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STRUCTURING FINANCE TO MEET CLIENT'S NEEDS

Full Paper

RISK ASSESSMENT IN LIFE-CYCLE COSTING FOR ROAD ASSET MANAGEMENT

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ABSTRACT

Queensland Department of Main Roads, Australia, spends approximately A$ 1 billion annually for road infrastructure asset management. To effectively manage road infrastructure, firstly road agencies not only need to optimise the expenditure for data collection, but at the same time, not jeopardise the reliability in using the optimised data to predict maintenance and rehabilitation costs. Secondly, road agencies need to accurately predict the deterioration rates of infrastructures to reflect local conditions so that the budget estimates could be accurately estimated. And finally, the prediction of budgets for maintenance and rehabilitation must provide a certain degree of reliability.

This paper presents the results of case studies in using the probability-based method for an integrated approach (i.e. assessing optimal costs of pavement strength data collection; calibrating deterioration prediction models that suit local condition and assessing risk-adjusted budget estimates for road maintenance and rehabilitation for assessing life-cycle budget estimates).

The probability concept is opening the path to having the means to predict life-cycle maintenance and rehabilitation budget estimates that have a known probability of success (e.g. produce budget estimates for a project life-cycle cost with 5% probability of exceeding).

The paper also presents a conceptual decision-making framework in the form of risk mapping in which the life-cycle budget/cost investment could be considered in conjunction with social, environmental and political issues.

1. INTRODUCTION

Australia has billions of dollars worth of civil infrastructure assets as roads, bridges, railways, buildings and other structures. Road assets alone are valued at around A$ 140 billion. As the condition of assets deteriorates over time, Queensland Department of Main Roads spends approximately A$ 1 billion annually in asset upkeep, which amounts to expenditure in the order of A$27 million per day.

Effective investment decision support relies on comprehensive, relevant and quality data of asset conditions; asset condition prediction modelling; and reliability assessment in life-cycle costing.

Research in the first stage of a CRC research project titled "Investment Decision Framework for Infrastructure Asset Management" concentrated on developing an effective methodology and framework for life-cycle budget/cost estimates for road asset management. Figure 1 shows the framework. There are three important tasks in the framework, namely;

Task 1: Optimisation of data collection. The method is used for analysing optimal amount of data collection. A case study was conducted to identify optimal intervals for pavement strength data collection. The result showed that for the same budget, pavement strength could be collected fivefold of currently collected data.

Task 2: Calibration of road pavement deterioration prediction models. The method is used for calibrating deterioration prediction models of asset condition for local conditions. Accurately predicting the rate of asset deterioration would result in accurately predicting fund allocation for maintenance and rehabilitation.

Task 3: Risk-adjusted assessment for life-cycle costing estimates for maintenance and rehabilitation. The method is used for assessing risk of errors in budget/cost estimates.

This paper presents concepts and methodologies of these three tasks and links them to the life-cycle budget/cost estimate for road asset management.

A conceptual decision-making framework in the form of risk mapping in which the life-cycle budget/cost investment could be considered in conjunction with social, environmental and political impacts is also presented for illustrating the concept. This research outcome can be applied to other forms of civil infrastructure such as railways, buildings, bridges, etc.

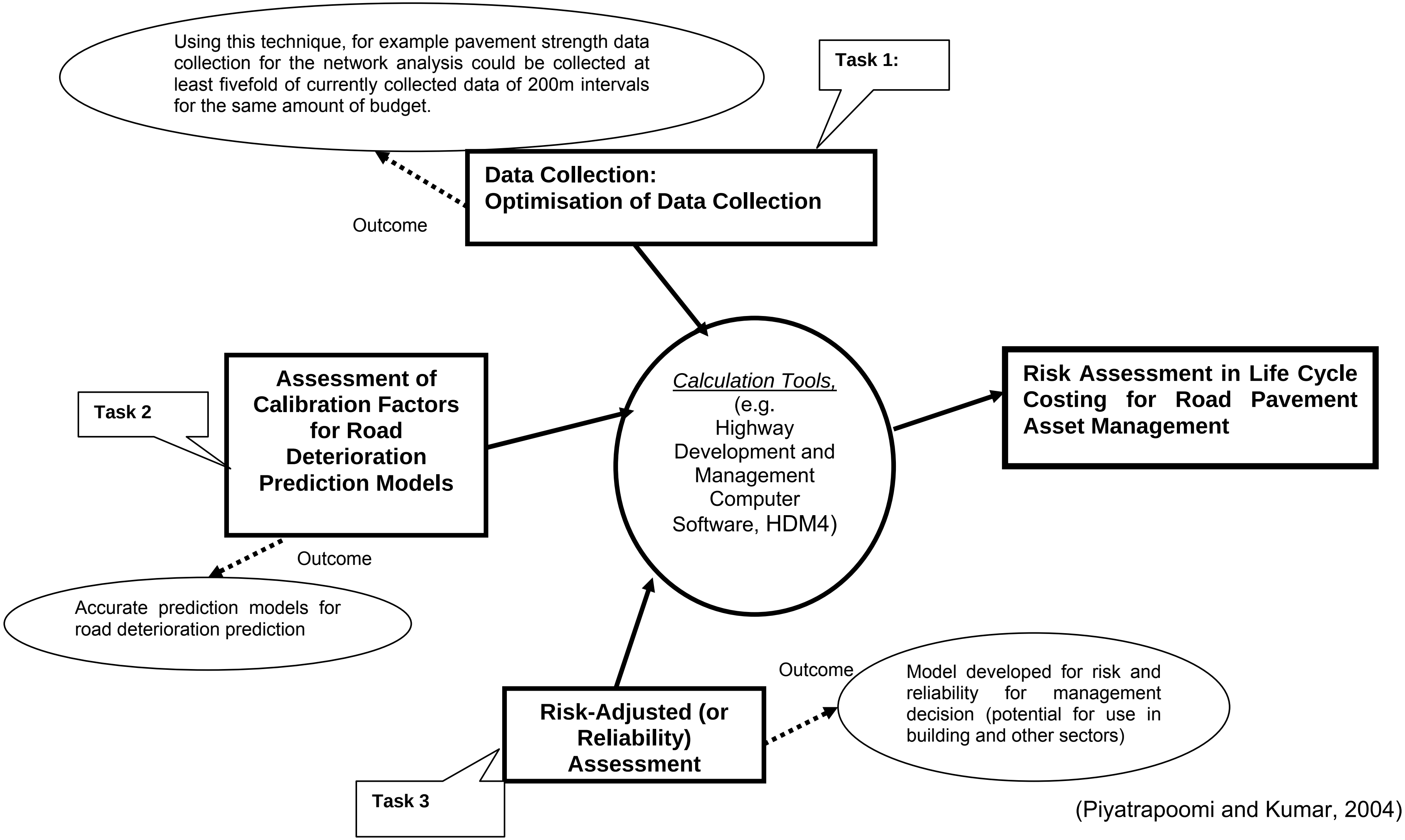

Figure 1 Investment Decision-Making Framework for Infrastructure Asset Management

