Assessment of the Impact of Climate Change on Road Maintenance

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ABSTRACT
Climate affects road deterioration, vehicle operating costs, road safety and the environment. Current and past pavement design guides and engineering models assume a static climate whose variability can be determined from past data. This fixed climate assumptions is often used in road management decision support models such as the Highway Design and Management system (HDM-4) to simulate future behaviour of road sections and consequently inform long-term road maintenance strategies and policies. Contrary to the assumption of a static climate in road management approaches, observations over the last 40 or 50 years show increasing trend in global warming. This raises the possibility that the severity and frequency of pavement defects may be altered leading to premature pavement deterioration and increased costs of managing and using roads. As a consequence, current road management strategies and policies may not offer sufficient resilience to increased frequency of future extreme climate events. A study was undertaken at the University of Birmingham to develop improved deterioration model for asphalt rut depth prediction. The approach used entailed the application of Bayesian Monte Carlo analysis. The output of the study will be used to improve existing road management systems such as HDM-4 and to consequently facilitate the investigation of strategies for adapting to future changes in climate.

Keywords: Bayesian Models, Climate Change, Deterioration Models, HDM-4, Rut Depth

1.0 INTRODUCTION

Pavement deterioration prediction models used to simulate the initiation and progression of key defects such as rutting and cracking are important components of road decision support systems such as the World Bank's Highway Design and Management System (HDM-4). Such systems are used by road authorities and general practitioners at the planning, programming and project levels of road management to investigate road improvement and maintenance policies, develop work programmes under budget constraints, compare road improvement and maintenance alternatives, evaluate appropriate standards for various classes of roads, and to determine the implication of marginal increase or decrease in funding levels on the road authority as well as road users. An important requirement of these models is that they must correctly consider all important factors that have significant impacts on pavement deterioration including but not limited to, traffic loading, road geometry, pavement material properties, and climate (Paterson, 1987). Climate and consequently climate change affects road deterioration, vehicle operating costs, road safety and the environment. There is a concern that the structure and model coefficients of existing deterioration models such as that implemented in HDM-4 do not properly account for predicted change in climate. This study is focused on asphalt rut depth deterioration prediction.

2.0 THE PROBLEM

The structure of current and past pavement deterioration models assume a static climate whose variability can be determined from past data over often not more than 30 years. This static climate assumption is often used as inputs into road management decision support models to simulate the long-term performance of road systems. The recently observed hot and dry summer of 2003 caused significant damage to road systems in the United Kingdom. Figure 1 shows plots of annual rates of rutting observed on trunk road sections located in East England against maximum summer temperatures in each road section by year from 2002 to 2005. Higher rates of rutting were observed in 2003 compared to other years. A similar trend to that shown in Figure 1 could not be replicated when other climate variables such as rainfall intensity and the number of days with snow lying were used instead of maximum summer temperature.

