

PROBABILITY BASED DATA ANALYSIS FOR ROAD ASSET MANAGEMENT



Noppadol Piyatrapoomi *
BSc, MEngSc, PhD



Professor Arun Kumar *
BEng (Civil), PhD(Purdue),
CP(Eng), FIE(Aust) MSCE



Justin Weligamage
BSc(Eng), MEngSc, MB
MIE, CPEng



Neil Robertson
BEng(Civil), MEngSc,
CPEng, MIE(Aust), RPEQ

Abstract

Road agencies require comprehensive, relevant and quality data describing their road assets to support their investment decisions. An investment decision support system for road maintenance and rehabilitation mainly comprise three important supporting elements namely: road asset data, decision support tools and criteria for decision-making. Probability-based methods have played a crucial role in helping decision-makers understand the relationship among road related data, asset performance and uncertainties in estimating budgets/costs for road management investment. This paper presents applications of the probability-based method for road asset management.

Introduction

Road assets in Australia are valued around A\$140 billion. As the condition of assets

deteriorates over time, close to A\$6 billion is spent on asset maintenance annually (i.e. A\$16 million per day). Main Roads and RMIT University have collaborated on this project through the Cooperative Research Centre for Construction Innovation. The research team has adopted the probability-based method to assist decision-makers to make decisions regarding road management investment more effectively. The probability-based method has been used for optimising budgets/costs incurred in collecting some expensive road asset condition information for network application, calibrating prediction models to reflect expected local deterioration rates and predicting investment budget/costs with reliable estimates. This paper briefly discusses the analysis methods, outcomes and their benefits.

*Professor Arun Kumar and Noppadol Piyatrapoomi are from RMIT University

Optimising costs for data collection for network analysis — probability-based analysis method

Road pavement condition information is expensive and time consuming to collect. Pavement strength data based on the falling weight deflectometer is one of them. Until new equipment is developed that will reduce collection costs there is a need to reduce costs by other means. Using a different mathematical method of analysis it is possible to reduce collection costs by extending the testing interval distance.

Deterministic analysis of data is used widely as it is taught in a broad range of tertiary studies and it is relatively easy to understand and manipulate data. However, when the data does not fit tightly around a specific function, analysis is often difficult and there is often a low level of confidence in the outputs of such analysis (ie. R^2 is low.). For example, the R^2 value in the following data set (Figure 1) is low; hence there is less confidence in using the regressed function.

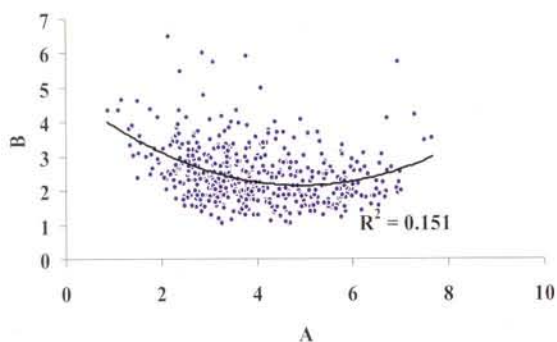


Figure 1 Analysis of data in x-y scale

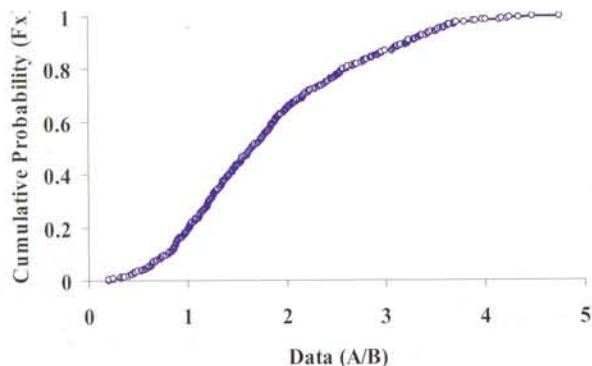


Figure 2 Analysis of data using Probability methods

A probability analysis of the same data reveals the following graph – Figure 2. Because the data fits well with the probability distribution, it confirms that the data set is valid. Additionally, the data set may be more easily modelled by the use of probability distribution.