2. METHOD OF OPTIMISING & RELIABILITY ASSESSMENT OF DATA COLLECTION

This method can be used for optimising data collection. A case study was conducted for identifying optimal intervals for road pavement strength data collection (Piyatrapoomi et al, Sept. 2003; Piyatrapoomi & Kumar, Jun. 2003). Methods for pavement strength data collection require test instruments to travel very slowly or to stop while loading the pavement and measuring surface deflections (a proxy for strength). Currently, pavement strength data are collected at 100m or 200m intervals which is time consuming and expensive.

Falling Weight Deflectometer (FWD) deflection test was used to collect the data (QDMR 2002). The data were collected at 200m spacing for outer and inner wheel paths for a 92km national highway in a tropical region of northeast Queensland.

It is hypothesised in the method 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"*.

Optimisation analysis was carried out by reducing data from the original data set to create new sets, which were in turn, tested to see whether they had similar mean, standard deviation and probability distribution to those found in the original data set. If the new data set possessed similar mean, standard deviations and probability distribution, the new data set would provide similar prediction outcomes.

Figure 2 shows the cumulative probability distributions of the original data set of 200m spacing intervals for both inner and outer wheel paths. The means and standard deviations for outer and inner wheel paths are given below. The probability distributions were log-normally distributed.

Ln(Deflection in microns) = N(6.05, 0.805) for outer wheel path
Ln(Deflection in microns) = N(5.95, 0.817) for inner wheel path

After the analysis, Figure 3 shows the cumulative probability distribution of 1000m intervals of the same 92km pavement strength data. The cumulative probability distribution of the data was fitted by a log-normal distribution with the mean and standard deviation of Ln(Deflection in microns) = N(5.913, 0.795).

The results indicate that the mean, standard deviation and the probability distribution of the data set of 1000m intervals are similar to the means, standard deviations and the probability distributions of the data set of 200m intervals. From the hypothesis, it is assumed that these two sets of data would provide similar prediction outcomes. Next, it is necessary to test the reliability in using the pavement strength data set of 1000m intervals in predicting life-cycle costing.

In the reliability assessment, the term "reliability" is defined as the percentage of discrepancy between the 95^{th} percentile budget/cost estimates and the budget/cost estimates calculated from the pavement strength data of 1000-metre intervals (Piyatrapoomi et al, Oct. 2004). The 95^{th} percentile value is a value that is commonly selected to provide an appropriate level of confidence (Ang and Tang 1975, Billinton and Allan 1992).

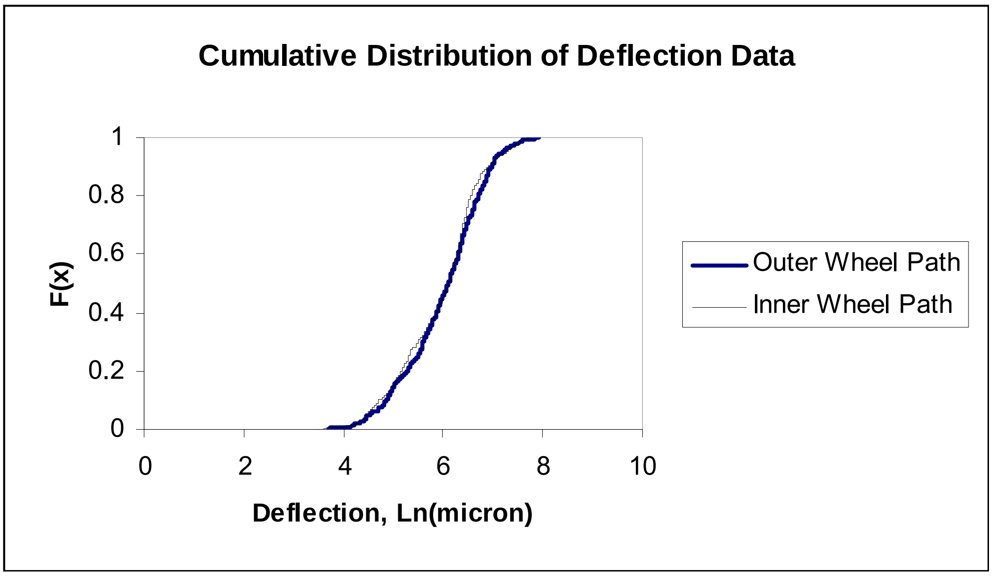

Figure 2 Cumulative distributions of pavement deflection sample data for outer wheel path and inner wheel path for a 92-kilometre national highway of Queensland

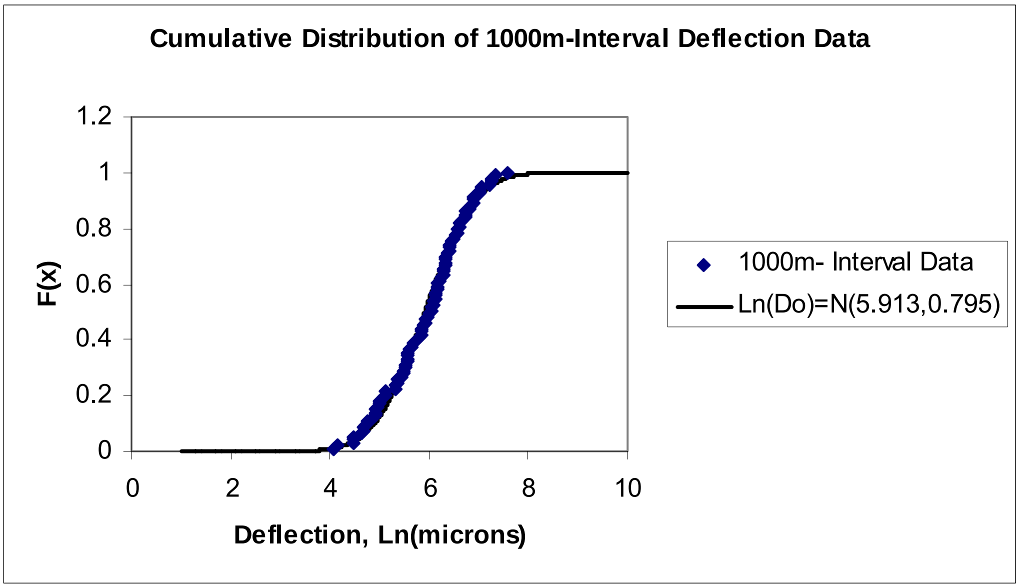

Figure 3 Cumulative distribution of deflection data set for 1000-meter interval of a 92-kilometre national highway of Queensland

