IDENTIFICATION OF CRITICAL INPUT VARIABLES FOR RISK-BASED COST ESTIMATES FOR ROAD MAINTENANCE AND REHABILITATION

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ABSTRACT: An estimation of costs for maintenance and rehabilitation is subject to variation due to the uncertainties of input parameters. This paper presents the results of an analysis to identify input parameters that affect the prediction of variation in road deterioration. Road data obtained from 1688 km of a national highway located in the tropical northeast of Queensland in Australia were used in the analysis. Data were analysed using a probability-based method, the Monte Carlo simulation technique and HDM-4's roughness prediction model. The results of the analysis indicated that among the input parameters the variability of pavement strength, rut depth, annual equivalent axle load and initial roughness affected the variability of the predicted roughness. The second part of the paper presents an analysis to assess the variation in cost estimates due to the variability of the overall identified critical input parameters.

KEY WORDS: Maintenance, rehabilitation, cost estimate, variation, variability, simulation, sampling

1. INTRODUCTION

Realistic estimates of short- and long-term costs for maintenance and rehabilitation of road assets should take into account the stochastic characteristics of asset conditions of road networks. The probability theory has been used in assessing risk-based costs for infrastructures by many researchers [1,2,3]. Very few studies were reported for road network analyses [4, 5] and no studies were reported to have incorporated stochastic characteristic of road asset condition into the cost estimate. It may not be feasible to incorporate the variability of all input parameters in cost analyses. A case study was conducted to identify input parameters that are critical for the prediction of road deterioration variation. The results of the case study indicated that among the variability of input parameters (i.e. pavement strength, traffic loading, pavement age, rut depth, cracking and initial roughness), pavement strength contributed significantly to the variability of predicted pavement roughness. Initial roughness, rut depth and annual average daily traffic contributed moderately.

This paper presents the results of a further study undertaken by the Australian Cooperative Research Centre for Construction Innovation to determine the variation in cost estimates for road maintenance and rehabilitation due to the stochastic characteristics of the identified critical input parameters. The variability of the identified critical input parameters including pavement strength, rut depth, annual average daily traffic, initial roughness of a 92km road length of a national highway located in tropical northeast of Queensland, Australia was statistically modelled and used in the analysis. A comparison of mean, mean plus one standard deviation and 95th percentile cost estimates for a five-year period is presented.

2. IDENTIFICATION OF CRITICAL INPUT PARAMETERS FOR PREDICTING VARIABILITY IN ROAD DETERIORATION

To identify the critical parameters that affect the variation of road deterioration condition, HDM-4 roughness deterioration model given in equation 1 was used in the analysis. The effect of an input variable on the annual change in roughness is assessed by assigning the probability distribution values of the input variable into equation 1, while keeping other variables constant. Monte Carlo simulation technique [6] was used to simulate sample data from the input probability distribution and the statistics of the output annual change in roughness were calculated. The effect of the variation of the input parameters on the variation of the output annual rate of change was measured by the coefficient of variation (Cov). The coefficient of variation (Cov) is the standard deviation divided by the mean *(σ/μ).* The same process was repeated to investigate the effects of the other variables on the annual change in road pavement roughness. The probability distributions of road condition parameters of 1688 km national highway located in the tropical northeast of Queensland in Australia were used. The probability distributions and statistical information (i.e. means and standard deviations) of pavement strength, pavement age (AGE3), annual equivalent standard axles (YE4), percentage (%) of cracking of total carriage way, standard deviation of rut depth and initial roughness were quantified for different pavement thicknesses. For calibration factors Kgp and Kgm, a default value of 1.00 was used.

$$\Delta RI = Kgp\ (\Delta RIs + \Delta RIc + \Delta RIr + \Delta RIt) + m\ Kgm\ RIa \qquad (1)$$