Probabilistic analysis is another methodology which may be used to view and analyse data. Because of the variable nature of the data collected for road asset management, the use of a probabilistic analysis has been found to be the most effective. This paper will discuss how probabilistic analysis may be applied to data collection for road asset management.

Applying the probability based analysis

The probability based method has been used to assess optimal intervals of pavement strength data collection for network application [1]. It was hypothesized in the analysis that “if the statistical characteristics (i.e. mean, standard deviation and probability distribution) of data sets were quantifiable, and if different sets of data possessed similar means, standard deviations and probability distributions, these data sets would produce similar prediction outcomes”. To illustrate the concept, Figure 3 shows the probability distribution of pavement deflection tests at 200 metre intervals for the outer and inner wheel paths of a 92 km section of road network located in wet and non reactive soil condition situated south of Townsville. The means and standard deviations for the outer and inner wheel paths deflections (microns) are given as $Ln^{outer} = N(6.05, 0.805)$ and $Ln^{inner} = N(5.95, 0.817)$. Since the statistical means, standard deviations and the probability distributions of the original pavement deflection data sets for outer and inner wheel paths were similar in values, the pavement deflection sample data of the outer wheel path were used for the optimisation analysis.

Figure 4 shows the probability distribution of pavement deflection data at 1000 metre intervals. The mean and standard deviation are $Ln^{Outer} = N(5.95, 0.817)$. The mean and standard deviation of the 1000 metre interval pavement deflection data are similar to the mean and standard deviation of the 200 metre interval pavement deflection data. The two data sets are log-normally distributed.