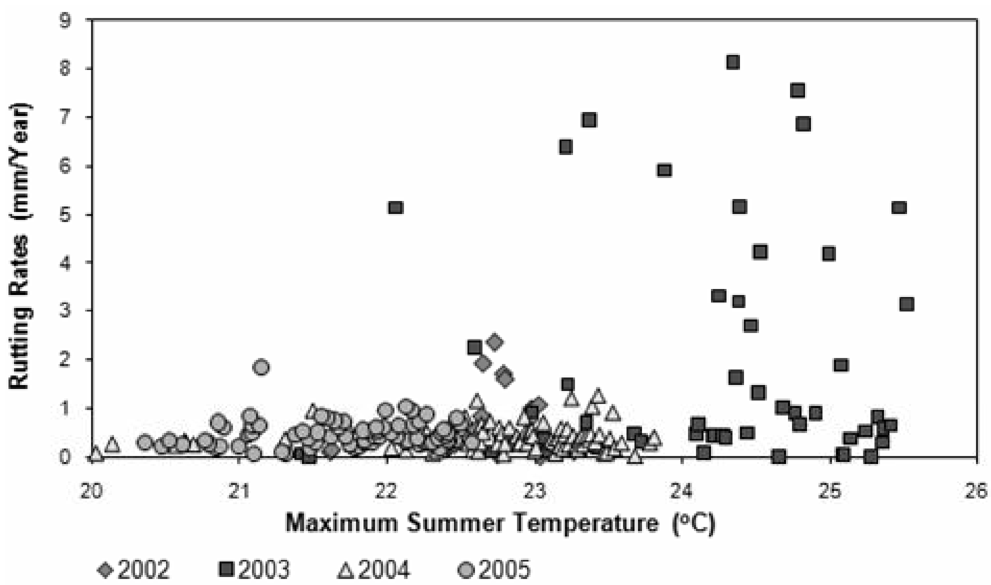

Figure 1: Annual Rutting and Corresponding Summer Temperature for Each Road Sections on Trunk Roads in East of England

According to information from the UK Climate Impacts Programme, in the East of England 5 percent of the years within the baseline period (1960 – 1990) had a 2003-type hot dry summer. The frequency of this climate event is predicted to significantly increase as summarised in Table 1. Table 1 summarises the predicted frequency of 2003-type hot dry summers in East England over 30 year periods or time for three green house gas emission scenarios. This raises the possibility that the severity and frequency of pavement defects and in particular asphalt rut depths on trunk roads in the UK may be altered leading to premature pavement deterioration and increased costs of managing and using roads. Road maintenance policies derived using deterioration prediction models or methodologies that assume a static climate and do not properly take into account other causes of deterioration are likely to underestimate the risks of increased frequency and severity of impacts associated future climate.

3.0 MODEL STRUCTURE

A study by Nunn et al. (1997), found that rutting on UK asphalt trunk roads is restricted to the top 100mm of the asphalt layer. This finding suggests that the problem of pavement deformation on UK asphalt trunk roads is that of surface deformation rather than structural deformation. The model structure adopted therefore considers variables that are deemed important for the performance of the pavement asphalt surfacing layers. A multiplicative model structure was used because the effects of variables that contribute to rut depth progression such as traffic loading, climate, and properties of asphalt surfacing materials is synergetic.

3.1 Existing Model Structure

The existing model structure given in Equation 1 is that implemented in the Highway Design and Management system (HDM-4).

$$\Delta\mathrm{RUT}_{\mathrm{mt}} = \alpha_0 \times \mathrm{CDS}_{\mathrm{m}}^{\alpha_1} \times \mathrm{YE4}_{\mathrm{mt}} \times \mathrm{Sh}_{\mathrm{mt}}^{\alpha_2} \times \mathrm{HS}_{\mathrm{m}}^{\alpha_3} \tag{1}$$

Table 1: Observed and Predicted Frequency of 2003-Type Hot and Dry Summers in East England

Time Slice	Green House Gas Emission Scenario	Percentage of 2003-type Summers
Baseline (1960 - 1990)	-	5
2020s [2011 - 2040]	Low	14
	Medium	15
	High	16
2050s [2041 - 2070]	Low	24
	Medium	30
	High	38
2080s [2071 - 2100]	Low	34
	Medium	49
	High	67

Source (UK Climate Impacts Programme)

Where $\Delta\mathrm{RUT}_{\mathrm{mt}}$ is the annual incremental change in plastic deformation within the asphalt layers of the pavement, in mm for road sections with surfacing material *m* during time period *t*; CDS_m is a continuous variable ranging in value between 0.5 and 1.5 and used as an indicator of the general level of binder content and stiffness relative to the optimal material design for specified asphalt surfacing mixes. $YE4_{mt}$ is the annual number of equivalent standard axles, in millions/lane on sections with surfacing material *m* during time period *t*; Sh_{mt} is the average speed of heavy vehicles on sections with surfacing material *m*, in km/h during period *t*; HS_m is thickness of bituminous layer on sections with surfacing *m*, in mm; and α_0 to α_3 are model coefficients given in Morosuik et al. (2001).

