08
TIE-

FINLAND'S PAVEMENT MANAGEMENT SYSTEM:
DATA AND MODELS FOR CONDITION OF ROADS
Translation of the report "TVH/Stk Sarja B No. 1/1988"

Riitta Olsonen, statistician
Roads and Waterways Administration, Finland
December 1988

CONTENTS

SUMMARY

The knowledge of road network conditions plays a central role in planning the maintenance and rehabilitation of roads. Resources should be applied in such a way that roads remain in the best possible condition. In this article my aim is to determine the necessity of information about road conditions for Finland's pavement management system (PMS). We found that the data collection planned for this PMS creates a good basis for all research on road conditions.
The pavement management system contains three hierarchical models; long and short term models for network level optimization and a project level model. In the network level models roads have been divided into categories according to traffic, region, bearing capacity, defects, rutting and roughness. In the optimization models we had to specify the condition change between these categories, the effects of actions or treatments on condition and the relation between road user costs and road condition. On the project level we concentrated on the condition of each road and possible changes.
Äijö and Miettinen (1987) carried out separate research concerning the effects of treatments (based on the Delphi technique). The road user costs in relation to road condition are based on "User Costs in Road Traffic" by Finland's Roads and Waterways Administration (1988).
This article deals with the evaluation of changes in road condition and the required collection of data. The first section concentrates on the condition variables for network level mo-

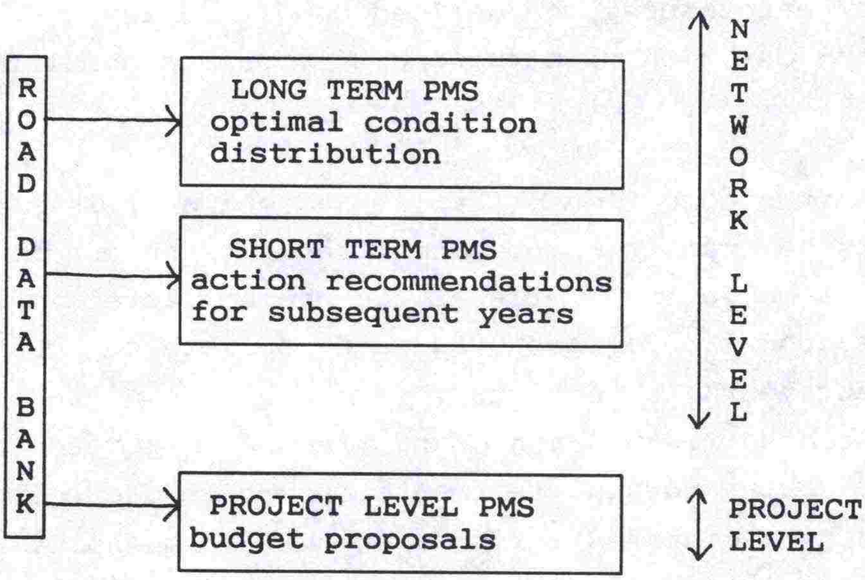
dels and a study of the model types. This is followed by a description of the data collection programme and the preliminary results.

The results indicate that only with appropriate experimental design using random sampling can valid condition models for road networks be guaranteed.

INTRODUCTION

An integrated system for pavement management (PMS) is under development in Finland's Roads and Waterways Administration (Design of the TVH Highway Investment Programming System, CSI 1986, Optimization Techniques for Planning Highway Improvements, CSI 1987, Thompson et al., 1987). It contains three levels which are presented in figure 1.

Figure 1: The structure of Finland's pavement management system



Long and short term models are tools used at the network level. The former is used to determine the best condition for roads while the latter gives the annual treatment distributions that lead most economically to the target. The project level system assists engineers in choosing the projects with the aid of short term recommendations and road condition data. For asphalt concrete roads the prototypes for network level models have been completed and those at the project level are near completion. Models for oil gravel and gravel roads are being developed.

The optimization at the network level is based on the Markov chain, i.e. each year the condition of roads depends on the condition during the previous year and applied treatments. This dependence is assumed to remain constant during any given period. Within this model the optimization is achieved by linear programming. The optimum is achieved by minimizing total road user and treatment costs. By applying the long and short term models we are able to determine:

a) the optimal condition distribution on roads
b) maintainable road network conditions with given budgets
c) the cost of maintaining the desired condition level
d) the cost and duration of attaining the desired condition level.

In this system the condition data plays a central role. At the network level the transition probabilities between condition categories must be defined while at the project level information on the condition of each road and possible changes during subsequent years is necessary.
In addition we need to know the connection between road condition and user costs and how treatments affect road conditions. The road data bank contains information that is measured at three to four year intervals. Both transition probabilities and evaluation of change in the condition of roads necessitate the collection of data during consecutive years. As it is impossible to measure the whole network every year, the transition probabilities must be estimated using suitable models based on random sample data.
The effects of road condition on user costs is currently being examined in RWA. We are already aware of the dependence on the scale "surface good-fair-poor" (User Costs in Road Traffic

1985) but better information will be available when road condition and road user costs have been measured simultaneously. Measurements for the evaluation of treatment effects have begun, but the preliminary results are based on the Delphi inquiry (Äijö, 1988).

There are two main types of statistical model. One determines which factors cause changes in road condition (causal models), the other indicates how road conditions will change (prediction models). These model types serve different purposes even though they may have similar explanatory (prediction) variables.
In the pavement management system we need to adopt prediction models. Prediction variables must be chosen from among data that can either be predicted or controlled.
Nevertheless, different types of models are needed at network and project levels. In the long and short term network level models it is sufficient to know the transition probabilities between condition categories. Meanwhile, at the project level it is necessary to predict the amount of change in condition variables.