$$\Delta RIs = a_0 \exp(mKgmAGE3)(1 + SNPK_b)^{-5} YE4$$

$$\Delta RI_c = a_0 \Delta ACRA$$

$$\Delta RI_r = a_0 \Delta RDS$$

$$\Delta RI_e = mK_{gm} RI_a$$

Where; Kgp is calibration factor, Default value = 1.0, ΔRI is total annual rate of change in roughness, ΔRIs is annual change in roughness resulting from pavement strength deterioration due to vehicles, ΔRIc is annual change in roughness due to cracking, ΔRIr is annual change in roughness due to rutting, ΔRIt is annual change in roughness due to pothole, ΔRIe is annual change in roughness due to climatic condition, a_0 is constants for roughness due to pavement strength, cracking and rut depth, m is environmental coefficient, Kgm is calibration factor for environmental coefficient, AGE3 is pavement age since last overlay or reconstruction, $SNPK_b$ is adjusted structural number of pavement due to cracking, YE4 is annual number of equivalent standard axles (millions/lane), ΔACRA is change in area of total cracking during the analysis year (% of total carriageway area), ΔRDS is change due to rutting during the analysis year (m/km), RIa is initial roughness of the analysis year

In appendix A, tables A1 to A6 show mean values, standard deviations and probability distributions of the input parameters, including pavement strength, rut depth, annual equivalent axle load (YE4, pavement age (AGE3) and percent cracking of total carriageway area, respectively. A detailed analysis is given in Piyatrapoomi et al. (2004) [7]. Tables B1 to B6 in Appendix B show mean values, standard deviation and probability distribution of the output annual change in roughness compared with the input parameters.

Table B1 shows that the Cov values of the output annual changes in roughness were greater than those of input pavement strength, while the Cov values of the output annual rate of change in roughness shown in other tables (Tables B2 to B6) were smaller than the variability of input parameters. These results indicated that among the variability of the input parameters, pavement strength had significantly influenced the variability of annual change in roughness since the variability of the output is greater than the variability of the input pavement strength.

The next important parameter that influences the output annual rate of change in roughness is the rut depth. The Cov values of the output annual change in roughness were 0.727, 0.784, 0.472 and 0.585, which resulted from the Cov values of input standard deviation of rut depths of 1.686, 1.971, 1.205 and 1.589, respectively. In this case, the Cov values of the output annual change in roughness decrease when compared with the Cov values of the input rut depth.

The annual equivalent of standard axles (YE4) and initial roughness contribute moderately to the variability of annual change in roughness. The Cov values of output annual change in roughness were in the range of 0.065 to 0.216 and of 0.053 to 0.131 resulting from Cov values ranging from 0.285 to 0.665 (for YE4) and from 0.228 to 0.335 (initial roughness), respectively. Pavement age and cracking had no significant effect on the variability in annual change in roughness. The effect of the variation of these identified input parameters on the cost estimates is investigated in the next section.

3. VARIATION IN PREDICTING COSTS FOR ROAD MAINTENANCE AND REHABILITATION

The preceding section indicated that pavement strength, rut depth, annual equivalent axle load and initial roughness contributed to the variability of annual change in road deterioration roughness. Pavement strength, rut depth, annual average daily traffic (AADT) and initial roughness were collected from a 92km national highway located in the tropical northern region of Queensland in Australia. The pavement strength data were collected by the Falling Weight Deflectometer (FWD) in 2002 at linear spacing of 200 metre intervals. The applied load was 50 kN and the deflections were measured in microns. Rut depth and initial roughness were collected by the Network survey vehicles (laser profile-metre) and the annual average daily traffic (AADT) were collected at various traffic data collection points and weigh-in-motion. Soil types in this area were classified as wet and non-reactive. This road section was categorised by the type of pavement, surface, sub-grade, and the volume of traffic. The type of pavement was a flexible pavement. Typical sections of the national highway network in this area represented 300mm-350mm granular base with spray seal surface.

In modelling the stochastic characteristics of road network condition for the analysis, a road network is divided into small sections. A section of one kilometre was chosen for the analysis for practical reasons. An analysis of smaller sections will be conducted to assess the accuracy of the results and to identify a best practical section for future analysis. Thus, the 92km national highway was divided into 92 sections. The probability distributions of pavement strength, rut depth, annual average daily traffic and initial roughness described in the preceding section were assigned for each kilometre to represent the variability of each kilometre. Latin-Hypercube sampling technique was used for sampling representative values from the probability distributions of the input parameters. Latin-Hypercube sampling technique has been widely used to sample small data to represent the variability of a given probability distribution [8]. Piyatrappomi (1996) [9] found that sampling observational values of thirty data points were enough to obtain good estimates of the means, standard deviations and probability distribution functions of output variables. To obtain better results, in this study forty data points were sampled for each kilometre to represent the variability of the identified input parameters. An example of sampling representative values for the analysis using the Latin-hypercube technique is given in Piyatrapoomi et al. (2005) [10].

