MANAGING ASSETS USING INFREQUENT INSPECTIONS

Authors M Black[◆], AT Brint[◆], JR Brailsford[+] & G Davidson[⊗]

Affiliations [◆] University of Salford, M5 4WT, UK
[+] EA Technology, CH1 6ES, UK
[⊗] 24seven Utility Services Ltd, UK

SUMMARY

Time Based and Condition Based Asset Management policies are modelled using a Markov Decision Process approach. This approach combines the ability to model the condition deterioration of a population of assets, with the ability to model the effects of maintenance decisions on that deteriorating population. It incorporates the costs and risks of maintenance decisions and calculates an average long term cost and risk. Different policies are then examined and a best policy evaluated. Deterioration of asset condition is modelled by defining a number of condition states and calculating transition probabilities of going from one state to the next. Available maintenance actions are do nothing, maintain and replace. The state of an item immediately after it has been maintained is modelled by assigning probabilities to the possible new states. Costs are allocated to each state for each action.

Simulated data is used to examine the effectiveness of the Markov chain as a model of the deterioration process. This data is generated by taking a normal distribution around the points on an average deterioration curve, but with a standard deviation based on the distance to a worst case deterioration curve. It is concluded that the Markov chain is a good model of the deterioration process and that it errs on the side of overestimating the deterioration that takes place. Hence it will tend to slightly overestimate the cost of the Asset Management policies.

Real data is used to model the effects and costs of Asset Management policies on the deterioration of tank paintwork for a population of 11kV ground mounted transformers. It is concluded that Condition Based Maintenance with regular inspections can offer significant savings over Time Based Maintenance.

Simulated data is used to examine the effectiveness of using a Markov Decision Process model for Asset Management policies. It is concluded that the Markov model slightly overestimates the policy costs but the optimal time interval for Time Based Maintenance is similar to that obtained from more accurate models. The Markov approach is seen to have an advantage over such models in its flexibility to analyse a wide range of policies.

GESTION DE BIENS AVEC INSPECTIONS PEU FRÉQUENTES

Auteurs M Black[◆], AT Brint[◆], JR Brailsford[+] & G Davidson[⊗]

Affiliations [◆] Université de Salford, M5 4WT, Royaume-Uni
[+] EA Technology, CH1 6ES, Royaume-Uni
[⊗] 24seven Utility Services Ltd, Royaume-Uni

SOMMAIRE

Les politiques de gestion des biens basée sur le temps et basée sur l'état des biens sont modélisées en utilisant l'approche du processus de décision de Markov. Cette approche combine la capacité de modéliser la détérioration de l'état d'une population de biens avec la capacité de modéliser les effets des décisions de maintenance sur cette population en cours de détérioration. Elle incorpore les coûts et risques des décisions de maintenance et calcule le coût et risque moyen à long terme. Différentes politiques sont ensuite examinées et la meilleure est évaluée. La détérioration de l'état des biens est modélisée en définissant un certain nombre d'états et en calculant les probabilités de passage d'un état à l'autre. Les actions de maintenance disponibles sont : ne rien faire, entretenir et remplacer. L'état d'un article aussitôt après la maintenance est modélisé en attribuant des probabilités aux nouveaux états possibles. Des coûts sont attribués à chaque état pour chaque action.

Il est utilisé des données simulées pour examiner l'efficacité de la chaîne de Markov comme modèle du processus de détérioration. Ces données sont engendrées en prenant une répartition normale autour des points d'une courbe de détérioration moyenne, mais avec un écart type basé sur la distance entre cette courbe et une courbe de détérioration dans le cas le plus défavorable. Il est conclu que la chaîne de Markov est un bon modèle du processus de détérioration et qu'elle tend à pécher par une surestimation de la détérioration qui a lieu. D'où sa tendance à exagérer légèrement le coût des politiques de gestion des biens.

