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A PROBABILISTIC PERFORMANCE MODEL FOR TRANSPORT INFRASTRUCTURE MANAGEMENT: THE CASE OF HIGHWAY PAVEMENT

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This paper deals with a model system for stochastically represent performance of road infrastructure. This system consists of two submodels which represent 1) deterioration and 2) repair intervention behaviors of a road agency. These are developed based on the concepts of failure time models (FTMs) using repair history, truck traffic volumes, pavement condition and age as explanatory variables. The future road performance is predicted based on the probabilities obtained by these submodels and the cohort survival concepts. Finally, sensitivity of expected pavement condition, reliability and maintenance costs to different budget levels and policy alternatives such as budgeting scenarios and priority criteria is evaluated.

Key Words : *pavement deterioration, stochastic models, infrastructure management.*

1. INTRODUCTION

The importance of management and maintenance of road infrastructure can be understood by examining the dire economic consequences of serious infrastructure deterioration. A good example of such a situation in the US has been given in "America in Ruins"$^{1)}$:

> America's public facilities are wearing out faster than they are being replaced. Under the exigencies of tight budgets and inflation, the maintenance of public facilities essential to national economic renewal has been deferred. Replacement of obsolescent public works has been postponed. New construction has been cancelled.
>
> The deteriorated condition of basic facilities that underpin the economy will prove a critical bottleneck to national economic renewal during this decade unless we can find ways to finance public works.

In Japan, the necessary maintenance cost has been almost fully budgeted through treasury loans and investment, so far. However, in the future, according to the rapid increase in road infrastructure stock (**Fig.1**) and the aging of the network, it will become difficult to budget for all the maintenance required. Therefore it is a necessity to provide information on when, where and how to repair in order to minimize the possible future damage cost due to budget shortage. Such information should also include the amount of direct and indirect costs incurred at any damage level.

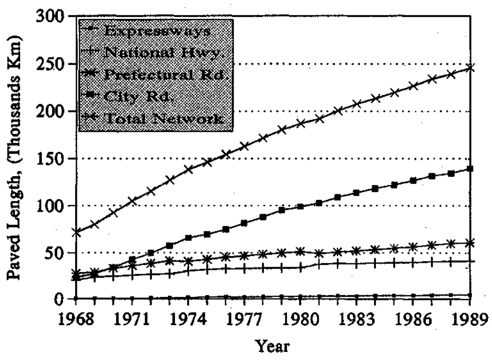

Fig.1 Growth of Japan's Paved Road Network.

Having recognized the importance of the above issue, we have developed a model system to provide such information, focusing on highway pavements as a typical example. The system is composed of the following elements (**Fig.2**):

1. model to forecast future road performance as an outcome of deterioration and repair intervention,
2. evaluation system of direct impacts on road users in terms of increase in vehicle operating costs, travel time, and ultimately transportation costs,
3. model to forecast indirect impacts on the regional economy in terms of production loss and disruption of development patterns,
4. GIS system to support the decision making process regarding road management.

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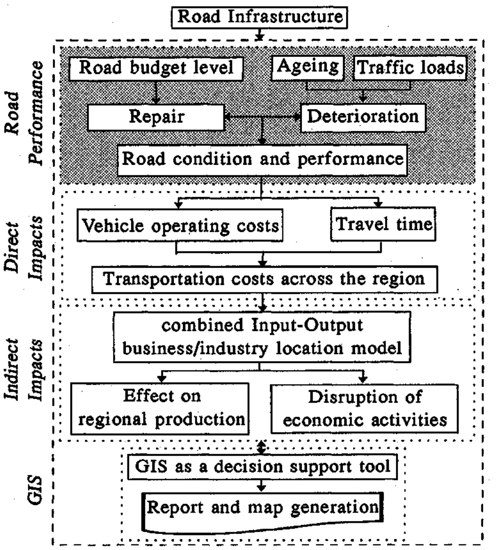


Fig.2 Elements and Flow Logic of the Overall Study.

This paper describes the development and application of the first component of the system, namely the deterioration and repair model. Discussions of the other components can be found in other references[2),3),4)].

2. STOCHASTIC MODELING OF PAVEMENT PERFORMANCE

(1) General Introduction and Objectives

Over the past two decades, a large number of pavement performance models were developed and used mainly for rationalizing planning in the area of pavement maintenance and repair. Most of these models can be categorized as deterministic models in which performance can be determined by a certain function, such as the equation of the AASHTO road test. Such deterministic models do not explain the variation in pavement condition with age[5)] shown in **Fig.3**. This variation is attributable to the complex interactions of several uncertain factors, such as traffic, materials, design, and environment, which result in various deterioration mechanisms difficult to express deterministically. As a result, a few probabilistic models were recently developed in which deterioration is treated in a probabilistic manner. These models apply techniques such as Markov chain and survivor curves; and employ transition matrices which describe the probability of transition between successive condition states[6)].

Review of the available examples of probabilistic models[5),7),8)] reveals the following points which need more considerations:

- The transition rate between any two successive condition states is assumed to depend only on the proceeding state of the pavement. Consideration of the effect of pavement age on the transition rates is also essential since age is the most significant factor influencing deterioration[6)].

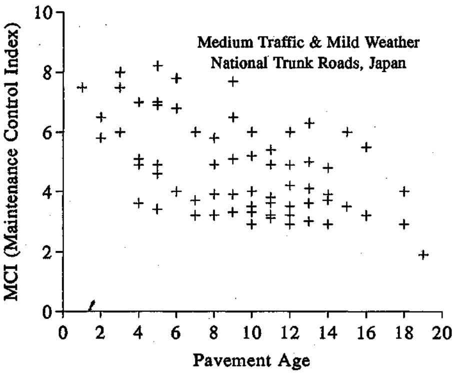


Fig.3 Variation of Pavement Condition with Age.

- In applying these models for performance prediction, repair intervention is treated as a deterministic event based on pavement condition. However, according to actual records of past repairs, selected sections are not always the worst ones. This disturbances in repair timing can be attributed to the subjective factors which have to be considered in the repair decision such as strategic, technical and financial constraints. Consequently, a probabilistic approach for predicting repair intervention is more realistic.