This article concentrates on describing both network and project level condition models, their estimation and data collection. We begin with condition variables chosen for the asphalt concrete PMS, their classification and the structure of transitions between them. This structure is similar to the oil gravel system. However, the gravel system will slightly differ as some of the gravel road condition variables are liable to change. Sections 2 and 3 discuss the different model types at network and project levels followed by data collection in section 4. Finally, the preliminary results for network level transition probabilities can be found in the last section.

1. CONDITION VARIABLES AND THEIR CLASSIFICATION FOR THE ASPHALT CONCRETE MODEL

A selection of condition variables for Finland's asphalt concrete roads has been investigated by factor analysis (Talvitie and Olsonen, 1988), which included clusters of road, traffic and condition data. It was found that asphalt concrete roads can be described using the factors "rutting", "geometry", "defects", "bearing capacity", "traffic" and "road width". Data on roughness was not available, but the variables left outside these factors were known from experience to correlate strongly with roughness. On the basis of these results we decided to choose bearing capacity, defects, rutting and roughness as condition variables for the asphalt concrete model. Factor analysis also provided strong grounds for leaving out geometry and road width because they made up their own factors and thus could be supposed to be independent of the chosen condition variables.

The optimization system based on the Markov model assumes that condition variables are classified into categories which cannot be too numerous for computational reasons and in order for a good understanding of the results. The achievement of good results necessitates sufficiently homogeneous categories so that the condition of roads can be adequately presented. These two factors restrict the amount of condition categories both from above and below. The effect of condition variables on the road standard is also heavily dependent on traffic volume and climatic conditions, and thus it is necessary to divide the road network into these two categories.

In order to define the climatic regions we reviewed condition distribution between the 13 existing road districts in Finland. We discovered that the country can be roughly divided into two fairly homogeneous regions; southern Finland, where the roads are clear throughout the year, and northern Finland, where the roads are covered in snow in winter.
On the basis of the condition distribution related to traffic volume roads were divided into three classes depending on traffic volume, with cutpoints set at 1,500 and 6,000 ADT.
Thus, we have six sub-networks for asphalt concrete roads that will be optimized separately, and the optimal budget allocation must be made after optimization (Optimization Techniques for Planning Highway Improvements, CSI 1986, pg.39). All subsequent road condition distributions will be assumed to be conditional on one of these six sub-networks.

In order to define the classification of condition variables we examined ranges, measuring accuracy and speed of change of each condition variable, and divided defects (V), rutting (U) and roughness (T) into three categories. Bearing capacity was divided into five categories as it undergoes slow change and this, we hoped, was one way of including the time factor. Thus, we ended up with 135 condition states (5x3x3x3).
As heavy traffic strains road structure more than light traffic, cutpoints for bearing capacity depend on traffic volume :

cutpoints fo bearing capacity (MN/m²)		ADT ≤1500	1501-6000	>6000
bearing capacity class	1	>230	>260	>330
	2	201-230	241-260	311-330
	3	171-200	221-240	251-310
	4	141-170	201-220	211-250
	5	≤140	≤200	≤210

Defects are measured as a proportion of road length. Combining different defect measurements (alligator, longitudinal and transverse cracking, patching, holes etc.) in a single dimension is problematic (e.g. Paterson, 1986). For the PMS system defects were defined as a weighted average of three defect types:

defects = 0.7 x alligator cracking
+0.2 x longitudinal cracking
+0.1 x patching (%).

The range of this measure is 0 - 100%, and cutpoints are 0% and 20%.

Rutting is measured as maximal rut depth (mm) from surface level, and cutpoints are 13mm and 19mm.

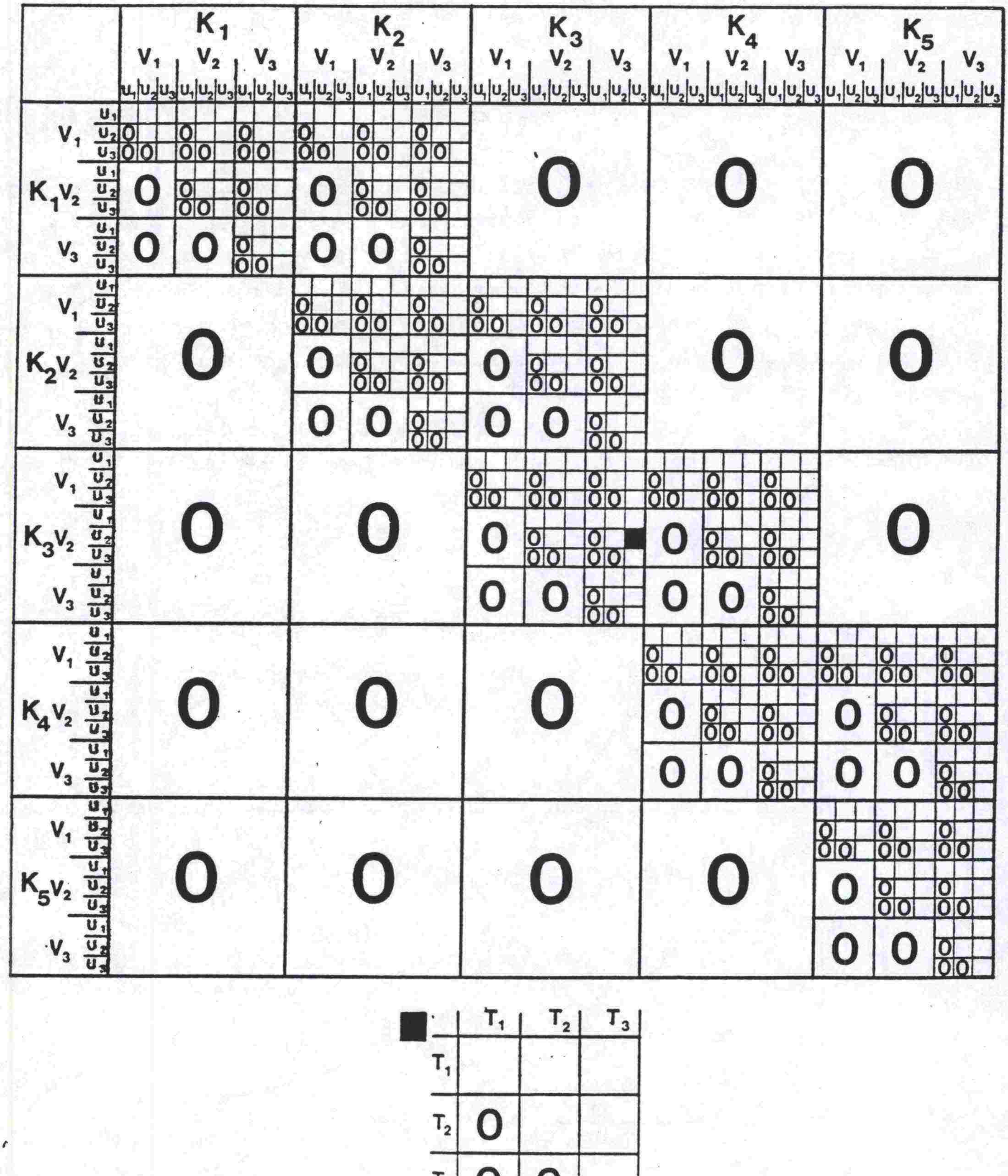
Roughness is measured either as longitudinal unevenness (m/1000m) or as a subjective PSR value. The recommended measure is the standardized IRI measure but because this system has not yet been adopted in Finland we used PSR with cutpoints at 2 and 3.5.

