



23<sup>rd</sup> Australasian Transport Research Forum  
Perth, Western Australia 29 September – 1 October 1999

## Optimising Road Maintenance Projects on a Rural Network Using Genetic Algorithms

Renlong Han  
*University of Western Australia*

---

### Abstract

Road maintenance, as a general concept, covers all the activities that are carried out to ensure that serviceability does not fall below some minimum level during the design life of a road. It includes routine maintenance, rehabilitation and even reconstruction. The key problem is to specify the kinds of treatments and when they should be applied on every road segment, all being subject to budget constraints. This paper presents a method of identifying road maintenance and renewal projects and of prioritising and scheduling all of these potential projects in a network during an analysis period, based on the principle of maximising the net benefits from limited expenditure. Traditional methods, such as total enumeration, linear and objective programming, dynamic programming, and effective gradient, have been restricted to a limited number of projects, and could not deal adequately with the interdependence of projects. A robust genetic algorithm is used to solve these combinatorial optimisation and dynamic investment problems, taking full account of interdependence. The entire model includes two important sub-models dealing with travel demand forecasts and prediction of road deterioration. The model is being tested on the road network in the Wheatbelt Southern Region of Western Australia.

---

### Contact Author

Renlong Han  
Department of Information Management and Marketing  
University of Western Australia  
Stirling Highway  
Nedlands WA 6009

Phone: +61 8 9380 1875  
e-mail: r1han@ece1.uwa.edu.au

Fax: +61 8 9380 1004

## Introduction

A problem facing road authorities is how to allocate the available funds to optimise the mix of continuous maintenance and periodic renewal in successive future years. Previous studies of investment optimisation have not, if ever, adequately considered the interdependencies of projects. The usual way to avoid this problem has been to ignore the interdependencies, assuming that the performance of individual road sectors is independent of each other (Ahmed 1983; Prastacos and Romanos 1987; Watanatada et al. 1987). On this assumption, the benefits from projects were calculated separately and then summed. The objective was to maximise the total benefits achieved from all proposed projects and determine the sequence of projects according to the calculated net present values or cost-benefit ratios. Such an evaluation has normally used fixed traffic demand forecasts for future periods, not considering dynamic traffic transfers.

Because evaluations have not taken interactions between projects into account, the selected project sequence tended to be an inadequate response to theoretically predictable changes in traffic demand and road conditions. When maintenance and new construction are optimised together, the upgrading of a degraded road segment becomes a potential project. Modified road segments affect traffic assignment throughout the road system, thus affecting costs and benefits over the entire network. It is reasonable to argue that all the projects are interdependent, at least to some extent, and that no project should be considered in isolation.

Once the assumption of mutual independence is relaxed, the number of feasible project combinations becomes extremely large. It is virtually impossible to use traditional methods such as linear and goal programming (Ahmed 1983; Watanatada et al. 1987) to solve the complicated combinatorial problem resulting from the inter-dependency of road projects. Including maintenance with new construction in a complicated road network makes optimising even more difficult. Genetic algorithm (GA) has proved to be an effective optimisation tool for such combinatorial problems. The central task is to find a method to optimise the mix of continuous maintenance and periodic renewal work in a planning period. Thus, the aim of this study is to develop a model to prioritise and schedule a sequence of maintenance and renewal work to maximise community benefit.

In order to predict dynamic traffic shifting based on projected road modifications, two subsidiary models, for traffic demand and road deterioration, are required. Calibration of the model for traffic demand forecasting has been achieved with a combined gravity and logit route choice model based on populations and economic activities. The road deterioration prediction model is being developed for the study area.