The main objective of this paper is to develop a probabilistic model for pavement deterioration and "failure", that is, need for repair that takes the above points into consideration. The concepts of failure time models (FTMs) for analyzing life expectations of mechanical and structural elements subject to random failure are particularly suitable for the aimed objective. Thus, these concepts are briefly introduced and applied to develop the model. Also application of the model to the prediction of the required amount of repair is demonstrated for a study road network. Changes in pavement condition and age-structure of the study network with time and different repair levels are given. The average reliability of the network is estimated from its age-structure and used as a measure of performance evaluation.

(2) Concepts of Failure Time Models

FTM is simply a probability distribution function of a non-negative stochastic variable representing the failure time of an individual from a homogeneous population group[10),11)]. The term failure does not necessarily mean physical failure. Rather, it refers to the occurrence of a predefined event. For instance, such an event might be defined as the occurrence of a specific change in pavement condition. Thus, referring to the time required for this change to occur as T, then the FTM is the probability distribution function of T, given that T is stochastic. In FTM, usually time is the only explanatory variable for failure. Thus, for accuracy, FTM should be constructed for homogeneous populations (other explanatory variables, e.g. traffic and pavement type, are treated as fixed parameters).

(3) Suitability of FTM

The suitability of FTM for modeling pavement deterioration and "failure" can be concluded from the following points:

- First, while several factors are interacting together to result in pavement deterioration, the effect of all these factors on pavement is inherent in the age (time) at which a specific condition is reached. Thus, for a homogeneous population, deterioration can be fully expressed in terms of pavement age.
- Second, according to **Fig.3**, the age at which a specific condition is reached varies from case to case. Thus, for pavements, this age can be considered as a non-negative stochastic variable.
- Third, deterioration/"failure" can be defined as a group of successive events or, in other words, a multi-stage failure. In deterioration modeling, these stages can be, for example, stage I: transition from excellent state to good state; stage II: transition from good state to fair state; and so on. As for "failure", it can be represented by one stage, that is transition from a "repair not required" state to a "repair required" state.
- Fourth, due to the variation of condition with age and the effect of the strategic, technical and financial factors on repair timing, the occurrence of any failure stage may happen at any age. Thus the transition rates to successive states can be represented by a continuous probability density functions.
- Finally, under the assumption of population homogeneity, the road sections under study can be divided into homogeneous populations based on the factors affecting the deterioration rate, such as traffic and pavement type.

From the above points, pavement deterioration/"failure" can be modeled in the form of a group of FTMs in which pavement age is the only variable. In the rest of the paper, it is assumed that the road network is divided into n homogeneous populations and deterioration/"failure" is represented as transition of condition over m states. The transition between any two successive condition states, e.g. from state k to $k+1$, represents one failure stage. Thus deterioration/"failure" is expressed by $m-1$ failure stages. This results in $(n*(m-1))$ failure time models, i.e. one model for each population class i, $(i=1,2,..,n)$, and failure stage j, $(j=1,2,..,m-1)$.

(4) Forms and Applications of FTM

The probability distribution function in FTM can be expressed in three different forms which are particularly useful in survival applications (**Fig.4**):

A probability density function (PDF) is the basic form of FTM for population i and failure stage j. This function can be in the form of any standard probability distribution such as Gamma, Weibull or Erlang (**Fig.4.a**). The general formula of this function is as follows:

$$\begin{aligned} f_{ij}(t) &= P(t \le T_{ij} \le t+\Delta t)/\Delta t \\ &= \phi(\alpha_{ij}, \beta_{ij}, t_{oij}, t) \end{aligned} \quad \cdots\cdots\cdots (1)$$

where, for population i, $P(t \le T_{ij} \le t+\Delta t)$ is the probability that failure stage j will occur between age t and $t+\Delta t$; ϕ is any form of theoretical probability distribution; t_{oij} is the minimum failure age, α_{ij} and β_{ij} are parameters.

A reliability function is the probability that a road section from population i will survive in condition state k at least t years (**Fig.4.b**). The general formula of this function can be derived from Eq. (1) as:

$$R_{ij}(t) = P(T_{ij} > t) = 1 - \int_0^t f_{ij}(t)\Delta t \quad \cdots\cdots\cdots (2)$$

The area under the reliability curve can be thought as the expected service life of a road section above state k and thus can be used as a performance indicator. Also the slope of the curve can be a good indicator for timing intervention actions. One should notice that the reliability curve resembles a typical condition-age relationship.

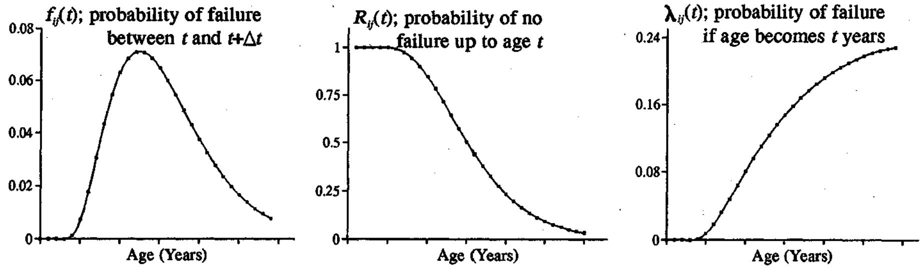
A failure rate is the instantaneous rate of transition from state k to $k+1$ at age t for road sections from population i (**Fig.4.c**). The general formula can be derived from Eqs. (1) and (2) as:

$$\lambda_{ij}(t) = P(T_{ij} < t+\Delta t \mid T_{ij} > t)/\Delta t = \frac{f_{ij}(t)}{R_{ij}(t)} \quad (3)$$

This form of the probability function can be used in predicting the amount of yearly transitions between successive condition states.

3. MODEL DEVELOPMENT

In this chapter, the concepts of FTM are applied to develop two submodels. The first is a deterioration submodel to predict the expected change in condition with age. The second is a "failure" submodel which describes the probability of repair intervention.



a. Probability Density Function　　b. Reliability function　　c. Failure rate

Fig.4 Typical Forms of the Probability Distribution Function in FTM.

