A Probability Method for Assessing Variability in Budget Estimates for Highway Asset Management

Noppadol Piyatrapoomi , Dr.
RMIT University, GPO Box 2476V, Melbourne 3001, Victoria, Australia,
Tel: 61 3 9925 1521, Fax: 61 3 9925 5595, Email: anthony.piyatrapoomi@rmit.edu.au

Arun Kumar, Professor
RMIT University, GPO Box 2476V, Melbourne 3001, Victoria, Australia
Tel: 61 3 9925 1515, Fax: 61 3 9925 5595, Email: arun.kumar@rmit.edu.au

Neil Robertson, Manager
Queensland Department of Main Roads, GPO Box 1412 Brisbane 4000, Qld, Australia
Tel: 61 7 3235 4976, Email: neil.f.robertson@mainroads.qld.gov.au

Justin Weligamage, Senior Engineer
Queensland Department of Main Roads, GPO Box 1412 Brisbane 4000, Qld, Australia,
Tel: 61 7 3120 7274, Email: justin.z.weligamage@mainroads.qld.gov.au

Abstract

There are inaccuracies in predicting maintenance and rehabilitation costs for road networks due to the variability and uncertainties in road network condition. To realistically predict maintenance and rehabilitation costs, stochastic characteristics of road network condition should be considered in the estimate. It may, however, not be feasible or practicable to include every single stochastic characteristic of road network conditions in the analysis. To explore this possibility in assessing variations in cost estimates, an analysis was conducted to identify input parameters that are critical for predicting road deterioration condition. Findings indicated that the variability in pavement strength significantly contributed to the variability of predicting road pavement deterioration. Based on this information, discrepancies in cost estimates due to the variability of pavement strength for road maintenance and rehabilitation were subsequently assessed.

This paper presents the results of an analysis that was undertaken to identify critical input parameters for road pavement deterioration prediction. The paper also presents a probability method developed for assessing the variation in road maintenance and rehabilitation.

INTRODUCTION

Realistic estimates of short- and long-term costs for maintenance and rehabilitation of road asset management should take into account the stochastic characteristics of asset conditions of road networks. The probability theory has been widely used in assessing life-cycle costs for bridge infrastructures by many researchers (*1,2,3,4,5*). Very few studies were reported for road networks (*6, 7*). In the existing studies, researchers usually made assumptions about the variability and probability distributions of input variables and maintenance/rehabilitation costs in estimating life-cycle costs. Quantification of errors in cost estimates due to the variability of input variables has not yet been reported in the literature.

It may not be feasible to incorporate the overall variability of input parameters in life-cycle cost analyses. To explore the possibility of incorporating every single stochastic characteristic in assessing variations in life-cycle cost estimates, a case study was conducted to identify input parameters that are critical for road deterioration prediction. 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 significantly affected road roughness deterioration.

This paper presents the results of this case study undertaken by the Australian Cooperative Research Centre for Construction Innovation. An analysis on the variability of pavement strength to assess variations in cost estimates is also presented. The cost estimates were calculated for a life-cycle of a 25-year period and presented in terms of probability distributions. The degree of variations can be investigated from such probability distributions.

IDENTIFICATION OF CRITICAL INPUT PARAMETERS FOR PREDICTING ROAD DETERIORATION

This section presents the results of an analysis conducted to identify critical input parameters that have a significant effect in the prediction of road deterioration. HDM-4 roughness deterioration model, which was used in the analysis, is a function of pavement strength, traffic loading, cracking, rut depth and initial roughness. The HDM-4 roughness deterioration model is given below:

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

$$\Delta RIs = a_0 \exp(mKgmAGE3)(1 + SNPK_b)^{-5} YE4$$
$$\Delta RI_c = a_0 \Delta ACRA$$
$$\Delta RI_r = a_0 \Delta RDS$$
$$\Delta RI_e = mK_{gm} RI_a$$

Where;

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

For this analysis, it is necessary to quantify means, standard deviations and probability distributions of road condition parameters. As a case study for the analysis, road data of 1688 km national highway located in the tropical northeast of Queensland in Australia was 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 and are presented in the appendix.

To identify the critical parameters that affect the prediction 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 in equation 1, while keeping other variables constant. Monte

Carlo simulation technique (*8*) was used to simulate sample data from the input probability distribution and the statistics of the annual change in roughness were calculated.

The same process was repeated to investigate the effects of the other variables on the annual change in road pavement roughness. The values of the parameters a_0 and m for equation 1 are given in Table 1. For calibration factors *Kgp* and *Kgm,* a default value of 1.00 was used.

The effect of the input parameters on the annual rate of change output was measured by the coefficient of variation (Cov). The coefficient of variation (Cov) is the standard deviation divided by the mean (σ/μ). Figures 1 to 6 show comparisons between the coefficients of variation (Cov) of the input parameters and the Cov of the output predicted annual rate of change in road roughness.