Transition probabilities depend on road treatments. Each treatment required its own transition probabilities

$$p(K_{t+1}, V_{t+1}, U_{t+1}, T_{t+1} | K_t, V_t, U_t, T_t). \quad (2.1)$$

Each set of condition states in the transition probability matrix (figure 2) contained the probability that from the condition state (K_t, V_t, U_t, T_t) in year t the road changed to the condition state $(K_{t+1}, V_{t+1}, U_{t+1}, T_{t+1})$ in the following year (t+1). The matrix has 135x135 cells.
The matrix in figure 2 represents transition probabilities when roads are not improved. The probabilities below the diagonal can be set at zero because conditions are not improved if nothing is done to the road. If improvement measures have been made, the probabilities over the diagonal can be set at zero.

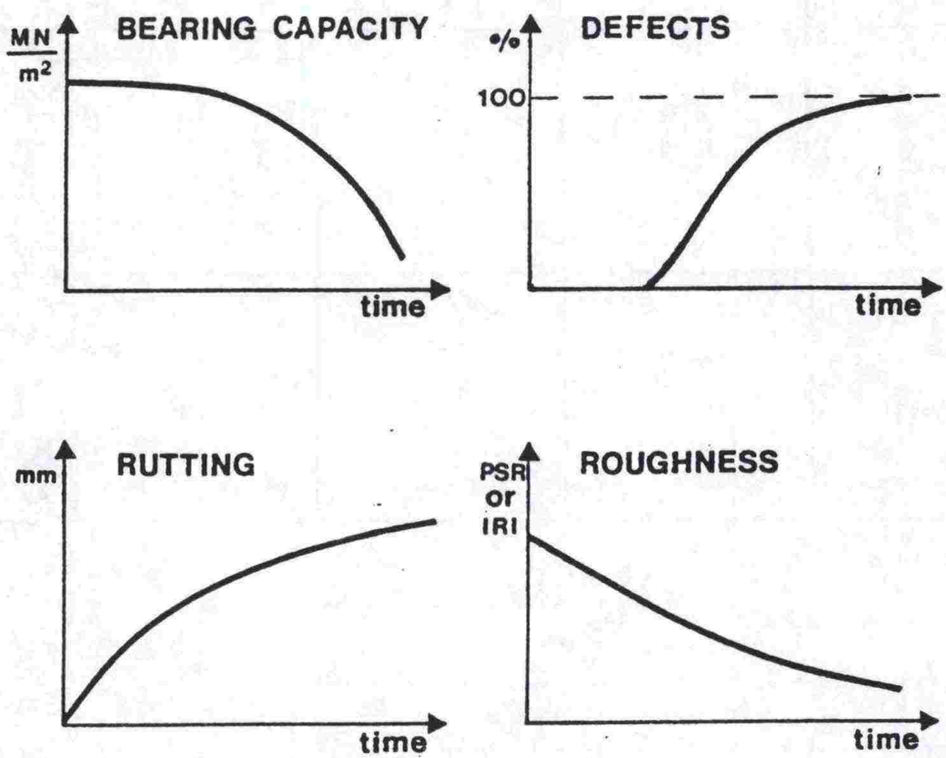
Figure 2: Transition probability matrix when road improvements are not made



2. CONDITION MODELS FOR THE PROJECT LEVEL

The project level PMS, or project analysis system (PAS), deals with road-by-road data. In the near future the road data bank will contain condition data needed for the PAS of each road. This data will not be collected every year, and in any case it is necessary to predict changes in future conditions. Thus, we have to construct models that describe the amount of condition change from one year to the next.
If no improvements are made, the condition variables defined in the preceding paragraph change accordingly (see figure 3).

Figure 3: Condition variables as function of time



The bearing capacity of a new road remains at the same level for a considerable time. After the deterioration begins the bearing capacity accelerates rapidly (Talvitie and Viren, 1985). Surface defects are non-existent after road improvements, but once they appear they will increase until the whole surface is defected (Paterson, 1986). Rutting begins immediately after treatment and is usually more rapid in the early stages (Korhonen, 1985). Deterioration of roughness also begins directly after treatment and, depending on the specific features of the road in question, may be rapid (Road Condition and Level of Service, VTT 1985).