(1) The Sample Road Network

Data on pavement condition and repair of the national trunk roads in Mie prefecture, Japan, is used for the development of the model. Selection of this study area is based on the availability of an up-to-date data base. The total length of the surveyed roads is about 355 km (1180 lane km). The whole sample network is located in an area with mild weather conditions. The data base contains various types of inventory and condition data given in increments of 100m sections or less for the years 1988 and 1991. Condition is given as the value of the maintenance control index (MCI) based on the amount of the surveyed distresses. Construction and repair history is available for more than 30 years. No data is available on the structural design of pavement layers nor on the subgrade strength. Because only a small percentage of the sections are concrete pavement, they are ignored. In developing the model, the data for 1988 is used for parameters estimation while the data for 1991 is used for model verification.

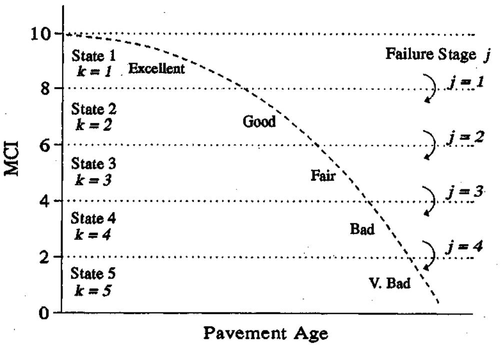


Fig.5 Condition States and Failure Stages.

(2) Deterioration SubModel

The purpose of this submodel is to predict the expected change in pavement condition with age. Condition here is expressed in MCI ranges. The ranges are defined by dividing the possible MCI values (10-0) into 5 condition states ($m = 5$) and thus 4 failure stages, as shown in **Fig.5**. The sample data for 1988 is divided into 4 homogeneous population classes ($n = 4$) based on two categories of traffic loads and two types of pavements as shown in **Table 1**. The sample data is not divided into 3 traffic categories in order to keep a sufficient sample size for each failure stage. The age of any section is calculated from the date of construction for new pavements and from the date of last repair for old pavements. The ages at which a transition in condition state has occurred for the sampled sections could not be directly calculated from the data base. Therefore, for any failure stage j, the age at which the MCI value of any section was in the range of $\pm v_j$ around the transition limit of this failure stage (e.g. MCI = 8 for stage 1) is considered as an age at which failure stage j has occurred. The values of v_j are taken as half the average yearly loss of MCI around the transition limit of each failure stage. The calculated ages are always measured from the year of opening the road for traffic after construction or repair rather than from the occurrence of the previous failure stage. The resulting sample sizes are given in **Table 1**.

Several theoretical PDFs were fitted to the calculated transition ages in each sample. The Weibull distribution, well known for modeling time-to-failure, is selected to represent ϕ, since it gave the highest average significance level and since it is also more practical to use the same function form for all the samples. The estimated parameters (α_{ij}, β_{ij}, t_{oij}) are given in **Table 1**. Since no data is available on failure stage 4, the parameters for this stage are estimated from the trends of the other stages. Average life expectancy (from the year of opening the road for traffic) before the occurrence of each failure stage is also given. As shown, all the significance levels of the fitted PDFs are above 0.8 which we take as satisfactory.

The forms of Eqs. (1), (2) and (3) for the Weibull distribution areas follows:

$$f_{ij}(t) = \frac{\alpha_{ij}}{\beta_{ij}}\left(\frac{t - t_{oij}}{\beta_{ij}}\right)^{\alpha_{ij}-1} exp\left[-\left(\frac{t - t_{oij}}{\beta_{ij}}\right)^{\alpha_{ij}}\right] \cdot\cdot (4)$$

Table 1 Parameters of the Deterioration Model.

Population class (i)	Failure Stage (j)	Sample Size	Model Parameters			Mean Life	Significance Level
			α_{ij}	β_{ij}	t_{oij}		
New pavement B&C traffic	1	128	1.77	12.38	2	13.0	0.9
	2	317	2.67	15.64	4	17.9	0.9
	3	44	3.52	16.16	7	21.6	0.95
	4	--	4.27	16.72	10	25.6	--
New pavement D traffic	1	62	1.27	5.81	1	6.4	0.9
	2	132	1.73	8.18	2	9.3	0.93
	3	27	2.13	9.73	4	12.6	0.92
	4	--	2.50	11.64	7	17.3	--
Old pavement B&C traffic	1	551	1.63	4.54	1	5.1	0.9
	2	759	2.26	7.69	2	8.8	0.87
	3	127	2.71	8.66	3	10.7	0.93
	4	--	3.00	9.70	4	12.8	--
Old pavement D traffic	1	742	1.11	3.92	1	4.7	0.79
	2	948	1.58	6.65	1.5	7.5	0.83
	3	292	1.80	7.39	3	9.5	0.89
	4	--	2.00	8.22	4	11.3	--

Traffic:- B: 250 - 1000 truck/day/dir
C: 1000- 3000
D: > 3000

Pavement:- New: Never been rehabilitated before
Old: Has been rehabilitated before

$$R_{ij}(t) = exp[-(\frac{t - t_{oij}}{\beta_{ij}})^{\alpha_{ij}}] \quad \cdots\cdots\cdots\cdots\cdots\cdots (5)$$

$$\lambda_{ij}(t) = \frac{\alpha_{ij}}{\beta_{ij}}(\frac{t - t_{oij}}{\beta_{ij}})^{\alpha_{ij}-1} \quad \cdots\cdots\cdots\cdots\cdots\cdots (6)$$

Figs.6 and **7** show the change in $R_{ij}(t)$ and $\lambda_{ij}(t)$ with age for each population class and failure stage. **Fig.6** shows that, in general, for the same traffic level, the reliability of "new pavements" is higher than that of "old pavements". This also indicates higher life expectancy for "new pavements". A similar trend is observed from the failure rate in **Fig.7** where lower rates and milder slopes are observed for "new pavements". This means that the performance of pavements after repair is inferior to that of original pavements. Regarding the effect of traffic, the reliability tends to be less for higher traffic loads. However, the rate of loss in reliability and increase in failure rate tends to be steeper for lower traffic loads as the road ages. This might be attributable to differences in the level of routine maintenance application, the effects of which would appear at later ages. As for the failure stage, as expected, it can be seen that the rates of failure at early pavement ages are higher for first failure stages than those for last stages. The trend is reversed at later ages. This means that most of the first transitions are expected to occur at early ages while most of the last transitions are expected to occur at later ages.