Table 1 Default values of m and a_0 for pavement strength, cracking and rut depth

Parameters	Values used
a_0 for pavement strength	134
a_0 for cracking	0.0066
a_0 for rut depth	0.088
m	0.025

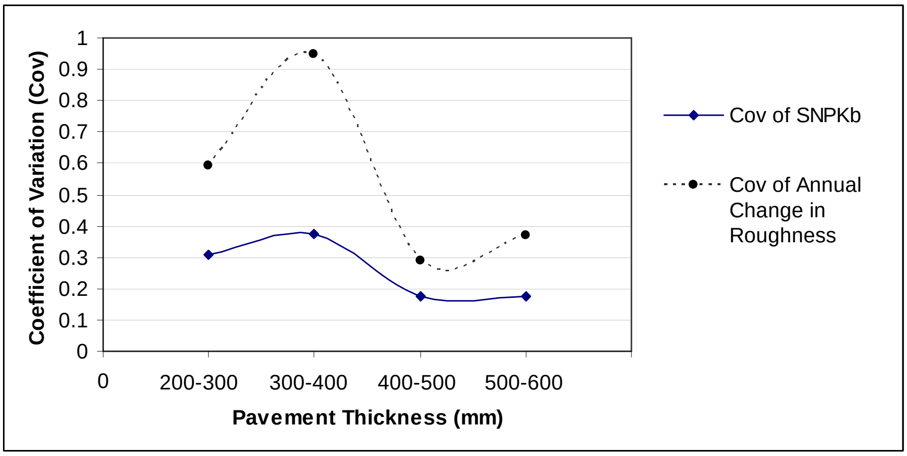

Figure 1 Comparison between the coefficients of variation (Cov) of the input pavement strength ($SNPK_b$) and of the output annual change in roughness.

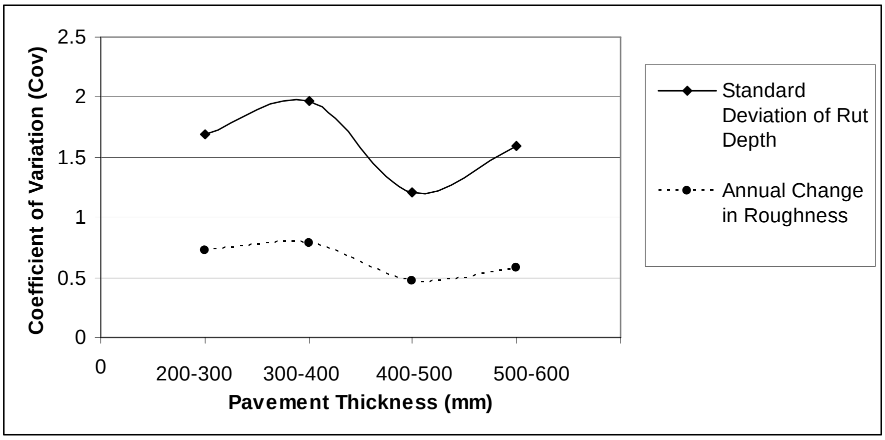

Figure 2Comparison between the coefficients of variation (Cov) of the input standard deviation of rut depth and of the output annual change in roughness.

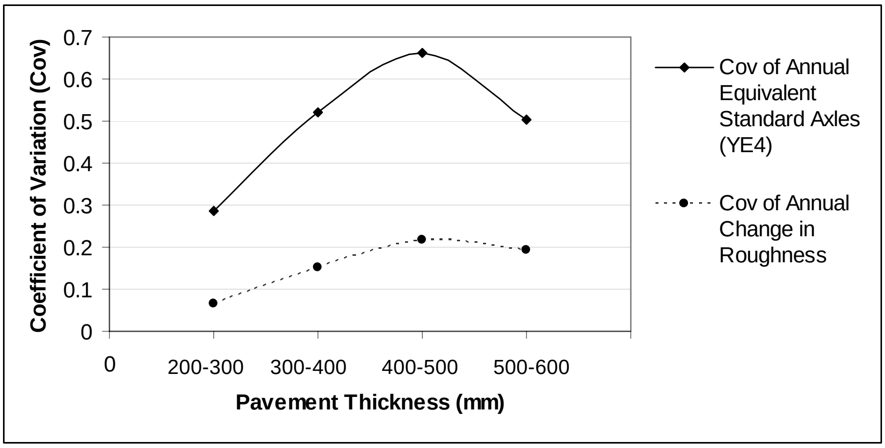

Figure 3 Comparison between the coefficients of variation (Cov) of the input annual equivalent standard axles (YE4) and of the output annual change in roughness.

