3172	20000	120002
a3[1]	0.1000	0.0201	1.34E-04	0.0604	0.0999	0.1392	20000	120002
a3[2]	0.0999	0.0199	1.25E-04	0.0604	0.1000	0.1388	20000	120002
a3[3]	0.0999	0.0200	1.30E-04	0.0604	0.0998	0.1390	20000	120002

KEY INDEXING a[b]: a=layer (1=asphalt, 2=base, 3=subbasel), b=material type, for a1 (1 =asphalt cement, 2=surface treatment), for a2 (1=gravel, 2=stabilized base, 3=Full depth asphalt mix) and, for a3 (1=stabilized, 2=gravel, 3=soil)

Results from Table 4 show that it is not possible to observe differences by material type when estimating values of the pavement layer strength coefficients. Hence, one can assume –for this case- that values of the coefficients do not vary by material type. Values of coefficient a_1, reflect a distribution centered on 0.330 with a 95% confidence that values of this coefficients vary from 0.211 to 0.448. The coefficient for the base layer (a_2) has a mean expectation of 0.199; its values may range from 0.08 to 0.31 with a 95% confidence and, the strength of the sub-base (a_3) can be expected to range from 0.0604 to 0.139 for the same confidence. These values reflect characteristics of local materials estimated from the observed data.

Producing probabilistic performance models per traffic intensity group

Two different approaches were utilized to produce performance models per traffic intensity: (1) Independent Bayesian models (i.e., no-pooled data) per traffic intensity group and, (2) Multilevel (i.e., partial-pool) Bayesian Regression model, which estimates group level parameters while considering interactions between groups.

Results from Independent Bayesian Models

Because the independent Bayesian model (i.e., no-pooled data model) is equivalent to analyze individual groups without considering cross interactions, individual results of it were used to establish a base case as presented in Table 6. Estimated probabilistic distributions for the intercept β and the estimated rate α for the high traffic class are presented by Figure 4.

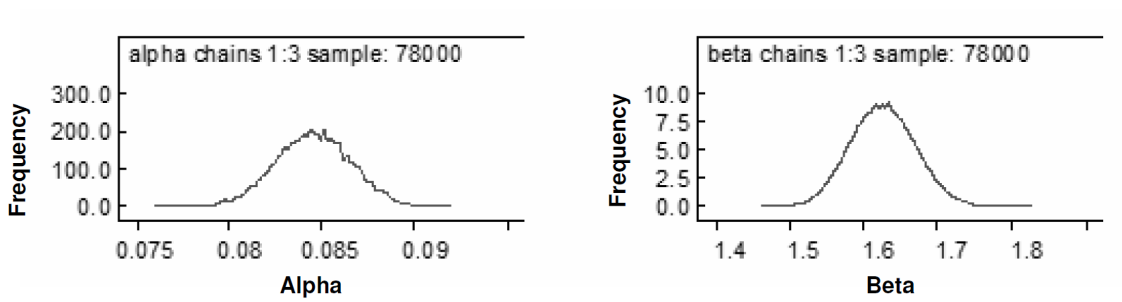

Figure 4 **Probabilistic distributions of parameters α and β on High traffic class**

The intercept mean expectation was found to be located at a value of (initial as-built quality of IRI) 1.626 m/km with a very narrow range of variation ranging from 1.544 to 1.712 for the 95% confidence interval. Results of the IRI's rate of deterioration showed a mean value of 0.0855, also with a very narrow variation for the 95% confidence interval ranging from 0.0803 to 0.0884. Chains were found to have good convergence and mixture after 10,000 samples even though they depart from dissimilar points (Figure 5).