(3) "Failure" SubModel

The "failure" submodel is a special case of the deterioration submodel with only two condition states ($m = 2$) and, thus, one failure stage f. The purpose of this submodel is to predict the probability that a road section will be selected for repair intervention.

Table 2 Parameters of the "Failure" Model.

Population Class (i)	Sample Size	Model Parameter		Significance Level
		Shape α_{if}	Scale β_{if}	
New pav., B traffic	1132	4.5	22.0	0.84
New pav., C traffic	365	2.7	13.9	0.65
New pav., D traffic	1743	2.4	17.7	0.87
Old pav., B traffic	437	3.0	14.3	0.70
Old pav., C traffic	204	2.9	13.7	0.54
Old pav., D traffic	1649	2.0	9.2	0.82

Traffic:- B: 250 - 1000 truck/day/dir
C: 1000- 3000
D: > 3000

Pavement:- New: Never been rehabilitated before
Old: Has been rehabilitated before

In this case, road data is divided into six homogeneous population classes, ($n = 6$), as shown in the first column of **Table 2**.

To estimate the model, the history (up to year 1988) of the ages at which repair works were applied is used. Such ages are calculated for "new pavements" as the time between construction and first repair, and for "old pavements" as the time between successive repairs. The Weibull distribution is selected here also to represent the ϕ form. Estimated values of α_{if}, β_{if} and the significance level are shown in **Table 2**. The parameter t_{oif} is given a value of zero since some sections were repaired twice in two successive years. For three of the classes, the significance level is lower than 0.8, and this might be explained by the relatively small sample size and the inhomogeneity of the sample due to the absence of necessary data. For the other classes, the significance levels are above 0.8 suggesting satisfactory fits. Further verification of the model is also given in the next chapter. The plots of the estimated reli-

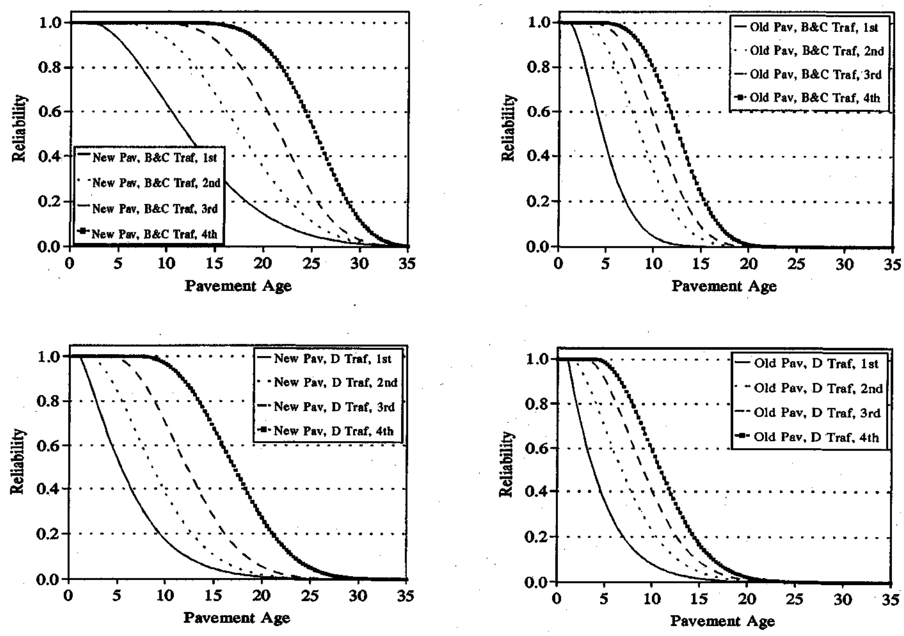


Fig.6 Deterioration SubModel: Pavement Reliability for Each Class and Failure Stage.

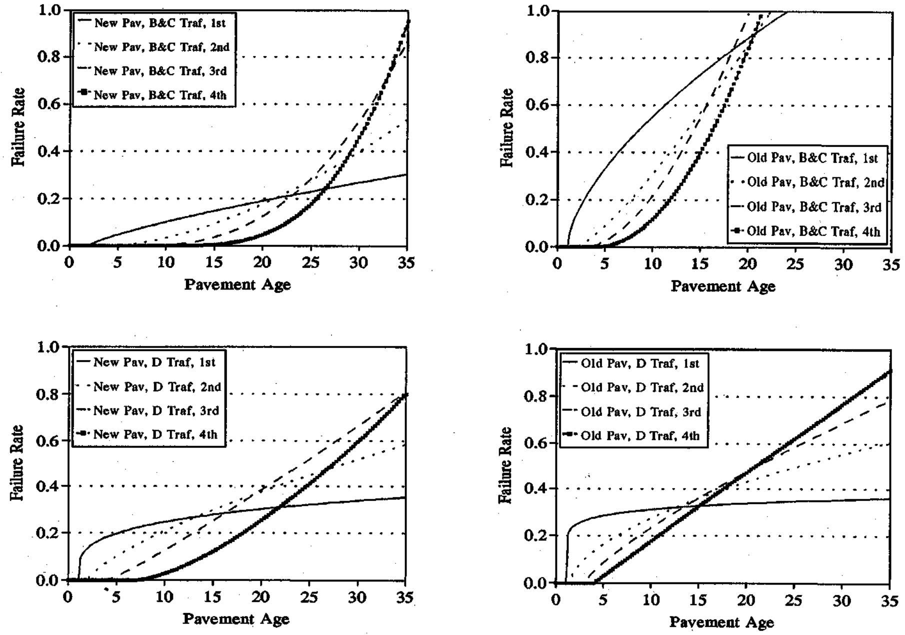


Fig.7 Deterioration SubModel: Pavement Failure Rate for Each Class and Failure Stage.

ability functions, $R_{if}(t)$, and "failure" rates, $\lambda_{if}(t)$, are shown in **Figs.8** and **9**. The figures show similar trends as those discussed in the case of the deterioration submodel.