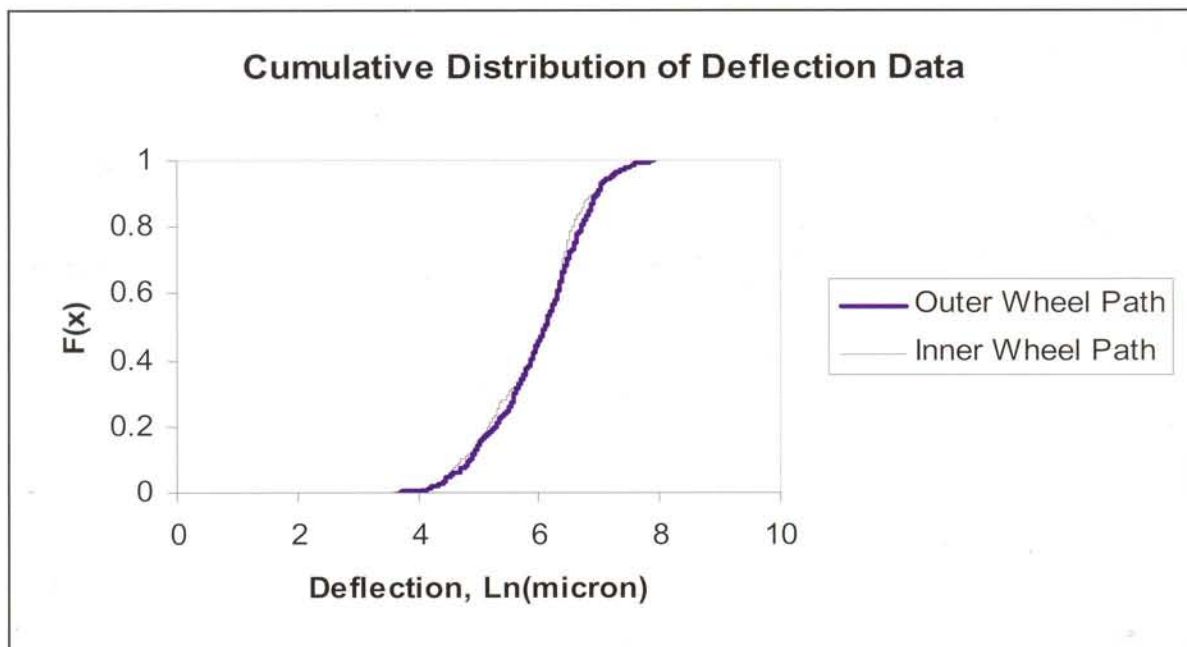


Figure 3. Cumulative distribution of deflection data set for 200 metre intervals

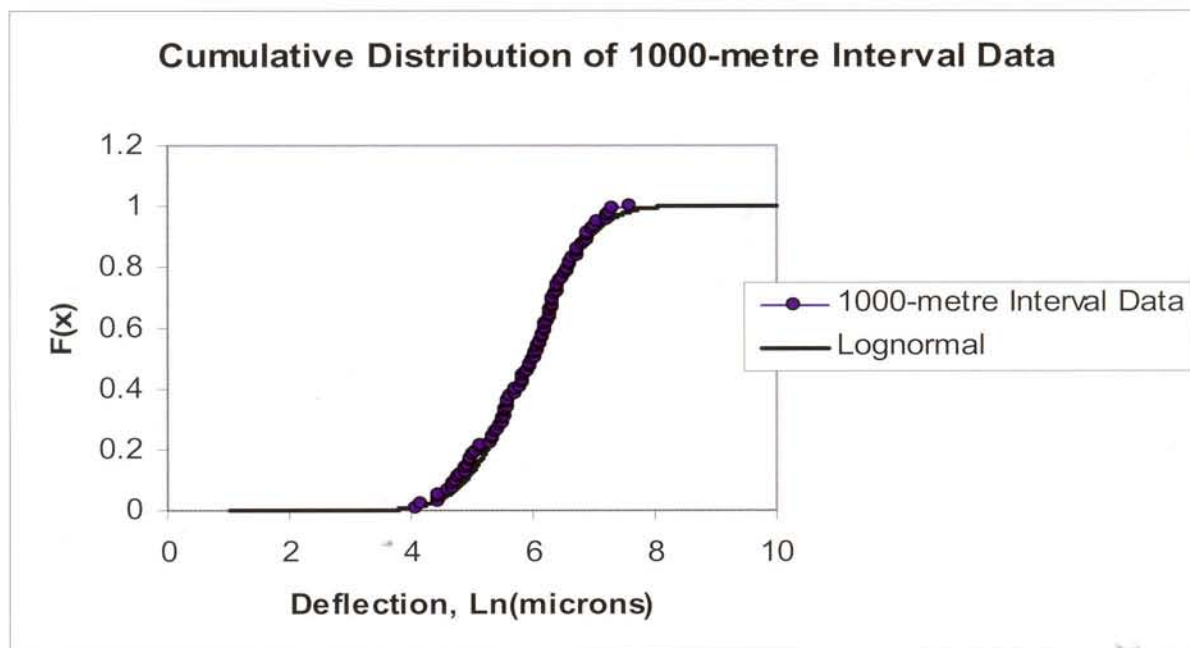


Figure 4. Cumulative distribution of deflection data set for 1000 metre intervals for outer wheel path

A reliability assessment was conducted to assess the prediction outcomes using two sets of deflection data of similar statistical characteristics. The reliability is tested by comparing cost estimates calculated from the 1000 metre interval deflection data and the 95th percentile cost estimates calculated from the 200 metre interval data. Details of the reliability analysis are given in Piyatrapoomi et al 2004 [2]. Figure 5 shows the differences in the cost estimates. The difference in five year

cost estimates is approximately 12 per cent, while the differences in cost estimates for 10, 15, 20 and 25 years are less than 4 per cent. The analysis method can be repeated to assess optimal intervals for network analysis for other types of soil and climatic conditions. While the analysis indicates that pavement strength data for network studies could be collected at larger intervals than currently occurs, the strength data intervals required for project work would remain at the same closely spaced intervals.

