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Probability Based Pavement Asset Management

Ray McGowan
Senior Engineer, PMS Pavement Management Services Ltd., Dublin, Ireland

Alan O'Connor
Professor, Dept. of Civil, Structural & Environmental Engineering, Trinity College Dublin, Dublin, Ireland

Kieran Feighan
Director, PMS Pavement Management Services Ltd., Dublin, Ireland

ABSTRACT: The paper presents a study on the use of Markov Processes in determining the optimal lifecycle management strategy for a pavement network. A comprehensive analysis of condition data recorded on the Irish national road network, which falls under the remit of Transport Infrastructure Ireland, is presented. Transition Probability Matrices are developed for alternative condition indicators and considering factors such as AADT. The use of homogeneous vs non homogenous chains is considered. Overall the technique is demonstrated to be central to pavement asset management.

Deterministic Pavement Deterioration models are commonly used due to their relative simplicity, ease of use, and familiarity. The modelling techniques include straight-line extrapolation, S-shaped curves, polynomial constrained least squares, and logistic growth models. Some of the disadvantages of deterministic models include the facts that: (i) models do not take into account the uncertainties in pavement behaviour under variable traffic load, (ii) developing models requires an accurate and comprehensive dataset and (iii) ideally, all variables that affect pavement deterioration should be included in the models.

Traditionally, pavement deterioration models predict either an absolute condition value for a given pavement age, or the incremental change of the condition from one year to another. Modelling uncertainty requires the use of probabilistic techniques. Among probabilistic models, the Markov model is the most popular approach to modelling pavement performance as Markov probabilities can be derived from as little as two years of pavement condition data collection. A critical component of the Markov model is the transition probability matrix (TPM). A TPM represents the probability that a segment will stay in a specific condition for a specific year. Generally, the TPM is calculated based on the historical pavement condition data.

There are large variations in construction type, pavement condition and traffic volumes across the Transport Infrastructure Ireland (TII) network. Accordingly, TII have broken the network into sub-networks based on construction (engineered or legacy) and traffic volumes to more effectively manage the network overall. This approach has led to 5 Sub-networks being established, enabling different levels of service, treatment strategies, intervention effects, intervention costs etc to be applied as appropriate. The 5 sub-networks are: Subnetwork 0 (1200 km) – Motorway and dual carriageway; Subnetwork 1(1200 km) - Engineered Single Carriageway; Subnetwork 2 (700 km) - Urban Pavements; Subnetworks 3 (1300 km) and 4 (1000 km) - Legacy Single Carriageway. The KPI's use the qualitative descriptors of Very Good, Good, Fair, Poor and Very Poor. Currently these condition classes are defined separately for the key pavement performance parameters of International Roughness Index (IRI), Rut Depth (RUT) and Longitudinal Evenness (LPV3). Estimations obtained using Markov transition probabilities are used to evaluate, probabilistically, the relative condition of a network as a function of time. Individual TPMs are developed for each sub-network, reflecting the very large difference in pavement response across sub-networks. The process makes possible the evaluation of the implication of alternative maintenance scenarios on network condition and to optimise budget spend as a function of time to maximise the condition of the network or to maintain the condition of the network above a prescribed limit, i.e. no more that 25% in Fair condition by Year X. Furthermore, alternative thresholds for condition states are analysed. TPMs are presented in the context of either homogenous and/or inhomogeneous chains, i.e. TPM's varying as a function of the considered time step. The results of the work provides TII with an extremely powerful asset management tool for optimal lifecycle management of its >5000km pavement network.