The performance data of 92-kilometre national highway segment was used in the analysis. Maintenance and rehabilitation budget/cost estimates for 5, 10, 15, 20 and 25-year periods were calculated starting from 2003. In the study, Highway Development and Management (HDM-4) System software package was employed in the analysis. HDM-4, developed by the International Study of Highway Development and Management (ISOHDM 2001), is a globally accepted pavement management system.

In this study, only the discrepancy influenced by the pavement strength was considered and compared. Thus, the variability of pavement strength was used in the calculation, while other input variables remained deterministic in the budget/cost estimates. The 95th percentile budget/cost estimate is obtained from the budget/cost estimates at the 95% probability of occurrence from the probability distribution as illustrated in Figure 4.

Figure 5 shows the discrepancies in percentage between the budget/cost estimates at the 95th percentile and the budget/cost estimates calculated from the optimal pavement deflection data of 1000-metre intervals. The differences between the 95th percentile budget/cost estimates and the budget/cost estimates calculated from the optimal data of 1000-metre intervals were calculated to be 12.23, 3.58, 2.85, 1.74 and 1.47, per cent for 5- and 10, 15-, 20- and 25-year periods, respectively.

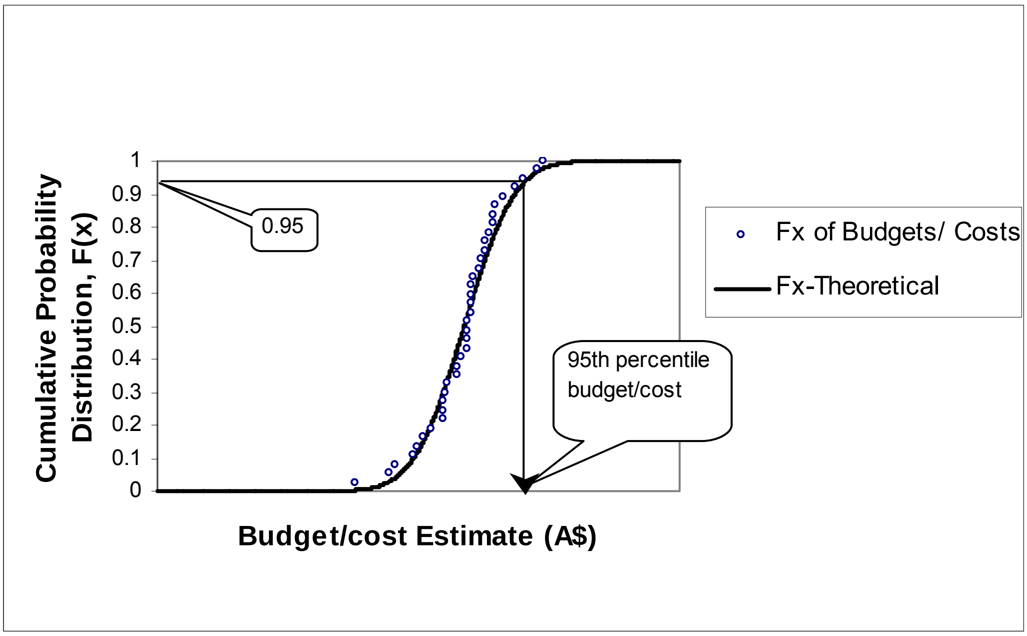

Figure 4 A typical cumulative distribution of budget/cost estimate

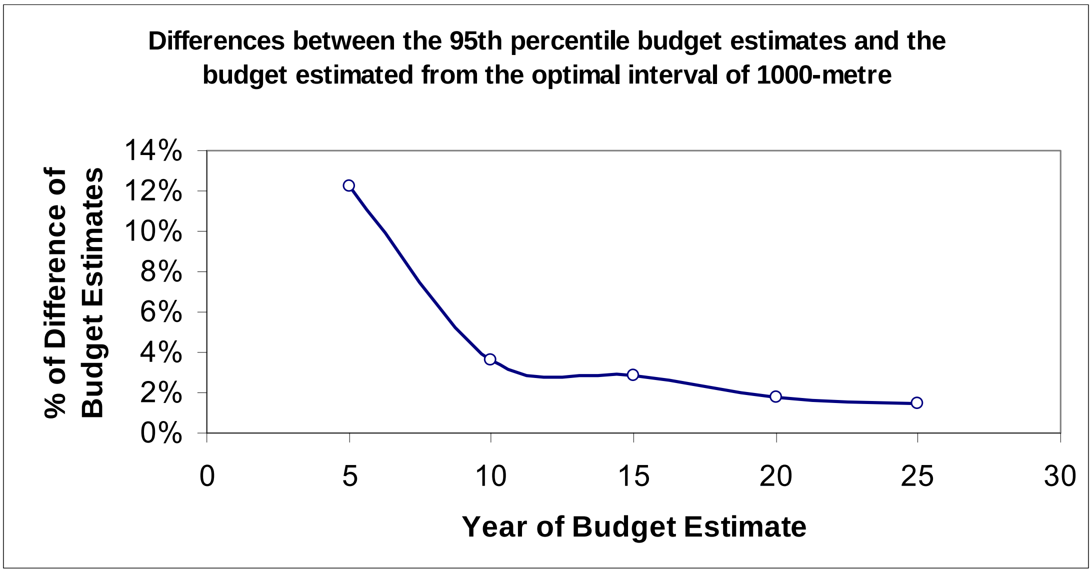

Figure 5 Percentage differences between mean budget/cost estimates and the 95th percentile budget/cost estimates for 5-, 10-, 15-, 20- and 25-year periods

It can be observed that the discrepancy between the cost estimated from the optimal pavement strength data of 1000-metre intervals and the 95th percentile for a life-cycle cost of maintenance and rehabilitation is very small (1.47%). In this case, by using this optimisation analysis method five times more highway strength could be assessed for structural strength within the same budget.