Pour modéliser les effets et les coûts des politiques de gestion des biens sur la détérioration de la peinture des cuves d'une population de transformateurs de 11 kV placés au sol, il est fait appel à des données réelles. Il est conclu que la maintenance basée sur l'état avec inspections régulières peut offrir des bénéfices significatifs par rapport à la maintenance basée sur le temps.

Il est utilisé des données simulées pour examiner l'efficacité du modèle de processus de décision de Markov dans les politiques de gestion des biens. Il est conclu que la chaîne de Markov surestime légèrement le coût des politiques mais l'intervalle de temps optimal pour la maintenance basée sur le temps est semblable à celui obtenu à partir de modèles plus précis. Il est considéré que l'approche Markov a un avantage par rapport à de tels modèles de par sa souplesse qui lui permet d'analyser une vaste gamme de politiques.

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INTRODUCTION

The Asset Management of electricity networks is driven by the need for policies that provide reliability and safety at a competitive cost. It is generally believed that the key to achieving this lies in controlling the condition of the assets. This is becoming increasingly possible as technological improvements have led to the development of Information Systems for the collection of condition information and improved non-invasive tests for condition. Hence databases of condition information are starting to become available and these will soon become more comprehensive and widespread. This trend is in turn driving the development of methods for Asset Management based on condition measures and these are the subject of this paper.

Traditionally large areas of Asset Management strategy have been based around time based preventative maintenance. Critical examination of these policies in UK Regional Electricity Companies has shown that they have not met the reliability and safety objectives for the overall network. Also, it is not clear how competitive they are in terms of cost, partly because the choice of time interval has usually been decided subjectively. Hence approaches based around condition information are now widely perceived as being preferable. The main technique that we will consider for doing this is the Markov Decision Process approach. This models how the condition of an item deteriorates by having a number of condition states along with transition probabilities for going from one state to the next Hoskins et al (1). Additionally Markov Decision Processes can have different levels of maintenance available (e.g. options such as retrofitting or refurbishment as described in Blakely (2) can be modelled). Markov Decision Processes have been very successful in formulating policies for road and bridge maintenance in the USA Golabi et al (3), Scherer and Glagola (4) – problems that have many similarities with maintaining electricity distribution networks.

Markov Decision Process Implementation Issues

A number of questions arise when implementing a Markov Decision Processes, for example:

1) How much cost-benefit improvement (if any) arise from applying a Markov Decision Process as opposed to a less complex maintenance strategy? Can we predict the likely benefit in advance?

2) What data is required to adequately fit the model? How can it be collected in a cost effective way?

3) Is there a way of deciding whether a Markov model is appropriate? How can we check that the model remains valid?

4) What is the best way to determine confidence intervals for our results? What is the best way to visually present the results of different policies?

Eleven UK distribution companies are sponsoring work to investigate these issues. 24seven Utility Services who are taking a leading role in this project, are committed to a maintenance policy of asset management based on condition measures. Therefore the company has introduced electronic data gathering on plant assets (see Lees and Dixon (5)) so as to greatly improve the effectiveness of collecting inspection data in the field and storing it centrally.

Although Markov Decision Processes can be applied to a wide range of network items, the concentration in this paper will be on the condition of the paintwork on 11kV ground mounted transformers. Consideration is given to how well Markov Decision Processes model deterioration, and different maintenance policies for ground mounted transformers are evaluated.

DETERIORATION OF CONDITION

Where condition information is only collected intermittently, modelling the expected deterioration of this condition becomes crucial to Condition Based Maintenance policies. Although modelling the deterioration of condition with time / usage as an average curve is natural (see Figure 1), it is difficult to develop an Asset Management policy based on such a curve because of the spread of conditions about the curve. For example, suppose we measure the overall condition index of an item at 20 years to be 50 (i.e. it is not on the “average” curve), how should we proceed?

Therefore we model the deterioration of condition as a Markov chain.