## Problem statement

In any regional network, various maintenance treatments are undertaken to keep roads to a specified service level. In general, these maintenance activities can be grouped into three categories:

- Routine works. These are undertaken each year wherever they are needed. Activities can be grouped into cyclic and reactive work types. Because of their variety and coverage of every road, they are viewed as continuous works and usually funded from the recurrent budget according to a criterion, say a fixed rate for a unit of road lane. A typical example is patching, which is carried out in response to the appearance of cracks or potholes.
- Periodic works. These include activities undertaken at intervals of a number of years to preserve the structural integrity of roads, or to enable roads to carry increased axle loadings. Work can be grouped into preventive, resurfacing, overlay and pavement reconstruction, which are carried out in response to measured deterioration in road conditions. Typical examples are resealing and overlay. Periodic works are usually considered as discrete projects and funded on a regular basis or from the capital budget.
- Development. These are construction projects identified as part of development planning activity. They are funded from the capital budget. Examples are the construction of new roads, or the upgrading of existing roads.

In order to optimise various treatments, all roads in a planning network are split into segments (say around 5 kilometres), which are viewed as potential maintenance or even renewal project possibilities depending on forecasts of traffic demand and road conditions. There are 1651.3 kilometres of highways and main roads in the study area, the number of total split segments being 329. Together with some proposed new projects, the number of potential projects to be considered as competing for investment is over 330. Routine maintenance is specified at a continuous fixed rate. A genetic algorithm is used to select and schedule this large number of potential projects in a period  $s$  (say 10 years). Project optimisation is based on the road segment level, but cost calculation is based on the link level. If the total number of links in the road network is  $n$ , then road project-scheduling problem is stated as follows.

$$\text{Minimise} \quad \sum_{i=1}^n \sum_{j=1}^l \frac{1}{(1+r)^j} (c_{ij} + c'_{ij}) \quad (1)$$

$$\text{Subject to:} \quad \sum_{i=1}^n x_{ij} c_{ij} \leq b_j \quad (2)$$

$$\sum_{j=1}^l x_{ij} \leq 1 \quad (3)$$

$$x_{ij} \geq 0 \quad (4)$$

where

$c_{ij}$  = costs of the scheduled road projects on link  $i$  in year  $j$

$c'_{ij}$  = road user costs on link  $i$  and in year  $j$

$x_{ij}$  = proportion of a scheduled road project on link  $i$  constructed in year  $j$

$b_j$  = the budget available for year  $j$

$l$  = the analysis period

$r$  = discount rate

### Methodology - GA

In order to solve the above scheduling problem, GA is the best available method. GA as a computational technique was first developed and analysed by Holland early in the 1970s, but it was not widely used until about 10 years ago, and the application to the field of transport was even later. GAs are robust search algorithms based on the mechanics of natural selection and natural genetics (Goldberg 1989). The mechanics of evolution are simple yet powerful. The basic idea is to generate an initial pool of solutions, represented as string structures, and then, through continuous copying, swapping, and modifying of partial strings in a manner similar to natural genetic evolution, to allow the solution pool to evolve toward better solutions.

A powerful aspect of GAs is their use as an optimisation technique in overcoming the combinatorial explosion of certain problems like prioritising and scheduling road maintenance projects. In a situation like this, GAs have been found to be a useful tool to provide a good and acceptable solution within a practical period of time (Goldberg 1989).

Another attractive aspect of GAs is the flexibility permitted in defining the objective. It is relatively easy to modify the objective function to suit a user's requirements without affecting the efficiency of the GA search. In the application to road-maintenance management, the objective function could be to minimise the present value of the maintenance costs, or to maximise the effectiveness for the community of the whole investment over an analysis period.

A third aspect of GAs is their ability to cope with practical constraints. It is easier to impose non-linear constraints than in traditional methods such as linear and goal programming. In the process of road project optimisation, the budget is the most common constraint, restricting the maximum expenditure within a predetermined analysis period or in every year. However, there can be other constraints such as labour and equipment, or an operational constraint that one project must be completed before another, or that a big project must be implemented in several continuous years.

A fourth important aspect of GA is its ability to handle a non-convex, multiple optima problem, where a traditional hill-climbing method may find only a local optimum. The main disadvantage of a GA is that it cannot reach the exact global optimum. However, experience indicates that a GA consistently yields a solution with a high probability of being at or near the global optimum.