3. CALIBRATING DETERIORATION PREDICTION MODELS

The variability in road condition data may arise from the variability in climatic conditions, soil conditions, user vehicles, etc. However, when the functions do not show a strong correlation or relationship with recorded data, these functions provide less confidence in predicting the deterioration rate for local conditions.

In this study the probability-based method (Ang & Tang 1975) and Monte Carlo simulation technique (Gray & Travers 1978) have been adopted for calibrating road deterioration prediction models. The methodology was used for calibrating road pavement roughness prediction models for Queensland conditions.

One of such deterioration model for predicting the rate of change in road pavement roughness suggested by The International Study of Highway Development and Management (ISOHDM 2001) is given below:

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

Where;

Kgp	=	calibration factor, Default value = 1.0
Kgm	=	calibration factor for environmental condition
ΔRI	=	total annual rate of change in road pavement roughness
ΔRIs	=	change in roughness resulting from pavement strength deterioration due to vehicles
ΔRIc	=	change in roughness due to cracking
ΔRIr	=	change in roughness due to rutting
ΔRIt	=	change in roughness due to pothole

The last term in the right hand side of the equation takes into account environmental condition.

Where;

Kgm	=	calibration factor for environmental condition
m	=	a constant taking into account environmental effects
RI	=	road pavement roughness of the start of the analysis year

Figure 6 illustrates the cumulative probability of annual rates of deterioration in road pavement roughness for three-year periods (i.e. 2000-01, 2001-02, and 2002-03). In this method, the input variables in Equation 1 are expressed in terms of the probability distribution. The rate of change (ΔRI) in Equation 1 will result in a probability distribution.

In the calibration, the probability distribution of the rate of change obtained from Equation 1 and the actual rate of change obtained from the recorded data are compared while the calibration factors are adjusted so that the two cumulative probability distributions achieve best fit.

Figure 7 illustrates the result of a comparison between the cumulative probability distributions of the actual rate of change of road pavement roughness and the rate of change of road pavement roughness obtained from Equation 1. Table 1 shows examples of calibration factors (Kgp and Kgm) of Equation 1.

The calibration factors (Kgm) are given for different percentiles that reflect the actual variability of the recorded data. The method yields calibrated models that closely replicate the actual variability in road network condition.

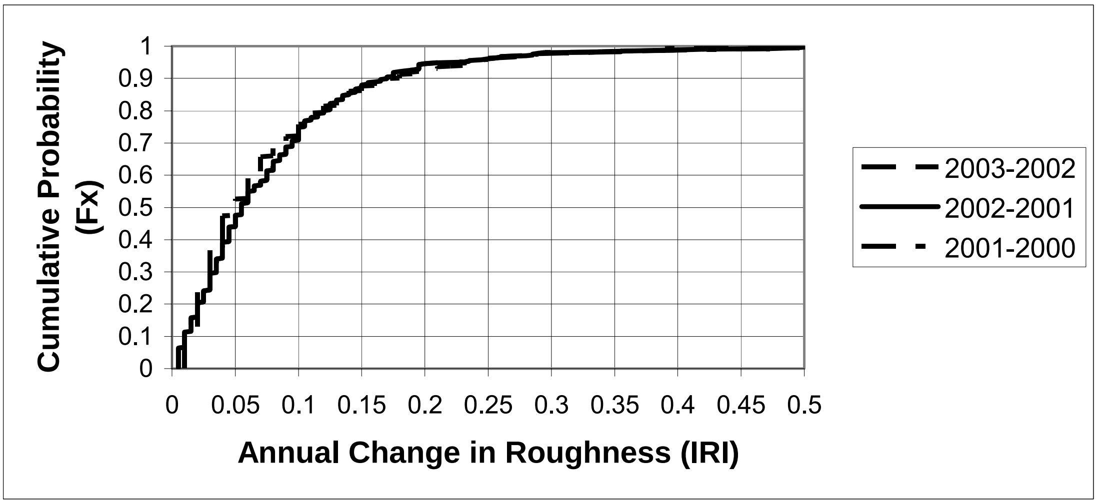

Figure 6 The cumulative probability distribution of the annual rate of change in road pavement roughness between the years 2002-03, 2001-02 and 2000-01

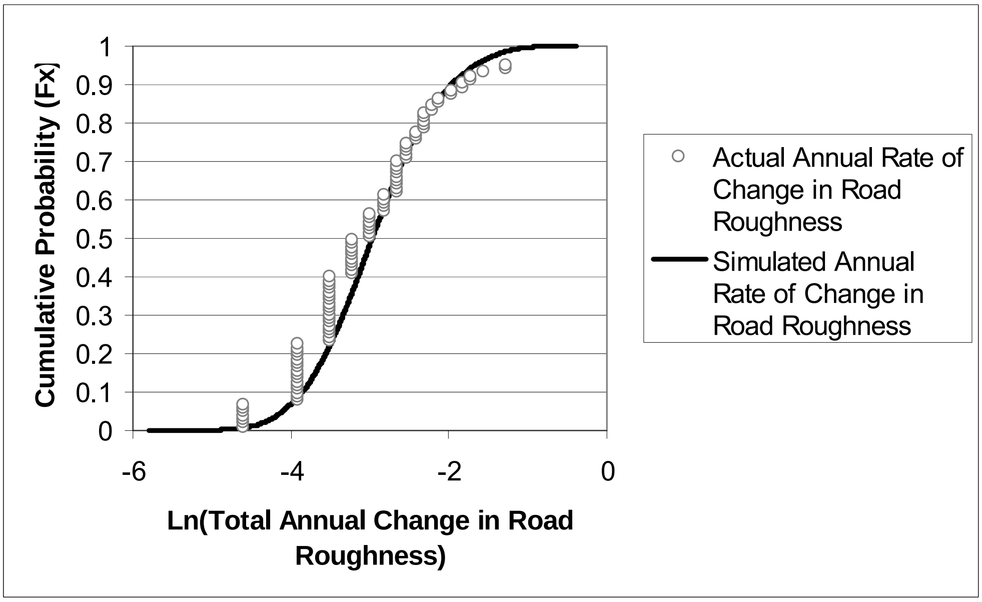

Figure 7 Comparison between the cumulative probability distributions of actual and simulated annual change in roughness for pavement thickness