As we shall have comparatively fresh condition measurements in the future, it will be worth exploiting these when calculating predicted conditions. Thus, the models predict changes in condition with time as follows:

$$\Delta \text{condition}_t = f(\text{condition}_t, \text{ other explanatory variables}),$$

where Δcondition$_t$ is the change in condition from year t to year t+1 and condition$_t$ is the condition in year t. The parametric model is different for different condition variables. For example, a linear regression model with logarithmized variables may be suitable for rutting.

There are no changes in defects for several years thus complicating the definition of a model family for the whole process. Paterson (1986) suggests that the initiation of defects is a separate process from the continuation of defects. This means that we need to estimate two different models for defects. The initiation of defects is a discrete process for which a suitable survival model can be estimated, while because the continuation of the defects is a continuous process it can be modelled using a more traditional model. The limited range of defects (0-100%) restricts the form of this model.

In preliminary trials we noticed that the models we could estimate with existing data were too inaccurate to be utilized in the PAS. We shall estimate these models once we have sufficient data, collected as described in section 4.

3. TRANSITION PROBABILITY MODELS

To estimate transition probabilities we divided the probability (2.1) into a product of conditional probabilities

(2.2) $$p(K_{t+1},V_{t+1},U_{t+1},T_{t+1}|K_t,V_t,U_t,T_t) =$$

$$p(K_{t+1}|K_t,V_t,U_t,T_t) \times$$
$$p(V_{t+1}|K_t,V_t,U_t,T_t,K_{t+1}) \times$$
$$p(U_{t+1}|K_t,V_t,U_t,T_t,K_{t+1},V_{t+1}) \times$$
$$p(T_{t+1}|K_t,V_t,U_t,T_t,K_{t+1},V_{t+1},U_{t+1}).$$

In this way we can examine the probabilities for each condition variable separately. The division of the probability (2.1) can be made in any order. Our order reflects the time order of condition variables so that bearing capacity has the slowest change while roughness is the most rapid. The formula (2.2) is only an identity, and the condition variables that actually affect the probability will be found once the models have been estimated. The probabilities also depend on region and volume class but when we consider network level probabilities all other explanatory variables are irrelevant.

The probabilities can be estimated in many ways. If the condition on all roads is measured every year it is possible to calculate the probabilities as proportions of road length that have shifted from one condition class to another.
The Arizona PMS uses a similar method (Way, Eisenberg and Kulkarni, 1982) together with models that predict change in road conditions. Way, Eisenberg and Kulkarni predict the amount of condition variables (change in defects and roughness) in any given year when the condition of the previous year is known. On the basis of these the condition distribution for the following

year is calculated. A sound estimate of road conditions is acquired when the annual condition measurements cover the whole network and the models are exact and up-to-date.

The probabilities (2.2) can also be estimated directly using suitable data collected during consecutive years. We can present each of the conditional probabilities for defects, rutting and roughness as a submatrix:

without treatment

$p(M_{t+1} \mid M_t, \ldots)$		M_{t+1} 1	2	3
M_t	1	p_{11}	p_{12}	p_{13}
	2	0	p_{22}	p_{23}
	3	0	0	1

with treatment

$p(M_{t+1} \mid M_t, A_k, \ldots)$		M_{t+1} 1	2	3
M_t	1	1	0	0
	2	p_{21}	p_{22}	0
	3	p_{31}	p_{32}	p_{33}

where M is any variable V, U or T and A is treatment. For bearing capacity we are able to use analogous 5x5-matrices.

Let us examine the first matrix more closely (the same examinations can also be applied for the second matrix and bearing capacity). For estimating figures p_{ij} we need two models, one when we know that $M_t=1$ (the first row) and the other when we know that $M_t=2$ (the second row).

In the second row the probabilities p_{22} and p_{23} ($p_{22}=1-p_{23}$) are binomially distributed. A suitable simple statistical model for this kind of response variable is a logistic regression model

$$\log(p/(1-p)) = \beta_0+\beta_1 x_1+\ldots+\beta_k x_k,$$

where $x_1,\ldots,x_k$ are the explanatory variables of the model and $\beta_0,\beta_1,\ldots,\beta_k$ are unknown parameters which will be estimated. The logistic regression model is one type of generalized linear model which is linear in parameters exactly like the usual linear regression model. There is a link function between regressor variable (probability p) and the linear function of explanatory variables which, in the case of the logistic model, covers the limited range (0-1) of p. More information on the theory of generalized linear models is available in McCullagh and Nelder's Generalized Linear Models (1983).

In the first row where we have $M_t=1$, the probabilities p_{11}, p_{12} and p_{13} are multinomially distributed. Once again we discover a suitable model among generalized linear models. Because the condition classes form an ordered group (M=1 is the best, M=2 fair and M=3 the worst class), the suitable model is the so-called ordinal logistic regression model

$$\log(\theta_j/(1-\theta_j)) = \delta_j - (\beta_0+\beta_1 x_1+\ldots+\beta_k x_k),$$

where $j=1,2$, $\theta_1=p_{11}$, $\theta_2=p_{11}+p_{12}$, variables $x_1,\ldots,x_k$ are the explanatory variables of the model and $\delta_1,\delta_2,\beta_0,\ldots,\beta_k$ are unknown parameters. More information about this model is available in McCullagh and Nelder (p. 103), in McCullagh's article (1980) and about the technique of estimation in the article by Ekholm, Green and Palmgren (1986).

In estimating the probabilities (2.2) the relevant explanatory variables $x_1,\ldots,x_k$ for each condition variable are the variables for which each condition variable is conditional (for instance explanatory variables for defects can be bearing capacity class K_t and K_{t+1}, rutting class U_t and roughness class T_t) and, naturally, traffic volume class and region.

One suitable possibility for defect probabilities is the defect initiation model (Paterson and Chesher, 1986) presented in the previous section because the best class of defects is precisely roads with no defects.

4. DATA COLLECTION

It has become evident in the above discussion that continuous condition data collection is necessary to estimate models and keep them up-to-date.