This model structure (Equation 1) does not include climate variables necessary for accounting for the impacts of future extreme climate events such as the 2003-type summers.

3.2 Improved Model Structure

The Improved model structure inlcudes additional variables deemed important for prediction of asphalt surface rutting that were not properly accounted for in the existing model structure. These additional variables inlcude road Gradient (G), asphalt binder Softening Point (SP), asphalt surfacing Voids in Mix (VIM), asphalt surfacing age (AGE) and climate variable $f\left(\mathrm{Cmax}_{\mathrm{imt}}\right)$. The improved model structure is given in Equation 2.

$$\Delta\mathrm{RUT}_{\mathrm{imt}} = \mathrm{YE4}_{\mathrm{imt}}^{\beta_{1\mathrm{m}}} \times \mathrm{Sh}_{\mathrm{im}}^{\beta_{2m}} \times \mathrm{G}_{\mathrm{im}}^{\beta_{3\mathrm{m}}} \times \mathrm{HS}_{\mathrm{imt}}^{\beta_{4\mathrm{m}}} \times \left(\frac{\mathrm{SP}_{\mathrm{im}}}{\mathrm{VIM}_{\mathrm{im}}} \times \left(\mathrm{AGE}_{\mathrm{imt}} + 1^{-4}\right)\right)_{imt}^{\beta_{5\mathrm{m}}} \times f\left(\mathrm{Cmax}_{\mathrm{imt}}\right) \tag{2}$$

Where $\mathrm{SP}_{\mathrm{im}}$ is the initial softening point of the asphalt binder of road section i for material type m, $\mathrm{VIM}_{\mathrm{im}}$ is the Voids in Mix for road section i with asphalt surfacing material m. $\mathrm{AGE}_{\mathrm{imt}}$ is the age of the most recent surfacing material on road section i with material type i during year t. The number $1\mathrm{x}10^{-4}$ is used to avoid numerical overflow.

The multiplicative function $f(\mathrm{Cmax}_{\mathrm{imt}})$ given in Equation 3 is a function of hot dry climate variable such as maximum summer temperature at road section i with material type m and during time period t derived from 5km gridded climate dataset for England.

$$f\left(\mathrm{Cmax}_{\mathrm{imt}}\right)=\left(1+\left(\frac{\theta_{1m}}{1+\exp\left(\theta_{2m}+\theta_{3m}\mathrm{Cmax}_{\mathrm{imt}}\right)}\right)\times \mathrm{T}_{\mathrm{HOLD}}\right) \tag{3}$$

The function is assumed logistic in nature and is formulated to simulate the increase in rut depth during 2003-type hot dry summer climate scenario. It is expected that at low air temperature rutting is mainly governed by the compaction effect of traffic loading on the pavement asphalt material using Equation 2. As temperature in combination with other factors increases, the asphalt in the mix becomes less viscous resulting in increased rates of rutting and Equation 2 would be adjusted using the logistic component in Equation 3. After the hot period, it is assumed that the bituminous mix will not change significantly hence Equation 2 would still be applicable.

A parameter $\mathrm{T}_{\mathrm{HOLD}}$ that takes binary numbers of 1 or 0 was adopted as an "on/off" switch for the logistic function given in Equation 3. $\mathrm{T}_{\mathrm{HOLD}}$ is assigned a value of 1 during hot dry summer years and a value of 0 otherwise. The completed improved asphalt surface rutting model is given in Equation 4.