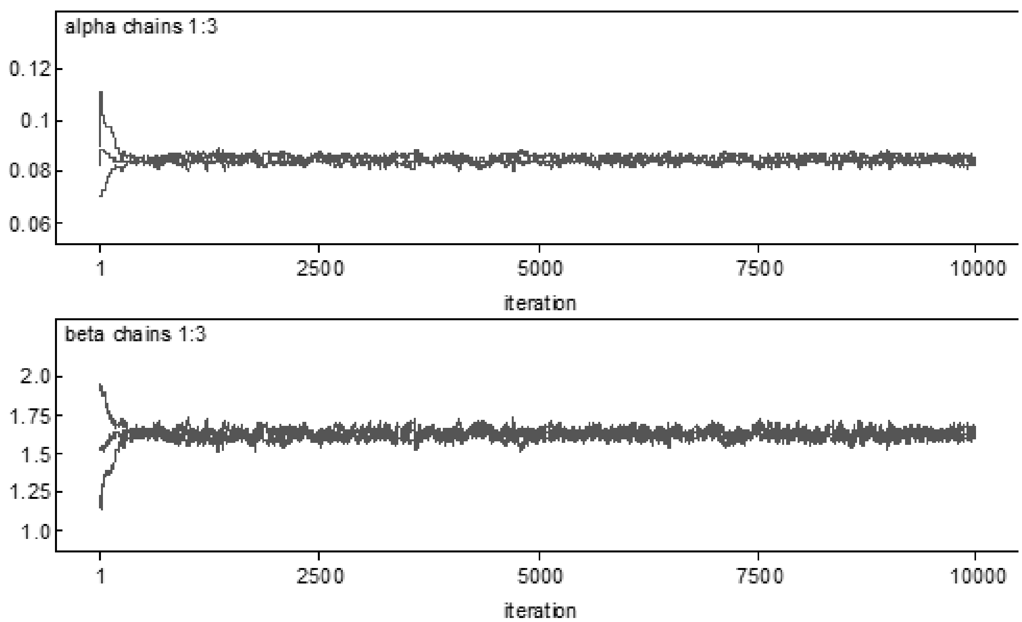

Figure 5 **Chains Convergence for parameter α and β on the high traffic class**

Comparison of traffic classes for the complete-pooled models presents unexpected trends with higher deterioration rates for lower exposure to traffic; this can be explained in part because of the decrease in the intercept of the models but mostly because of the lack of consideration of how the data obey to a structure with traffic classes. Also because the Break Points used to generate pairs of apparent age – IRI values constrained the levels of age-IRI pairs to be confined below the corresponding break point, creating flat platoons at every break point level as one can observe in Figure 2. This situation effectively affects the fitting process returning an exponential curvature that tries to adjust to the observations but fails to recognize the existence of traffic classes.

Results from multilevel model

Results from the multilevel model provided a better estimation of the parameters. The as-built and rate of deterioration for the low and medium traffic intensity groups were the same, though the high traffic intensity group presented a higher rate of deterioration and a higher initial value (intercept) which corresponded to reasonable expectations.

Table 5. Value of Parameters for the partial-pooled model

Node	mean	sd	MC error	2.50%	median	97.50%
alpha[1]	0.07998	0.009926	1.03E-04	0.06035	0.08008	0.09906
alpha[2]	0.08003	0.01002	1.01E-04	0.06047	0.07998	0.09949
alpha[3]	0.08435	0.001233	7.85E-05	0.08185	0.08441	0.08657
beta[1]	1.4	0.2481	0.002603	0.9092	1.401	1.882
beta[2]	1.398	0.2509	0.002278	0.9067	1.399	1.889
beta[3]	1.627	0.02675	0.001648	1.579	1.626	1.681

Comparison of Results

Table 6 compares the no-pooled model base case per traffic class with the multilevel model. As seen models from low and medium traffic intensity can be merged into one category, this confirms preliminary observations from the deterministic performance model on Figure 3.

Table 6. Comparison of Values of parameters for the no-pooled and multilevel models

Parameter / Traffic Class	Base Case: No-pooled Model			Multilevel (partial-pooled model)		
	Low	Medium	High	Low	Medium	High
α	0.0843	0.0960	0.1083	0.0798	0.0800	0.0844
β	1.628	1.269	1.110	1.400	1.400	1.627

Figure 6 presents an example of a deterministic performance model for the low traffic intensity class; enveloping curves for the 95% confidence interval demonstrate the model capability to capture associated uncertainty. A similar model can be prepare for the high traffic intensity class.