The ability of GAs to overcome the problem of combinatorial explosion, the flexibility in adapting the objective function, the ability to impose various constraints to a user's requirements, and to handle non-convex, multiple optima problems make them a useful tool in road project planning.

**Optimising Process**

Coding is an important step for genetic algorithms, continuous integer numbers being selected for this study. All of the split road segments plus the proposed new projects are coded as integer numbers from 1 to *N*. The specific optimisation processes are as follows:

First, using GA generate one solution of the problem, a GA chromosome being a random sequence (e.g., 1, 2, 3, ..., *N*) for the *N* potential projects;

Second, perform the following steps year by year for the analysis period;

- By reference to criteria and standards, determine how each identified segment is to be maintained and what sort of treatment is to be carried out according to the predicted road conditions in the rank order set by the first step,
- Estimate the cost of the projects to be implemented,
- Arrange the projects in an implementation timetable, according to the yearly budget and other constraints,
- Carry out traffic assignment on the basis of population and GDP forecasts using the travel demand model.
- Forecast road deterioration, measured on the roughness scale,
- Calculate vehicle operating costs.

Third, calculate the total costs of the entire network, that is, the objective function.

Figure 1 shows a conceptual example of road segments given different treatments such as routine, patching, resealing, overlaying and reconstruction. When roughness is over 9 m/km, reconstruction is undertaken.

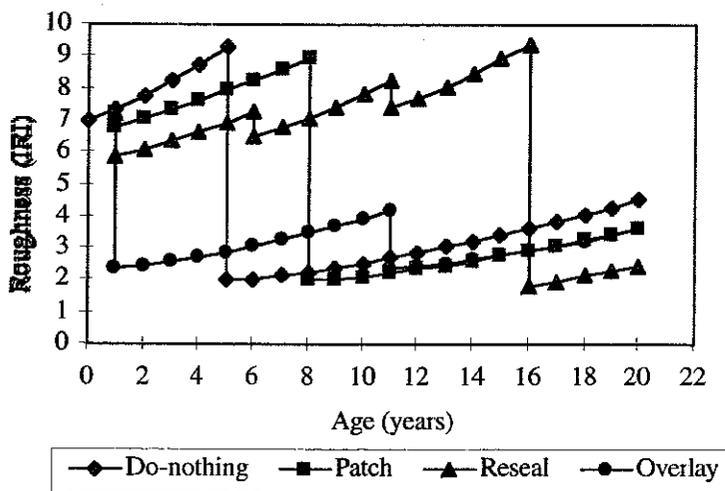


Figure 1 Different maintenance treatments at different roughness levels

The above three steps must be repeated for each member of the population of GA chromosomes or strings (e.g. 1000) multiplied by the number of generations (e.g. 1000), until the optimal or near optimal result is found. The solution is the optimal timetable. However, in this application for a 30-year period, traffic assignment will be performed  $30 \times 1000 \times 1000$  (i.e. 30,000,000) times. This is a heavy burden in computing time and dominates the entire computing process.

**Travel demand forecast**

A one-step simultaneous model is used to forecast travel demand. Assigning traffic volumes to routes between origin and destination (OD) pairs usually requires knowledge of both the road network conditions and the number of trips made between each OD pair, but no information is available for OD trips. To overcome this data deficiency and to forecast traffic volumes on each route a combined gravity and logit choice model has been developed.

The following three reasons make it necessary to forecast traffic demand for passenger cars and freight vehicles separately.

- Freight vehicles contribute much more to road deterioration than passenger cars;
- The generation of passenger cars is more related to the population of OD zones, while the generation of freight vehicles is more related to the economic activities in OD zones; and
- Tourism influences the attraction of car trips to a tourism destination significantly, but has little influence on truck travel.

