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# Report
# Development of a Methodology for Assessing Variation in Maintenance and Rehabilitation Costs

## Research Project No: 2003-029-C-02

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Leaders in Construction and Property Research

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# PREFACE

This report presents a method for assessing variation in cost estimates for road maintenance and rehabilitation. The report is part of a CRC CI research project 2003-029-C "Maintenance Cost Prediction for Roads". The aim of this research project is to estimate variation in life-cycle costing for road maintenance and rehabilitation by taking into account the variability of road asset conditions.

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# EXECUTIVE SUMMARY

In the previous research CRC CI 2001-010-C "Investment Decision Framework for Infrastructure Asset Management", a method for assessing variation in cost estimates for road maintenance and rehabilitation was developed. The variability of pavement strength collected from a 92km national highway was used in the analysis to demonstrate the concept.

Further analysis was conducted to identify critical input parameters that significantly affect the prediction of road deterioration. In addition to pavement strength, rut depth, annual traffic loading and initial roughness were found to be critical input parameters for road deterioration. This report presents a method developed to incorporate other critical parameters in the analysis, such as unit costs, which are suspected to contribute to a certain degree to cost estimate variation. Thus, the variability of unit costs will be incorporated in this analysis.

Bruce Highway located in the tropical east coast of Queensland has been identified to be the network for the analysis. This report presents a step by step methodology for assessing variation in road maintenance and rehabilitation cost estimates.

# 1. 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 such as Kong and Frangopol (2003), Zayed et.al. (2002), Kong and Frangopol (2003), Liu and Frangopol (2004), Noortwijk and Frangopol (2004), and Novick (1993). Very few studies were reported for road networks (Salem et. al. 2003, Zhao et. al. 2003). 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. Frangopol et. al. 2001 suggested that additional research was required to develop better life-cycle models and tools to quantify risks, and benefits associated with infrastructures. By taking into account the variability of the stochastic characteristics of road asset conditions, variation in the cost estimates can be investigated. Decision-makers can make informed decisions in estimating costs. 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. 90$^{th}$ or 95$^{th}$ percentile).

It is evident from the review of the literature that there is very limited information on the methodology that uses the stochastic characteristics of asset condition data for assessing budgets/costs for road maintenance and rehabilitation (Piyatrapoomi and Kumar, Sept. 2004). This report presents a methodology for assessing variation in cost estimates for life-cycle cost analysis. This report builds upon the knowledge developed in the CRC CI research project no. CRC CI 2001-010-C and literature review presented in the CRC CI Report no. 2003-029-C/001.

# 2. Proposed Methodology for Assessing Variation in Life-Cycle Costs for Road Maintenance and Rehabilitation

The aim of the proposed method is to incorporate the variability of road asset conditions and other critical input parameters along the road network into the assessment of life-cycle cost estimates.

The first step in this method is to define a performance function that transforms input variables into maintenance and rehabilitation budgets. The second step is to define the input variables. A performance function for budget estimates for road maintenance and rehabilitation may be written as:

$$G = \frac{1}{(1+r)^t} \sum_{1}^{t} \sum_{1}^{n} f\left(Z_1 Y_{1,n,t}, Z_2 Y_{2,n,t}, ..., Z_m Y_{m,n,t}\right) \qquad (1)$$

Where $G$ is the total budget expressed in terms of probability distribution. $m$ is the number of critical input variables, the variability of which is considered in the analysis. $n$ is number of road sections ($1,2,3,\ldots,n$). $Y_{1,n,t}$, $Y_{2,n,t}$, $\ldots$, $Y_{m,n,t}$ are random variables of input variables with known probabilities of section $n$ in year $t$. $Z_1, Z_2, \ldots, Z_n$ are random transform functions representing model errors in prediction. $n$ is the number of road sections used in the analysis. $t$ is the total year used for the life-cycle budget estimates. $r$ is the discount rate.

The calculation of Equation 1 is the subject of determining the relationship between input statistics and output statistics (i.e. how the variability of input variables affects the variability of output variables). The calculation of the probability of Equation 1 becomes difficult since the transform function is complicated. It involves using current road asset conditions, current and forecasting road usage values and deterioration prediction models to predict road deterioration conditions; selecting maintenance and rehabilitation standards; and optimising different budget scenarios to obtain optimal budget estimates. Equation 1 can become highly non linear.

To this end, a simulation method is desirable for the statistical assessment of the input and output relationship. A simplified sampling technique such as the Monte Carlo Simulation technique (Gary an Travers, 1987) may require a larger number of data to be sampled to represent an overall variability of an input variable. The Latin hypercube sampling technique, as extensively studied by Iman and Conover (1980), provides a satisfactory method for selecting small samples of input variables so that good estimates of the means, standard deviations and probability distribution functions of the output variables can be obtained.

## 3. Framework for Assessing Variation in Cost Estimates

Figure 1 shows the schematic chart of the framework assessing variation in cost estimates for life-cycle road maintenance and rehabilitation.

1. The first task is to identify critical input parameters that significantly affect road deterioration condition and hence budget estimates.
2. Establish probability distributions and statistical information (means, standard deviation and etc.) of the stochastic characteristics of the critical input variables of the road network.
3. Use Latin-Hypercube Sampling Technique to sample data from the probability distributions of the identified critical input parameters.
4. Use a calculation tool to estimate costs (HDM-4 is used in this study).
5. Input sampled data of the critical input parameters in HDM-4 for statistical analysis
6. Conduct a series of HDM-4 analyses to obtain the statistics of the output life-cycle costs.
7. Quantify the statistical information (e.g. probability distribution, mean, standard deviation, etc) of the output life-cycle costs.
8. Investigate the degrees of variation for the established probability distributions of the outcome life-cycle costs.