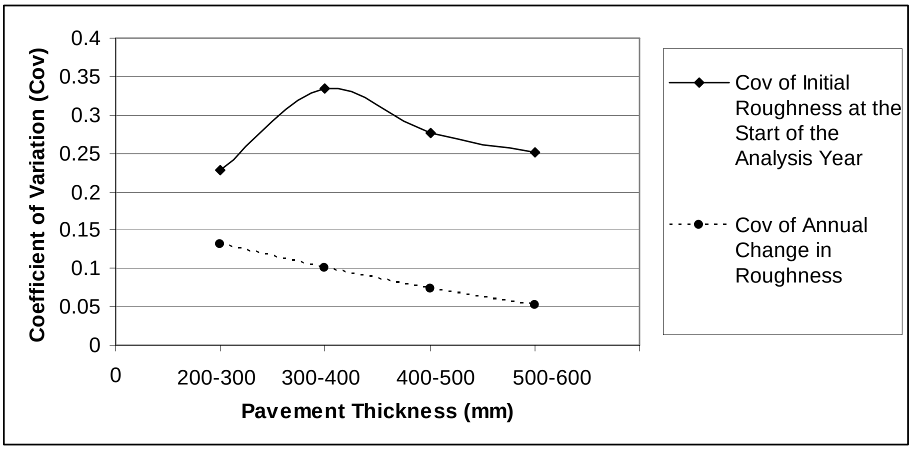

Figure 4 Comparison between the coefficients of variation (Cov) of the input initial roughness and of the output annual change in roughness.

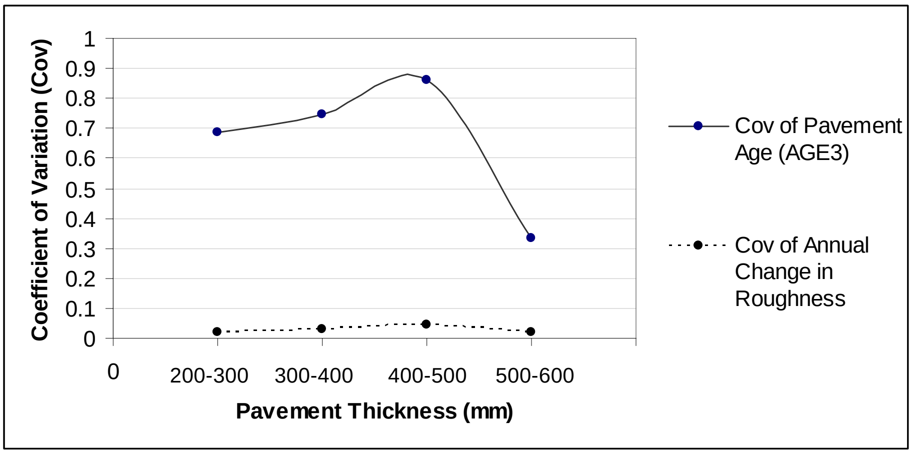

Figure 5 Comparison between the coefficients of variation (Cov) of the input pavement age (*AGE3*) and of the output annual change in roughness.

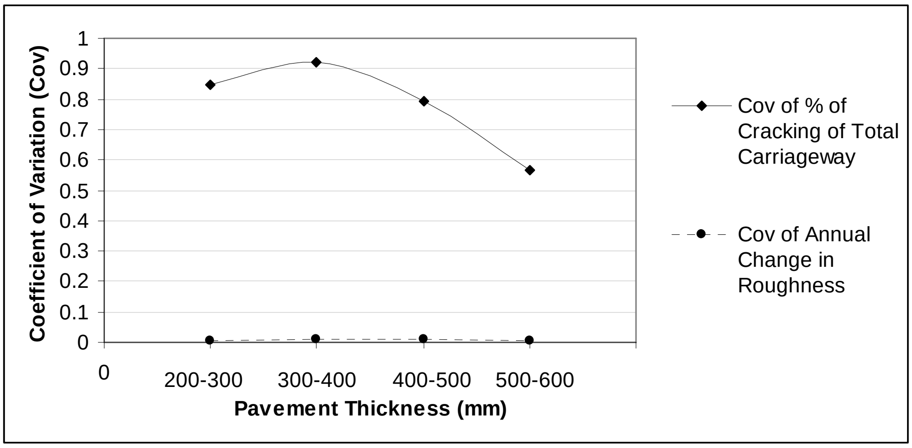

Figure 6 Comparison between the coefficients of variation (Cov) of the input % cracking of the total carriageway and of the output annual change in roughness.

Figure 1 shows that the coefficients of variation (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 Figures 2 to 6 were smaller than the Cov values of the 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 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 the input standard deviation of rut depth 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.