Therefore, two different gravity models, one for passenger cars and the other for freight vehicles, respectively combining with a logit route choice model, form the two travel demand models. Local agricultural and mining freight traffic is estimated separately and deducted from truck traffic before the general model is calibrated. The two demand models are:

$$\text{Passenger car} \quad F_i = \sum_{\forall r \in O} \sum_{\forall s \in S} \sum_{\forall k \in K_{ij}} \frac{\delta_i^k \alpha [\Omega_r P_r P_s]^\beta e^{-\theta u_{rs}^k}}{C_{rs}^\gamma \sum_{\forall k \in K_{ij}} e^{-\theta u_{rs}^k}} \quad (5)$$

$$\text{Freight vehicles} \quad F_i = \sum_{\forall r \in O} \sum_{\forall s \in S} \sum_{\forall k \in K_{ij}} \frac{\delta_i^k \alpha [G_r G_s]^\beta e^{-\theta u_{rs}^k}}{C_{rs}^\gamma \sum_{\forall k \in K_{ij}} e^{-\theta u_{rs}^k}} \quad (6)$$

where

$F_i$  = estimated traffic flow on link  $i$

$P_r, P_s$  = the populations of origin  $r$  and destination  $s$

- $\Omega = \xi^\tau$ , where  $\xi$  = tourism attraction factor;  $\tau = 0, 1, \text{ or } 2$  meaning neither, one, or both of origin and destination zones are recognised tourism destinations
- $G_r, G_s$  = Gross Domestic Product (GDP) of origin  $r$  and destination  $s$
- $C_{rs}$  = separation (distance or time) between origin  $r$  and destination  $s$
- $u_{rs}^k$  = travel cost (distance or time) by route  $k$  between origin  $r$  and destination  $s$
- $\delta_i^k$  = equal to 1 if link  $i$  is on route  $k$ , 0 otherwise
- $\beta, \gamma$  = trip demand elasticities with respect to population product and distance
- $\alpha$  = a scale parameter
- $\theta$  = a distribution parameter

On the basis of road network information, population and gross domestic product of OD zones, and observed road link flows, the parameters in the joint models (5) and (6) can be calibrated by minimising the total difference between estimated link flows and observed link flows. This has been done by maximum likelihood methods. For this non-convex problem, a combined genetic algorithm and Newton's method was used to reach the global optimum (Han 1998).

Data and results

The road network in the study comprises the Significant Roads in the draft Roads 2020 Regional Road Development Strategy 1997 (MRWA 1997), for the Wheatbelt Southern Region. For modelling purposes, it was also necessary to include other regions in Western Australia and the other states of Australia, each being treated as a single zone. In the network specified, there are 125 nodes, 194 links, and 39 OD zones of which six in or near the study area, are recognised as tourism destinations. Data include:

- Car counts on the 136 links in the Southern Wheatbelt study area,
- Link lengths for the 194 links on the whole network,
- Populations of the 39 OD zones.

The final solutions for car travel obtained with Newton's method using GA's results as the starting point are shown in Table 1. It can be seen that the calibrated parameter values are reasonable; and the tourism attraction parameter  $\xi$  of 1.55 indicates that the population of a recognised tourism destination has 55% more attraction power than a normal population. The  $R^2$  of 0.947 shows the calibrated model fits the data well. The 't' ratios of all five parameters give a high level of confidence that the parameters are non-zero.

Table 1 Optimum from Newton's Method Applied to the Genetic Algorithm Results

Parameter	Parameter Estimate	Standard error	't' ratio
Scalar ( $\alpha$ )	2.5901	0.1836	14.1
Population Elasticity ( $\beta$ )	0.5563	0.0030	184.5
Negative of Distance Elasticity ( $\gamma$ )	1.6508	0.0114	144.4
Logit Parameter ( $\theta$ )	0.0484	0.00081	59.7

Visitor Attraction ( $\xi$ )	1.5561	0.1039	15.0
$R^2 = 0.947$			

Also, the likelihood ratio test of two models which include a tourism attraction factor against a restricted model without such a parameter shows that the influence of tourism on visit attraction should certainly be taken into account, at least in the study area.

### Roughness prediction models

Roughness is widely used as an indicator of road deterioration. It is used to measure performance for pavement design, pavement maintenance and cost analysis over the life of a road.