One should notice that the developed "failure" submodel directly reflects the past and current repair intervention level followed by the road agency. Applying this model without any constraints on the budget would be a prediction of the future needs assuming continuation of the current repair strategy (budget, priorities, techniques and etc.). In this case, rate of repair of the road sections from population i and age t years, $r_i(t)$, would equal the "failure" rate $\lambda_{if}(t)$. The effect of changing the level of repair bud-

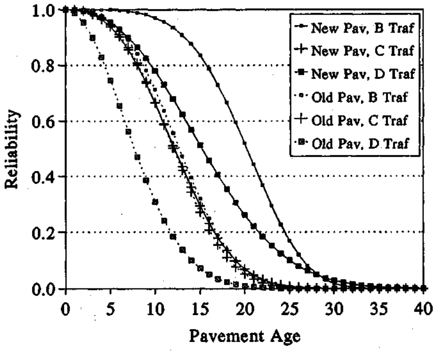


Fig.8 "Failure" SubModel: Pavement Reliability.

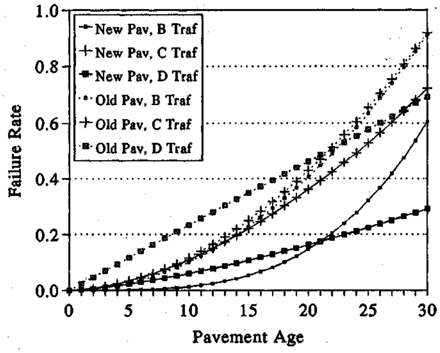


Fig.9 "Failure" SubModel: Pavement Failure Rate.

get can be reflected by accordingly changing the rate of repair, $r_i(t)$, for example to a fraction of $\lambda_{if}(t)$ in the case of reducing the budget.

As for the effect of repair on condition, it is treated as a probabilistic phenomenon also. For lack of relevant data, a repair efficiency matrix (**Table 3**) is adapted from Ref. 7. This matrix gives the probability that a road section moves to a certain condition state after applying a specific type of repair. Although this matrix is developed for pavements in cold areas using condition states based on PSI, we use it because a more appropriate matrix could not be obtained. On the other hand, repair type selection is assumed to follow deterministic rules.

(4) Performance Simulation System

Applying the submodels to simulate the performance of a road network entails repeating the process of estimating the expected yearly transitions in condition and possible repair and its effect, year by year over the analysis period. Since the process is probabilistic, it must be repeated a sufficient number of times, as in Monte Carlo simulation, to get the most probable future performance. Schematic representation of the process of modeling transitions and repair of road sections from population i over one year is shown in **Fig.10**. As shown, the population is divided into cohorts based on the age and condition state at the beginning of the first year of the analysis period, e.g. cohort N_1. At the end of this year, the sections in each cohort split into two parts due to deterioration. The first part contains those sections whose condition transferred to next condition state. This part moves to another cohort, e.g. N_2. The probability of any section to move to this cohort equals the failure rate of its original cohort, $\lambda_{ij}(t)$. The rest of the sections moves to another cohort, e.g. N_3, without changing their condition state. This step is repeated for all cohorts.

Table 3 Repair Efficiency.

Traffic Level	Repair Type	Probability of Moving to State *j* after Repair				
		1	*2*	*3*	*4*	*5*
B	Reconstruction	1.0	0.0	0.0	0.0	0.0
	Over Lay*	0.773	0.227	0.0	0.0	0.0
	Surface Dressing*	0.551	0.381	0.051	0.017	0.0
C	Reconstruction	1.0	0.0	0.0	0.0	0.0
	Over Lay*	0.534	0.417	0.04	0.004	0.003
	Surface Dressing*	0.395	0.462	0.103	0.024	0.015
D	Reconstruction	1.0	0.0	0.0	0.0	0.0
	Over Lay*	0.240	0.451	0.240	0.051	0.017
	Surface Dressing*	0.145	0.591	0.199	0.054	0.011

*(After Reference 7)

The next step is to simulate the selection of sections for repair using the "failure" submodel. A percentage equaling $r_i(t) * 100$ out of the sections in those cohorts with age t are selected for repair. In the selection, priority is given for those sections with a worse condition state. The type of selected repair (reconstruction, overlay, or surface dressing) is based on the class and state of the pavement. The rest of the sections are selected for routine maintenance. This step is repeated for each age class.

As for the effect of repair, at the beginning of the following year, the repaired sections move to cohorts with zero age and a probable state based on the efficiency of the type of the selected repair. However, the after repair state is always better than that before repair, e.g. sections selected for repair from N_3 moving to N_4 or N_5. On the other hand, the sections selected for routine maintenance age by one year but stay at the same state, e.g. moving from N_3 to N_6. At this point, the age-structure, MCI-structure and average reliability of the network can be determined from the resulting distribution of sections among the cohorts. This process is then repeated until the end of the analysis period.

A PC program is written and linked to the data base to perform the above process on a study network. The algorithm of this program is shown in

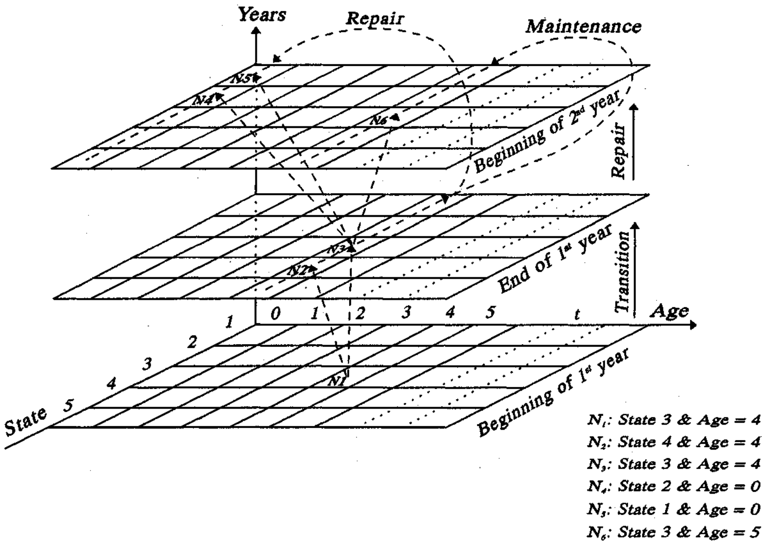


Fig.10 Schematic Representation of the Simulation Process.