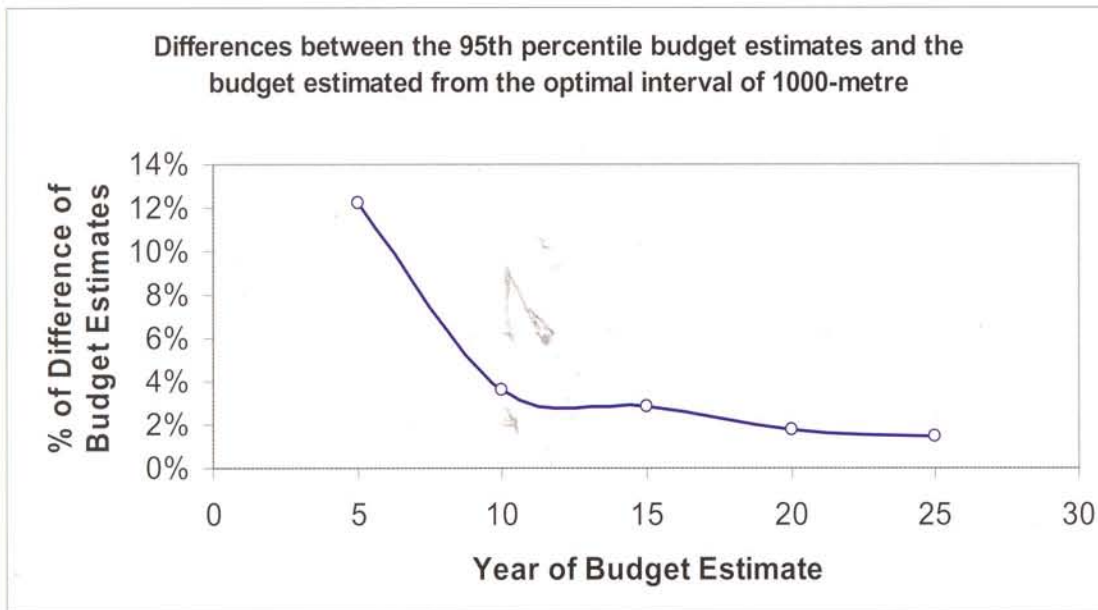


Figure 5. Percentage differences between the 95th percentile budget

Calibration of deterioration prediction model

A model that can accurately predict the rate of road deterioration condition will enable road asset managers to predict the correct budget for maintaining road infrastructures. However, it is essential to calibrate the deterioration prediction models to reflect the actual rate of road pavement deterioration for local conditions. Attempts have been made in almost every country to calibrate deterioration prediction models to suit each country's specific conditions. In the absence of a rigid mathematical analysis a calibration factor of 1.0 is usually applied in the software analysis. However, research has found actual calibration factors to be significantly less than this.

The variability in road data arising from the variability in climatic condition, soil condition, user vehicles and so forth has given less confidence in using the calibrated functions when the functions do not show a strong correlation or relationship with recorded data. A method using probability-based theory in assessing the calibration factors for road deterioration prediction models has been developed [3] by the project team. The method is based on the probability-based method and Monte Carlo simulation technique. In this method, the degree of goodness-of-fit between the calibrated function and recorded road data are explicitly assessed and identified. Thus, this method gives a higher degree of confidence in using the calibrated models.

The method has been applied in determining the calibration factors (as a case study) of the deterioration prediction models of road pavement roughness for Queensland. The calibration factors are associated with road asset management software, *Highway Development Management* (HDM4), developed by the World Bank [4]. HDM4 software is used by Road Network Management Division of Main Roads. In the road pavement deterioration model used in this study, the total annual rate of change in road pavement roughness is a function of pavement strength deterioration, pavement cracking, pavement rutting, pothole and climatic condition as given in Equation 1 [4].

$$\frac{\Delta RI}{RIa} = Kgp (\Delta RI_s + \Delta RI_c + \Delta RI_r + \Delta RI_t) + m Kgm \tag{1}$$

Where; Kgp is calibration factor, Default value = 1.0, ΔRI is total annual rate of change in roughness, ΔRI_s is annual change in roughness resulting from pavement strength deterioration due to vehicles, ΔRI_c is annual change in roughness due to cracking, ΔRI_r is annual change in roughness due to rutting, ΔRI_t is annual change in roughness due to pothole, ΔRI_e is annual change in roughness due to climatic condition, m is environmental coefficient, Kgm is calibration factor for environmental coefficient, RIa is initial roughness of the analysis year.