$$\Delta\mathrm{RUT}_{\mathrm{imt}}=\mathrm{YE4}_{\mathrm{imt}}^{\beta_{1m}}\times \mathrm{Sh}_{\mathrm{im}}^{\beta_{2m}}\times \mathrm{G}_{\mathrm{im}}^{\beta_{3m}}\times \mathrm{HS}_{\mathrm{imt}}^{\beta_{4m}}\times\left(\frac{\mathrm{SP}_{\mathrm{im}}}{\mathrm{VIM}_{\mathrm{im}}}\times \mathrm{AGE}_{\mathrm{imt}}\right)_{imt}^{\beta_{5m}}\times\left(1+\left(\frac{\theta_{1m}}{1+\exp\left(\theta_{2m}+\theta_{3m}\mathrm{Cmax}_{\mathrm{imt}}\right)}\right)\times \mathrm{T}_{\mathrm{HOLD}}\right)+\varepsilon_{\mathrm{imt}} \tag{4}$$

Where ε_{imt} is the error term; β_{1m} to β_{5m}, and θ_{1m} to θ_{3m} are model coefficients to be estimated for each surfacing material type.

4.0 BAYESIAN ESTIMATION OF MODEL COEFFICIENTS

Bayesian inference combines information from observed data with prior knowledge about the model coefficients (referred to as priors) to give updated distribution of the model coefficients (referred to as posterior), which is described using Bayes theory as:

$$\mathrm{p}\left(\beta,\theta/\mathrm{X},\Delta\mathrm{RUT}\right)=\frac{\mathrm{p}\left(\mathrm{X},\Delta\mathrm{RUT}/\beta,\theta\right)\mathrm{p}\left(\beta,\theta\right)}{\int \mathrm{p}\left(\mathrm{X},\Delta\mathrm{RUT}/\beta,\theta\right)\mathrm{P}\left(\beta,\theta\right)\mathrm{d}\left(\beta,\theta\right)} \tag{5}$$

P(β, θ/ X, ΔRUT) = posterior distribution of elements of the vector β or θ given observed data including explanatory or independent variables (X) and dependent variables (ΔRUT); P(X, ΔRUT/ β, θ) = the likelihood of the observed data given the model coefficients β or θ; and, P(β, θ) = prior distribution of the model coefficients sets of β and θ.

The main difference between estimation of model coefficients using ordinary least square and Bayesian approach is that the latter associates a probability distribution with model coefficients β and θ. This probability distribution known as *prior* distribution p(β) or p(θ) quantifies uncertainties in model parameters before data becomes available (Desole, 2007).

4.1 Definition of Prior Probabilities

The prior distribution of the model coefficients were assumed to be normally distributed with mean μ and precision τ which can be denoted as N(μ,τ). The precision τ is defined as the reciprocal of the variance. The means μ of the prior distribution were largely based on the existing model coefficients specified in HDM-4 documentation (Morosuik et al, 2001). Non-informative or vague priors with mean of 0 and precision of 0.001 were assumed for model coefficients of additional variables included in the improved model structure. The assumed prior distribution is given in Table 2.

Table 2: Summary of Prior Distribution of Model Coefficients

Variables	Model Coefficients	Prior Distribution	Data Source
Traffic Loading (YE4)	β_1	N(1, 0.001)	Morosuik (et al., 2001)
Heavy Vehicle Speed (Sh)	β_2	N(-0.78, 0.001)	Morosuik (et al., 2001)
Road Gradient (G)	β_3	N(0, 0.001)	Vague prior
Asphalt Surfacing Thickness (HS)	β_4	N(0.71, 0.001)	Morosuik (et al., 2001)
Asphalt Surfacing Properties (SP*AGE/VIM)	β_5	N(0, 0.001)	Vague prior
Climate Variables	θ_1, θ_2, θ_3	N(0, 0.001)	Vague prior

4.2 Likelihood Specification

In Bayesian analysis likelihood specification refers to the assumption of the underlying distribution of the observed response variable. The observed incremental rut depth data which was assumed to be independent and identically distributed was stochastically represented as

$$\Delta \mathrm{RUT}_{\mathrm{imt}} \sim N[W(x)]$$

Where W(x) is a deterministic function given in Equation 4 comprising explanatory variables and model coefficients. N is the underlying statistical distribution of the data which was assumed to be normally distributed.