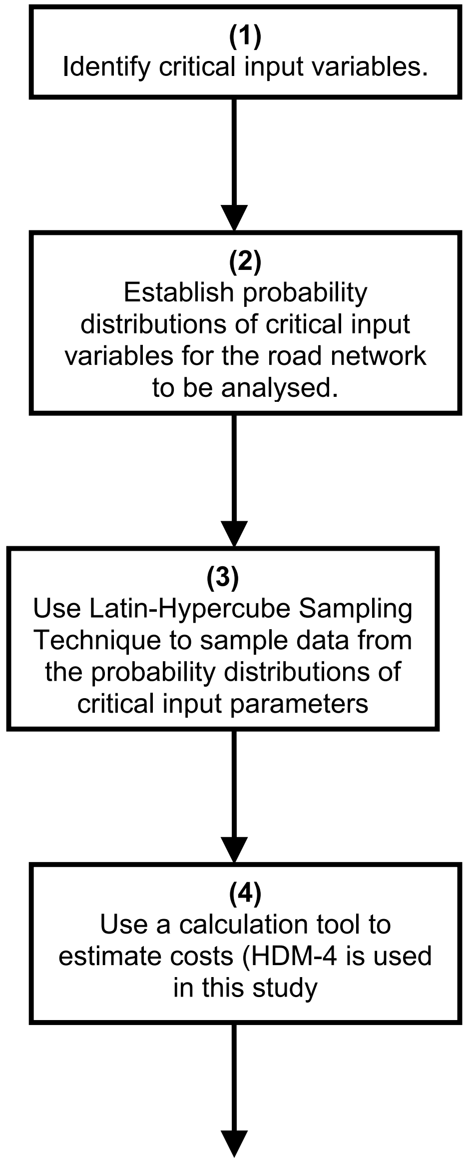


Figure 1 Flow chart for assessing variation in life-cycle costs (Flow chart continued)

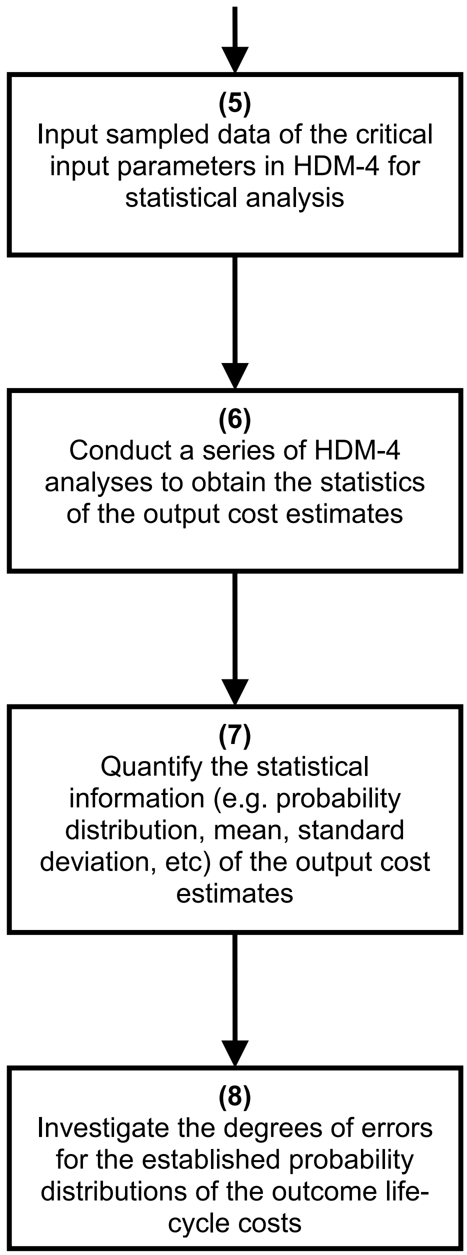


Figure 1 Flow chart for assessing variation in life-cycle costs (continued)

## 4. Step 1: Identification of Critical Input Parameters

An important step in the analysis is to identify critical input parameters. It may not be feasible to incorporate the variability of all input parameters in the analysis. To explore the possibility of incorporating the variability of input parameters that are critical for road deterioration prediction, a case study was conducted to identify such parameters. HDM-4 roughness deterioration model was used in the analysis. The HDM-4 roughness deterioration model is a function of pavement strength, traffic loading, cracking, rut depth and initial roughness of the analysis year. The HDM-4 roughness deterioration model is given below: HDM-4, developed by the International Study of Highway Development and Management (ISOHDM), is a globally accepted pavement management system (ISOHDM 2001). Full details of HDM-4 deterioration models are given in HDM-4 documentation-volume 4.

$$\Delta RI = Kgp\ (\Delta RIs + \Delta RIc + \Delta RIr + \Delta RIt) + \Delta RIe \qquad (1)$$

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

Where;

| | | |
|---|---|---|
| *Kgp* | = | 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) |
| *ΔACRA* | = | 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 |

Road data of 1688 km national highway located in the tropical northeast of Queensland, Australia, was used in the analysis. The probability distributions and statistical information of pavement strength, pavement age (AGE3), annual equivalent standard axles (YE4), percent (%) of cracking of total carriage way, standard deviation of rut depth and initial roughness were quantified. An extensive analysis using probabilistic method was conducted to determine the relationships between the annual rate of change in road pavement roughness and annual equivalent standard axles (YE4), pavement ages (AGE3) and pavement thickness. The analysis of these data shows a strong relationship between the annual rate of change in road pavement roughness and pavement thickness. Tables 1 to 6 show the result of the statistical analysis of the road condition parameters for different pavement thicknesses.

**Table 1 Means, standard deviations and the probability distributions of pavement age (*AGE3*) for pavement thicknesses 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 2 Means, standard deviations and the probability distributions of annual equivalent of standard axle load (*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 3 Means, standard deviations and the probability distributions of modified structural 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 4 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 5 Means, standard deviations and probability distributions of standard deviation rut depth**

| 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 6 Means, standard deviations and probability distributions of roughness (*IRI*) at the start of the analysis year**

| 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 |

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 other variables remain constant. Monte Carlo simulation technique 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 7. The calibration factors *Kgp* and *Kgm* used default values of 1.00.