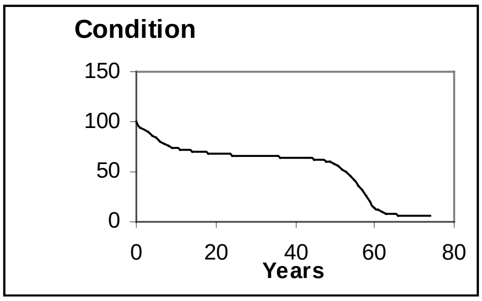

Figure 1: Average deterioration curve

Markov Chain approach

This assumes that the condition of an item falls into one of a number of states and that there is a (transition) probability of an item transferring from one state to a worse state in a given year. For example, typical states might be; pristine, good, showing signs of wear, and poor. In our work we assume that after an elapsed time of a year, an item's state will be either the same or be in the neighbouring worst state, i.e. an item's condition cannot improve nor can it deteriorate by more than one state per year.

A further Markov chain assumption is that the transition probability between any two states remains the same independent of how long an item has been in a state.

Condition data

We consider two sources of condition information – real and simulated data. While it is important that the method can be applied to practical situations i.e. it can use real data, the advantage of the simulated data is that the true answers are known.

Description of real data. The condition of the paintwork on 11kV ground mounted transformers was categorised into 4 states: state 1 - good, state 2 - some peeling, state 3 - noticeable rust, state 4 - extensive rust.

The results of extracting a sample of 309 transformers from a company database are given in Table 1.

Description of simulated data. The user enters both the curve that is considered to represent the average item condition at a particular time, and the curve that represents the worst item condition if there was a population of 100 items. For a given age, simulated condition data is generated as a Normal distribution with mean given by the average curve and standard deviation coming from the worst curve. The user also defines the condition values for the state boundaries.

TABLE 1 – The condition of the sampled transformers

Time	Number in each state			
(years)	1	2	3	4
1	5	1	0	0
2	1	1	0	0
3	25	3	0	0
4	20	2	0	0
5	11	3	0	0
6	12	6	3	0
7	21	9	1	0
8	14	14	0	1
9	21	14	0	0
10	21	10	1	0
11	27	19	5	0
12	7	8	3	0
13	6	5	1	0
14	5	2	1	0

Figures 2 and 3 show examples of two such curves along with the state boundaries. Note that as our condition ranges between 0 and 100, as the two curves approach condition 0, they begin to converge.

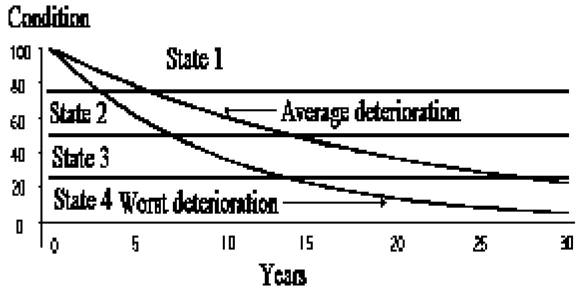

Figure 2: Widely spaced average and worst case curves

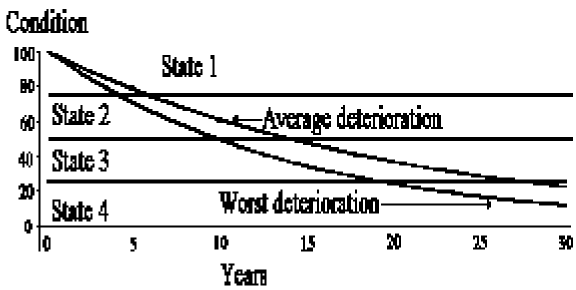

Figure 3: Closely spaced average and worst case curves

Alternative degradation models can be utilised, e.g. the Delay Time concept (see Christer (6)) is a framework that has been widely employed in industries such as building and industrial plant maintenance. It assumes that there are three condition regions: satisfactory, defective (e.g. a hairline crack is present) and failed. The probability of moving from satisfactory to defective is constant, but the chance of moving from this state to the failed state is dependent on the time spent in this state. The aim is to set the inspection period so that items are caught in the defective condition before they actually fail. Future work is planned to compare other degradation models with the one adopted in this paper.