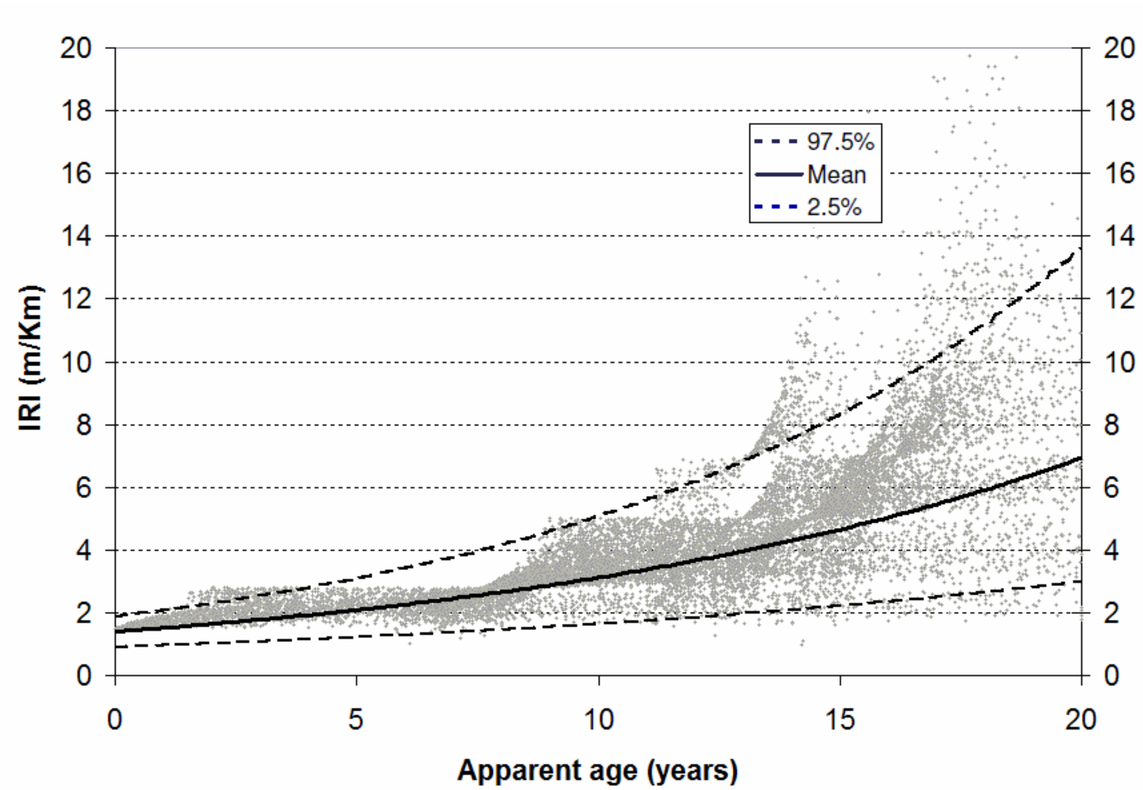

Figure 6 Deterioration model with variability for 95% confidence interval

CONCLUSIONS

This paper has presented an approach for developing reliable performance prediction modeling in the presence of limited historical data. Information from condition surveys conducted at only two different times were used for this task. The pavement deterioration mechanistic model suggested by the World Bank with international roughness index (IRI) as the response in terms of traffic loading (ESALS) and pavement strength (thickness) was modified for such purpose. However, the development of a novel approach to provide “age” to the condition observations was required. Hence, the use of an apparent age as a surrogate for the current level of condition was a key component for developing an initial performance curve. Therefore, the next step was to develop a multilevel Bayesian regression modeling which extends that initial model to account for reliability in the prediction. The case study of the Costa Rica network demonstrated that it is possible to create a performance model from only two time steps of historical observations of the causal factors.

Moreover this Bayesian regression model was used to calibrate several mechanistic model parameters at once, unlike inefficient traditional approaches when calibrations are done one at a time by fixing the rest of the model parameters. It was demonstrated that Bayesian regression modeling is capable of estimating the AASHTO pavement layer coefficients for the Costa Rica road network. Values of structural layer coefficient for the surface layer (a_1) reflect a distribution centered at 0.330 with a 95% confidence that ranges from 0.211 to 0.448. The structural coefficient for the base layer (a_2) has a mean of 0.199 and values varying from 0.08 to 0.310 for a 95% confidence interval. The AASHTO layer coefficient strength of the sub-base (a_3) was found to range from 0.060 to 0.139 at 95% confidence with a mean of 0.099.

Multilevel modeling proved to take into consideration the way in which data is structured and interrelated, delivering better estimation of the parameters and therefore improving the reliability of the performance model.

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