1. MARKOV CHAIN MODELLING OF PAVEMENT DETERIORATION

Markov chain modelling is a probabilistic method that is used in a variety of pavement management systems (Kulkarni, 1984, Carnahen et al., 1987, Thompson et al., 1987, Butt et al. 1987, Butt, 1994, Corotis et al., 2005, Costello et al., 2005, Hassan et al., 2015) to build probabilistic models that predict pavement degradation. Markovian models require an initial condition state vector and a transition probability matrix (TPM). The number of TPM's is conditional on the system's homogeneity; if the degradation of the network is constant throughout time, one TPM suffices for the model, but variability in network degradation requires more than one TPM. The future state of pavement intervals depends on the present state of the intervals, not the past state/s, which is a feature of Markov models.

In applying Markov chain modelling to the problem of pavement degradation, the condition states of the pavement segments are assumed to range from *State 1*, which represent the proportion of the pavement segments in near-perfect condition, to *State n*, which represent the proportion of the pavement segments in very poor condition, i.e. the pavement segment is completely damaged/degraded. The present/current condition of the pavement segments is represented as a vector and it is named the *Initial condition state vector* with notation a_0:

$$a_0 = (State\ 1, State\ 2, \dots, State\ n) \qquad (1)$$

Markov chain modelling then employs *Transition Probability Matrices* (TPM's) to predict the future condition of pavement segments as they degrade as a function of time. Probabilities of transition are stored in a matrix in which rows correspond to the present state and columns to the future state. The elements of the TPM are referred to with the notation p_{ij}, where i indicates the row and j indicates the column of the matrix element. The general form of a 5x5 transition matrix is presented in Table 1.

Table 1: General form of a Transition Probability Matrix, P.

Moving from State *i*	**To State *j***				
	State 1	**State 2**	**State 3**	**State 4**	**State 5**
State 1	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}
State 2	0	p_{22}	p_{23}	p_{24}	p_{25}
State 3	0	0	p_{33}	p_{34}	p_{35}
State 4	0	0	0	p_{44}	p_{45}
State 5	0	0	0	0	$p_{55} = 1$

The following six rules must be considered when developing transition matrices:

1. Transition probabilities, p_{ii} (p_{11}, p_{22}, p_{33}, p_{44}) – main diagonal (highlighted with orange in **Error! Reference source not found.**), denote the proportion of the pavement segments remaining in condition *i* after one time step (e.g. 1 year) has passed.
2. Values below the main diagonal (highlighted with grey in **Error! Reference source not found.**) are generally represented with zeros,

suggesting that the pavement segments condition cannot improve without treatment (p_{ij} = 0 for $i>j$). Where improvements/repairs are modelled the lower diagonal is non zero.

3. Values above the main diagonal (highlighted with green in **Error! Reference source not found.**) indicate the probability of the pavement segments in condition i moving to a lower condition within one time step.
4. The element p_{55} equal to unity suggest that the pavement segment has reached its worst state of degradation and cannot deteriorate further.
5. All elements of the matrix should be positive.
6. The sum of elements in each row should be equal to 1.0.

The elements of a TPM may be calculated based upon survey data using Equation 2 (Ortiz-García et al. 2006):

$$p_{ij} = N_{ij}/N_i \qquad (2)$$

Where N_{ij} represents the total number of pavement segments moving from state i to state j following one time step, and N_i is the total number of pavement segments in state i at the start of the time step.

Error! Reference source not found. presents a numerical example of a TPM, with Figure 1 presenting a directed graph to illustrate this information. In the table the following condition states are considered: Very Good (VG), Good (G), Fair (F), Poor (P) and Very Poor (VP). The threshold values for each performance indicator condition state are as specified by the managing authority. Table 3 illustrates the classification system adopted per subnet by TII.

Table 2: Numerical Example of a Transition Probability Matrix.