The most important technical aspect of a model to prioritise and schedule maintenance and new projects is the development of a sub-model of pavement deterioration. For the purpose of this study, roughness is adopted as the single criterion for measuring road deterioration. The purpose of a road deterioration model is to predict future roughness as the road ages and traffic changes.

### Current roughness models

The roughness models currently used in Australia include the roughness prediction model in the NIMPAC Road Planning Model (NAASRA 1981), the ARRB model (Martin and Taylor 1994), and the World Bank's HDM3 model (Watanatada et al. 1987). On the bases of the NIMPAC model, Main Roads Western Australia (MRWA) developed a modified model suitable for use in Western Australia (Lloyd and Pyke 1996).

#### Age based models

The simpler version of the NIMPAC and MRWA models are based on estimates of the relationship between roughness and age, roughness being a quadratic function of age. Prerequisites for using this kind of model successfully for prediction are:

- Normal maintenance has been conducted and will continue;
- Pavements are suitably designed for their traffic loadings in the life cycle; and
- Other extrinsic factors affecting pavements are common to all roads

Models based on age do not deal with the effects of other important factors such as traffic loadings and pavement structure strength.

#### HDM3 model

The best known road assessment model is the Highway Design and Maintenance Standards Model (HDM3) (Watanatada et al. 1987), which was developed by the World Bank for the evaluation of road projects in developing countries. Its sub-model, the road deterioration model, has been applied widely by road authorities (Bein et al. 1989; Miller and Loong 1990). The deterioration model, which estimates the combined effects

of traffic, environment and age on the condition of the road, has two forms: incremental and aggregate.

The incremental model estimates the changes in roughness over time. The components are (1) structural deformation due to the number of equivalent standard axles (ESA's) and structural number (2) surface condition, related to changes in cracking, potholing and rut depth variation and (3) an age-environment-related roughness term. However, this model excludes maintenance effects for all flexible pavement types.

Under relatively good maintenance, the superficial defects, cracking, potholing and rutting, do not critically affect roughness progression on roads in lightly trafficked areas and are excluded from the model for the study area. Omitting rutting and cracking for this particular set of roads, Paterson's model is reduced to (Oppy and Parkin 1994):

$$dR(t) = \alpha e^{mt} (1 + SNC)^\gamma dNE4 + mR(t)dt \quad (7)$$

where

$dR(t)$  = increase in roughness over time  $dt$

$SNC$  = modified structural number of pavement strength

$dNE4$  = number of ESA's in period  $dt$

$m$  = environmental coefficient

$\alpha$  and  $\gamma$  = parameters to be calibrated

The HDM3 road deterioration model in its aggregate form estimates roughness at a particular time, being

$$R(t) = [\alpha(1 + SNC)^\gamma NE4 + R_0]e^{mt} \quad (8)$$

where

$R(t)$  = road roughness at time  $t$

$t$  = pavement age since latest overlay or reconstruction

$R_0$  = initial road roughness at time  $t = 0$

$SNC$  = modified structural number of pavement strength

$NE4$  = cumulative number of ESA's since latest overlay or reconstruction

This is the typical mechanical-empirical model for road deterioration forecasting. It was claimed to be transferable because mechanical principles were used to guide the general form and combination of parameters in the relationship (Paterson 1989). However, when used in countries other than Brazil, where it was developed, the parameters should be re-calibrated to suit local conditions (Bein et al 1989; Cox and Rolt 1986). The aggregate model does not consider the influence of maintenance practices for flexible pavement types.

## ARRB model

To overcome disadvantages of the above models, ARRB developed a roughness prediction model which takes account of the effects of maintenance on pavement behaviour (Martin and Taylor 1994).

$$R(t) = R_0 + A \times \left( \frac{I + 100}{SNC} \right)^a \times t^b \times \left[ 1 + \frac{B \times L^c}{(ME + 200)^d} \right]$$

where

$R(t)$  = roughness at time  $t$

$R_0$  = initial roughness

$I$  = Thornwaite Index

$SNC$  = modified structural number of pavement strength

$t$  = pavement age since construction, reconstruction or major rehabilitation

$L$  = annual traffic load in average cumulative equivalent standards axles

$ME$  = average annual maintenance expenditure, sum of routine and periodic maintenance

$A, B, a, b, c, d$  = parameters to be calibrated

However, data on pavement-related maintenance since a road's construction, including routine and periodic, is not usually available.