Table 1 Calibration factors (Kgp and Kgm) for the annual rates of change in road pavement roughness

Calibration Factor (Kgp)	Calibration Factor (Kgm)	Calibration Factor (Kgm)	Calibration Factor (Kgm)	Calibration Factor (Kgm)
	50^{th} Percentile	70^{th} Percentile	80^{th} Percentile	90^{th} Percentile
0.20	1.0	1.20	1.70	2.90

4. RISK-ADJUSTED ASSESSMENT IN LIFE-CYCLE BUDGET/COST ESTIMATES

The preceding two sections addressed two important areas in assessing life-cycle budget/cost for asset management, namely;

(a) Optimising data collection for monitoring asset conditions
(b) Predicting the rate of change in asset deterioration

When it is affordable, overall current conditions of assets could be monitored and the rate of change in road deterioration is accurately predicted for local condition. The variability of budget/cost estimates arising from the variability of asset conditions remains an important issue.

This section presents a method that takes into account the variability of asset condition in assessing budget/cost estimates.

To demonstrate the methodology, only the variability of pavement strength was considered in the analysis. To assess the effect of the variability of input parameters on the output budget/cost estimates, the simplest method is to simulate representing values from the probability distributions of input variables and assess the variability of the output parameter.

The Latin hypercube sampling technique, as extensively studied by Iman and Conover (1980), appears to provide 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. A practical method in assessing risk-adjusted budget/cost estimates is to adopt the Latin Hypercube Sampling Technique.

CASE STUDY

The performance data from the 92-kilometre national highway segment located in a tropical region of northeast Queensland in Australia was used in the risk-adjusted assessment of budget/cost estimates for road maintenance and rehabilitation as a case study.

The steps in the analysis are given below:

1. Establish probability distributions and statistical information (means, standard deviations) of input variables. In this case study, only the variability of pavement strength has been statistically quantified.

2. Simulate sampled data from the probability distributions of pavement strength to represent its variability in the analysis.
3. Conduct a series of analyses using Highway Development Management System (HDM-4) to obtain the statistics of the output budget/cost estimates (ISOHDM 2001).
4. Establish probability distributions and determine the statistical information of the output budget/cost estimates.
5. Assess the interested probability of occurrence of the budget/cost estimates from the output probability distributions.

Figures 8 and 9 show the mean and standard deviation of pavement strength for the 92km national highway. The probability distribution of the pavement strength was log-normally distributed.

For the analysis, the 92-kilometer road segment was divided into 92 sections of 1000-meter in length. Each 1000-meter section has its own pavement strength characteristic. For each kilometre, the variability of pavement strength characteristic is represented by the probability distribution of the Structural Number (SN). The variability of the pavement strength was taken into account in the analysis by using the Latin Hypercube sampling technique. In this study, forty sets of the Structural Numbers (SN) for each kilometre were simulated and used in the analysis.

Figure 10 shows a typical cumulative probability distribution of pavement strength sampled by the Latin hypercube sampling technique for one kilometre.

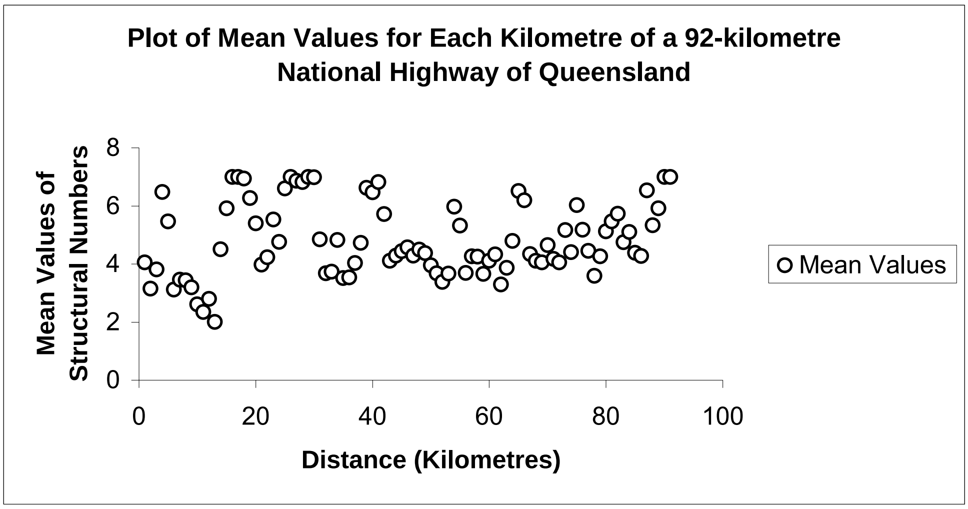

Figure 8 Mean values of each kilometre of a 92-kilometre National highway of Queensland

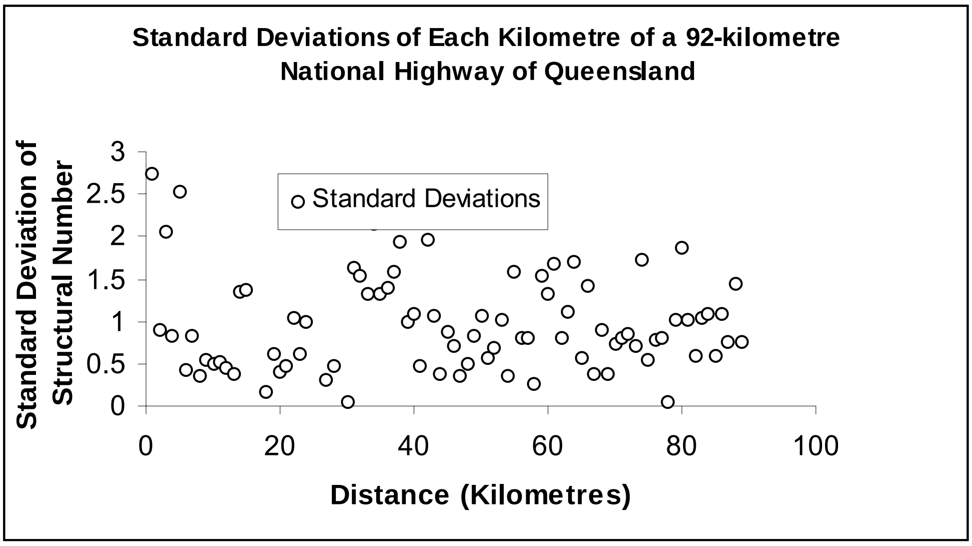

Figure 9 Standard deviations of each kilometre of a 92-kilometre National highway of Queensland