Moving from State *i*	**To State *j***				
	VG	**G**	**F**	**P**	**VP**
VG	0.9	0.08	0.01	0.005	0.005
G	0	0.8	0.1	0.07	0.03
F	0	0	0.7	0.2	0.1
P	0	0	0	0.6	0.4
VP	0	0	0	0	1

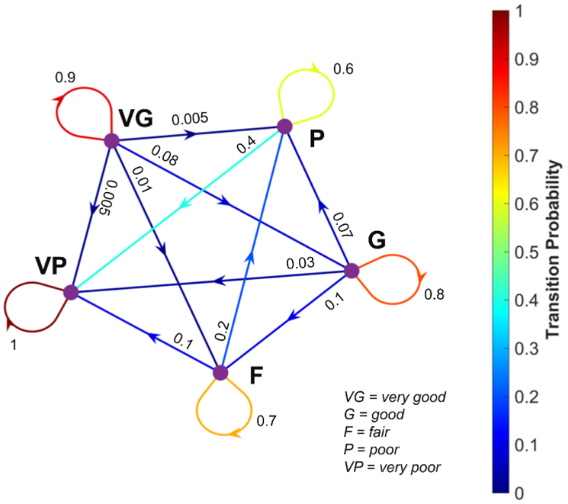


Figure 1: Directed Graph of Transition Probabilities.

Table 3: TII Network Condition Category Thresholds

		Subnet Number				
	Cat.	0	1	2	3	4
IRI	VG	<1.5	<2	<2.7	<2.7	<3
	G	1.5 to 2	2 to 2.5	2.7 to 3.2	2.7 to 3.2	3 to 4
	F	2 to 2.5	2.5 to 3	3.2 to 4	3.2 to 4	4 to 5
	P	2.5 to 3	3 to 3.5	4 to 5	4 to 5	5 to 7
	VP	>3	>3.5	> 5	> 5	>7
RUT	VG	<3	<3	< 4	< 4	< 6
	G	3 to 5	3 to 5	4 to 6	4 to 6	6 to 9
	F	5 to 6	5 to 6	6 to 9	6 to 9	9 to 15
	P	6 to 9	6 to 9	9 to 15	9 to 15	15 to 20
	VP	>9	>9	> 15	> 15	>20
LPV3	VG	< 1	< 1	< 2	< 2	< 2
	G	1 to 2	1 to 2	2 to 3	2 to 3.5	2 to 4
	F	2 to 3	2 to 3	3 to 4	3.5 to 5	4 to 7
	P	3 to 4	3 to 4	4 to 6	5 to 7	7 to 10
	VP	> 4	> 4	> 6	> 7	> 10

The first row in Table 2 shows the probabilities of pavement segments in *very good* (VG) condition moving to any of the *good*, *fair*, *poor* and *very poor* conditions. The probability that pavement segments in *very good* condition will stay in the same very good condition is 0.90. This means that 90% of the pavement segments will not deteriorate after one time step. There are 8% of pavement segments that will degrade from *very good* to *good* condition. Only 1% will downgrade from *very good* to a *fair* condition and a combined 1% from *very good* to *poor* and *very poor* condition. The third row represents the transition probabilities for pavement segments in *fair* (F) current condition. The probability of staying in the same *fair* condition is 0.70. The pavement segments cannot move to a better condition (good or very good) without repair works, therefore, the values in the columns associated with these two conditions is 0 (zero). There is a probability of 0.20 for transitioning from *fair* to *poor*, and 0.10 for moving from *fair* to *very poor*, respectively. For each of the five states, colours are used in Figure 1 to show the transition probabilities. Moreover, arrows indicate the transitioning from State *i* to State *j*.

Using Equation 2 in combination with available survey data recorded on TII's network, per 100m interval, from 2010 to 2019 considering IRI, LPV and RUT, TPM's were developed for Subnets 0, 1, 2, 3 & 4, with the % distribution across the network as described in Table 4. Table 5 details the total data set available noting that one side of the road (i.e. direction) is surveyed each year, therefore each sample unit has data for every second year.

Table 4: TII Subnet Classifications.

Subnet No.	Classification	% Of Network
0	Motorway/DC	23%
1	Engineered Pavements	22%
2	Urban Areas	13%
3	High Traffic Non-Engineered	24%
4	Low Traffic Non-Engineered	18%

Table 5: Data Summary.