Calculation of transition probabilities

When using real data, the transition probabilities are calculated using the weighted least squares method (see Hoskins et al (1)). However the population has been right censored as preventative maintenance has taken place meaning that there are relatively few items older than 11 years and none older than 14 years. Therefore weighted least squares underestimates the transition probability from state 3 to state 4. So this probability was taken to be the reciprocal of the estimated expected time for an item to deteriorate from state 3 to state 4 – this was estimated as 14 years.

An alternative approach is to calculate the transition probabilities by tracking the changes in state of each individual item. This provides a better understanding of the deterioration process but was not possible here because the data was a 'snapshot' of the population. The Asset Management database in use by 24seven Utility Services retains historical condition information and so this approach can be tested in later years.

When using simulated data, we determine the length of time taken by the average condition curve to cross neighbouring state boundaries and then use the reciprocal of this time as our transition probability. Note that this takes no account of the variation of condition about the average curve.

Analysing the deterioration of condition

We would like to use the transition probabilities to predict how many items are in each state say 10 or more years after maintenance. Comparing these frequencies with the actual frequencies would provide a measure of how well the Markov chain model is approximating the real situation. Up to 10 years the agreement was found to be good, although it was noted that predictions from data for early life (4 years) were found to overestimate the degradation at later time (10 years). More observations beyond 10 years are required to reduce the influence of the statistical fluctuation of the frequencies since the numbers in states 3 and 4 are low. Therefore we will concentrate on the simulated data. Figure 4 gives the fraction of the items in each state at 5, 10 and 15 years as predicted by the Markov chain for the data set defined by the curves in Figures 2 and 3. As the transition probabilities in the Markov model are derived from the average deterioration curve, they are the same for both figures. The actual fractions of the items in each state for these data sets are given in Figures 5 and 6.

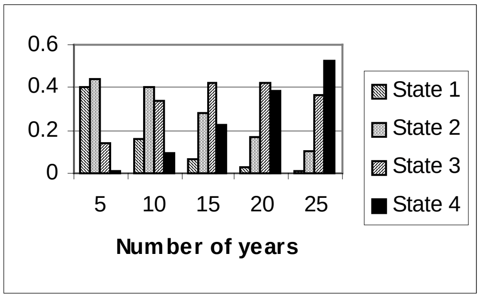

Figure 4: Markov model fractions in each state

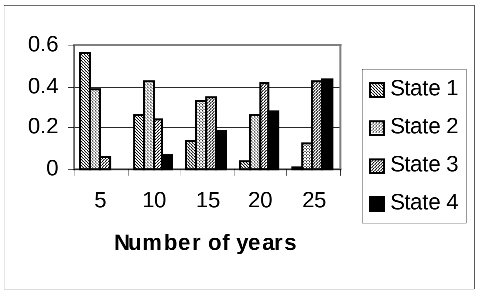

Figure 5: Actual fractions in each state as generated from the curves of Figure 2.

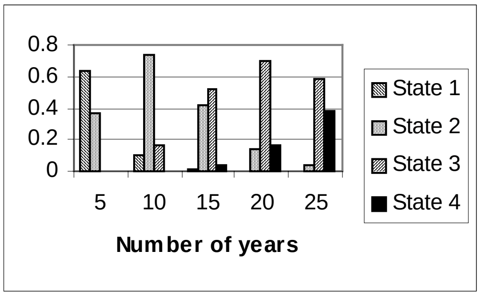

Figure 6: Actual fractions in each state as generated from the curves of Figure 3.