The probability distributions, means and standard deviations of the pavement data, rut depth, annual average daily traffic (AADT) and initial roughness of each kilometre of the 92 kilometre road length were quantified. Figures 1 to 8 show mean values and standard deviation values of pavement strength, rut depth, annual average daily traffic (AADT) and initial roughness at the start of the analysis year. The pavement strength used in the analysis was represented by the Structural Number (SN). Structural Number is used globally in pavement management systems to predict structural capacity and the life of pavement structures at the network or project level [12,13,14]. Table 1 gives the percentages of vehicles that were used to convert the annual average daily traffic (AADT) to the annual equivalent axle load (YE4). The results of the statistical analysis indicated that the pavement strength data and rut depth and initial roughness are log-normally distributed. AADT was modelled by a normal distribution. Having the mean values, standard deviation values and types of probability distributions, the probability distributions of pavement strength, rut depth, annual average daily traffic and initial roughness can be established. As mentioned, Latin-Hypercube sampling technique was used to sample representative values of the variability of the input parameters for the analysis.

Table 1. Traffic composition and annual increase

AADT	Cars (%)	Trucks & Buses (%)	Articulated Vehicles (%)	Road Trains (%)	Annual Increase (%)
1500-5000	85	7	7	1	2
5001-10000	83	7	8	2	2
>10000	89	7	3	1	4

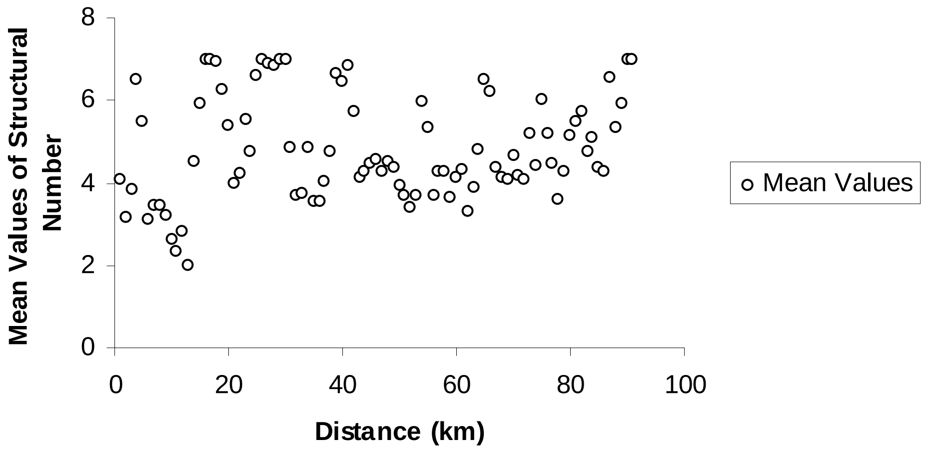

Figure 1. Mean values of the Structural Number for each kilometre of a 92km national highway of Queensland

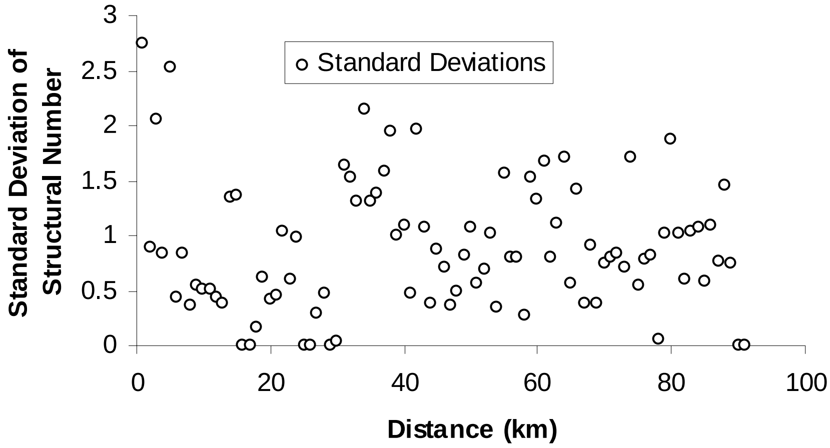

Figure 2. Standard deviations of the Structural Number for each kilometre of a 92km national highway of Queensland