The effect of the input parameters on 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 $(\sigma/\mu)$. Tables 8 to 13 show comparisons between the coefficients of variation (Cov) of the input parameters and of the predicted annual rate of change in road roughness.

**Table 7 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 |

**Table 8 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 |
| $(\Delta RI)$ | 0.594 | 1.00 | 0.289 | 0.368 |

**Table 9 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 10 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 11 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 |

**Table 12 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 13 Comparison between the coefficient of variation (Cov) of the input initial 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 8 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 9 to 13) 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 the 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.

# 5. Step 2: Establish Probability Distributions of Critical Input Parameters

From the previous section, the critical input parameters identified include pavement strength, rut depth, annual equivalent standard axle loads and initial roughness. The next step in the analysis is to establish the probability distributions of the stochastic characteristics of these critical input parameters along the road network.

## 5.1 Establish Probability Distribution of Pavement Strength

For illustration, Figure 2 shows the stochastic characteristic of pavement strength for a 92 km national highway located in the tropical northeast of Queensland. The pavement strength is quantified 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 (Rhode 1994, Rhode and Hartman 1996, Salt and David 2001, O'Brien 2002). From the data presented in Figure 2, the probability distributions of pavement strength were quantified for each kilometre. Figure 3 shows an example of probability distributions of the structure number (SN) for each kilometre of the first five kilometres. Details of the analysis are given in Piyatrapoomi and Kumar (2003).

The structural numbers are usually determined from pavement deflection data which are obtained when the pavement is subjected to a "standard" load. Pavement deflection data can be converted into pavement strength by using a number of available functions (O'Brien 2002, Rhode 1996, Rhode 1994, Salt and David 2001, Evdorides 1999). In this study, the Falling Weight Deflectometer (FWD) deflection tests were used to collect pavement strength data.

In this test method, the FWD equipment applies impulse loading to a circular plate in contact with the pavement surface. When the pavement surface is subjected to the load, the pavement yields, and a deflection bowl is created. Surface deflections at various distances from the centre of loading are measured through a series of geophone sensors at fixed distances from the load and stored in a data file. Details of the Falling Weight Deflectometer (FWD) can be found in O'Brien, 2002.

Pavement deflections can be transformed into structural numbers by many recommended functions (Rhode 1996, Rhode 1994, Salt and David 2001, Evdorides 1999). Robert's function was tested with a large data set of a wide range of New Zealand unbound granular pavements. Many functions were used and it was found that Robert's function yielded a reasonably close relationship to $r^2 > 0.9$ (Salt and Stevens 2004).

Robert’s function is given as;

$$SNP = 12.992 - 4.167 Log(D_o) + 0.936 Log(D_{900}) \quad (2)$$

Where;

| | | |
|---|---|---|
| *SN* | = | the Structural Number |
| *Do* | = | pavement deflection under load cell |
| *D900* | = | pavement deflections at locations 900mm from the load cell |

The adjusted structural number due to cracking was taken as 97.5 percent of the structural number obtained from Robert’s function.

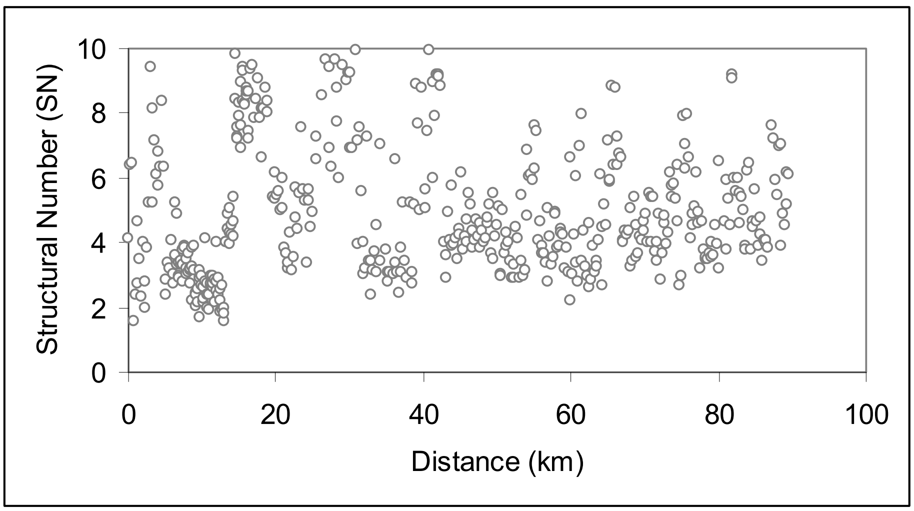


Figure 2 Pavement strength expressed in terms of the Structural Number (SN) along the road length of a 92 km national highway

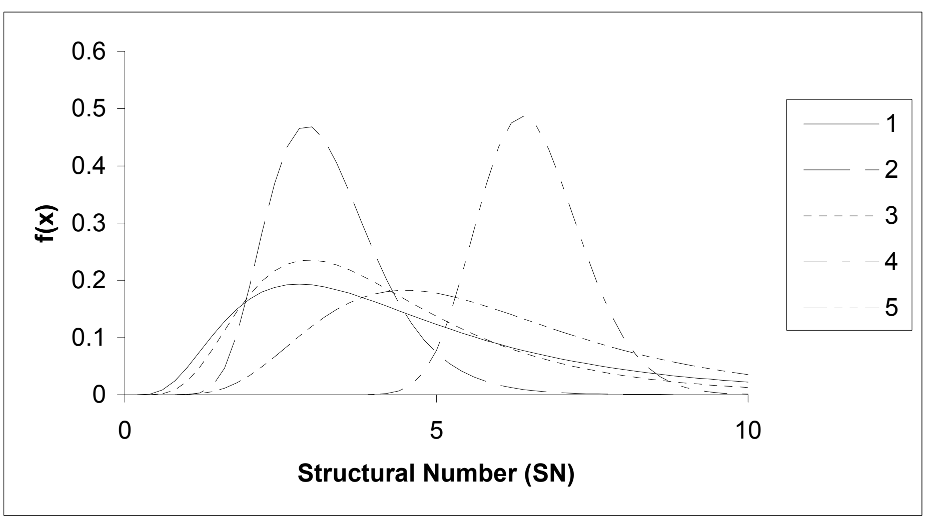


Figure 3 Typical probability distributions of Structural Numbers of the first five kilometres of the 92-Kilometre.