Direction 1			Direction 2		
SubNet	*No. of records*	*Unique roads per SubNet*	*SubNet*	*No. of records*	*Unique roads per SubNet*
0	11959	25	0	11965	25
1	11923	54	1	12161	54
2	6736	58	2	6742	58
3	12617	50	3	12609	50
4	9825	28	4	9577	28
NaN values	40	40	NaN values	36	36
Total	53100	66	Total	53090	66

Furthermore, in considering the Subnets TPM's, traffic volume, i.e. AADT, was considered to differentiate the TPM's. In this context for Subnet 0, TPM's were developed for the case of AADT < 20,000, 20,000<AADT<40,000 and AADT>40,000. In this context, Table 6 presents the TPM for IRI, considering SubNet 0, for AADT <20,000. It is observed that a high percentage (over 95 %) of pavement segments will remain in the same condition state after one duty cycle. Similar subdivision was performed for Subnets 1, 2, 3 & 4 reflecting traffic volumes.

Table 6: TPM for IRI Subnet 0, AADT<20,000.

Moving from State *i*	**To State *j***				
	VG	**G**	**F**	**P**	**VP**
VG	0.9817	0.0177	3.75E-04	1.13E-04	1.12E-04
G	0	0.9753	0.0227	0.0017	3.0E-04
F	0	0	0.9684	0.0279	0.0037
P	0	0	0	0.96	0.04
VP	0	0	0	0	1

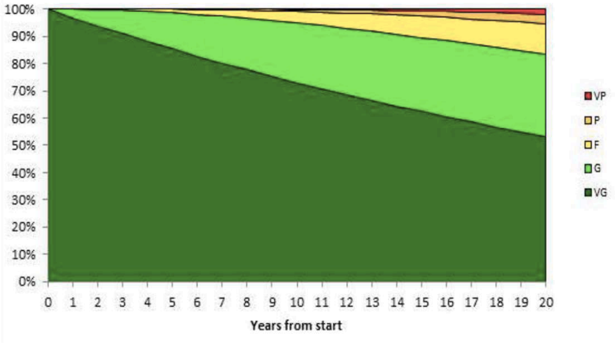
After defining both the initial vector and the TPM, Equation 4 can be employed to determine the probability distribution of the condition states at any particular time, *t*:

$$a_t = a_0 P^t \qquad (4)$$

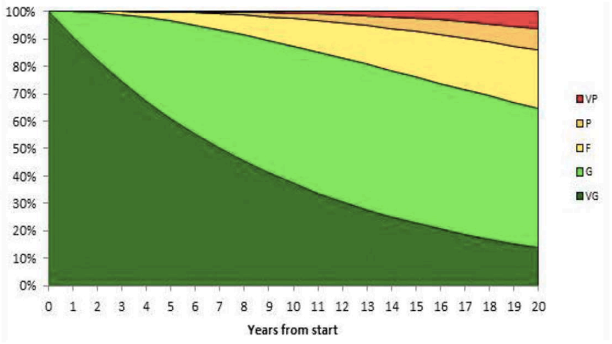
Where a_0 is the initial condition vector, P^trepresents the TPM raised to the power of t, t is time in years, and a_t depicts the distribution of pavement segments condition at time t.

An example of degradation over a 20-year period is presented below, in Figure 2. Illustrated is the evolution in condition considering Subnet 0 for varying AADT based upon IRI, where the x-axis depicts the time interval in years since the start of the analysis, i.e. a 20 year horizon.

Similarly, Figure 3(a), presents general degradation for Subnet 1 based upon TPM's developed from survey records for segments with AADT>5000. While Figure 3(b) presents general degradation for the non-engineered pavement class from Subnet 4 for AADT>5000.