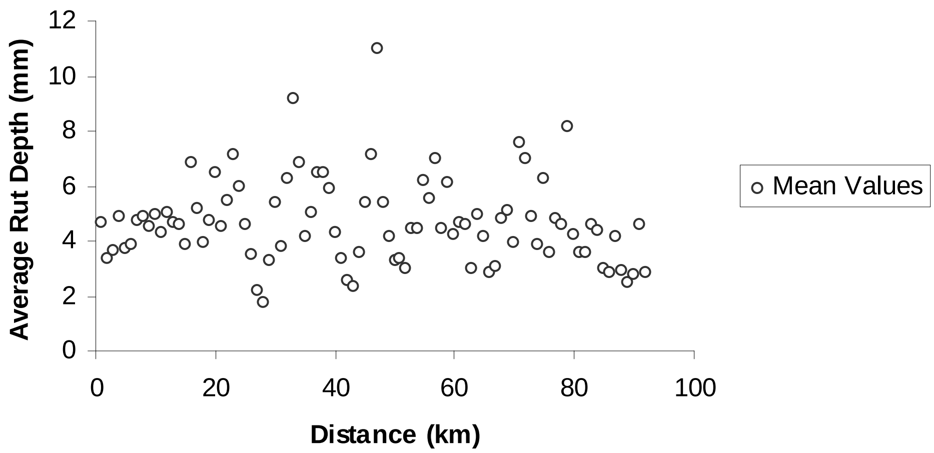

Figure 3. Mean values of average rut depth for each kilometre of a 92km national highway of Queensland.

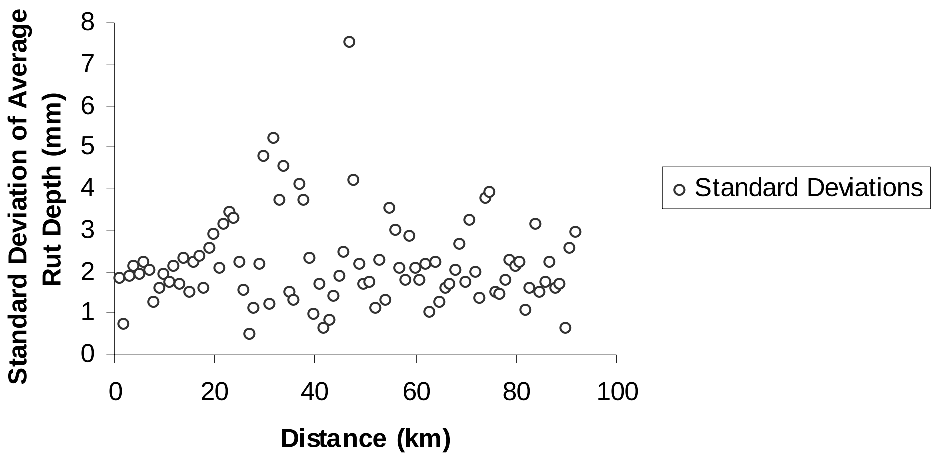

Figure 4. Standard deviations of average rut depth for each kilometre of a 92km national highway of Queensland

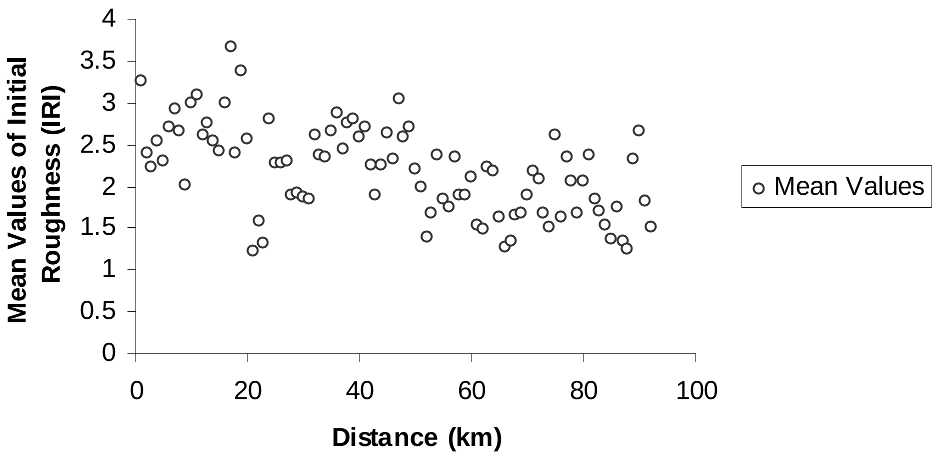

Figure 5. Mean values of initial roughness for each kilometre of a 92km national highway of Queensland