## The specific model for this study

The HDM3 road deterioration model has been selected as the basis for this study. Even though it does not include maintenance practice, one can assume, for the aggregate model, that the recent past and current routine and periodic maintenance regime will remain unchanged. However, for the incremental model, recent maintenance expenditure (say from 1997 to 1998) is not difficult to extract. Based on the form of the HDM3 incremental model, a revised incremental model is being developed and calibrated for the study area.

When models (7) and (8) are adapted to local conditions, usually two parameters,  $\alpha$  and  $\beta$ , are calibrated from field data, while other parameters are based on the HDM3 results (Martin and Taylor 1994; Paterson 1986). In this situation, the parameters can be calibrated by linear regression.

In order to make the aggregate model (8) more suitable for local conditions, this study generalised it to the following form, even the initial roughness being specified as a parameter  $\xi$ .

$$R(t) = [\alpha(1 + SNC)^{\beta} (NE4)^{\theta} + \xi] e^{\beta t} \quad (9)$$

Model variables

Model (9) includes three independent variables: age, modified structure number and traffic. Age and traffic are the same as in the previous studies (Martin and Taylor 1994; Paterson 1989). With regard to the modified structure number, SNC, available information on pavement strength is falling weight deflection and curvature. The curvature, the difference in vertical deformation between the point 0 and 200 mm, is an important and useful indicator for assessing pavement strength. The bigger the curvature, the faster the pavement deteriorates. If measured deflection is converted to a modified structural number as before (Miller and Loong 1990; Watanatada et al. 1987) information will be lost. In this study, the measured curvature is used directly as a variable in the roughness prediction model. Then model (9) becomes

$$R(t) = [\alpha(\text{Curvature})^\gamma (NE4)^0 + \xi] e^{\beta t} \quad (10)$$

Calibration of the aggregate model

Newton's method was used to maximise the likelihood function of model (10). However, the solution space is not strictly convex. A quadratic hill-climbing method was first used to find a start point to the convex space (Goldfeld et al. 1966), and then the Newton's method was used to find the optimum (Greene 1997).

Data and results for the aggregate model

The study area chosen meant that the scope of the study was limited to flexible pavements with seal surfacing in a semi-arid subtropical non-freezing environment.

In the study region, surface deflection has been measured at intervals of roughly 800 metres. There were 6148 deflection and curvature records, of which 3092 records were for left lanes and 3056 for right lanes. Data files of roughness, traffic and age were combined and matched with the files based on the falling weight measuring positions. Finally, 3689 valid records were available for model calibration after deleting invalid records.

For this study, a starting point was selected by reference to the HDM3 results to begin the hill climbing. In most cases, the problem converged in less than 100 iterations. The calibrated results are shown in Table 2.

Table 2 Calibration results using the Newton's hill-climbing method

Parameter	Parameter Estimate	Standard error	't' ratio
Scalar ( $\alpha$ )	0.3703	0.09258	4.00
Environmental Factor ( $\beta$ )	0.0091	0.00038	24.14
Curvature Parameter ( $\gamma$ )	1.1711	0.31699	3.69

Traffic Parameter ( $\theta$ )	0.6776	0.25084	2.70
Initial Roughness ( $\xi$ )	1.7820	0.02843	62.68

$R^2 = 0.133$

All parameters converged to reasonable values and the 't' ratios indicate that the parameter values are all significantly different from zero at the 1% level. The relatively low  $R^2$  of 0.133 suggests that the model misses some important contributors to variability.