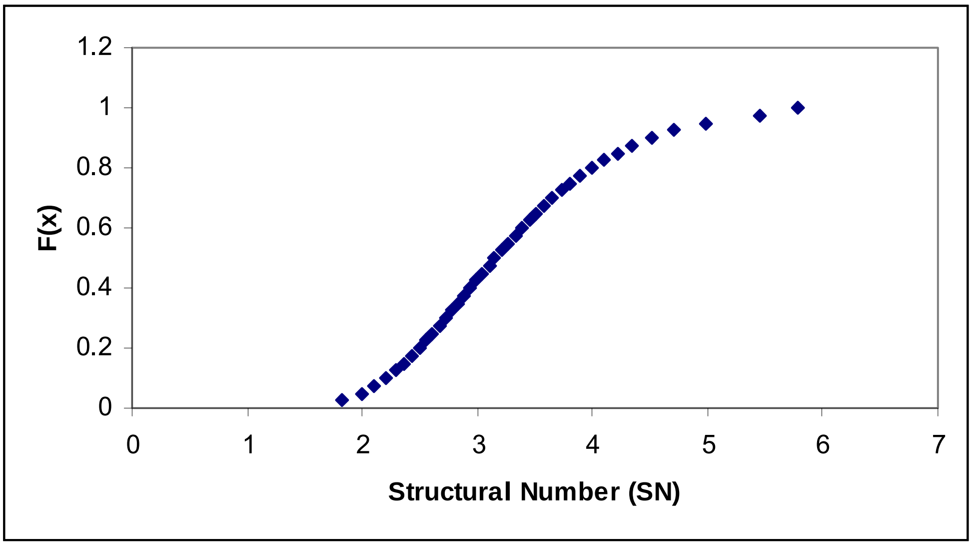

Figure 10 A typical cumulative distribution of Structural Number representing pavement strength sampled by Latin Hypercube Sampling Technique of one kilometre section for a 92-kilometre national highway

A series of analysis was conducted to obtain the statistical output of the life-cycle budget/cost estimates. HDM-4 computer software was used for this purpose. Details of the analysis can be found in Piyatrapoomi and Kumar (Aug. 2003).

Figure 11 shows the cumulative distribution of budget/cost estimate for maintenance and rehabilitation for a 25-year period. The probability distribution of the budget/cost estimates was log-normally distributed.

It can be seen from Figure 11 that the probability distribution can be explained by forty data points.

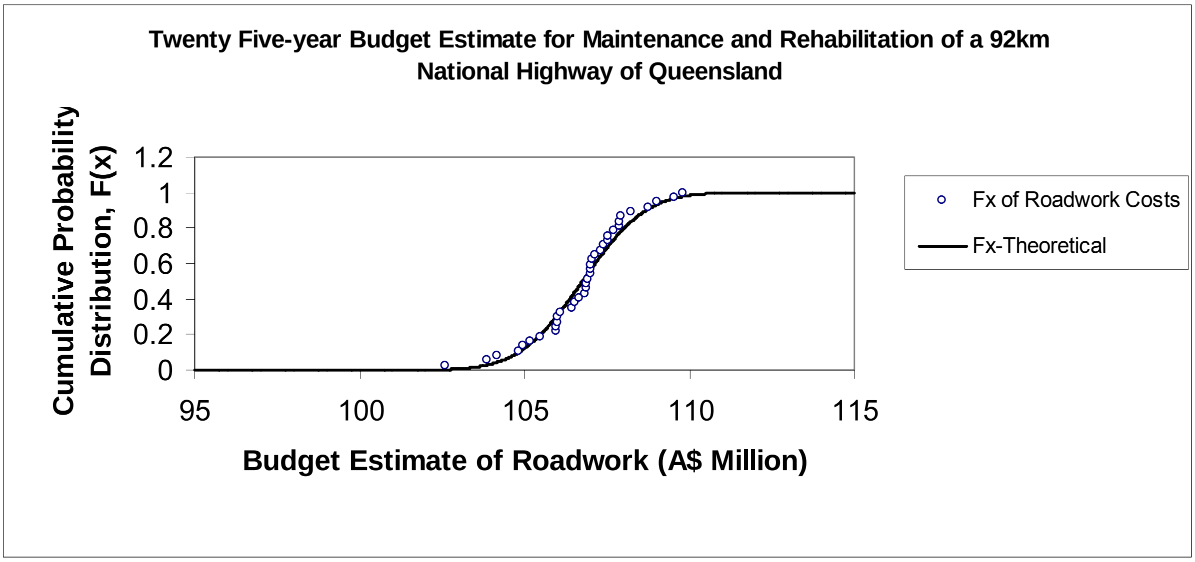

Figure 11 Cumulative distribution of budget/cost estimate for 25-year roadwork cost of a 92-kilometre National highway of Queensland (roadwork includes maintenance and rehabilitation)

The term "risk adjusted" in budget/cost estimate is defined as the budget/cost that is specified with a level of probability of occurrence. Asset managers could also make use of this information to select the budget/cost estimate of an appropriate probability of occurrence or with the probability of occurrence that they are comfortable with.

For example they may choose a budget/cost estimate of 5% probability of exceeding (or the 95th percentile budget/cost estimate). Figure 11 the budget/cost estimates which have 5% probability of exceeding was calculated to be A$ 109 million for a 25-year budget/cost estimate.

5. RISK ASSESSMENT INVESTMENT DECISION FRAMEWORK FOR INFRASTRUCTURE ASSET MANAGEMENT

An investment decision framework in the form of risk map in which social, environmental, political issues and other risk related issues could be incorporated in the assessment has been introduced by Piyatrapoomi and Kumar (Piyatrapoomi et al 2004, Piyatrapoomi & Kumar, Jan. 2003).