4.3 Estimation of Model Coefficients

The Windows version of Bayesian Updating using Gibbs Sampler (WinBUGS) was used to derive the marginal distribution of the model coefficients. The marginal distributions were achieved after a large number of iterations and when the Markov chain converges to a target distribution. The convergence is required for the sampled value to represent a random draw from the marginal distribution. This was achieved by simultaneously running three Markov chains. The first 10,000 iterations of each chain deemed to include the random draws before convergence or "burn-in" were discarded. Convergence was considered achieved when the traces of the chains were found to be overlapping. The estimated model coefficients are presented in the next section.

4.4 Estimated Model Coefficients

Model coefficients were estimated for asphalt road sections with Dense Bituminous Macadam surfacing. The estimated posterior distribution of the model coefficients are presented in Figure 3. Model variables such as traffic loading, vehicle speed, and hot dry climate with posterior model coefficients clustered away from zero are considered important for the prediction of annual incremental rut depth. Variables with coefficients scattered around zero are less important. In addition the sign (negative or positive) associated with the mean values of the estimated model coefficients given in Figure 3 are consistent with theory. For example the mean model coefficient for traffic loading ($\beta 1$) has a positive association which is consistent with the fact that as traffic loading increases asphalt surface rutting is expected to increase. Similarly the model coefficient for heavy vehicle speed ($\beta 2$) has a negative association which suggests that as heavy vehicle speeds decreases the asphalt surfacing is expected to become more susceptible to rutting due to increased stresses associated with increased heavy loading time on the road pavement.

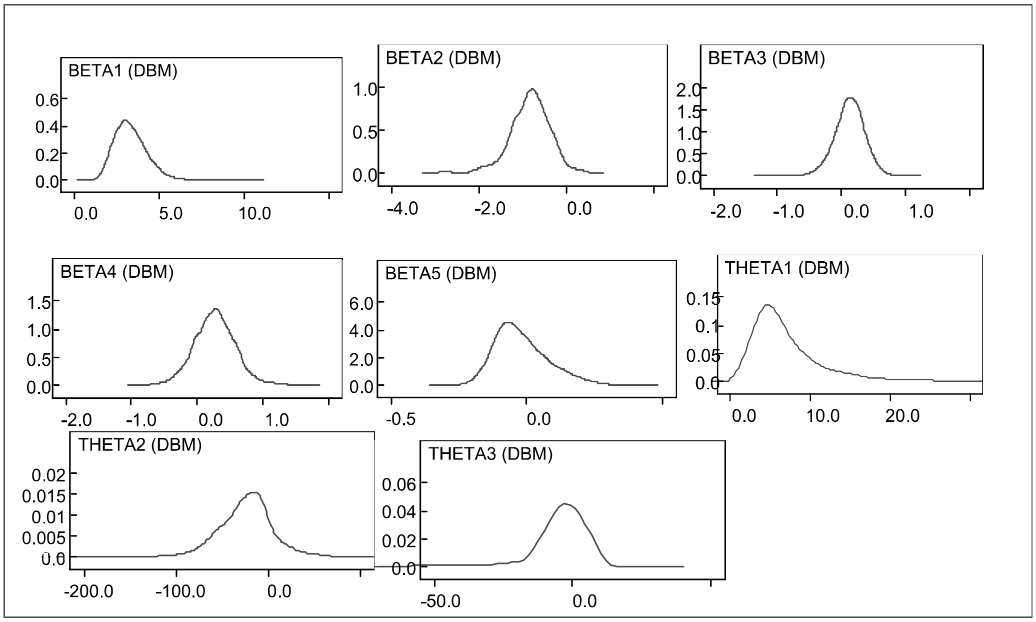

Figure 3: Posterior Distribution of Model Coefficients

5.0 CASE STUDY

A case study was undertaken using data obtained from the UK Highways Agency and the UK Climate Impacts Programme. Climate predictions used in the case study was provided for the low, medium and high green house gas emission scenarios. For each of these emission scenarios future climate data was available in the form of probability distributions for four 30 year time slices denoted as 2020s (2011 to 2040), 2030s (2021 to 2050), 2040s (2031 to 2060) and 2050s (2041 to 2070). The results reported in this paper are for the medium emission scenario only.