Using the probability-based calibration method, the calibration factors for the annual rates of change in road pavement roughness are shown in Tables 1 and 2.

Pavement Thickness	Calibration Factor (Kgp)	Calibration Factor (Kgm) 50 th Percentile	Calibration Factor (Kgm) 70 th Percentile	Calibration Factor (Kgm) 80 th Percentile	Calibration Factor (Kgm) 90 th Percentile
200-300 mm	0.55	1.0	1.50	2.10	3.10
300-400 mm	0.35	1.0	1.50	2.35	3.20
400-500 mm	0.25	1.0	1.10	1.80	2.80
500-600 mm	0.20	1.0	1.20	1.70	2.90

Table 1. For tropical region of Queensland (Bruce Highway)

Pavement Thickness	Calibration Factor (Kgp)	Calibration Factor. (Kgm) 50 th Percentile	Calibration Factor (Kgm) 70 th Percentile	Calibration Factor (Kgm) 80 th Percentile	Calibration Factor (Kgm) 90 th Percentile
100-200 mm	0.78	1.0	1.37	2.00	3.20
200-300 mm	0.48	1.0	1.10	1.53	2.50
300-400 mm	0.48	1.0	1.14	1.64	2.75
400-500 mm	0.43	1.0	1.10	1.50	2.40

Table 2. For dry region of Queensland (Landsborough Highway)

The annual rates of change in road roughness for different percentiles are presented in the tables. The percentiles of the annual rate of change reflect the actual variability observed in the recorded data. These calibrated factors for the road deterioration prediction model for road pavement roughness would provide realistic annual rates of change of road pavement roughness. Hence, the prediction of pavement performance would provide realistic estimates for road maintenance and rehabilitation budgets with a certain level of confidence.

Assessment of variation in budget/cost estimates

Variation and risk of uncertainties are inevitable in engineering projects and infrastructure investments. Currently, road asset managers need to make their decisions under risk and limited variability information on investment. The variability of maintenance and rehabilitation budgets based on risk-adjusted pavement performance is one of the key factors affecting the investment decision-making, and thereby the allocation of funds.

To enable the effective management of any infrastructure asset, managers must have knowledge about the variability of deterioration rates. This information may be critical where it is necessary for estimating funding allocations and estimating

associated risks. A methodology for risk-adjusted assessment for budget estimates for road maintenance and rehabilitation has been developed [5]. The method has been applied in assessing life-cycle costs and variation in the cost estimates for a road network of approximately 4500 km located in the state of Queensland as a case study. The variability of asset condition and annual average daily traffic (AADT) for the Queensland network has been taken into account. Life cycle cost estimates for a 25-year period starting from year 2006 were calculated and illustrated in Figure 6. Figure 6 also shows the mean cumulative costs. The mean total cost estimates were calculated to be approximately \$1.8 billion. The variation estimates were taken as one standard deviation above the mean values. Figure 7 shows the variation in cost estimates of one standard deviation. The variation in cost estimates for the first five years was calculated to be approximately \$20 million. The variation in cost estimates for the year 2030 was calculated to be approximately \$137 million. Decision-makers can take the mean estimates in their budget/cost predictions, however they need to be aware that there are certain variations in the prediction due to the variability of asset conditions and AADT. The increment in AADT was assumed to be 2% annually.