The highly significant parameter  $\beta$  with t ratio of 24.14 represents the influence of environmental and ageing factors. Its calibrated value of 0.0091 is less than the standard value of 0.016 for semi-arid subtropical non-freezing regions (Miller and Loong 1990). The apparent reason is that good maintenance retards the progression of roughness due to ageing under the environmental influences.

The calibrated initial roughness  $\xi$ , 1.782 m/km, equivalent to 45.9 Nassra counts/km, is a reasonable value, but is a little higher than that NIMPAC's 40.9, and MRWA's 42.3 (Lloyd and Pyke 1996).

Validity of the calibrated model

Figure 2 shows that the modelled roughness points cluster around a straight line through the heart of the measured roughness points. This reflects the fact that the model does not fit the sample data well because it lacks some important variables such as maintenance expenditure to explain the variations. This modelled line shows a rate of roughness progression of about 1% a year. The increase is kept down by the maintenance partly compensating for deterioration due to environment and traffic.

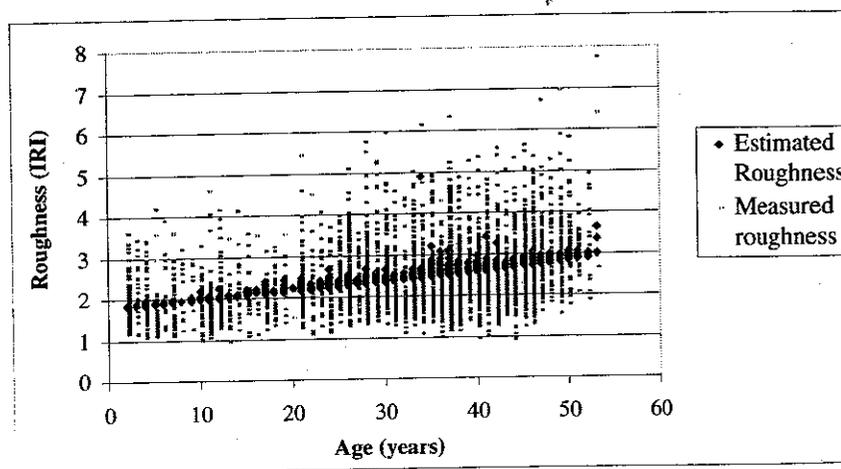


Figure 2 Modelled roughness and measured roughness

Nevertheless, the calibrated model shows the average trend in road deterioration over the entire road network under normal maintenance practice, most effects of age, traffic and environmental factors being masked by maintenance. If there is no change in practices, it can be used to predict the roughness. However, this model is inadequate for the purpose of prioritising and scheduling maintenance activities.

To overcome the shortcoming of the aggregate model, an incremental or progression model including a maintenance factor is being developed and calibrated with data for recent years.

### **Project optimisation**

Once the travel demand and road deterioration models are calibrated, they can be used to forecast travel demand and road deterioration. Passenger cars from which most road user cost savings come are forecast from population projections; and freight vehicles, which contribute most to road pavement deterioration, are predicted from gross domestic product projections and agricultural and mineral production. Also pavement roughness is predicted from estimated truck traffic.

The other important thing is to apply a suitable model of the effects of roughness on vehicle operating costs. After all of the component models are estimated, a genetic algorithm can be used to optimise the sequence of projects.

Genetic algorithm, as an optimisation method, is fundamentally different from conventional methods in that it generates a project sequence first, and then determines the merit of the specific sequence of projects in terms of benefits achieved. For the specified sequence, dynamic traffic forecasting and prediction of pavement deterioration can be done for successive years. Project costs are calculated and projects are arranged in a timetable under annual budget constraints. Also the treatments for each segment are determined, and vehicle operating costs calculated. Finally, the objective function for each sequence is estimated at a given discount rate.

The genetic algorithm first randomly generates a population of chromosomes, being project sequences, to form a generation. Then through genetic operators, reproduction, crossover and mutation, the objective functions are improved from generation to generation. Finally, the optimal solution is found after many generations' evolution. This solution is the project sequence which will achieve the highest investment returns.