In some cases, pavement structure data (either deflection or pavement layer data) may not be available, and alternative methods of calculation will need to be used. Australian Road Research Board's method can be used as it needs only few input data to calculate the structural capacity of the pavement. This method requires only few input data such as annual average daily traffic and pavement age. We may not be able to characterise the variability of pavement strength for small sections using this method. Most Australian road authorities recognised the importance of pavement structural data on investment decision process. Currently, they plan to acquire more pavement structural data with additional investment at network level. To this end, it was suggested by the research team that the variability of pavement structural data of the analysed road length will be reassigned for each small segment of the road length.

### 5.2 Establish Probability Distribution of Annual Equivalent Standard Axle Load

To determine the annual number of equivalent standard axles, it is necessary to transform the annual average daily traffic (AADT) into the annual equivalent standard axles.

Four types of vehicles were categorised by Queensland Department of Main Roads, namely:

- Passenger cars
- Rigid trucks
- Articulated semi-trailer trucks and
- B-Double trucks and road trains

Table 14 summarises some typical proportions of each vehicle type identified by Queensland Department of Main Roads. These percentages were assessed and used by the Queensland Department of Main Roads for the purpose of assessing road pavement condition. In reality, the mix proportions of vehicle classes in the traffic stream have their own variability characteristics.

Table 15 gives the coefficients that transform the annual average daily traffic into the equivalent standard axle counts. The annual average daily traffic (AADT) was collected at various traffic data collection points and weigh-in-motion sites.

Further study will be conducted to assess the variability of the percentage of vehicles for Queensland road networks. An analysis will also be conducted to explore the possibility to assess the variability of the coefficients (ESA Factors) that transform vehicle types into the equivalent standard axle load.

**Table 14 Percentages of vehicle types used in the analysis**

| Number of vehicles | Passenger cars (%) | Rigid trucks (%) | Articulated trucks (%) | B-Double / Road Trains (%) |
|---|---|---|---|---|
| 1500-3000 | 76 | 10 | 10 | 4 |
| 3001-5000 | 83 | 7 | 8 | 2 |
| 5001-10000 | 83 | 7 | 8 | 2 |
| > 10001 | 89 | 7 | 3 | 1 |

**Table 15 ESA Factors for Vehicle Classes.**

| Passenger cars | Rigid trucks | Articulate trucks | B-Double / Road Trains |
|---|---|---|---|
| 0.0008 | 2.74 | 3.89 | 4.93 |

### 5.3 Establish Probability Distribution of Rut Depth

Rut depths were collected by the Network survey vehicles (laser profilometer). The average rut depth and rut depth standard deviation are used for HDM-4 analysis. The probability distributions of the average rut depth for small sections are established.

### 5.3 Establish Probability Distribution of Initial Roughness

Roughness is collected by the Network survey vehicles (laser profilometer). Initial roughness is the roughness recorded at the start of the analysis year and is measured in the international roughness index (IRI). The probability distributions of IRI for small sections of a road network are established.

## 6. Step 3: Modelling Road Networks for HDM-4 Analysis

Highway Development and Management (HDM-4) System software will be used to conduct a series of life-cycle cost analyses. HDM-4, developed by the International Study of Highway Development and Management (ISOHDM), is a globally accepted pavement management system. 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. The Strategy Analysis Option was employed in this study in assessing the effects of the variability of pavement strength on the estimate of maintenance and rehabilitation budgets.

In modelling road networks for HDM-4 analysis, a road network is divided into small sections. Pavement characteristics including pavement type, pavement condition, traffic loading and climatic zone are assigned for each section according to recorded data. The probability distributions, mean values and standard deviations of critical input parameters were identified for each section. Framework for modelling critical input parameters for assessing the life-cycle cost statistics is given below:

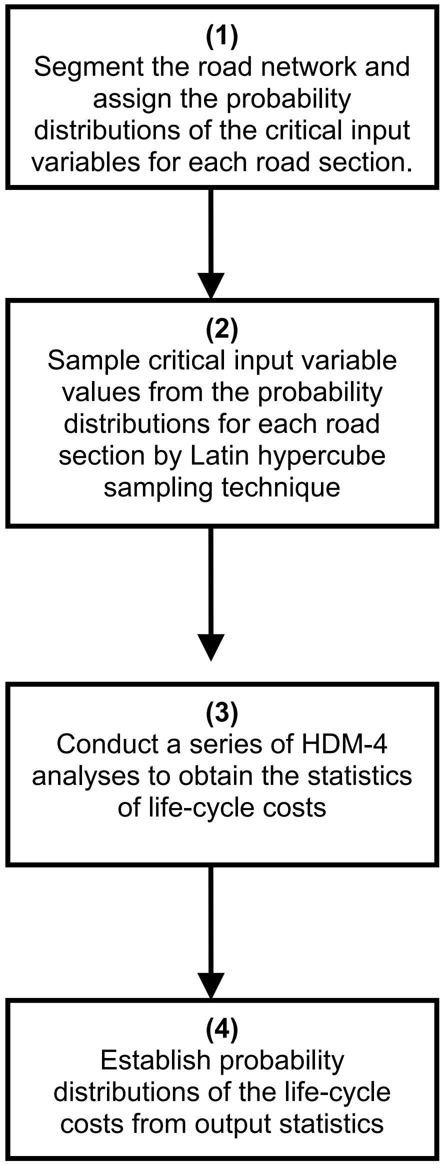


Figure 4 Flow chart for modelling road networks for HDM-4 analyses

# 7. Step 4: Simulating Sample Data of Critical Input Parameters by Latin-Hypercube Sampling Technique

Input parameters that have been identified as critical for assessing variation in life-cycle costs include:

1. Pavement strength (quantified by the structural number (SN))
2. Annual change in rut depth (expressed in terms of standard deviation rut depth)
3. Traffic loading (expressed in terms of annual equivalent standard axle loads)
4. Initial roughness (IRI)
5. Unit costs

Unit costs are expected to contribute a great deal to the variation in life-cycle cost estimates. Thus, the effect of the unit costs in the variation is also investigated. The probability distributions, mean values and standard deviations of these critical parameters for each road section are quantified. Sample values of these critical input parameters are sampled by Latin-Hypercube sampling technique.

In the Latin-Hypercube sampling technique, the probability distributions of the structural numbers, annual change in standard deviation rut depth, annual equivalent standard axle loads, initial roughness and unit costs are divided into N intervals with equal probability. For example, the probability distributions of the critical input parameters divided into ten equal probabilities are given in Figures 5 to 9. The areas of 1 to 10 in the figures have equal probabilities of occurrence.

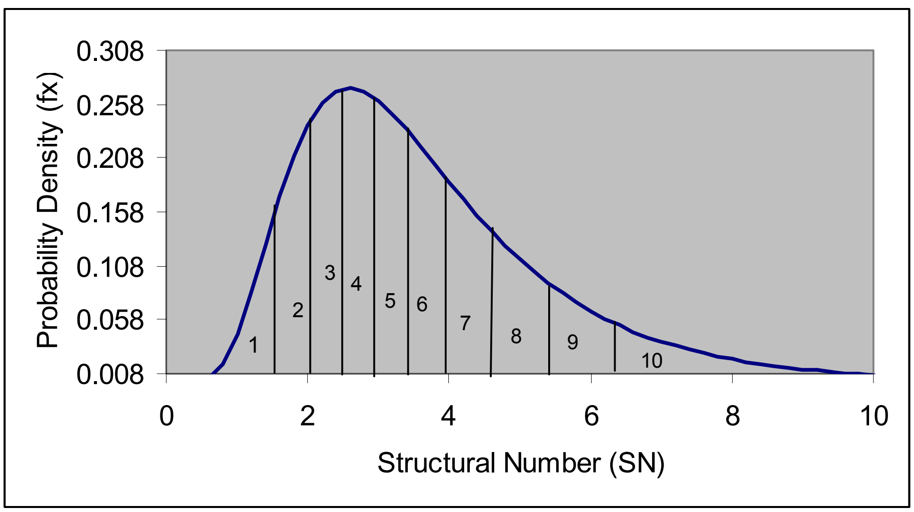


Figure 5 An example of a probability distribution of structure numbers (SN) divided into ten equal probabilities

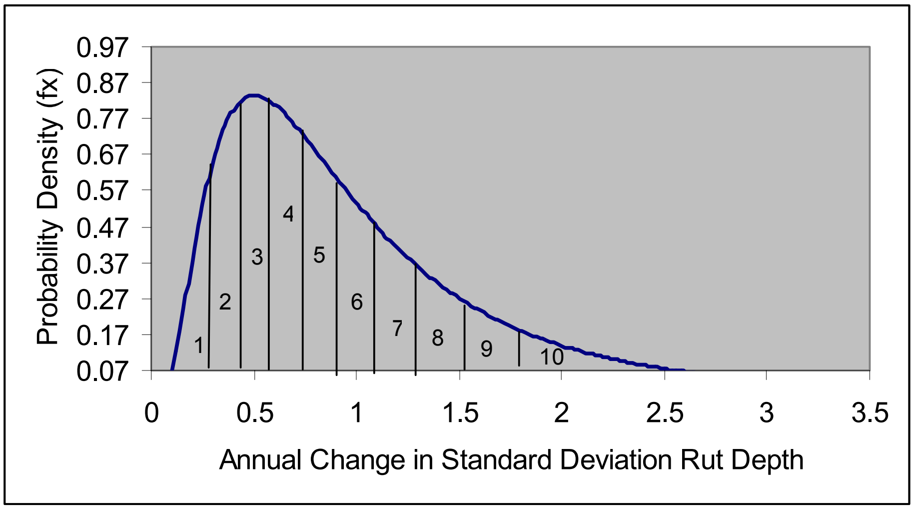


Figure 6 An example of a probability distribution of annual change in standard deviation rut depth divided into 10 equal probabilities of occurrence

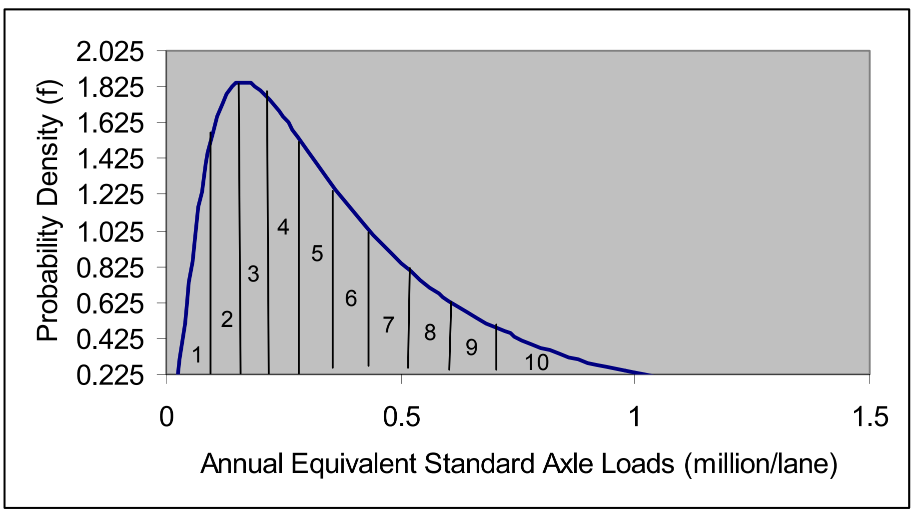


Figure 7 An example of a probability distribution of annual equivalent standard axle loads divided into 10 equal probabilities of occurrence