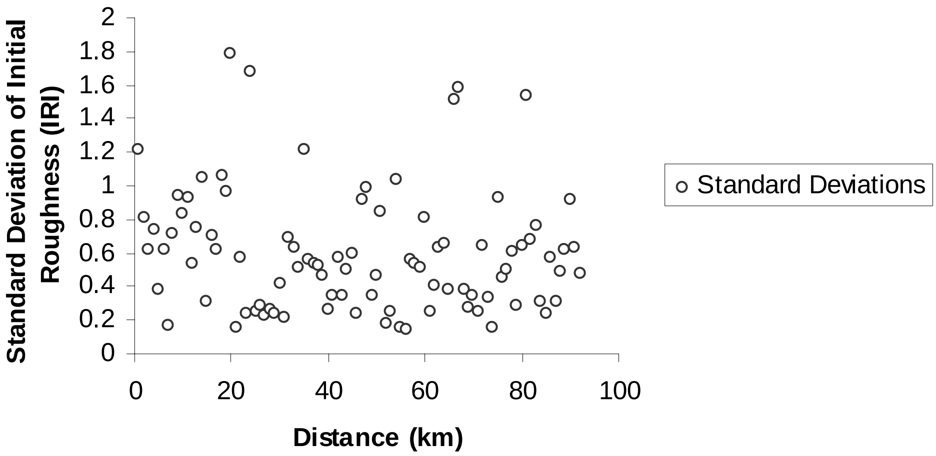

Figure 6. Standard deviation of initial roughness for each kilometre of a 92km national highway of Queensland

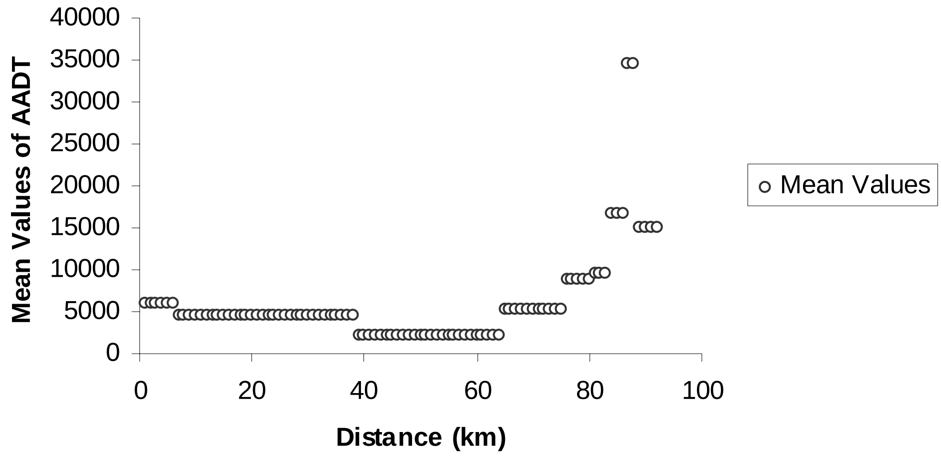

Figure 7. Mean values of annual average daily traffic for each kilometre of a 92km national highway of Queensland.