Fig.11. The algorithm is composed of the following parts:

1. Deterioration prediction using sections' characteristics and their corresponding failure rates $\lambda_{ij}(t)$ and a randomly generated number.
2. Prediction of repair intervention by population class and age group based on corresponding "failure" rates $\lambda_{if}(t)$. Individual sections are then selected based on their conditions, available budget, and repair priority in the cases of limited budgets.
3. Simulation of repair effect based on the type and efficiency of selected repair and a randomly generated number.
4. Evaluation of conditions using the resulting expected age and condition of each section and repair and maintenance costs.

Parts 1, 2, and 3 are repeated several times for the analysis period based on a predefined number of iterations. Step 4 utilizes the average results of all the iterations to yield the most probable performance.

The program is equipped with portable algorithm for generating a random number with uniform deviates. Basic input data on road network conditions is accessed directly from the road data base. Also other inputs are interactively entered by the user to decide budget levels, scenarios, repair policies and analysis period. The output is in the form of files containing yearly expected conditions and repair needs.

4. MODEL APPLICATION

The developed model can be a part of a network level pavement management system (PMS). Its main application is predicting the expected future change in condition and need for repair, allowing the expected required future budget to be determined. Furthermore, outcomes of modified policies, such as changing budget amount, budgeting scenarios and allocation priority criteria, can be determined; and thus policies can be evaluated and compared. The outcomes can be presented in the form of changes in the age- and condition-structure of the network. The resulting average reliability of the network can be also determined and used as an indicator for its performance. Results of applying the model to the trunk roads of Mie prefecture starting with their condition in 1988 through 1995 are illustrated and briefly discussed in this chapter. The application considers two scenarios; 1) continuation of the current repair level and 2) reduction of the current repair level. Also a comparison between actual and predicted 1991 condition is made for further verification of the model. The results given in this chapter are related to the whole study network not a certain route.

(1) Current Repair Level

This application assumes continuation of the current budget level and thus repair amount. In this case, the rate of repair, $r_i(t)$, equals the "failure" rate, $\lambda_{if}(t)$. Some of the performance prediction results are as follows:

a) Validity Test for the Model

For further model evaluation, the actual condition in the year 1991 is compared with the expected 1991 condition predicted using both the developed model and a deterministic model developed by the Japanese

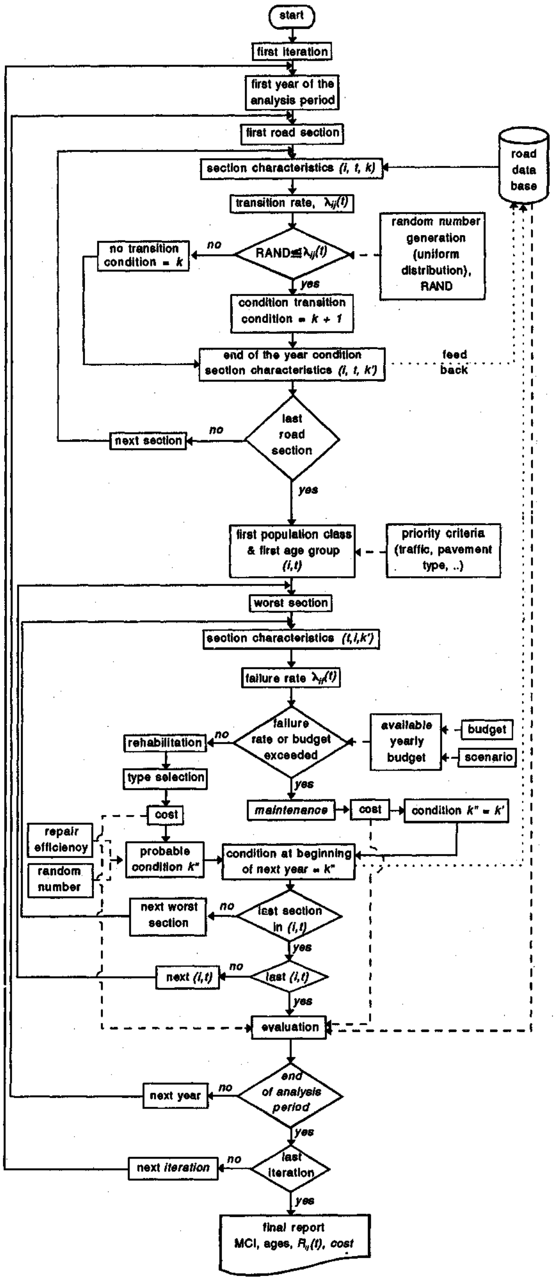
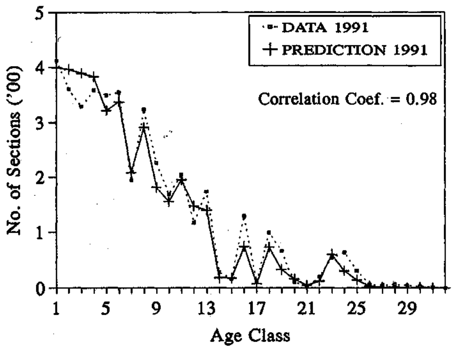
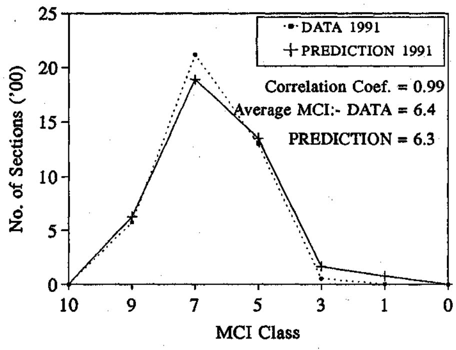