VARIABILITY IN PREDICTING COSTS FOR ROAD MAINTENANCE AND REHABILITATION

This section presents an analysis of variability in cost estimates for road maintenance and rehabilitation. The results in the preceding section indicated that pavement strength had the highest impact in the variability of annual change in road deterioration roughness. In this section, the effect of the variability of pavement strength in cost prediction for road maintenance and rehabilitation for a life-cycle cost for a 25-year period is examined.

An extensive collection of pavement strength data was conducted for a 92 kilometre of the same national highway used in the analysis in the preceding section. The pavement strength data were collected by the Falling Weight Deflectometer (FWD) in 2002 at linear spacing of 200 metre intervals. Soil types in this area were classified as wet and non-reactive. This road section was categorised by the type of pavement, surface, subgrade, 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. The applied load was 50 kN and the deflections were measured in microns.

The probability distributions, means and standard deviations of the pavement data of each kilometre of the 92 kilometre road length were quantified. 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 (*9,10,11*).

The results of the statistical analysis indicated that the pavement strength data are log-normally distributed. Details of the analysis are given in Piyatrapoomi and Kumar (*12*) and Piyatrapoomi et. al. (*13*). Figures 7 and 8 present the mean and standard deviation values of the pavement strength of each kilometre for the 92 kilometre road length.

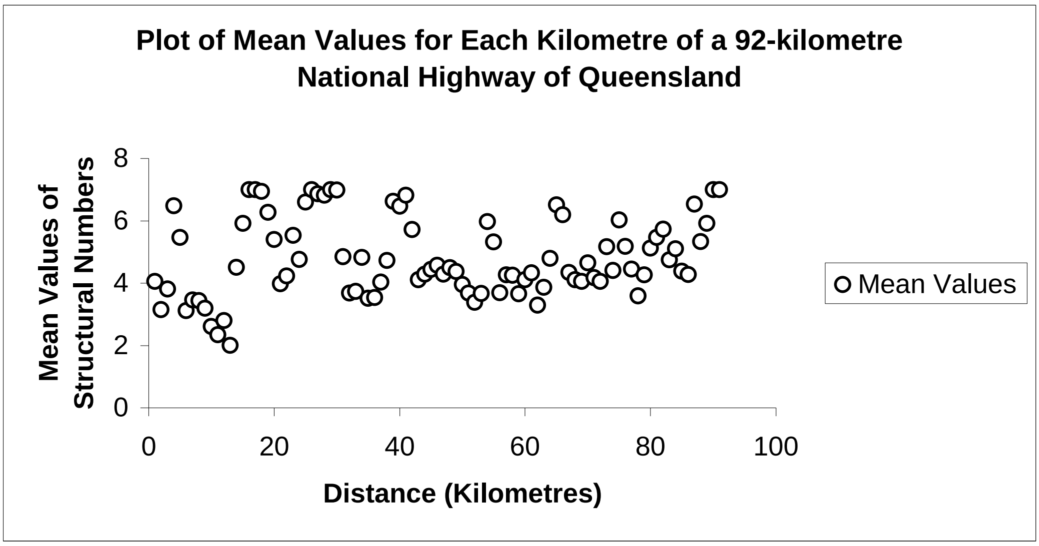

Figure 7 Mean values of each kilometre of a 92-kilometre national highway of Queensland.