We can see that the Markov model closely mirrors Figure 5 (i.e. the situation defined by Figure 2 where a large spread in condition about the mean as time increased was simulated) with the difference being that it is slightly more pessimistic about the deterioration rate. There is a greater difference between Figures 4 and 6 (where a smaller spread in condition about the mean was simulated) with the Markov model generally being significantly more pessimistic. Consequently, when also taking account of the fit to the real data, we can conclude that the Markov chain is a good model of the deterioration process but that it errs on the side of overestimating the deterioration that takes place. Hence it will tend to slightly overestimate the cost of the Asset Management policies.

ASSET MANAGEMENT POLICIES

Two types of preventative maintenance policy are considered; time based and condition based.

Time based

Recently an approach for determining a more objective time interval for time based policies has been put forward Brint (7). This is based around sampling a number of items and from this sample inferring the expected conditions of the unsampled items. Time Based Maintenance has the advantage that it is simple to implement and avoids the need for inspections, but its weakness is that it treats all items the same irrespective of their condition.

Condition based

When managing assets based on condition, we need to specify the time between inspections, the condition when an item needs to be maintained and the condition when it needs to be replaced. Once these have been specified, the overall cost of the policy follows from the deterioration of condition and the failure rate of an item in a particular condition. Hence how the deterioration is modelled is crucial to estimating the cost of the specified policy.

Costs and risk

In these examples we will assume that the cost of painting a ground mounted transformer is £250 if it is in state 2 or 3. Part painting, at lower cost, may be carried out for a transformer in state 2 and this could be modelled if required. However if it reaches state 4, then the cost rises to £10,000 as the transformer is then replaced. We will assume that a substation inspection costs £10. While other items could be inspected at the same time as the tank paintwork, we will disregard this cost saving and also that the frequency of inspection may be influenced by other inspection needs on the site.

For items that can experience safety critical failures e.g. 11 kV oil filled switchgear, Asset Management policies need to control the risk of failure. Markov Decision Processes can achieve this by assigning a risk of an item failing when it is in a given condition. As the approach assigns a probability to the chance of being in each condition, an overall risk can be calculated. More importantly, the relative risk of the proposed policy compared with the current policy, can be determined.

Evaluation of the best policy: real data

For the ground mounted transformer paintwork sample, the transition probabilities were determined as 0.057 for state 1 to 2, 0.036 for state 2 to 3, and 0.07 for state 3 to 4. Combining these with the above costs leads to the following long run expected annual costs:

Time based, maintain every 8 years	£42
Time based, maintain every 10 years	£43
Time based, maintain every 12 years	£43
Maintain in state 3, inspect every year	£16
Maintain in state 3, inspect every 2 years	£18
Replace in state 4, inspect every year	£159

These are the expected costs per transformer – to get the overall cost you need to multiply by the total number of ground mounted transformers (approximately 29,000 in the case of 24seven Utility Services). From the results we can see that Condition Based Maintenance with regular inspections can offer significant savings over Time Based Maintenance. The replacement only policy is seen to be unacceptable. By running a number of different policies through the model, we can determine the best maintenance and inspection intervals.

Evaluation of the best policy: simulated data

Assuming the same costs as for the real data, we can analyse the effects of different policies on the simulated data generated from the curves of Figures 2 and 3. A Markov Decision Process analysis will allow us to evaluate a wide range of policies. The accuracy of this approach can be assessed by comparing it with a second more accurate method based on counting the actual number of simulation points in each state at each age. This second approach is limited, however, in that it cannot be applied to many situations. It is straightforward to apply it to time based policies as the cost is just dependent on the number in each state when the maintenance time occurs. For condition based policies it is more difficult if the interval is more than one year. For yearly inspections the average time to maintenance for each item is worked out by counting the number of new items in state 3 each year. So in Table 2 we assume that we have 8 new items in state 3 for year 6, 9 in year 7 (the total number of items in states 3 and 4 minus the old state 3 and 4 items), and 6 in year 8.

TABLE 2 – The condition of the sampled transformers

Time (years)	Number in each state			
	1	2	3	4
6	56	36	8	0
7	42	41	16	1
8	37	40	19	4

However if we are inspecting less frequently and so we do not maintain in year 7, we cannot say what the position will be in year 8. Essentially the problem is that we are not tracking items from year to year.