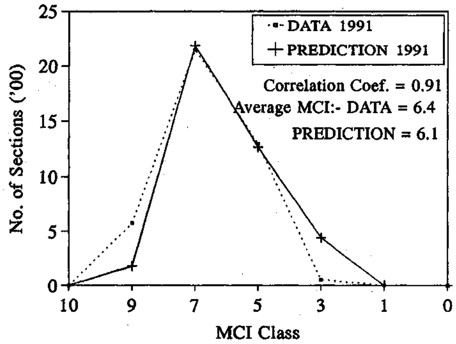
Fig.11 Algorithm of the Simulation System.



a. Age Structure (Probabilistic)



b. MCI-Structure (Probabilistic)



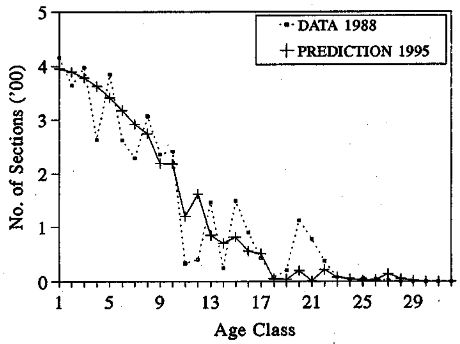
c. MCI-Structure (Deterministic)

Fig.12 Real and Predicted Age- and MCI-Structure in 1991.

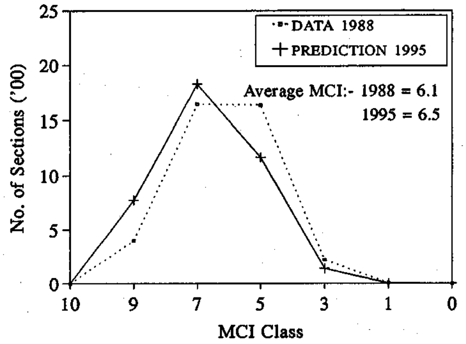
Ministry of Construction[9]. Results of the comparison is shown in **Fig.12** using the network age- and MCI-structure. It can be seen that condition prediction using the developed model is in close agreement with the actual condition. In general, this agreement is better than that obtained using the deterministic model. Though the indicators in the two comparisons in **Figs.12.a** and **12.c** are different, the overall comparison is still significant since the prediction of future repair by the deterministic model is based on MCI while in the proposed approach it is based on the road age. Thus, such a result is another verification for the developed model and shows its higher accuracy in predicting future performance.

b) Future Age- and MCI-Structure

Fig.13 shows the predicted age- and MCI-structure in year 1995 as compared with those in 1988. The figure shows an expected slight rejuvena-



a. Age-Structure



b. MCI-Structure

Fig.13 Predicted 1995 Age- and MCI-Structure of the Study Network.

tion and increase of the average MCI of the network. However, such improvement leaves the network not so far from the "fair condition" zone. This may indicates a need to increase the current repair level should a soundly reliable road network be targeted by year 2000. Under the current repair level, total required budget is predicted to be about 12.2 billion yen (7 years), an average 1.5 million yen/lane-km a year.

(2) Reduction of the Current Repair Level

This application is carried out to predict the changes in the performance of the network if the current budget level (for repair) were to be cut by legislators to 80% or 60% of its current level. Also, alternative repair policies which can be followed by the road agency to cope with budget limitations are examined. These policies are:

1. Setting different allocation criteria for distributing the limited budget among the sections which need repair. The assumed priority criteria are, respectively, older pavement-higher traffic, higher traffic-older pavement and lower traffic-older pavement.
2. Setting different scenarios for distributing the available budget over the investment period.

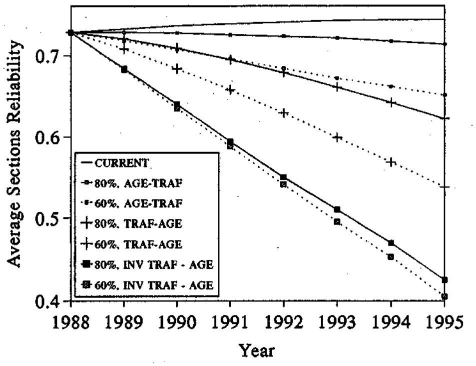


Fig.14 Average Reliability Assuming Different Budget Levels and Allocation Priorities.

The examined scenarios are 1) equally distributed, 2) gradually increasing, and 3) gradually decreasing.

In each case, the rates of repair, $r_i(t)$, are estimated by modifying the "failure" rates, $\lambda_{if}(t)$, according to the assumed cut. The changes in the age- and MCI-structure are predicted in each case. The resulting average reliability of the network based on the predicted age-structure is also computed. The followings are some of the performance prediction results under limited budget and alternative policies:

a) Budget Level and Allocation Priority

Fig.14 shows the prediction of the average reliability of the network assuming different budget levels and priority criteria. The results show that, for older pavement-higher traffic priority criteria, for example, 20% reduction in the budget from its current level would result in a 4% decrease in the possible average reliability by 1995, while a 40% reduction would result in an 11% decrease. This shows the effect of the cumulative damage due to budget shortage. Moreover, the increasing slope of the curves with time indicates that such an effect would be much larger in the long run. As for priority setting, the criteria of older pavement-higher traffic results in both better reliability and performance. The outcome of selecting unsuitable priority criteria can be seen from the result that the 60% budget level with older pavement-higher traffic priority criteria would result in better performance than an 80% budget level with higher traffic-older pavement criteria. Another effect of cutting the repair budget can be seen in **Fig.15**, which shows that in the cases with limited repair budget, an increase in the budget for routine maintenance is expected.