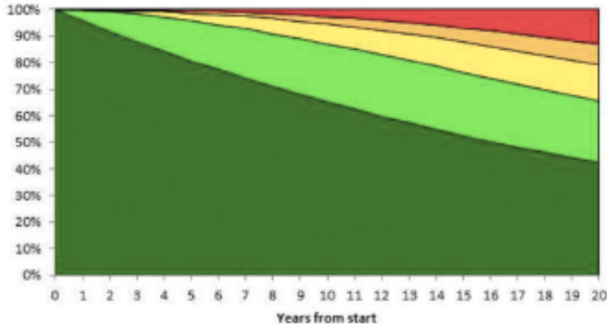
(a) AADT < 20,000



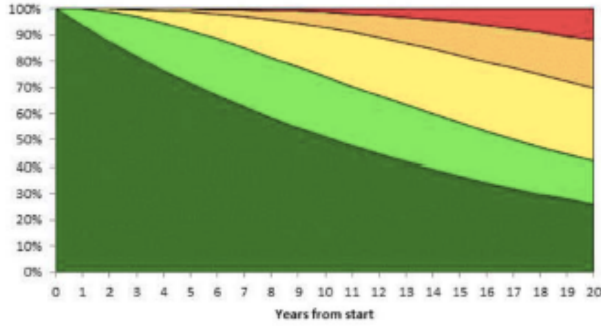
(b) 20,000 < AADT < 40,000

Figure 2: Subnet 0 – IRI- General Degradation.

Markov chain modelling can be used in this way in evaluating the condition of an asset or a network of assets throughout their lifespan. Estimations obtained using Markov transition probabilities can be used to evaluate, probabilistically, the relative condition of a network and its assets as a function of time. Evolution of individual indicators can be analysed or combined indicators can be developed. The process makes possible the evaluation of the implication of alternative maintenance scenarios on network condition and to optimise budget spend as a function of time to maximise the condition of the network or to maintain the condition of the network above a prescribed limit, i.e. no more that 25% in condition X by Year Y. Furthermore, alternative thresholds for condition states can be analysed. Significantly, TPM's may be developed for either homogenous and/or inhomogeneous chains, i.e. TPM's varying as a function of the considered time step and condition state (Butt et al., (1987).



(a) Subnet 1, AADT > 5,000



(b) Subnet 4, AADT> 5,000

Figure 3: (a) Subnet 1- IRI - General Degradation, (b) Subnet 4 - IRI - General Degradation .

2. VALIDATION OF DEVELOPED TPM'S

TPM's were developed across three condition indicators (IRI, RUT, LPV3) for data recorded between 2010 and 2019. The data employed to develop the TPM's was recorded in odd and even years on alternate sides of the carriageway, i.e. survey performed in direction 1 in even years and direction 2 in odd years. In order to validate the developed TPM's a number of alternative validation scenarios were considered.

Scenario I: The data per the 2017 dataset was assumed to be the initial vector and the 2019 dataset was the field data. The TPM is assumed to be the average of the first seven matrices derived, namely the average of TPM's derived for the inspection periods 2010-2012, 2012-2014, 2014-2016, 2016-2018, 2011-2013, 2013-2015 and 2015-2017.

Scenario II: A second verification was to consider both odd and even years. The field data consists of total number of road segments in different condition states as inspected in 2018 and 2019. The average TPM as per Scenario I was used.

Scenario III: The TPM was redefined as the average of 2010-2012, 2012-2014, 2011-2013 and 2013-2015. The initial Vector and data vector are the same as those used in Scenario II.

In the subsequent analysis the predicted condition in 2019 was compared to actuals. The results presented in Tables 7, 8 and 9 demonstrate very good agreement. It is noted that the precision of the agreement is a function of the indicator considered, i.e. IRI, RUT or LPV3.

Table 7: Validation of Asset Condition Measurement and Prediction - IRI Subnet 0, AADT<20,000.