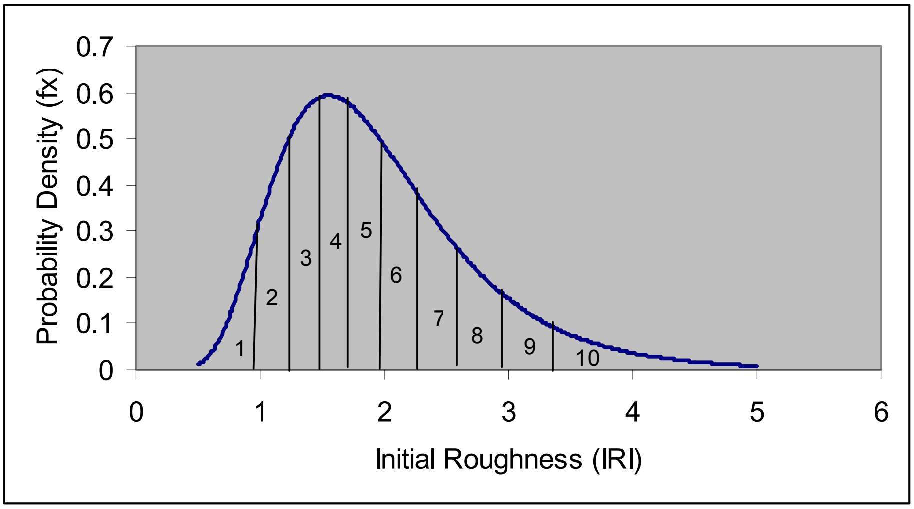


Figure 8 An example of a probability distribution of initial roughness divided into 10 equal probabilities of occurrence

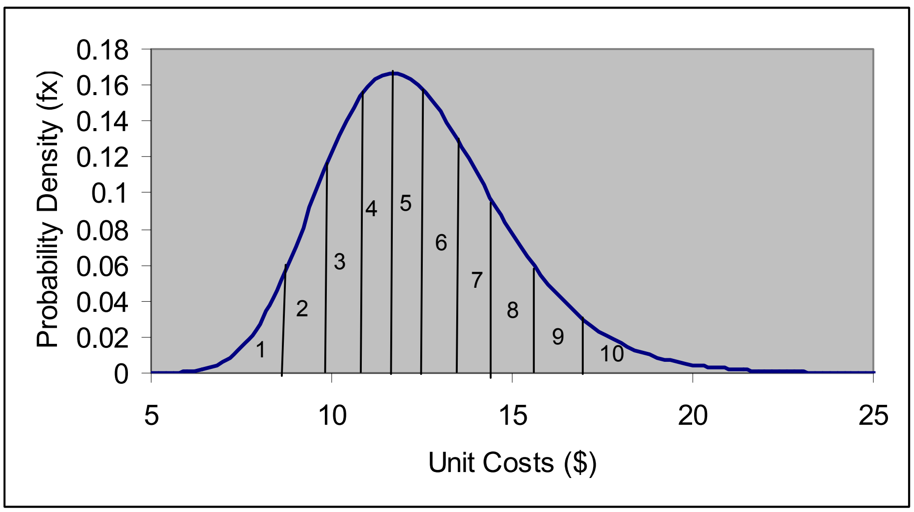


Figure 9 An example of a probability distribution of unit costs divided into 10 equal probabilities of occurrence

In Latin-Hypercube sampling technique, the probability distributions of the critical input parameters are identified for each road section. One sample is randomly selected to represent the sampled value of each interval.

Piyatrapoomi (1996) 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 the probability distributions of the critical input parameters were divided into forty intervals, each interval having 2.5 per cent probability of occurrence. One value of each interval is randomly selected to be the observed value of each interval, so that forty sampled values are obtained for each kilometre. Details of the Latin

Hypercube Sampling Technique can be found from the original paper (Iman and Conover, 1980).

## 8. Steps 5 and 6: Input sampled data of the critical input parameters for HDM-4 for analyses and conduct the analysis

In this study, the effect of each critical input parameter on cost estimates is investigated. As mentioned, the critical input parameters include:

1. Pavement strength (quantified by the structural number (SN) )
2. Annual change in rut depth (expressed in terms of standard deviation rut depth)
3. Traffic loading (expressed in terms of annual equivalent standard axle loads)
4. Initial roughness (IRI)
5. Unit costs

From the previous section, forty values were sampled from the probability distribution of one critical parameter to represent its variability for each kilometre. Forty HDM-4 input data files are prepared for the analysis to assess the effect of that critical input parameter on the cost estimates. In such an analysis, the values of other input parameters remain constant, whilst only the values sampled from the probability distribution of the considered critical input parameter are varied for each kilometre. A series of HDM-4 analysis runs is executed to obtain the statistics of the output cost estimates. The probability distribution and statistical information of the output cost estimates statistics are quantified. The degree of variation is investigated using the coefficient of variation (i.e. the standard deviation value divided by the mean value).

The same process is repeated for investigating the impact of the other critical input parameters on the cost estimates.