In Finland there are approximately 15,000 km asphalt concrete public roads making it impossible to measure them all every year. Therefore, we need to choose an adequate number of roads that will be measured every year. The roads must be selected in such a way that all condition class combinations are represented and the results can be generalized to concern the whole road network. The first requirement means that we must select an equal number of roads from each condition class combination while the second determines that we have to choose a random sample within each combination.

In the PMS the asphalt concrete network has been divided into two regions and three traffic volume classes. The condition variables are bearing capacity, defects, rutting and roughness. To achieve the best possible estimate for each condition state (condition class combination) it must have equal weights in the sample. We have to choose the sample from the road data bank where we have information concerning region, traffic and bearing capacity, but not yet on other condition variables.

The most efficient way to choose the sample is by factorial design, where as factors we selected all relevant variables which were classified in the same way as in the PMS. In this way we arrived at the following factors: region (2 levels), volume class (3 levels) and bearing capacity (5 levels). For rutting, defects and roughness we had to find a substitute in the road data bank that expressed the variation in these condition variables. The most suitable would be the age of surface, for which we used four and nine years as cutpoints. These cutpoints were chosen so that the range of the logarithm of age was divided into three parts of equal length. These cutpoints give weight to younger surfaces which is appropriate for the accuracy of rutting estimates as rutting proceeds linearly with the logarithm of surface.

Thus we have an arrangement of 2x3x5x3 experimental runs as our factorial design. We decided to measure a total of 1,500 roads (each 1,000m in length) which means 17 repetitions in each run. As we took a simple random sample of 17 roads in each run we believed that the results could be generalized so as to concern the whole asphalt concrete network.

Selection of a sample for asphalt concrete roads

From the road data bank we aggregated a file of road sections, homogeneous with respect to factors. The data in this file was divided into 90 groups based on the following factors; region, traffic volume, bearing capacity and age of surface. Within these groups a simple random sample was taken, among road sections which were at least a thousand metres long. The road data bank of 1.1.1987 contains 9,984 homogeneous road sections that are at least one kilometre long and are distributed among the factors as demonstrated in table 1.

In the traffic volume class "ADT more than 6,000" we do not have sufficient data for 17 repetitions in every bearing capacity class. Because we are measuring roads during several consecutive years and each road surface has varying ages, we decided to include 50 roads in each bearing capacity class. (See table 2 for number of roads selected.)

Condition data, bearing capacity, defects, rutting and roughness will be measured every year on these roads and the transition probabilities when no improvements are made will be estimated on these. If any road undergoes treatment during the measuring period, we shall include it in the study and use the data while estimating probabilities for treatments.

Table 1: Distribution of asphalt concrete roads (km), including only road sections over one kilometre

region	ADT	b.cap. class	age of surface ≤3yrs	4-9yrs	>9yrs	sum
south	≤1500	1	221	269	130	620
		2	62	157	42	261
		3	100	169	49	318
		4	62	202	58	322
		5	152	235	115	502
		sum	597	1032	394	2023
	1501-6000	1	1075	730	209	2014
		2	190	129	30	349
		3	154	93	32	279
		4	82	76	39	197
		5	181	278	68	527
		sum	1682	1306	378	3366
	>6000	1	375	50	1	426
		2	39	5	1	45
		3	154	20	0	174
		4	40	10	0	50
		5	40	9	2	51
		sum	648	94	4	746
north	≤1500	1	249	129	133	511
		2	152	139	63	354
		3	124	82	61	267
		4	130	24	49	203
		5	63	31	23	117
		sum	718	405	329	1452
	1501-6000	1	443	232	113	788
		2	133	118	42	293
		3	158	141	31	330
		4	138	129	38	305
		5	160	230	82	472
		sum	1032	850	306	2188
	>6000	1	30	3	3	36
		2	31	0	0	31
		3	41	8	13	62
		4	39	6	1	46
		5	28	2	4	34
		sum	169	19	21	209

Table 2: Number of asphalt concrete roads measured

region	ADT	b.cap. class	age of surface ≤3yrs	4-9yrs	>9yrs	sum
south	≤1500	1	17	17	17	51
		2	17	17	17	51
		3	17	17	17	51
		4	17	17	17	51
		5	17	17	17	51
		sum	85	85	85	255
	1501-6000	1	17	17	17	51
		2	17	17	17	51
		3	17	17	17	51
		4	17	17	17	51
		5	17	17	17	51
		sum	85	85	85	255
	>6000	1	17	32	1	50
		2	39	5	1	45
		3	30	20	0	50
		4	40	10	0	50
		5	40	9	2	51
		sum	166	76	4	246
north	≤1500	1	17	17	17	51
		2	17	17	17	51
		3	17	17	17	51
		4	17	17	17	51
		5	17	17	17	51
		sum	85	85	85	255
	1501-6000	1	17	17	17	51
		2	17	17	17	51
		3	17	17	17	51
		4	17	17	17	51
		5	17	17	17	51
		sum	85	85	85	255
	>6000	1	30	3	3	36
		2	31	0	0	31
		3	29	8	13	50
		4	39	6	1	46
		5	28	2	4	34
		sum	157	19	21	197

As the variability in condition data is considerable, as has been demonstrated by past research, it is of utmost importance to minimize this.

Study of the effects of treatments

The effects of treatments will be measured separately by choosing the roads from the annual project plan every year. The treatments have been grouped in the PMS (we have seven groups in the asphalt concrete model), and they all require their own transition probabilities. From each group we randomly selected an adequate number of roads which are measured immediately prior to treatment and a year later. In all likelihood this data should be measured during the course of several years before we have enough information to estimate the probabilities described in section 3.
During the summer of 1988, about 30 roads in each treatment group were measured and this will be repeated in the summer of 1989.

Correlations with other condition research

The experimental design we chose made it possible to measure other factors connected with the PMS or road conditions in general. For instance, in the summer of 1988 measurements for user cost (vehicle costs) were based on a sub-design of these roads.