### **Conclusion**

Because this study relaxes a crucial assumption that individual road sectors are independent of each other, It makes the number of combinatorial solutions extremely large. Optimising from so many possible project combinations cannot be handled by traditional methods but can be done by genetic algorithm.

The gravity model and the logit route choice model of the conventional four-steps were combined into a single model for travel demand forecasting. A genetic algorithm combined with Newton's method was used to calibrate this non-linear model.

Maximum likelihood is also an effective procedure to calibrate the HDM3 roughness prediction model under local conditions. Of the two available models, incremental and aggregate, it is easier to extract maintenance information for the incremental model. Furthermore, the incremental model is more suitable for predicting future roughness.

This study will extend the methods to the difficult problem of cyclical renewal versus continuous maintenance. Development of a model enabling road authorities to allocate their limited funds optimally will help to resolve the perennial problem of allocation between maintenance and major projects. The model will be able to prioritise and schedule maintenance and road projects for successive future years.

#### Acknowledgement

The author would like to thank Mr. Geoff Murray, Mr. Andrew Pyke, Mr. John Murphy and Ms. Joanne Jurica of Main Roads Western Australia for supplying data and valuable suggestions. The author also would like to thank Professor John Taplin for his valuable input. Any errors in the paper are the sole responsibility of the author. Renlong Han holds an Overseas Postgraduate Research Scholarship for his PhD study with Professor Taplin.

#### References

- Ahmed, N U (1983) An analytical decision model for resource allocation in highway maintenance management *Transportation Research* 17A(2), 133-138
- Bein, P, Cox, J B, Chursinoff, R W, Heiman, G H and Huber, G A (1989) Application of HDM3 pavement deterioration model in Saskatchewan pavement management information system *Transportation Research Record* 1215, 60-69
- Cox, J B and Rolt, J (1986) An integrated approach to pavement design based on HDM III pavement performance and vehicle operating cost relationships *Proceedings 13th ARRB Conference*, 135-149
- Goldberg, D E (1989) *Genetic algorithm in searching, operation and machine learning* Massachusetts: Addison Welsley Publishing Company, Inc.

Goldfeld, S M Quandt, R E and Trotter, H F (1966) Maximization by Quadratic Hill-climbing *Econometrica* 34(3), 541-551

Greene, W H (1997) *Econometric Analysis* New Jersey: Printice-Hall

Han, R L (1998) Calibration of parameters for a combined gravity and traffic assignment model *Proceedings of Progress in Optimisation II: Contribution from Australia* Perth: Kluwer (in press)

Lloyd, B and Pyke, A (1996) The Main Roads Western Australia mean age/roughness model and its application in road life expectancy forecasting Main Roads, Western Australia, Perth

Martin, T C and Taylor, S Y (1994) Like-cycle costing: prediction of pavement behaviour *Proceedings 17th ARRB Conference 17(6)*, 187-206.

Miller, M J E and Loong, K Y (1990) Pavement management: development of a life cycle costing technique *Bureau of Transport and Communications Economics*, Melbourne: BTCE

MRWA (1997) *Roads 2020 regional road development strategy Main Roads, Western Australia* Perth: MRWA

NAASRA (1981) *Computer System: NIMPAC Road Planning Model* Victoria: NIMPAC

Oppy, E T and Parkin, A K Pavement performance models for road agency and user requirements *Proceedings 17th ARRB Conference 17(4)*, 137-151.

Paterson, W D O (1986) Prediction of road deterioration for pavement management and policy evaluation *Proceedings 13th ARRB Conference 13(4)*, 216-226

Paterson, W D O (1989) A transferable causal model for predicting roughness progression in flexible pavements *Transportation Research Record* 1215, 70-84

Prastacos, P and Romanos, M (1987) A multiregional optimization model for allocating transportation investments *Transportation Research* 21B(2), 133-148

Watanatada, I Harral, C G William D O Paterson, Dharieshear, A M Bhandari, A and Tsunokawa, K (1987) *The Highway Design and Maintenance Standards Model* Baltimore: The Johns Hopkins University Press