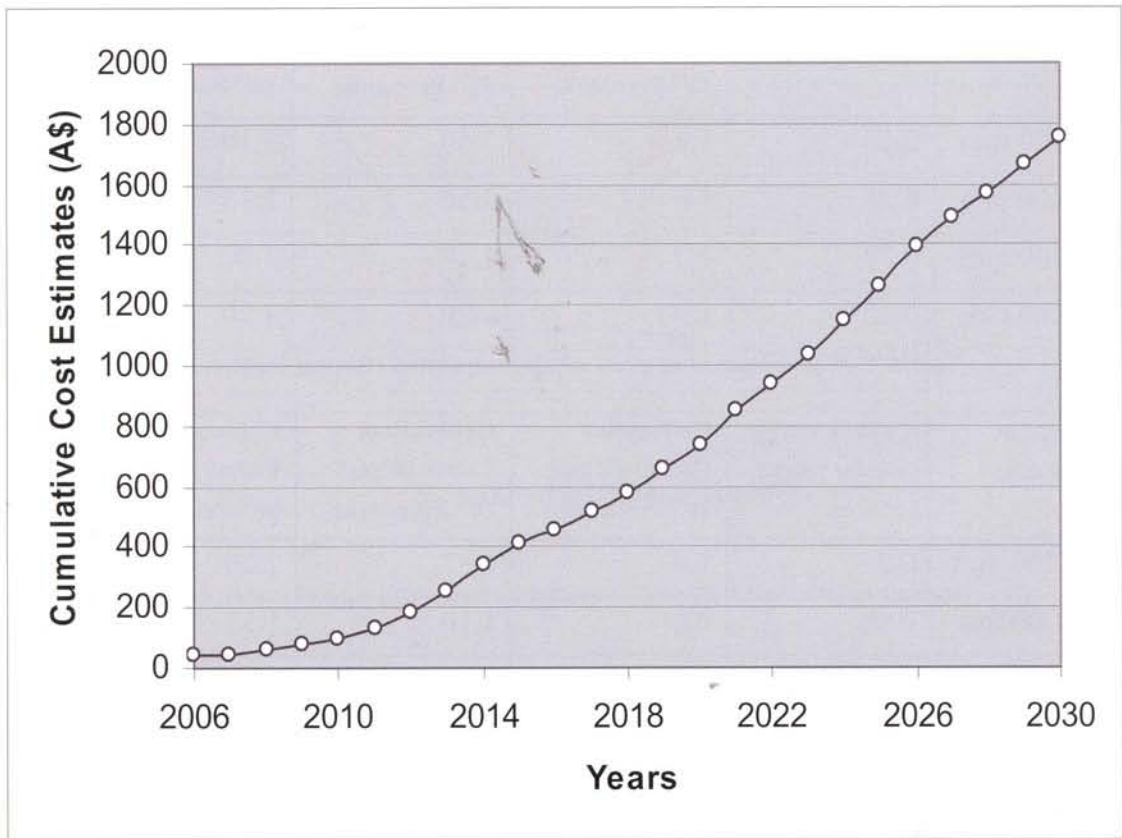


Figure 6. Mean cumulative costs for maintaining road pavement of a 4500 km road network in Queensland for a 25-year life-cycle period beginning from 2006