The aggregate effect of the critical input parameters on the cost estimates can be linearly combined as follows:

$$\sigma^2(B) = \sum_{i=1}^{n} a_i^2 \sigma_{X_i}^2 \qquad (2)$$

Where $\sigma^2$= overall variance of the cost estimates representing the error in cost estimates, $a_i$= constants, $a^2{}_{Xi}$= variance of cost estimates contributed by each critical input parameter.

Alternatively, the overall variance, $\sigma^2$, of a cost estimate is obtained by including the variability of all critical input parameters in a single analysis. The procedure of the Latin-Hypercube sampling technique for such analysis is given below:

1. The probability distribution of each critical parameter is divided further into equal probabilities. The probability distribution is divided into forty equal probabilities.

2. Randomly select one sample value from each of the divided probabilities. One value represents the sampled value of a divided probability. The same process is repeated for the remaining divided probabilities to obtain forty

values representing the overall sampled values of the probability distribution. By using the Latin-Hypercube sampling technique, the overall variability of a probability distribution can be represented, in this case, by forty sample data.

3. Randomly select one value from the forty sampled data for each critical input parameter. Therefore, there are five sampled values representing five critical input parameters. The sample process is repeated for the remaining sampled data of the critical input parameters. Hence, there are forty sets of the critical input parameters. The variability of each critical input parameter is represented by each set of data using the random sampling process.

4. The above random process is applied for each or one kilometre. The same process is repeated for the other kilometres of the road network to be considered in the analysis.

5. There are forty data sets of the critical input parameters. The variability of all critical input parameters is randomly selected and represented in these forty input data sets.

# 9. Steps 7 and 8: Statistical analysis of outputs and investigation of variation in cost estimates

There are forty output files obtained from a series of HDM-4 analyses. The costs for maintenance and rehabilitation are calculated for each year. For an illustration, a road network of 92km national highway was used in the analysis. Details of the analysis are given in Piyatrapoomi et. al. (2004) and Piyatrapoomi and Kumar (2004). The variability of pavement strength (i.e. structural number) was considered. The forty values of cost estimates for each year were statistically analysed. Figure 10 shows undiscounted mean values and standard deviations for each year cost estimate for a 25-year analysis period. From Equation 1, the discounted life-cycle costs are obtained by multiplying life-cycle costs with the discount factor, given below:

$$\alpha = \frac{1}{(1+r)^t}$$

Where: $\alpha$ = discount factor, $r$ = discount rate, $t$= length of time (years).

Figure 11 shows the resulting coefficients of variation of the cost estimates for the 25-year period.

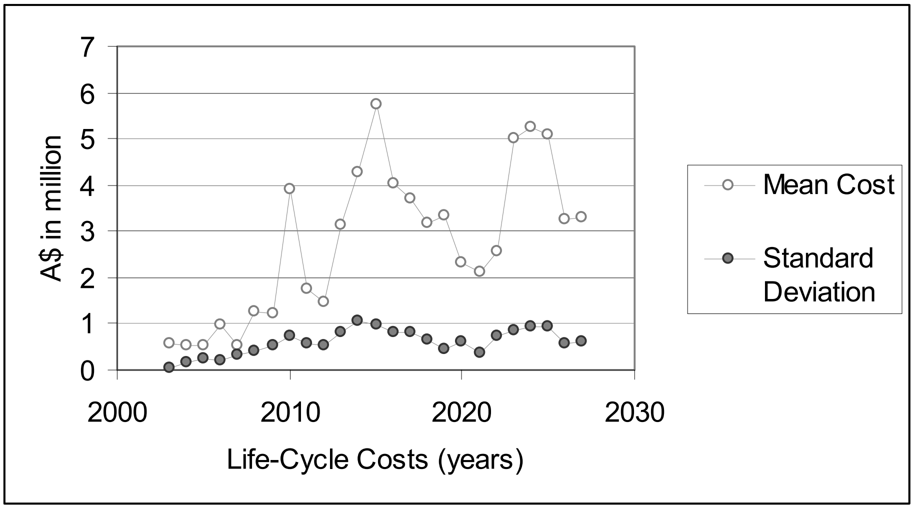


Figure 10 Mean and standard deviation values of cost estimates for a 25-year analysis period

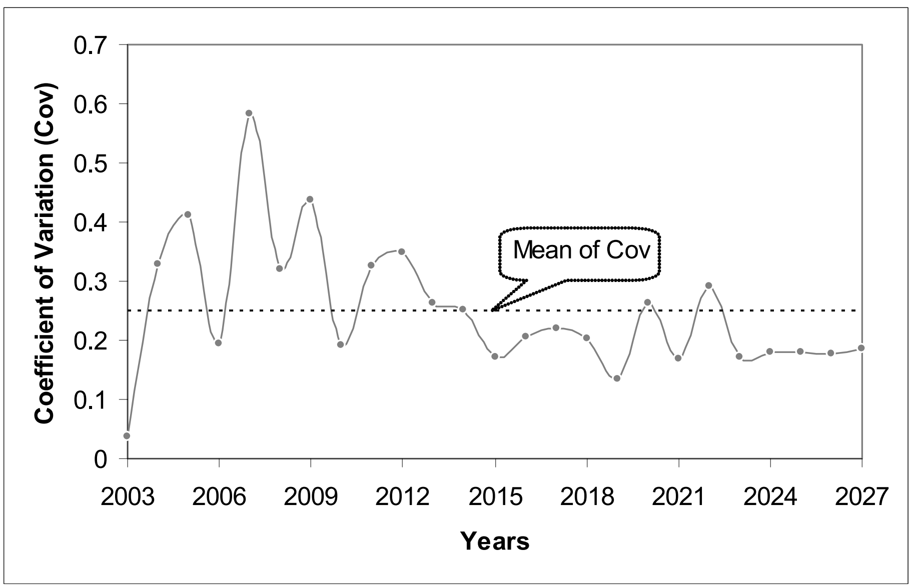


Figure 11 Coefficients of variation (Cov) for 25-year life-cycle cost estimates

The degree of variation in cost estimates can be assessed by the coefficients of variation (Cov's). Figure 11 shows the coefficients of variation of cost estimates for the 25-year analysis period. In this case the largest coefficient of variation value is 0.59 occurring in year four (2007). The coefficient of variation was very small (0.034) for the first year of the analysis. This is due to the fact that only routine maintenance was required. The coefficients of variation are in the range of 0.18-0.43 when major maintenance and rehabilitation were required. The mean of the coefficients of variation is 0.24.