Initial Vector	Prediction		Data	
Scenario 1				
	No. Sections	%	No. Sections	%
3845	3554	71.36	3557	71.43
943	1147	23.03	1141	22.91
145	207	4.15	213	4.28
33	51	1.03	45	0.90
14	22	0.43	24	0.48
Scenario 2				
	No. Sections	%	No. Sections	%
7670	7089	70.19	7130	70.59
1993	2390	23.66	2351	23.28
327	454	4.50	463	4.58
76	116	1.15	107	1.06
34	51	0.50	49	0.49
Scenario 3				
	No. Sections	%	No. Sections	%
7670	7079	70.09	7130	70.59
1993	2389	23.66	2351	23.28
327	456	4.52	463	4.58
76	119	1.17	107	1.06
34	57	0.56	49	0.49

Table 8: Validation of Asset Condition Measurement and Prediction - RUT Subnet 0, AADT<20,000.

Initial Vector	Prediction		Data	
Scenario 1				
	No. Sections	%	No. Sections	%
2834	2231	62.70	2263	63.60
674	1138	31.99	1042	29.29
33	125	3.52	154	4.33
17	62	1.74	92	2.59
0	2	0.06	7	0.20
Scenario 2				
	No. Sections	%	No. Sections	%
6985	5498	66.67	5649	68.50
1177	2384	28.91	2190	26.56
56	246	2.99	261	3.16
29	115	1.39	139	1.69
0	3	0.04	8	0.10
Scenario 3				
	No. Sections	%	No. Sections	%
6985	5727	69.45	5649	68.50
1177	2211	26.82	2190	26.56
56	207	2.51	261	3.16
29	98	1.19	139	1.69
0	3	0.04	8	0.10

Table 9: Validation of Asset Condition Measurement and Prediction – LPV3 Subnet 0, AADT<20,000.

Initial Vector	Prediction		Data	
Scenario 1				
	No. Sections	%	No. Sections	%
4801	4651	89.48	4601	88.51
390	526	10.12	563	10.83
3	13	0.26	26	0.50
3	3	0.06	5	0.10
1	4	0.08	3	0.06
Scenario 2				
	No. Sections	%	No. Sections	%
9684	9382	89.13	9306	88.41
814	1088	10.34	1151	10.93

23	39	0.37	56	0.53
4	9	0.09	8	0.08
1	8	0.07	5	0.05
Scenario 3				
	No. Sections	%	No. Sections	%
9684	9416	89.46	9306	88.41
814	1054	10.01	1151	10.93
23	36	0.34	56	0.53
4	9	0.09	8	0.08
1	10	0.09	5	0.05

3. PAVEMENT MANAGEMENT STRATEGIES

Having developed and validated TPM's for the Irish network it is now appropriate to employ these in determining the optimal maintenance strategy for the network, by subnet, over a specified time horizon e.g. 20 years. In doing so it is necessary to identify treatment options, to cost these treatment options and to determine appropriate thresholds where they are to be applied. By way of example Table 10 lists four alternative treatment options with an associated Trigger for action.

Table 10: Treatment Type and Trigger

Treatment Type	Trigger
Replace Surface	IRI, RUT or LPV = F
Overlay	IRI, RUT or LPV = P **OR** RUT = VP
Strengthen	IRI, RUT or LPV = VP
Reconstruct	IRI or LPV = VP **AND** RUT = VP

Where Replace Surface implies a treatment with the objective of sealing of pavement surface, improving skid resistance, roughness and rutting. Overlay has the objective to increase Strength, retard aging, improve or restore surface characteristics, improve or restore functionality. Strengthen has objectives to increase Strength, retard aging, improve or restore surface characteristics, improve or restore functionality. Finally the objectives of Reconstruct are to: increase capacity and pavement strength to provide a long life pavement. In all cases it is necessary to categorise the performance of the repair in terms of associated triggers for intervention, e.g. Table 11 for RUT, and the unit costs (e.g. per m^2) per intervention by subnet.