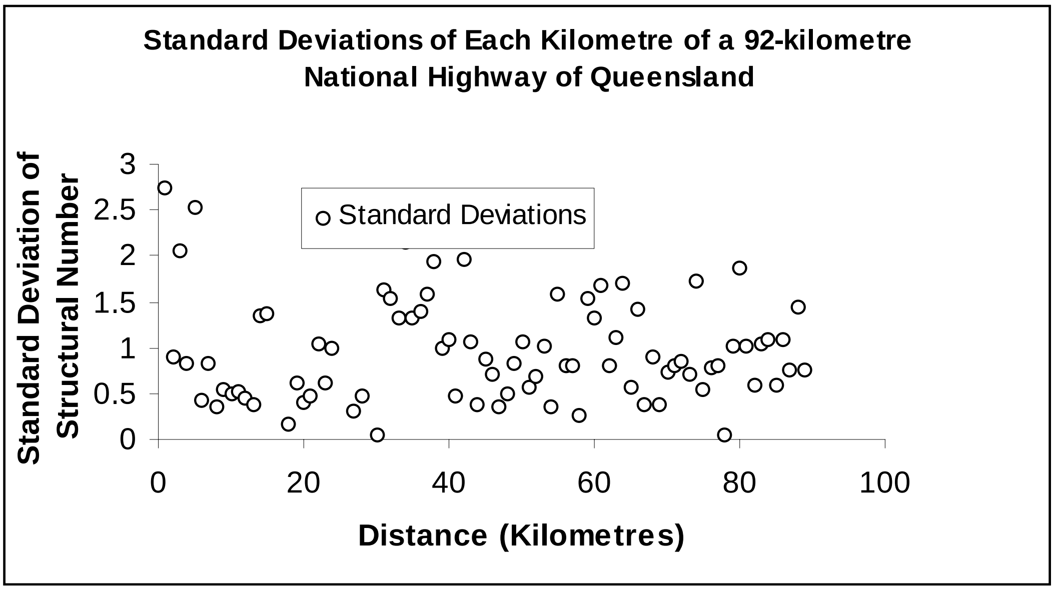

Figure 8 Standard Deviations of each kilometre of a 92-kilometre national highway of Queensland.

Figure 9 shows examples of the probability distributions of pavement strength. Details of these probability distributions for the 92-kilometres are presented in Piyatrapoomi and Kumar (*14*).

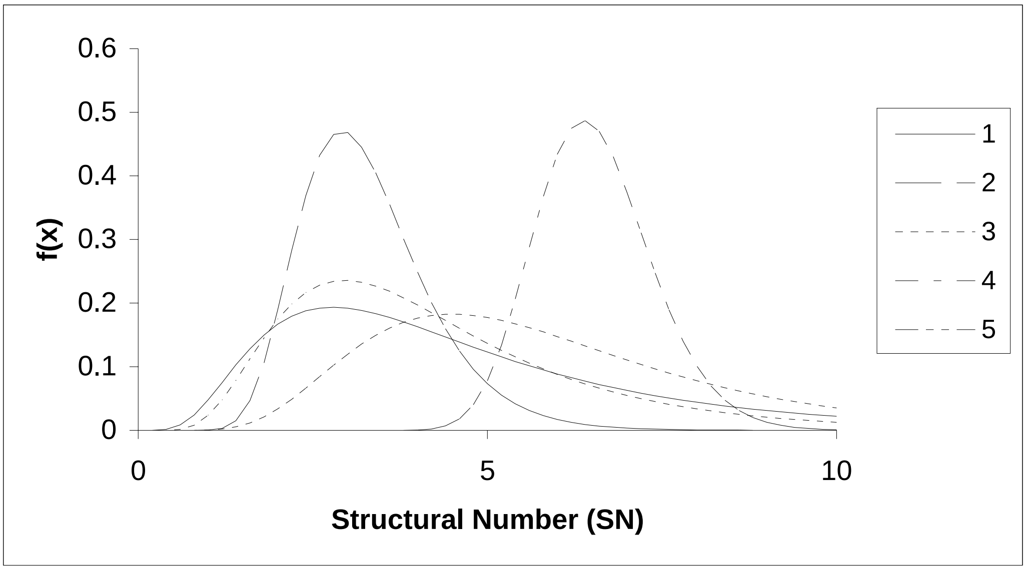

Figure 9 Typical probability distributions of Structural Numbers of the first five kilometres of the 92-Kilometre.

A series of analyses were conducted to obtain the statistical output of the life-cycle cost estimates. Life-cycle costs for maintenance and rehabilitation were estimated for a 25-year period starting from 2003. Four classes of vehicle types were used in the analyses, including short vehicles (85 per cent), trucks (7 per cent), articulated vehicles (7 per cent) and road-trains (1 per cent). Increases in the number of vehicles were estimated at two per cent annually for all four types of vehicles.

In this study, Highway Development Management System (HDM-4), developed by the International Study of Highway Development and Management (*15*), was used for calculating the life-cycle costs. HDM-4 is a computer software package used for planning, budgeting, monitoring and management of road systems. There are three analysis options in HDM-4. These analysis options include (1) Strategy Analysis, (2) Program Analysis and (3) Project Analysis. The Strategy Analysis Option was employed in this study to predict a life-cycle cost.

The steps in assessing the variability in cost estimates are given below.

1) The probability distributions of the Structural Numbers of each kilometre for the 92-kilometre national highway were established.
2) Latin-Hypercube sampling technique (*16*) was used to simulate the Structural Numbers (SN) from the probability distributions to represent the variability of pavement strength in the analysis. In the Latin Hypercube sampling technique, the probability distribution of the pavement strength of each kilometre is divided into small intervals with equal probabilities. Piyatrapoomi (*17*) found that sample values of thirty data points were sufficient to obtain good estimates of the means, standard deviations and probability distribution functions of output variables. To obtain more accurate results, in this study the probability distribution of pavement strength was divided into forty intervals, each interval having 2.5 per cent probability of occurrence. A single value of each interval is randomly selected to be the observed value of each interval, so that forty Structural Number values are obtained for each kilometre. Figure 10 shows a typical cumulative distribution of the Structural Number sampled by the Latin-Hypercube sampling technique.