From the statistical information of the cost estimates, i.e. the probability distribution, mean and standard deviation values, a level of confidence in costs can be estimated. A reasonable level of reliability for cost estimates each year can be calculated from the output probability distributions. For instance, a 95$^{th}$ percentile cost estimate can be investigated. A 95th percentile cost estimate is an estimate that there is only 5% chance that the cost will exceed the estimated value. 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 and the mean estimate (approximately 50th percentile).

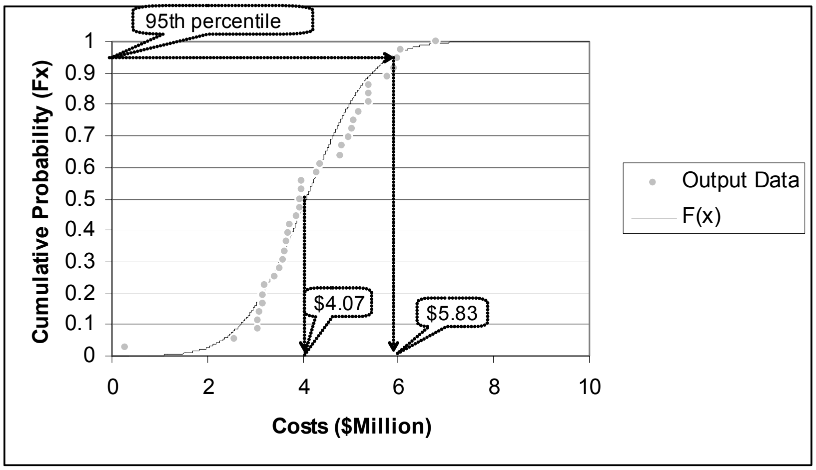


Figure 12 Cumulative probability distribution of a cost estimate for year 2014.

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 an approximately 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.

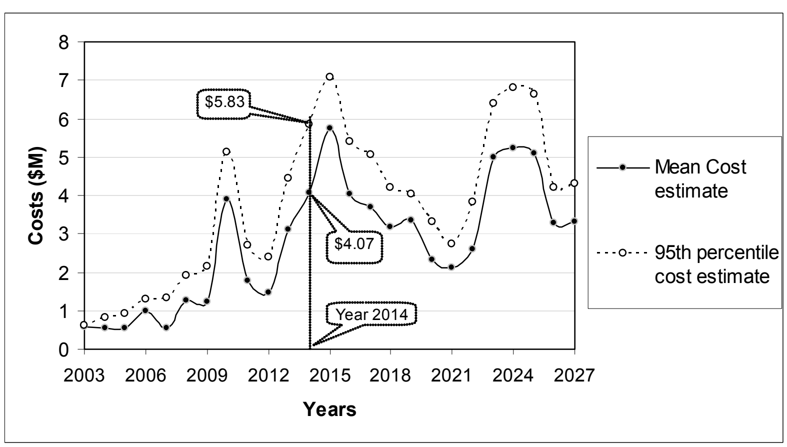


Figure 13 Comparison between the mean cost estimates and the 95th percentile cost estimates for 25-year maintenance and rehabilitation cost estimates.

# 10. Conclusions

This report presents a methodology for assessing variation in cost estimates for road maintenance and rehabilitation. This method is based on the probability-based analysis and Latin-Hypercube sampling techniques. Five parameters were identified as critical input parameters for variation in cost estimates. These parameters include pavement strength, rut depth, annual equivalent standard axle loading, initial roughness and unit costs. The variability of the critical input parameters is included in the analysis by the Latin-Hypercube sampling technique. An example of variation in cost estimates for a life-cycle cost of a 92km national highway was presented for illustration. The variation in cost estimates can be expressed in terms of the coefficient of variation (Cov). For this case study, the Cov values of the cost estimates were in the range of 0.134 to 0.59. The coefficient of variation was very small (0.034) for the first year of the analysis. This is due to the fact that only routine maintenance was required. The coefficients of variation are in the range of 0.18-0.59 when major maintenance and rehabilitation were required. The mean of the coefficients of variation is 0.24.

The output statistical information of the cost estimates were useful information for further analysis in selecting cost estimates with a certain degree of confidence (e.g. 95$^{th}$ percentile at which there is a 5% chance that the cost would be greater). A 95$^{th}$ percentile costs can be estimated for the cost on a yearly basis or cumulative costs. A comparison between the mean and the 95$^{th}$ percentile cost estimates for a 25-year maintenance and rehabilitation was presented.

In this research project, other critical input parameters will be incorporated in the analysis to further assess the effect of other critical parameters on the cost estimates.

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Noppadol Piyatrapoomi obtained his Ph.D. degree from the University of Melbourne. He has practiced as a civil and structural design engineer for ten years before he joined RMIT University Melbourne, Australia in 2002 His research interests include the application of risk and reliability in decision-making for infrastructure asset management; assessment of public risk perception on engineering investments; risk and reliability assessment of structures; seismic risk and reliability assessment of structures; the application of an evolutionary method for data analysis. He developed an evolutionary method of data analysis during his Ph.D. study. This method can be used to refine existing functions and develop new formulas by using probability, statistical, and risk assessment theories in the analysis. The method provides a more fine-grained analysis and yields more accurate results and better fitness of data than commonly used methods, such as regression or correlation analyses.

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