Division between regions, traffic volume, bearing capacity and pavement age, and random sampling within these sub-groupings ensure that we have reliable data on the condition of the complete road network which is also applicable in other research. The measurement programme is fairly extensive and costly, so it would be advantageous to utilize this programme in other condition studies.

Corresponding measuring programmes for oil gravel and gravel roads have been set in motion as well. Thus, all the acquired data will provide a truly comprehensive knowledge of road conditions of the whole Finnish network.

5. PRELIMINARY RESULTS FOR TRANSITION PROBABILITIES WHEN ROAD CONDITIONS ARE NOT IMPROVED

Because the data collection described in the previous chapter was begun as recently as in the summer of 1988, the first models were estimated using previous data.

Data on bearing capacity can be found in the road data bank, but no information exists concerning change in bearing capacity.

The Technical Research Centre of Finland has measured rutting and defects annually from 1982 (see e.g. Condition of Asphalt Concrete Roads in 1985, VTT 1986). The data collected during 1982-1985 was based on 3,560 km of roads that contained data both on rutting and defects for two consecutive years. These were combined with information from the road data bank which was divided into 2,708 homogeneous road sections.

Roughness data was collected separately in 1979-1983 on 26 roads. Each road was ca. three km long (Road Condition and Level of Service, VTT 1985), and the units used were cm/km and PSR. In addition, rutting and defects were observed, but the rutting data was insignificant and the defects were measured in square metres.

Transition probabilities for bearing capacity

As data of changes in bearing capacity was not available, we had to estimate these probabilities using different methods to those adopted previously. We presumed that bearing capacity changes so slowly that any shift in condition class is restricted to a move into an adjacent class, and therefore we needed to only estimate probabilities $p(K_{t+1}=j+1|K_t=j)$, where $j=1,2,3,4$.
The estimation proceeded as follows:
We have models for bearing capacity as a function of the ESAL count and other explanatory variables (Talvitie ja Viren, 1985). These are used to calculate bearing capacity for future years for each road. Traffic is supposed to grow according to RWA's traffic forecast (Predictions for Traffic and Car Volume for 1986-2010).
We began with 1985 and divided the six region-traffic volume classes into five bearing capacity classes. Then we calculated the number of kilometres which would shift to a lower class during 2001-2010. We were forced to choose such remote years because of the slow changes in bearing capacity. Otherwise, we would not have acquired positive probabilities for all classes. When we assume that the transition probability for one year (p) is the same for the whole period, we can calculate it from the probability for several years (n) with the formula

$$p = 1 - (1 - p_n)^{1/n}.$$

These probabilities were calculated within each 30 region-traffic volume-bearing capacity class using as p_n the quotas that had shifted by a class until the years 2001-2010. The means and standard deviations of these probabilities are found in table 3.
Standard deviations are so small (except in the first case) that we may consider them to be satisfactory for bearing capacity transition probabilities for the present.

Table 3: Transition probabilities for bearing capacity $p(K_{t+1}|K_t)$

region	ADT	bearing cap. class	mean	standard dev.
south	≤1500	1	.00048	.00043
		2	.00153	.00016
		3	.00223	.00022
		4	.00184	.00087
	1501-6000	1	.00289	.00075
		2	.01278	.00072
		3	.01595	.00131
		4	.02002	.00233
	>6000	1	.00417	.00089
		2	.02718	.01432
		3	.01597	.00315
		4	.02960	.01343
north	≤1500	1	.00037	.00017
		2	.00046	.00020
		3	.00036	.00017
		4	.00043	.00003
	1501-6000	1	.00218	.00042
		2	.00728	.00140
		3	.00482	.00147
		4	.00649	.00163
	>6000	1	.00779	.00419
		2	.06627	.02809
		3	.01920	.00370
		4	.03096	.00619

Transition probabilities for defects, rutting and roughness

Because some of the data concerning rutting, defects and roughness was acquired over consecutive years, we estimated the preliminary models for these condition variables, as described in section 3. On average, the transitions were as follows:

Table 4: Transitions between condition states as averages (%)

defects

		V_{t+1} 1	2	3
V_t	1	57.5	41.3	1.2
	2	0	92.0	8.0
	3	0	0	100

rutting

		U_{t+1} 1	2	3
U_t	1	87.9	11.6	0.5
	2	0	88.7	11.3
	3	0	0	100

roughness

		T_{t+1} 1	2	3
T_t	1	20.9	79.1	0.0
	2	0	96.5	3.5
	3	0	0	100

The attempt to estimate a generalized linear model with this data did not succeed as we had anticipated. We were unable to obtain ordinal logistic regression models because of an insufficient number of observations in the cells $M_{t+1}=3|M_t=1$. We were forced to estimate these probabilities as averages.

The first estimates for transition probabilities

We tried logistic regression models for probabilities $P(M_{t+1}=2|M_t=1)$ and $P(M_{t+1}=3|M_t=2)$, M=V, U or T. Results are presented below. Notation p = logit(x) means that log(1/(1-p)) = x. The figures in parentheses represent "coefficient/its deviation" which expresses the precision of the coefficient. Figure n is the number of observations and ϱ^2 is analogous to the coefficient of determination (R^2) in linear regression.