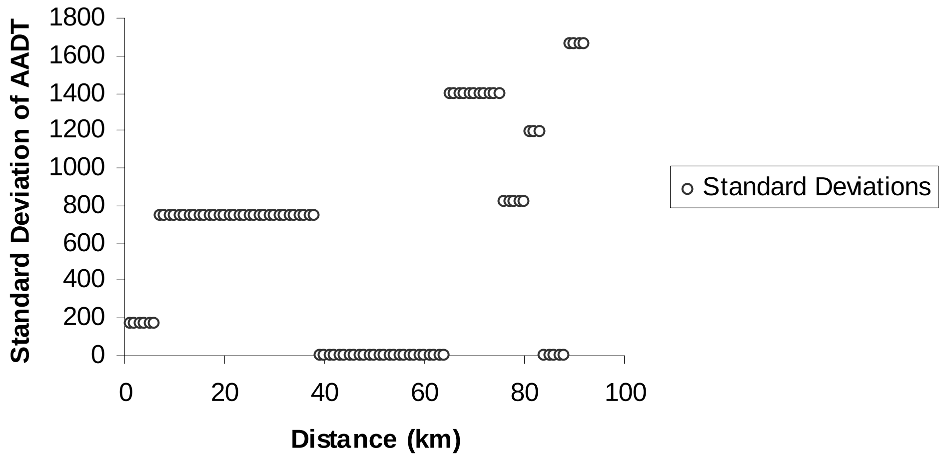

Figure 8. Standard deviations of annual average daily traffic for each kilometre of a 92km national highway of Queensland

Highway Development and Management (HDM-4) System software will be used to conduct a series cost analyses. HDM-4, developed by the International Study of Highway Development and Management (ISOHDM), is a globally accepted pavement management system [11]. It is a computer software package used for planning, budgeting, monitoring and management of road systems. There are three analysis options in HDM-4, which include: (1) Strategy Analysis, (2) Program Analysis and (3) Project Analysis. For this study, cost estimates for a five-year period were assessed for strategic analysis. A series of analyses using HDM-4 software were conducted to obtain the statistical output of cost estimates for maintenance and rehabilitation. Forty output data points of cost estimates were obtained from such an analysis.

3.2 Result of Analysis

Cost estimates for five years maintenance and rehabilitation were calculated. There are forty values for cost estimates to represent the variability in the cost prediction. From the forty values of the cost estimates, the probability distributions, mean values and standard deviations were quantified. The degrees of variation were estimated in terms of the coefficient of variation (Cov). Figure 9 shows the coefficients of variation (Cov) of the cumulative costs for a five year period. The figure indicated that by taking into account the variability of the input parameters, the coefficient of variations (Cov) of the output five-year cost estimates are in the range of 0.41 to 0.55. Figure 10 shows mean, mean plus one standard deviation and 95th percentile cost estimates. The 95th percentile cost estimates were twice the value of the mean cost estimates. A 95th percentile cost estimate is an estimate that there is only 5% chance that the cost will exceed the estimated value, whilst there is approximately 50% chance that cost will exceed the mean estimate. Selecting a mean cost estimate may result in an under estimate of a budget since there is approximately 50% chance that costs would be greater than the mean estimate. Figure 10 also presents mean plus one standard deviation cost estimates. Decision-makers can make informed decisions based on the variation in cost estimates. They can choose a budget based on the level of confidence they require. They may also need to investigate asset performance against different cost estimates (e.g. 95th, 90th, 80th percentiles etc.). For instance, if we allocated a budget equal to a certain percentile budget, we would like to know what would be the probability of pavement roughness that were greater than a maximum roughness threshold. A method using the probability theory to assess this relationship is being developed under the Australian Cooperative Research Centre for Construction Innovation, project no. 2003-029-C.

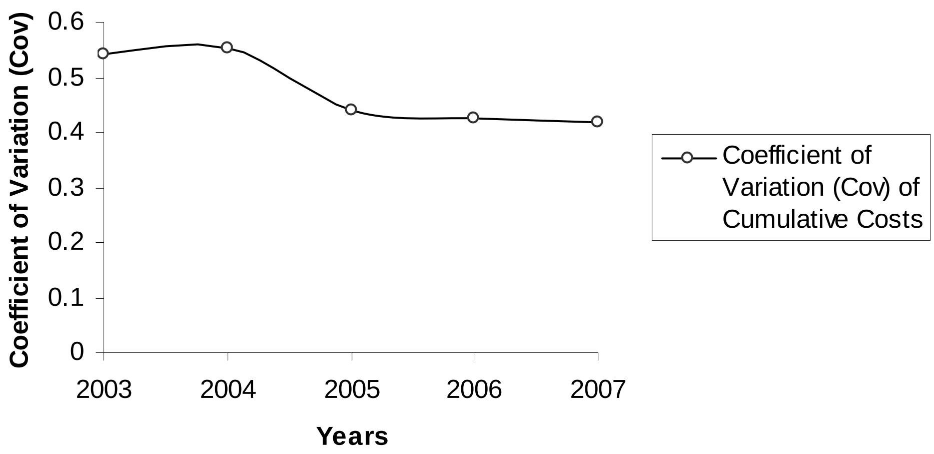

Figure 9. Coefficients of variation (Cov) for five year cumulative cost estimates.