In the temporal analysis following repair action, two strategies to model inhomogeneity were followed (a) TPM's were derived to represent the behavior of improved segments and these were employed following an intervention and (b) when a reconstruction was applied to a non-engineered pavement (Subnet 3 or 4) the performance was reclassified to be represented by the TPM for an engineered pavement.

Table 11: Treatment Trigger Matrix

		RUT Class				
		1	2	3	4	5
Comfort Class*	1	N	N	S	O	O/T
	2	N	N	S	O	O/T
	3	S	S	S	O	O/T
	4	O	O	O	O	O/T
	5	T	T	T	T/R	R

*Comfort Class = Max of IRI and LPV Class

Where N = No Treatment, S = Replace Surface, O = Overlay, T = Strengthen and R = Reconstruct.

On the basis of this treatment trigger strategy and employing the probabilistic models of deterioration per AADT as derived from records and validated as above it is possible to identify the suite of optimal interventions over a given time horizon for a pavement network, Figure 4. Furthermore, it should be considered whether a 'hybrid' indicator, combining the various individual indicators should be used (COST 354, 2008).

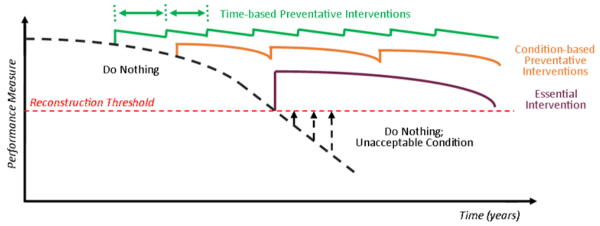
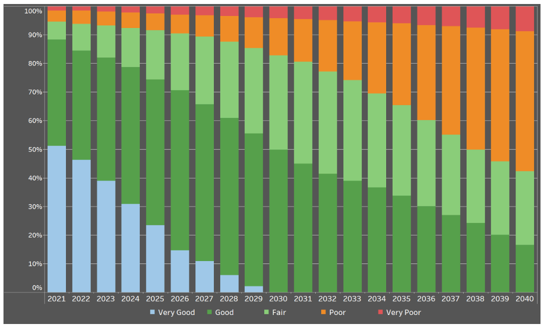
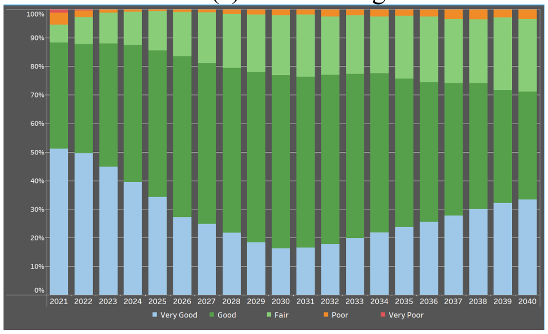


Figure 4: Optimising Pavement Lifecycle Strategy.

By way of example Figure 5 presents the network condition as a function of an optimized suite of interventions for (a) a Do-Nothing and (b) Budget A intervention scenario. The optimization was performed using the software dTIMS, TII's PAM system. As can be seen in the Do-Nothing scenario the network is essentially consumed over the time horizon whereas with the budget intervention scenario, a steady state is approached. It should be noted that an additional constraint on the optimization can relate to the % of the network in a Good or better condition.



(a) Do Nothing



(b) Budget Scenario A

Figure 5: Alternate Budget Scenarios.

4. CONCLUSIONS

The purpose of this paper is to present the calibration of Transition Probability Matrices (TPM's) for 3 pavement characterization parameters. The matrices, which present the probability of transition between condition states, are calibrated on the basis of survey data collected over a multi-annual period. TPM's are then employed in a Markov Process to determine the evolution of condition states with time and to predict condition as a function of time. In concert with alternative pavement management strategies, the process may be employed to predict the condition of the network under alternative budget scenarios. Applications of the methodology further arise in Risk Based Asset Management activities to provide for optimal performance management of the network.

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