3) Within the divided forty equal probabilities of each kilometre, a random selection of a sampled value of the Structural Numbers from each of the 92 probability distributions was undertaken. Ninety-two Structural Numbers were obtained, each value representing the Structural Number of each kilometre. These 92 Structural Number values were used as input values for HDM-4 analysis in estimating the maintenance and rehabilitation budget.
4) At this point, there are thirty-nine intervals remaining for each kilometre to be sampled and represented in the analysis. Repeat step 3 until all forty values of data have been randomly selected for the analysis. Thus, there are now a total of forty sets of the Structural Numbers, each set containing the Structural Numbers of the 92-kilometre national highway.
5) Conduct forty HDM-4 analyses to produce forty sets of the outputs.
6) Establish the mean values, standard deviation values and probability distribution of the cost estimates from the forty sets of the outputs.

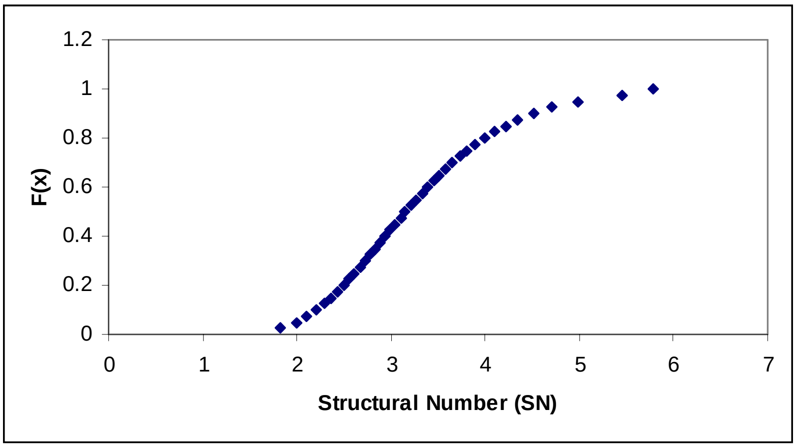

Figure 10 A typical cumulative distribution of Structural Number sampled by Latin Hypercube Sampling Technique.

Thus, there are forty values for yearly 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 for each year. The degrees of variation were estimated in terms of the coefficient of variation (Cov). The coefficient of variation (Cov) is the standard deviation divided by the mean value. Figure 11 shows the coefficients of variation (Cov) for each year for the life-cycle costs of 25 years starting from 2003.

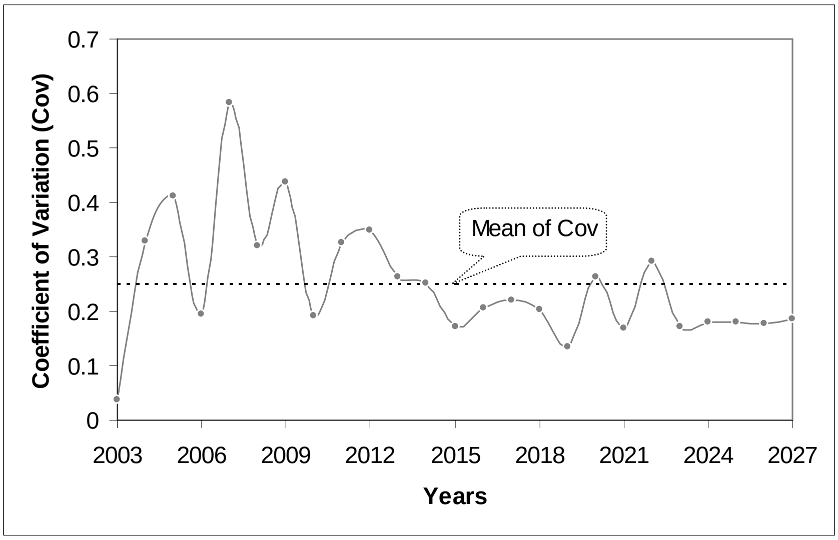

Figure 11 Coefficients of variation (Cov) for 25-year life-cycle cost estimates.

The average value of the coefficient of variation (Cov) for a 25-year cost estimate is 0.24. The figure shows a very low value of Cov (i.e. 0.036) for 2003 which is the starting year of the analysis. The Cov value was low because routine maintenance was required in the starting year. The Cov values fluctuated between 0.20-0.59 (or 20-59 per cent variations) when major maintenance or rehabilitation works were required. A reasonable level of reliability for cost estimates each year can be calculated from the output probability distributions. Figure 12 shows an example of the probability distribution for a cost estimate for year 2014. The figure shows how to calculate the mean and the 95th percentile cost estimate. 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 a 50% chance for the mean estimate.