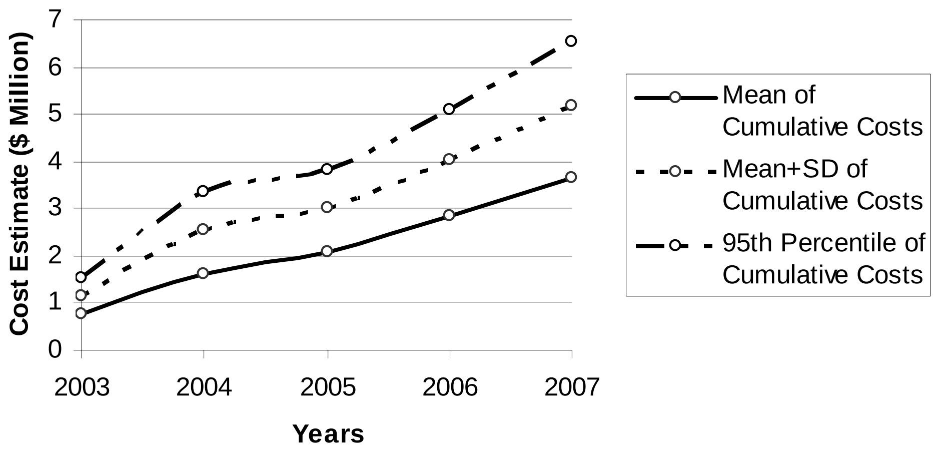

Figure 10. Mean, mean plus one standard deviation and 95th percentile cost estimates

4. CONCLUSIONS

Critical input parameters for estimating the variability in road deterioration have been identified. These critical input parameters include pavement strength, rut depth, percent cracking per carriage way and initial roughness. Variations in cost estimates due to the variability of these input parameters were assessed. The variability of input parameters were collected from a 92 km of a national highway located in the tropical northern region of Queensland. Cost estimates for a five year period were calculated as an illustration. The results indicated that 95th percentile costs were estimated to be twice that of the mean cost estimates. A 95th percentile cost estimate is an estimate that there is only 5% chance that the cost will exceed the estimated value, whilst there is an approximately 50% chance that cost will exceed the mean estimate. Further research study will be conducted to assess the asset performance against different percentile cost estimates. For instance, by allocating a budget equal to mean plus one standard deviation or a 95th percentile cost estimate, what would be the probability of pavement roughness that were greater than a maximum roughness threshold. Decision-makers can make informed decisions based on the information on the level of confidence in cost estimates and level of asset performance. A research project 2003-029-C "Maintenance Cost Prediction for Roads" funded by the Australian Cooperative Research Centre for Construction Innovation will investigate this issue.

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APPENDIX A:

Table A1. Means, standard deviations and the probability distributions of adjusted structure number (*$SNPK_b$*) for pavement thickness of 200-300 mm, 300-400 mm, 400-500 mm and 500-600 mm

Thickness	Parameter	Mean	Standard Deviation	Probability Distribution
200-300 mm	$SNPK_b$	3.73	1.17	Log-normal
300-400 mm	$SNPK_b$	3.70	1.39	Log-normal
400-500 mm	$SNPK_b$	3.64	0.64	Log-normal
500-600 mm	$SNPK_b$	3.64	0.64	Log-normal

Table A2. Means, standard deviations (*SD*) and probability distributions of standard deviation rut depth for pavement thickness of 200-300 mm, 300-400 mm, 400-500 mm and 500-600 mm

Thickness	Parameter	Mean (mm)	Standard Deviation (mm)	Probability Distribution
200-300 mm	*SD of rut depth*	0.64	1.08	Log-normal
300-400 mm	*SD of rut depth*	0.70	1.38	Log-normal
400-500 mm	*SD of rut depth*	0.73	0.88	Log-normal
500-600 mm	*SD of rut depth*	0.78	1.24	Log-normal

Table A3. Means, standard deviations and the probability distributions of annual number of equivalent standard axles (*YE4)* for pavement thickness of 200-300 mm, 300-400 mm, 400-500 mm and 500-600 mm