The concept of risk mapping will be discussed in this section and illustrated using the risk information presented in the preceding section. In order to provide life-cycle budget/cost for maintenance and rehabilitation for the 92km national highway for a 25-year period, there may be two budget scenarios, namely:

Scenario 1: The government could provide a budget of A$115 million
Scenario 2: The government could provide a budget of A$ 95 million

The probability distribution of life-cycle budget/cost estimate shown in Figure 11 can be used to assess the probability of occurrence of these two budget scenarios. These two scenarios can be plotted in the risk map according to the probabilities of occurrences. From Figure 11, the quantitative measure of risk can be calculated as follows:

$\Re$ = P(1-Pr)

Where:

$\Re$ = quantitative measure of risk expressed in terms of probability
Pr = cumulative probability

Figure 12 shows the probabilities of occurrences resulting from the budget of scenario 1 (A$115 million) and from the budget of scenario 2 (A$ 95 million). The probability that the project would be successful with a budget of A$ 95 millions was very low. The risk was almost certain that the project would not be successful. While the probability that the project would be successful with a budget of A$115 million was very high. Thus, the risk was low.

This risk map can be used as a tool to manage risk and adjust project allocations based on cost-benefit and risk. In risk mapping, the levels of risk can be quantified qualitatively or quantitatively. The X-axis is the magnitude of the resultant consequences, which range from being insignificant to highly significant. The Y-axis is the level of risk, which ranges from rare chance to certain chance of occurrence. It could be expressed in terms of quantitative measures of probability of occurrence. Intolerable region is the region where risks are high and the impact of the consequences is significant. Tolerable region is the region where risks are low and the impact of the resultant consequences is low. Moderate region is the region where risks and the impact of the consequences are at moderate levels.

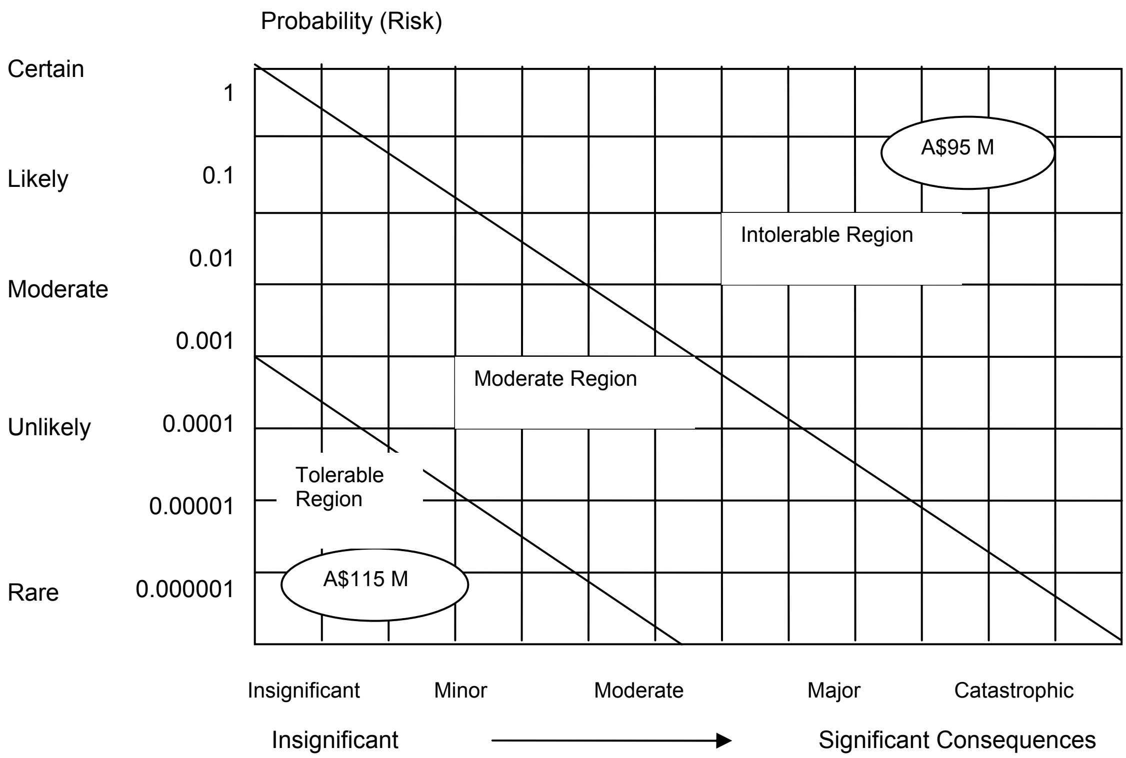

Figure 12 An illustration of plotting two budget scenarios into risk map

Decision-makers may need to incorporate other factors into consideration. These factors may include social, environmental, or political issues. Figures 13 and 14 illustrate this by plotting risks and consequences related to social, environmental and political issues into the risk map for the two budget scenarios.

In Figure 13, by providing a budget of A$ 115 million for maintenance and rehabilitation of the 92-kilometre National Highway for a life-cycle cost of a 25-year period, risks and consequences on social, environmental and political issues were expected to be low.

Social issues that may involve traffic noises and accident rates could be kept at a minimum level since pavement conditions are kept in good condition. Road users would be happy with the service provided by the government. Political issue might not be a major concern. Environmental risk and consequences would be kept at a low level resulting from less fuel consumption, less tyre-wear and less expenses for vehicle maintenance and repairs.

In Figure 14, by providing a budget of A$ 95 million for maintenance and rehabilitation, risks and consequences on social, environmental, economic and political issues are expected to be high.

Social issues on accident rates and the level of noise could be high since pavement conditions could not be maintained in good condition. Political issue might become a big issue. Environmental risk and consequences would be high since high fuel consumption due to delays, high tyre-wear and high costs for vehicle maintenance and repairs.