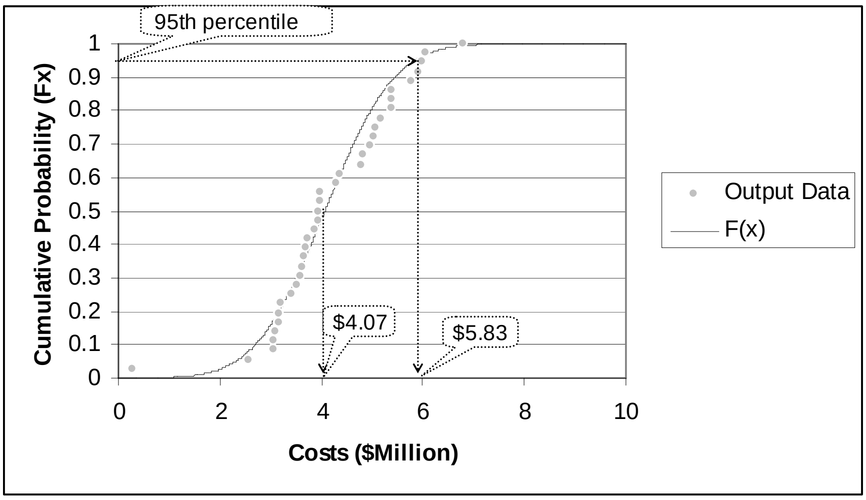

Figure 12 Cumulative probability distribution of a cost estimate for year 2014.

Figure 13 shows a comparison between the mean and the 95th percentile cost estimates for a 25-year maintenance and rehabilitation. For illustration, the mean cost estimate for the year 2014 is $4.07 million, while the 95th percentile is $5.83 million. In this case, there is a 50% chance that the cost will exceed $4.07 million, while there is only a 5% chance that the cost will exceed $5.83 million. Decision-makers can make informed decisions based on this information on the level of confidence they require. They can also investigate asset performance against different cost estimate percentiles (e.g. 95th, 90th, 80th etc.). For instance, we may want to know that by allocating a budget equal to the 95th percentile cost estimate, what would be the probability of pavement roughness that were greater than a maximum roughness threshold. A research project 2003-029-C "Maintenance Cost Prediction for Roads" funded by the Cooperative Research Centre for Construction Innovation will investigate this issue.

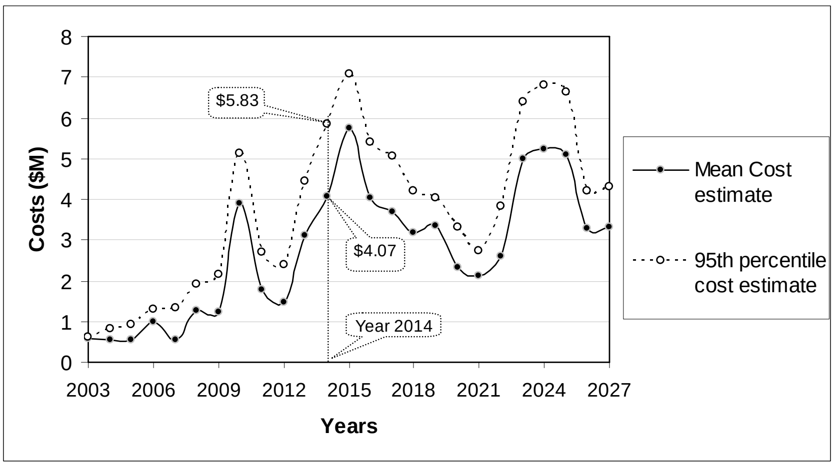

Figure 13 Comparison between the mean cost estimates and the 95th percentile cost estimates for 25-year maintenance and rehabilitation cost estimates.

CONCLUSION

The results of an analysis in identifying critical input parameters for estimating the variability in road deterioration have been presented. The outcome of the analysis indicated that the variability of pavement strength significantly contributed to the variability in predicting road deterioration. Variations in cost estimates due to the variability of pavement strength for road maintenance and rehabilitation were assessed. The variability of pavement strength was collected from a 92 km of a national highway located in the tropical northern region of Queensland. The variation in the cost estimates were presented by the coefficient of variation (Cov), which is the standard deviation divided by the mean value. Latin-hypercube sampling technique was used to sample the variability of the pavement strength for the analysis. The coefficients of variation (Cov) for maintenance and rehabilitation costs for a life-cycle of 25 year period were calculated. In this case study, the Cov values of the cost estimates were in the range of 0.134 to 0.59. The output statistical information of the cost estimates produced useful information for further analysis in selecting cost estimates with a reasonable degree of reliability (e.g. 90th or 95th percentile). A comparison between the mean and the 95th percentile cost estimates for a 25-year maintenance and rehabilitation was presented.