Thickness	Parameter	Mean	Standard Deviation	Probability Distribution
200-300 mm	*YE4*	0.48 (million/lane)	0.137 (million/lane)	Log-normal
300-400 mm	*YE4*	0.69 (million/lane)	0.36 (million/lane)	Log-normal
400-500 mm	*YE4*	0.74 (million/lane)	0.49 (million/lane)	Log-normal
500-600 mm	*YE4*	0.99 (million/lane)	0.50 (million/lane)	Log-normal

Table A4. Means, standard deviations and probability distributions of roughness (*IRI*) at the start of the analysis year for pavement thickness of 200-300 mm, 300-400 mm, 400-500 mm and 500-600 mm

Thickness	Parameter	Mean (IRI)	Standard Deviation (IRI)	Probability Distribution
200-300 mm	*Initial IRI*	1.84	0.47	Log-normal
300-400 mm	*Initial IRI*	1.85	0.62	Log-normal
400-500 mm	*Initial IRI*	1.70	0.47	Log-normal
500-600 mm	*Initial IRI*	1.74	0.44	Log-normal

Table A5. Means, standard deviations and the probability distributions of pavement age (*AGE3)* for pavement thickness of 200-300 mm, 300-400 mm, 400-500 mm and 500-600 mm

Thickness	Parameter	Mean	Standard Deviation	Probability Distribution
200-300 mm	*AGE3*	5.48 (years)	3.77 (years)	Log-normal
300-400 mm	*AGE3*	5.04 (years)	3.76 (years)	Log-normal
400-500 mm	*AGE3*	5.03 (years)	4.32 (years)	Log-normal
500-600 mm	*AGE3*	6.04 (years)	2.01 (years)	Log-normal

Table A6. Means, standard deviations and probability distributions of percentage of cracking per carriage way

Thickness	Parameter	Mean	Standard Deviation	Probability Distribution
200-300 mm	*% of crack*	0.157	0.113	Log-normal
300-400 mm	*% of crack*	0.235	0.216	Log-normal
400-500 mm	*% of crack*	0.276	0.219	Log-normal
500-600 mm	*% of crack*	0.326	0.185	Log-normal

APPENDIX B:

Table B1. Comparison between the coefficient of variation (Cov) of the input pavement strength ($SNPK_b$) and of the output annual change in roughness

Parameters	200-300mm	300-400 mm	400-500 mm	500-600mm
	Cov	Cov	Cov	Cov
$SNPK_b$	0.308	0.376	0.175	0.175
(ΔRI)	0.594	1.00	0.289	0.368

Table B2. Comparison between the coefficient of variation (Cov) of the input standard deviation of rut depth and of the output annual change in roughness

Parameters	200-300mm	300-400 mm	400-500 mm	500-600mm
	Cov	Cov	Cov	Cov
SD of rut depth	1.686	1.971	1.205	1.589
(ΔRI)	0.727	0.784	0.472	0.585

Table B3. Comparison between the coefficient of variation (Cov) of the input annual equivalent standard axles (YE4) and of the output annual change in roughness

Parameters	200-300mm	300-400 mm	400-500 mm	500-600mm
	Cov	Cov	Cov	Cov
YE4	0.285	0.522	0.662	0.505
(ΔRI)	0.065	0.153	0.216	0.194

Table B4. Comparison between the coefficient of variation (Cov) of the initial input roughness and of the output annual change in roughness

Parameters	200-300mm	300-400 mm	400-500 mm	500-600mm
	Cov	Cov	Cov	Cov
Initial IRI	0.228	0.335	0.276	0.252
(ΔRI)	0.131	0.100	0.074	0.053

Table B5. Comparison between the coefficient of variation (Cov) of the input pavement age (*AGE3*) and of the output annual change in roughness

Parameters	200-300mm	300-400 mm	400-500 mm	500-600mm
	Cov	Cov	Cov	Cov
AGE3	0.688	0.746	0.859	0.333
(ΔRI)	0.0195	0.031	0.043	0.019

Table B6. Comparison between the coefficient of variation (Cov) of the input % of cracking of the total carriageway and of the output annual change in roughness

Parameters	200-300mm	300-400 mm	400-500 mm	500-600mm
	Cov	Cov	Cov	Cov
% of cracking	0.847	0.919	0.793	0.567
(ΔRI)	0.005	0.009	0.008	0.006