Estimates for defects:

1) $$p(V_{t+1}=2|V_t=1,K_t,U_t,T_t,K_{t+1},\text{region},ADT) = \text{logit}(\underset{(3.7)}{-.205} - \underset{(5.0)}{.638}\ ADT3),$$

where

$$ADT3 = \begin{cases} 0 & \text{when } ADT \le 6000 \\ 1 & \text{when } ADT > 6000. \end{cases}$$

There were n=1709 observations and ϱ^2=1.1%. Transition probabilities calculated with this model are

ADT	≤6000	>6000
$p(V_{t+1}=2\|V_t=1,ADT)$	.449	.301

2) $$p(V_{t+1}=3|V_t=2,K_t,U_t,T_t,K_{t+1},\text{region},ADT) = \text{logit}(\underset{(8.7)}{-1.45} - \underset{(6.3)}{1.58}\ ADT2 - \underset{(3.1)}{2.28}\ ADT3),$$

where ADT3 is the same as before and

$$ADT2 = \begin{cases} 0 & \text{when } ADT \le 1500 \text{ or } ADT > 6000 \\ 1 & \text{when } 1500 < ADT \le 6000. \end{cases}$$

The statistic ϱ^2 has the value 8.5%, n=949 and the probabilities are

ADT	≤1500	1501-6000	>6000
$p(V_{t+1}=3 \mid V_t=2, ADT)$	.190	.046	.023

Estimates for rutting:

1) $p(U_{t+1}=2 \mid U_t=1, K_t, V_t, T_t, K_{t+1}, V_{t+1}, \text{region}, ADT)$

$$= \text{logit}(\underset{(13.1)}{-3.80} - \underset{(6.1)}{.992}\ \text{region} + \underset{(4.8)}{.694}\ V_{t2} + \underset{(4.8)}{2.23}\ V_{t3} + \underset{(6.5)}{1.76}\ ADT2 + \underset{(7.1)}{2.19}\ ADT3),$$

where ADT2 and ADT3 are the same as before, region is =0 in southern Finland and =1 in northern Finland, and when i=2,3,

$$V_{ti} = \begin{cases} 1 & \text{when } V_t = i \\ 0 & \text{otherwise.} \end{cases}$$

The statistic ϱ^2 has the value 8.3%, n=2411 and the probabilities are

$p(U_{t+1}=2 \mid U_t=1, V_t, \text{region}, ADT)$

region	V_t	ADT class ≤1500	1501-6000	>6000
south	1	.022	.115	.167
	2	.043	.207	.286
	3	.173	.549	.651
north	1	.008	.046	.069
	2	.016	.088	.129
	3	.072	.311	.409

2) $p(U_{t+1}=3 \mid u_t=2, K_t, V_t, T_t, K_{t+1}, V_{t+1}, \text{region}, ADT)$

$$= \text{logit}(\underset{(10.0)}{-2.33} + \underset{(3.0)}{1.39}\ ADT3),$$

where ϱ^2=4.5% and n=259. The probabilities are

ADT class	≤6000	>6000
$p(U_{t+1}=3 \mid U_t=2, ADT)$	.089	.283

We were unable to acquire any models for **roughness probabilities** that would have described connections between transition probabilites and other condition variables, region or traffic classes.

Some criticism

Results of this first round were poor. The models explained very little about the variation in transitions. We therefore concluded that with the above data we are unable to acquire reliable models for transition probabilities.
Another possibility was to calculate the probabilities directly as average percentages from tables that have been divided according to those variables that seem to affect the probabilities. In this way we acquired uneven and partly illogical results as the data did not cover all condition class combinations.
In spite of these weaknesses, the explanatory variables in the above results had coefficients that were statistically significant and logical. Thus, we used these probabilities to test the long term optimization programme and discovered that the optimum was attained merely by chance. We concluded that this was because the probabilities changed mainly according to traffic volume. Success in optimization demands more variation between condition classes particularly within each region-traffic model.

We concluded that as we had the values of the observations in the data (in previous estimations we used classes), it would be

possible to obtain more sensitive models by using the values of explanatory variables instead of their classes.
Calculating the transition probability estimates for each condition state with the aid of these models was more problematic than with the earlier models (pgs 25-27) which provided them directly owing to the fact that the values of explanatory variables in each combination of condition class had to be defined. However, generalization of the available data was not possible because it was not collected randomly. We presumed that we would obtain the probabilities from these new models by using figures calculated from the complete data. The estimates acquired using this method were as accurate as those in the models of the first round.

The second estimates for transition probabilities

Using the values of explanatory variables instead of their classes produced a result in the desired direction. In most of the new models we used bearing capacity as a new explanatory variable. Optimization of the network level models was considerably more successful.
Below, the second round results are briefly presented for defects, rutting and roughness.

Estimates for defects

1) $p(V_{t+1}=2|V_t=1) =$

$$\text{logit}(\underset{(5.1)}{2.98} - \underset{(5.9)}{.418} \log(ADT) + \underset{(2.0)}{.00221} \text{ age of surface}*U_t)$$

$\varrho^2 = 1.8\%$ ja n = 1709

Table 5: Estimates for defect probabilities $p(V_{t+1}=2|V_t=1)$

		ADT ≤1500	1501-6000	>6000
U_t	≤13	.558	.443	.319
	14-19	.600	.486	.358
	>19	.618	.505	.375

2) $p(V_{t+1}=3|V_t=2) =$

$$\text{logit}(\underset{(4.5)}{6.58} - \underset{(5.5)}{1.14} \log(ADT) - \underset{(1.0)}{.00179} K_t)$$

$\rho^2 = 7.8\%$ ja n = 949

Table 6: Estimates for probabilities $p(V_{t+1}=3|V_t=2)$

		ADT ≤1500	1501-6000	>6000
K_t	1	.145	.046	.011
	2	.169	.055	.013
	3	.173	.056	.014
	4	.181	.059	.015
	5	.196	.065	.016