In all the following policies we replace items that are found to be in state 4.

Using the Markov Decision Process approach to estimate the long run expected costs per item gives:

Time based, maintain every 4 years	£76
Time based, maintain every 5 years	£74
Time based, maintain every 6 years	£75
Time based, maintain every 8 years	£91
Maintain in state 3, inspect every year	£27
Maintain in state 3, inspect every 2 years	£45
Maintain in states 2 and 3, inspect every year	£52
Maintain in states 2 and 3, inspect every 2 years	£43
Maintain in states 2 and 3, inspect every 3 years	£43
Maintain in states 2 and 3, inspect every 4 years	£48

Evaluating policies using the simulation data from the curves of Figure 2 gives:

Time based, maintain every 4 years	£63
Time based, maintain every 5 years	£50
Time based, maintain every 6 years	£42
Time based, maintain every 8 years	£80
Maintain in state 3, inspect every year	£26
Maintain in states 2 and 3, inspect every year	£39

Using the simulation data from Figure 3's curves gives:

Time based, maintain every 4 years	£63
Time based, maintain every 5 years	£50
Time based, maintain every 6 years	£42
Time based, maintain every 8 years	£31
Maintain in state 3, inspect every year	£27
Maintain in states 2 and 3, inspect every year	£46

As expected the Markov model slightly overestimates the policy costs but the resulting best time interval for Time Based Maintenance is similar to that obtained from the data of Figure 2 (i.e. ≈ 6 years). The situation of Figure 3 leads to fewer items ending up in a bad condition, the best time interval here is significantly longer than for the Markov model.

A major advantage of the Markov approach lies in its flexibility to analyse a wide range of policies. In this work we have investigated a range of condition based maintenance policies and compared them with a number of time based options. Clearly this could be extended to consider other options that users may require to test.

CONCLUDING REMARKS

This paper has looked at how well the Markov approach models deterioration, and evaluated different Asset Management policies on real and simulated data.

Ongoing work. Besides the implementation issues raised in the introduction, a number of issues are currently being investigated:

A wider variety of simulation curves – than the Weibull curves that are currently available (see Figures 2 and 3).

Further analysis of real and simulated data – Many studies similar to the ones reported in this paper need to be carried out so that general principles can be found.

Combining real and simulated data – As was shown by the real data transition from state 3 to 4, sometimes both calculated and estimated transition probabilities are needed. A framework for doing this would be valuable.

Better degradation modelling – It would be beneficial to be able to predict the number in future states using the worst deterioration curve as well as the average.

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References

1. Hoskins RP, Strbac G and Brint AT, 1999, "Modelling the Degradation of Condition Indices" IEE Proc on Gen, Trans and Dist, 146, 386-392

2. Blakeley R, 1997, "A UK Manufacturer's View - New Switchgear and Aftermarket Options" Presented at *IEE Colloquium on Switchgear: Retrofit, Refurbish, or Replace - the Asset Manager's Dilemma*, London, 21 October 1997, colloquium number 1997/348

3. Golabi K, Kalkarni RB and Way GB, 1982, "A State Wide Pavement Management System"Interfaces,12,5-21

4. Scherer WT and Glagola DM, 1994, "Markovian Models for Bridge Maintenance Management" ACSE Journal of Transportation Engineering, 120, 37-51

5. Lees M and Dixon M, 1999, "Experience in Implementing a Condition-Based Asset Management System with Hand-Held Electronic Data Capture". CIRED 99. 15th Int. Conf. on Elec Dist Nice. France.

6. Christer AH, 1999, "Developments in delay time analysis for modelling plant maintenance" J. of the Operational Research Society, 50, 1120-1137

7. Brint AT, 2000, "Sequential inspection sampling to avoid failure critical items being at an at risk condition" J. of the Operational Research Society, 51, 1051-1059