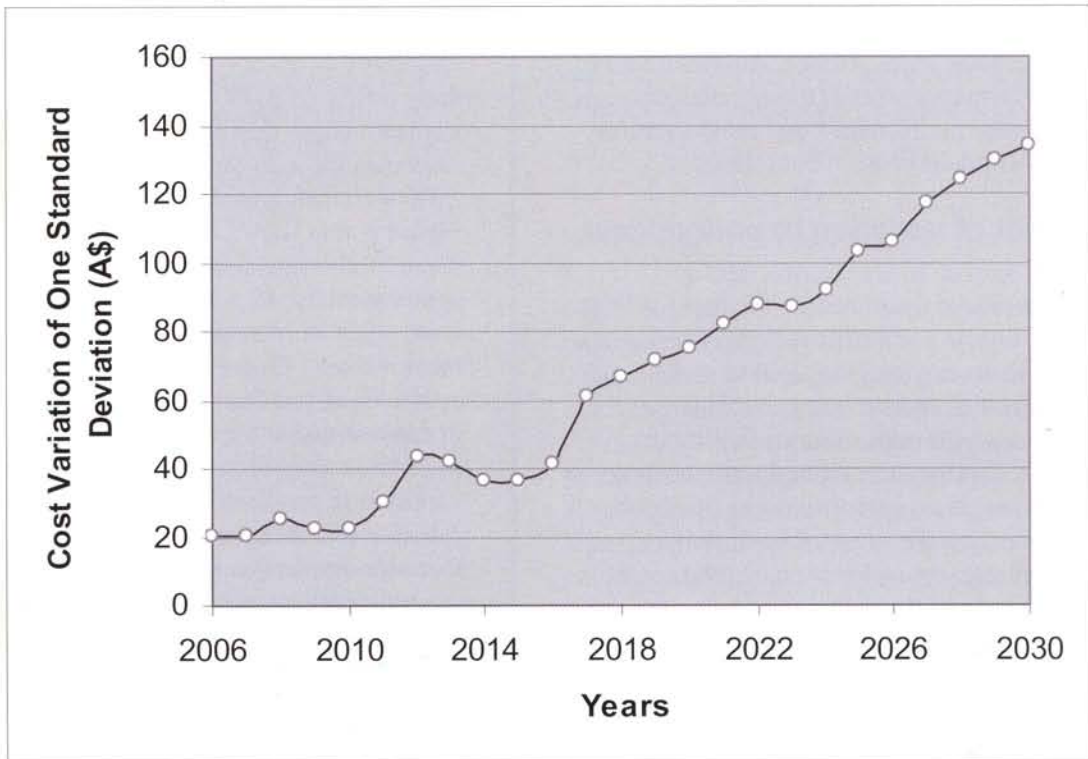


Figure 7. The variation in cost estimates of one standard deviation

Conclusions

This paper presented probability-based methods for road network pavement management investment analysis. The probability-based methods allow us to understand the relationships among asset data items that describe any road network. The methods have already begun to improve understanding of road asset performance characteristics. The methods also allow us to understand the relationship among the variability of asset conditions, variation in budget/cost estimates and the degree of uncertainties in budgeting for investment. The application of the probability-based

methods for road network investment analysis presented in this paper include optimising test intervals for pavement strength data collection for network application, calibrating pavement deterioration prediction models and assessing variation and uncertainties for life-cycle cost estimates. As illustrated in this paper probability-based methods have greater applications in solving engineering problems involving uncertainties and large variation in engineering data. This paper presented some applications that used probability-based methods to solve engineering problems for road asset management investment

References

- 1 Piyatrapoomi N, Kumar A, Robertson N, Weligamage J. 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. June 2004.
- 2 Piyatrapoomi N, Kumar A, Robertson N, Weligamage J. Reliability of optimal intervals for pavement strength data collection at the network level. *Proceedings of the 6th International Conference on Managing Pavements*, Brisbane, Queensland, Australia. October 19-24 2004.
- 3 Piyatrapoomi N, Kumar A, Robertson N, Weligamage J. 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. June 2004.
- 4 The International Study of Highway Development and Management (ISOHDM), *Highway Development Management (HDM4)* version 1.3, University of Birmingham, UK. 2001.
- 5 Piyatrapoomi N, Kumar A, Robertson N, Weligamage J. A probability method for assessing variability in budget estimates for highway asset management. *Proceedings 5th International Conference on Road and Airfield Pavement Technology*, Seoul, South Korea. May 10-12 2005.
- 6 Rhode G. Determining pavement structural number from FWD Testing. *Transport Research Record 1448*, TRB, National Research Council, Washington, D.C. 1994.
- 7 Rhode G, Hartman A. 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. 1996.
- 8 Salt G, David S. Pavement performance prediction: determination and calibration of structural capacity (SNP). *20th ARRB Transport Research Conference*, Victoria, Australia. 2001.

Acknowledgements

The authors wish to acknowledge the cooperation of the Cooperative Research Centre for Construction Innovation. The views expressed in this paper are those of the authors and do not necessarily represent the views of other organisations.