Estimates for rutting

1) $p(U_{t+1}=2|U_t=1) =$

$$\text{logit}(\underset{(11.1)}{-8.49} + \underset{(9.0)}{.891} \log(ADT) - \underset{(2.3)}{.00171} K_t$$

$$- \underset{(5.7)}{.938}\ \text{region} + \underset{(4.1)}{.048} V_t)$$

region = 0 in southern region, elsewhere = 1

$\rho^2 = 8.2\%$ ja n = 2411

Table 7: Estimates for probabilities $p(U_{t+1}=2|U_t=1)$

ADT	bear.cap.	0	1-20	>20
south		V_t		
≤1500	1	.047	.053	.171
	2	.055	.062	.196
	3	.057	.064	.202
	4	.060	.067	.211
	5	.065	.073	.226
1501-6000	1	.117	.130	.357
	2	.136	.151	.397
	3	.139	.154	.404
	4	.145	.161	.417
	5	.157	.174	.439
>6000	1	.291	.316	.632
	2	.327	.355	.671
	3	.333	.361	.677
	4	.345	.373	.689
	5	.366	.395	.708
north				
≤1500	1	.019	.021	.075
	2	.022	.025	.088
	3	.023	.026	.090
	4	.024	.027	.095
	5	.027	.030	.103
1501-6000	1	.049	.055	.178
	2	.058	.065	.205
	3	.059	.067	.210
	4	.062	.070	.219
	5	.068	.076	.234
>6000	1	.138	.153	.402
	2	.160	.177	.444
	3	.164	.181	.451
	4	.171	.189	.464
	5	.184	.203	.487

2) $p(U_{t+1}=3|U_t=2) =$

$$\text{logit}(\underset{(4.7)}{-17.4} + \underset{(4.3)}{1.96}\log(ADT) - \underset{(1.2)}{.003534}K_t)$$

$\rho^2 = 11.4\%$ ja n = 259

Table 8: Estimates for probabilities $p(U_{t+1}=3|U_t=2)$

bear.cap.	ADT ≤1500	1501-6000	>6000
1	.005	.044	.358
2	.008	.062	.443
3	.008	.066	.457
4	.009	.073	.485
5	.011	.086	.531

Roughness

$$p(T_{t+1}=3|T_t=2,K_t,V_t,U_t,K_{t+1},V_{t+1},U_{t+1}) =$$
$$\text{logit}(\underset{(1.0)}{1.46} - \underset{(2.4)}{.0241}\ K_t)$$

ϱ^2 = 42% ja n = 26

Table 9: Estimates for probabilities $p(T_{t+1}=3|T_t=2,K_t)$

bear.cap.	1	2	3	4	5
$p(T_{t+1}=3\|T_t=2,K_t)$	.001	.015	.022	.050	.122

For probabilities $p(T_{t+1}=2|T_t=1)$ we were unable to find any model mainly because of the small amount of data. The estimated average was .791.

The above results appeared logical and applicable but they nevertheless have several drawbacks. The lack of data concerning roughness is obvious in the results of network level models. The user costs depend mostly on roughness and their magnitude dominates the optimization, so that accurate estimation of roughness probabilities is very important.
Bearing capacity is used as an explanatory variable in most of the above models, but its coefficient is frequently fairly inaccurate. In future years, when we have observations which have been measured simultaneously at the same points they are likely to produce better models.

The third estimates for transition probabilities

The results of the second round presented above are currently being used in the network level models for asphalt concrete. As we have noticed, these estimates are calculated using data which has not been specifically collected for this purpose. They are therefore strictly speaking not suitable, but formed the best data available to us.

The measuring programme described in chapter 4 was not begun until summer 1988. According to current plans, in the autumn of 1990 we should have data from two consecutive years thus enabling us to estimate new models. For bearing capacity this may be too a short a period in which to come up with adequate results as changes are slow, but for other condition variables we can expect far more reliable results.

Bibliography:

Condition of Asphalt Concrete Roads in 1985, VTT/TIE, research report 535, Espoo 1986 (in Finnish).

Design of the TVH Highway Investment Programming System (draft), Cambridge Systematics, Inc. (1987)

Ekholm, Anders; Green, Mick; and Palmgren, Juni (1986) Fitting Exponential Family Nonlinear Models in GLIM 3.77, GLIM Newsletter No. 13.

Korhonen, Riitta (1985) Rutting Models for Asphalt Concrete Rroads, TVH 713102 (in Finnish).

McCullagh, P. (1980) Regression Models for Ordinal Data (with discussion), J.R.Statist.Soc.,B,42,109-142.

McCullagh, P. and Nelder, J.A. (1983) Generalized Linear Models. Chapman and Hall, London.

Optimization Techniques for Planning Highway Improvements. Cambridge Systematics, Inc. (1986)

Paterson, William D.O. (1986) Prediction of Road Deterioration and Maintenance Effects: Theory and Qualification, Volume III, The Highway Design and Maintenance Standards Study, The World Bank.

Paterson, William D.O. and Chesher, Andrew P. (1986) Application of Failure-Time Theory to the Prediction of Surfacing Distress, paper prepared for presentation at the 65th Annual Meeting of the Transportation Board, January 1986.

Predictions for Traffic and Car Volume for 1986-2010, TVH and TASKU, TVH 713092, Helsinki 1987 (in Finnish).

Road Condition and Level of Service. Results from experimental roads in 1979-1983, VTT/TIE, research report 429, Espoo 1985 (in Finnish).

Talvitie, Antti and Olsonen, Riitta (1988) Selecting Asphalt Concrete Condition States for Finland's Highways, paper prepared for presentation at the 67th Annual Meeting of the Transportation Research Board, January 1988.

Talvitie, Antti and Viren, Riitta (1985) Decrease of Bearing Capacity as Function of Traffic Loading, TVH, memo (in Finnish).

Thompson, P.D., Neumann, L.A., Miettinen, M. and Talvitie, A. (1987) A Micro-Computer Markov Dynamic Programming System for Pavement Management in Finland, North American Conference on Managing Pavements, Vol 1.

User Costs in Road Traffic 1988, Roads and Waterways Administration vol. 11, Helsinki 1988.

Way, George B., John Eisenberg and Ram B. Kulkarni (1982) Arizona Pavement Management System: Phase 2 - Verification of Performance Prediction Models and Development of Database, Pavement Management, Transportation Research Record 846.

Äijö, Juha and Miettinen, Martti (1987) Selection and Timing of Road Maintenance, Determination of the Effects of Actions Using the Delphi Method, Viatek Oy (in Finnish).