In this study, the coefficients of variation (Cov) of the output cost estimates were calculated from the variability of pavement strength only. The Cov values of the cost estimates that resulted from the variability of other critical input variables should be investigated further.

ACKNOWLEDGEMENT

The authors wish to acknowledge staff at Asset Management Branch in the Department of Main Roads, Queensland in Australia for providing technical data and support. The views expressed in this paper are of the authors and do not represent the views of the organizations.

REFERENCES

1. Kong, J.S. and Frangopol, D.M. (2003). Life-Cycle Reliability-Based Maintenance Cost Optimisation of Deteriorating Structures with Emphasis on Bridges, *Journal of Structural Engineering ASCE*, Vol. 129, No. 6 (pp. 818-828).

2. Zayed, T.M., Change, L-M. and Fricker, J.D. (2002) Life-Cycle Cost Analysis using Deterministic and Stochastic Methods: Conflicting Results, *Journal of Performance of Constructed Facilities ASCE*, Vol. 16, No. 2 (pp. 63-74).

3. Kong, J.S., Frangopol, D.M. (2003). Evaluation of Expected Life-Cycle Maintenance Cost of Deteriorating Structures, *Journal of Structural Engineering ASCE*, Vol. 129, NO. 5, (pp. 682-691).

4. Liu, M. and Frangopol, D.M. (2004). Optimal Bridge Maintenance Planing Based on Probabilistic Performance Prediction, *Engineering Structures* Elsevier Ltd. (pp. 991-1002).

5. Noortwijk, J.M.v and Frangopol, D.M. (2004). Two Probabilistic Life-Cycle Maintenance Models for Deteriorating Civil Infrastructures, *Probabilistic Engineering Mechanics*, Elsevier Ltd.

6. Salem O., AbouRizk, S., and Ariaratnam, S. (2003). Risk-Based Life-Cycle Costing of Infrastructure Rehabilitation and Construction Alternatives, *Journal of Infrastructure System ASCE*, Vol. 9 No. 1 (pp.6-15).

7. Zhao, T., Sundararajan, S.K. and Tseng, C-L. (2003). Highway Development Decision-Making Under Uncertainty: A Real Options Approach, *Journal of Infrastructure Systems ASCE*, Vol. 10, No. 1, (pp. 23- 32).

8. Gray, K. G. and Travers, K. J. The Monte Carlo Method. Stipes Publishing Company, Illinois, USA, 1978.

9. Rhode, G. T. 1994 Determining Pavement Structural Number from FWD Testing. Transport Research Record 1448, TRB, National Research Council, Washington, D.C.

10. Rhode, G. T., and A. Hartman. 1996 Comparison of Procedures to Determine Structural Number from FWD Deflections. Combined 18th ARRB Transport Research Conference and Transit New Zealand Land Transport Symposium, New Zealand.

11. Salt, G., and S. David. 2001 Pavement Performance Prediction: Determination and Calibration of Structural Capacity (SNP). 20th ARRB Transport Research Conference, Victoria, Australia.

12. Piyatrapoomi, N., Kumar, A., Robertson, N., & Weligamage, J. (Oct. 2004) 'Reliability of Optimal Intervals for Pavement Strength Data Collection at the Network Level' In: Proceedings of the 6th International Conference on Managing Pavements, Oct. 19-24, Brisbane, Queensland, Australia.

13. Piyatrapoomi, N., & Kumar, A., (Jun. 2004) 'Assessment of Calibration Factors for Road Deterioration Models', CRC CI Report No. 2001-010-C/009, The Cooperative Research Centre for Construction Innovation, Queensland University of Technology, Brisbane, Queensland, Australia.

14. Piyatrapoomi, N., and Kumar, A., (Aug. 2003) 'A Methodology for Risk-Adjusted Assessment of Budget Estimates in Road Maintenance and Rehabilitation', CRC CI Report No. 2001-010-C/008, The Cooperative Research Centre for Construction Innovation, Queensland University of Technology, Brisbane, Queensland, Australia.

15. The International Study of Highway Development and Management (ISOHDM), Highway Development Management (HDM4) version 1.3, University of Birmingham, UK, 2001.

16. Imam, R.L., and Conover, W.J. (1980) Small Sample Sensitivity Analysis Techniques for Computer Models, with an Application to Risk Assessment. Communication in Statistic, A9 (17), 1749-1842.

17. Piyatrapoomi, N. (1996) *A Probabilistic Study of Seismic Vulnerability and Reliability of R/C Building in Bangkok*. Ph.D. Dissertation, The University of Melbourne, Australia.

APPENDIX

Table A1 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 A2 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 A3 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 A4 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

Table A5 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 A6 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