The progress of the average MCI for each budget level assuming the older pavement-higher traffic priority criteria is shown in **Fig.16**. It can be seen that the trends of MCI matches that of the aver-

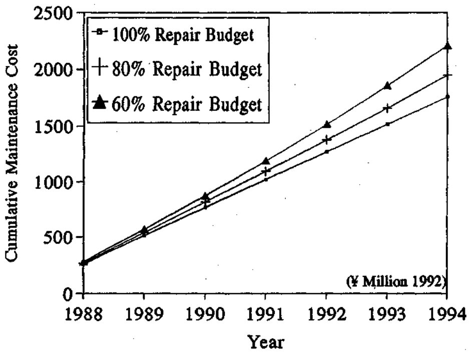


Fig.15 Cumulative Cost of Routine Maintenance for Different Budget Levels.

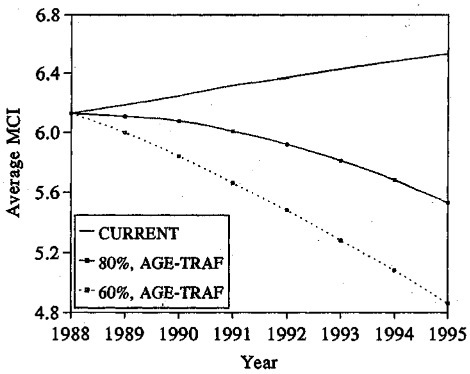


Fig.16 Progress of MCI Under Different Budget Levels.

age reliability shown in **Fig.14**. This observation may support the use of reliability as an indicator for pavement performance. The use of such an indicator has the advantage, over the use of MCI, that it is calculated from the age-structure of the road network which is readily obtainable unlike the data necessary to calculate the MCI values.

b) Budgeting Scenario

Fig.17 shows the results of different allocation scenarios of the total available budget over the investment period. In the cases of gradually increasing/decreasing budget allocation, the rate of increase/decrease is assumed to be 5% per year. The priority criteria are fixed as older pavement-higher traffic for all scenarios. As shown, the final network average reliability is higher in the case of gradually increasing budget. On the other hand, the performance is better in the case of gradually decreasing budget. However, the future additional cost to remaintain a better condition would be the highest for the "decreasing" scenario. Such a conflict can be resolved by comparing this cost with the savings in user costs resulting from better performance.

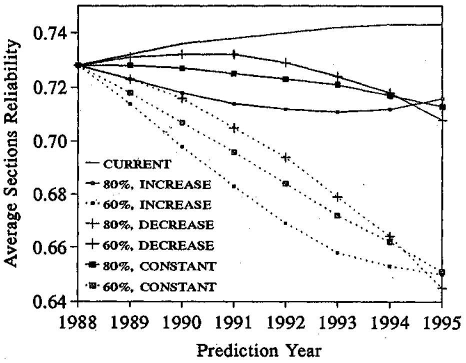


Fig.17 Average Reliability Assuming Different Budget Levels and Distribution Scenarios.

5. CONCLUSIONS

This paper discusses a road performance model as a part of a model system for supporting the process of road infrastructure management. Taking pavement as a typical example of part of infrastructure, a new approach for modeling its deterioration and "failure" as a probabilistic phenomena by employing the concepts of failure time models (FTMs) is presented. The process of deterioration is described by a group of FTMs which gives the probability distribution function of transition over subsequent condition states as a function of pavement age. On the other hand, "failure" is described by a separate FTM which gives the probability of transition from a "repair not required" state to a "repair required" state. Results of simulating change in condition and repair applications obtained by applying the developed model to a study road network show good agreement with actual conditions. Such an agreement can be mainly attributed to the following:

1. Treating the deterioration and "failure" processes as stochastic phenomena, which is more realistic. This allows for consideration of variations in pavement condition with age which is normally ignored in deterministic models,
2. Considering the effect of pavement age on the transition rates between subsequent condition states unlike other probabilistic models, and
3. Modeling "failure" process separately from deterioration so that the effect of factors other than condition, on repair timing, e.g. strategic, technical and financial considerations, is accounted for in the model.

The developed model also provides an indicator for pavement performance in terms of its reliability, that is, probability of no failure. Such an indicator is calculated from road age data which is easy and inexpensive to collect. Furthermore, reliability analysis may also be carried out while considering the network's spatial relations, e.g. links connectivity and redundancy. This helps better allocation of repair throughout the network leading to higher traffic flow reliability.

The developed model is then applied for estimating the future performance of the trunk roads in Mie prefecture under different budget levels and repair policies. Some of the findings can be summarized as follows:

1. A slight improvement in the future performance of the study network is expected under the current repair level. However, after such improvement, the condition is not far from the "fair condition" zone.
2. The short-term negative effect of reducing the repair budget by 40% from its current level would be 3 times as high as the effect of 20% reduction, showing the effect of cumulative damage due to budget cuts.
3. Selection of unsuitable priority criteria for budget allocation can offset the positive effect of relatively high budget levels.
4. In the case of limited budget, better performance can be obtained by distributing the budget over the budgeting period so that it is gradually decreasing with time.

Finally, we integrated the developed model with other models for quantifying direct and indirect costs incurred at any road condition. These models include evaluation systems for the direct impacts on the facility's users and the indirect impacts on the regional economy. The resulting system can help rationalizing planning in the area of road infrastructure management. The developed system can be also easily adapted for modeling deterioration and repair of other types of infrastructure. With such systems in hand, infrastructure renewal strategies commonly based on "the fire-alarm strategy" are likely to be abandoned in favor of strategies based on predicted information.

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交通インフラ管理のための確率的パフォーマンスモデル

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本論文は，道路社会資本の管理のための，道路機能を確率的に表現する新しいモデルシステムに関するものである．モデルシステムは，1）劣化過程と2）道路当局の維持管理行動を表現する2つのサブモデルを有している．両サブモデルは，破壊時間モデルの考え方に基づくもので，説明変数は，舗装の補修歴，重量トラック交通量，舗装状態，新設又は補修後の年数から成っている．将来の道路機能は，以上のモデルより得られる劣化と補修の確率とコホートサバイバルの考え方に基づいて予測される．予算カットのシナリオと補修優先基準（交通量や舗装年令など）の組合わせごとに，将来のネットワーク上各区間での舗装状態の分布，ネットワークの信頼性，および必要期待補修費がどのように変わるかの感度予測が示される．