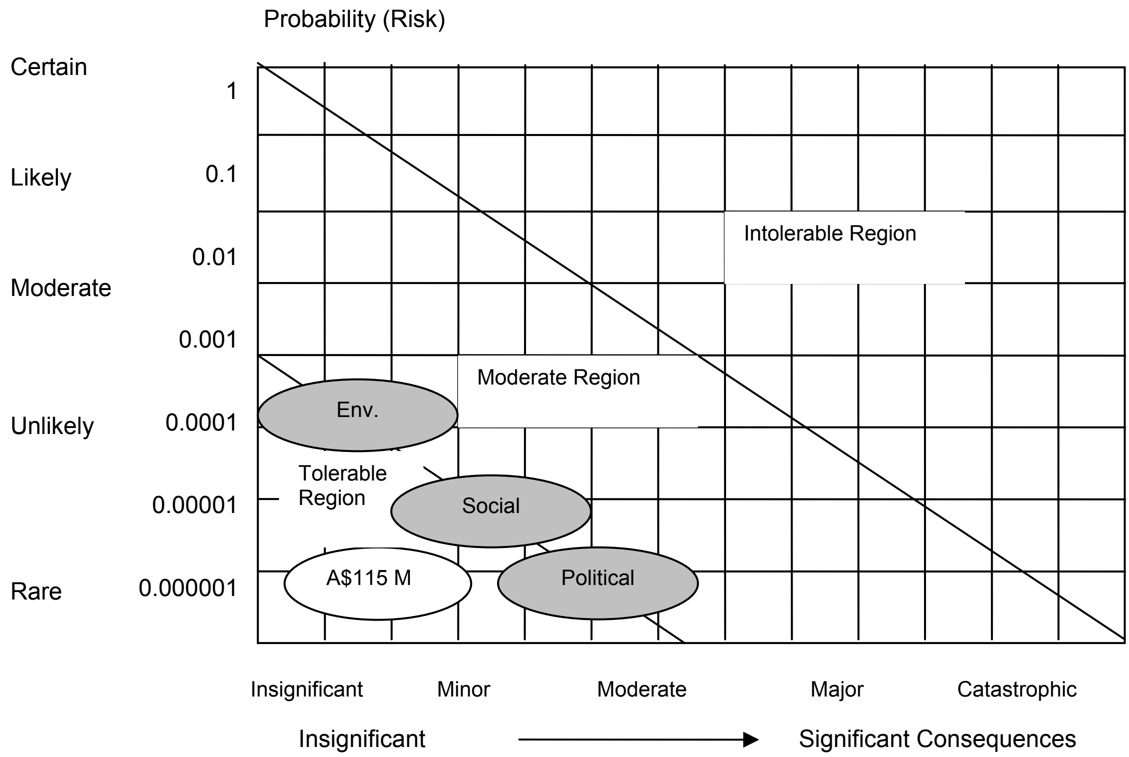

Figure 13 An illustration of plotting social, environmental economic and political impacts for budget scenario 1

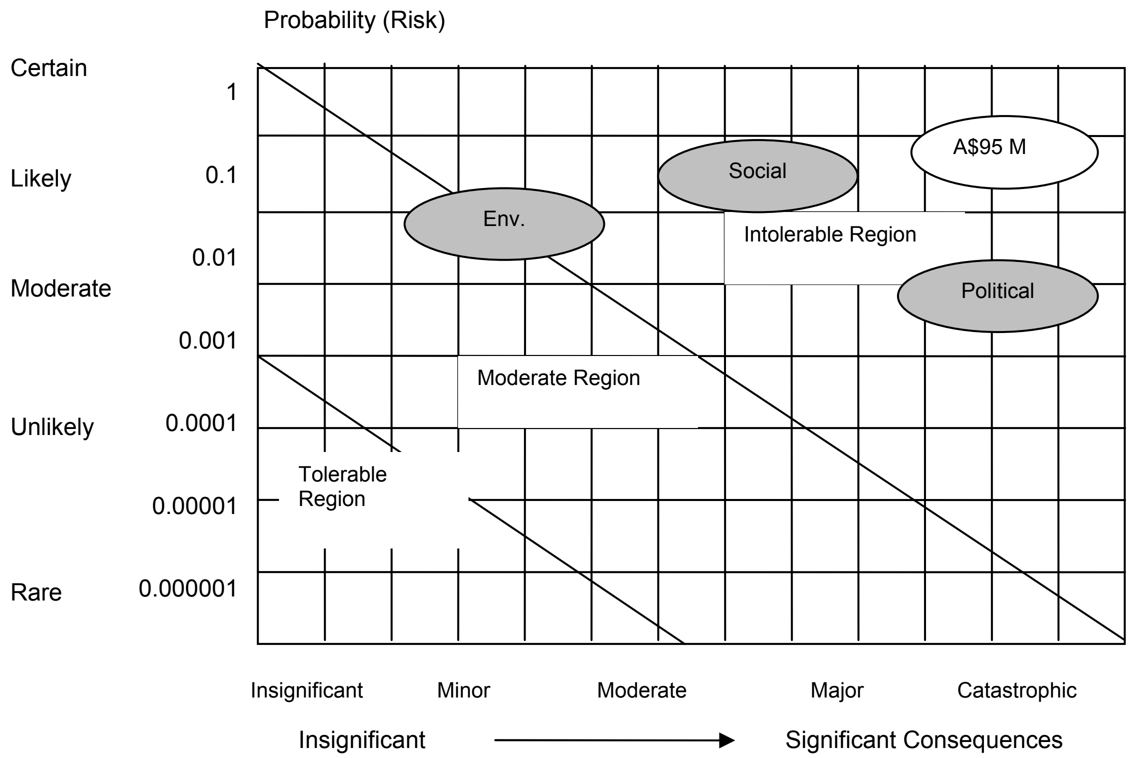

Figure 14 An illustration of plotting social, environmental, economic, and political impacts for budget scenario 2

Different scenarios would provide in depth information for decision-makers to trade-off between cost and benefit. Risk mapping provides information on risk levels and consequences of the decision-making.

In Figures 13 and 14, social, environmental and political issues were presented only for illustrating the concept of the risk map. Further assessment needs to be conducted to address risks and consequences of these issues.

6. CONCLUSION

In this paper, a methodology for assessing life-cycle budget/cost estimates for road asset management is presented. Three gaps have been identified and need to be addressed including data collection, calibration of road deterioration prediction models and risk-adjusted assessment in budget/cost estimates. The paper presented methodologies to solve these three issues.

The optimisation and reliability assessment method can be used in analysing optimal amount of data collection. More data could be collected for the same budget.

The calibration method can be used for calibrating deterioration prediction models in predicting deterioration rates of road infrastructures to suit local conditions.

The risk-adjusted assessment in budget/cost estimates can be used in assessing the variability of budget/cost estimates arising from the variability and uncertainty of critical input variables.

The paper also presented a risk map concept for investment decision-making in which social, environmental and political issues could be incorporated for consideration.

The methodology and concept could be used for other types of infrastructure asset management investment such as railways, bridges, buildings etc.

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