The following approach was followed:

1. For the analysis year t =1 deterministic input variables comprising traffic loading, heavy vehicle speeds, and road gradient, asphalt material surfacing and material properties were defined in bespoke prototype model.

2. During the analysis year t = 1 a set of stochastic input variables n=1 comprising model coefficients given in Figure 3 and climate data were randomly sampled.

3. The annual incremental rut depth for year t=1 and the set of stochastic random samples n=1 was calculated using Equation 4. This step is repeated for 5000 sets of stochastic random variables.

4. Steps 1 to 3 were repeated for each year t=2 to 30 for each time slice for which climate data was available.

The output of the analysis was a distribution of incremental rut depths in each year. The mean predicted cumulative rut depths for the four time slices are given in Figure 4. The results of the case study suggest that the future prediction of rut depths is highly sensitive to future climate predictions.

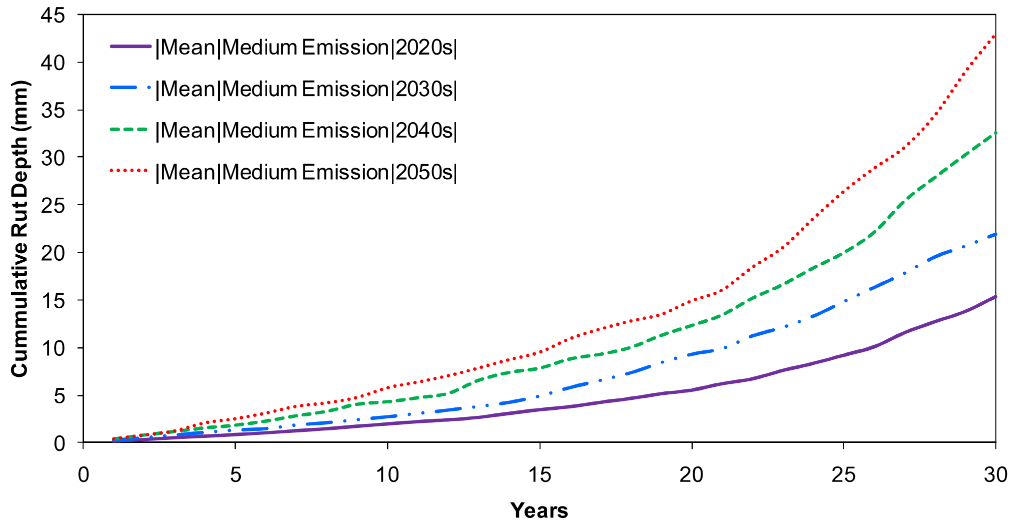

Figure 4: Mean Cumulative Rut Depth Prediction for Medium Emission Scenario for four Time Slices

6.0 CONCLUSION

This study has demonstrated the need for pavement deterioration models used in decision support systems such as HDM-4 to be improved to allow the impact of future climate events to be accounted for in road performance modelling. Model coefficients for an improved rut depth prediction model were estimated using a Bayesian approach. The approach associates probability distribution to estimated model coefficients thereby ensuring that uncertainties inherent in the observed data are reflected in the predicted model coefficients. The study methodology can be applied in any climatic zone or country provided appropriate data are available. Work is continuing towards linking the developed model with HDM-4 decision support tool. This will provide authorities and general practitioners with the capabilities to investigate the impact of various future climate scenarios on road agency as well as road user costs thereby facilitating improved choices necessary to adapt to the inevitable impacts of climate change.

7.0 REFERENCES

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