MANAGING UNCERTAINTY AND UPDATING PARAMETERS IN ELECTRICITY DISTRIBUTION ASSET CONDITION BASED RISK INVESTMENT MODELS

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ABSTRACT

This paper draws on several years of experience of developing condition based risk models at Northern Powergrid, examining how actual experience has influenced further model development in particular with regard to forecasting techniques and the updating of model parameters. Of special interest are the following aspects of our experience: degradation forecast error; unforeseen effects on asset condition; parameter uncertainty. We conclude that, models developed at Northern Powergrid provide useful investment decision support in the production of robust business plans as long as the model limitations are fully understood and managed.

INTRODUCTION

In the last decade condition based risk models have started to become established within electricity distribution networks, fuelled by technological advances in collecting and storing condition information; accessibility of models already applied within civil infrastructure networks; and a desire within DNO's to make smart decisions. It is important though to be aware that it takes time to arrive at a model in which the parameters are relatively stable and the functionality fully agreed upon. This is due to high levels of inherent complexity and uncertainty in particular associated i) with forecasting model error; ii) with asset condition information not captured due to random/unforeseen effects; and iii) with input data and judgements about condition bands and weightings. This paper focuses on understanding and managing uncertainty in the degradation forecasts and on re-evaluation and updating of modelling parameters.

UNCERTAINTY IN FORECASTING

Typically the rate of asset health degradation can be forecast in condition based risk models either by using probabilistic techniques such as Markov chains or via ageing curves [1].

Choosing the asset health degradation model

The choice of model will depend on its suitability for the type of degradation and also on ease of implementation. A curve based model may not be suitable for example for civil assets with a key degradation mode of cracking produced by random shocks. The use of curves in electrical asset reliability modelling has a strong history however and this is the approach employed in Northern Powergrid's models.

Curve descriptions of degradation modes

Figure 1 shows an example illustrating how a curve can capture key features of a degradation model. It shows a complex S-shaped curve model for an oil degradation process in which there is rapid initial deterioration in oil condition, and then a period of equilibrium before significant degradation starts to occur due to oxidation, ingress of additional water, or tank contamination. Natural deterioration is modelled as a drift through time down from the good as new overall condition index values towards the worst condition value. It is implemented as a weighted average between the average and worst deterioration curves. The assumption is that if an item is deteriorating badly it continues to deteriorate badly. Each item in the population follows its natural deterioration drift but at each time period takes a random displacement step from this drift via use of a random walk [2].

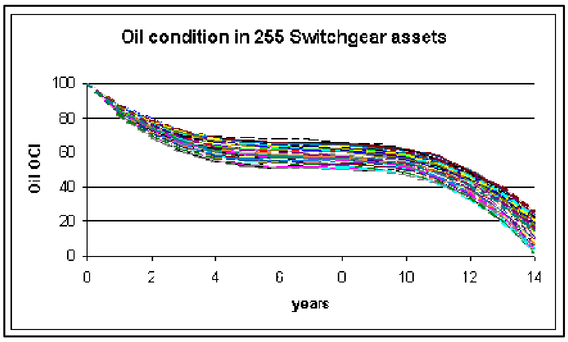

Figure 1. Complex Switchgear oil degradation model

Suitability and ease of implementation

Whilst curves such as those in figure 1 are valid for use in modelling they can also be fairly complicated both in terms of implementation and in determining what the input parameters should be. In practice therefore more simplistic exponential curve based models have generally been implemented in electricity distribution networks.

A basic exponential curve is valid in engineering terms because it accurately describes a degradation mode true to most of our assets, of accelerating degradation rates as health further deteriorates. It is also a good curve for implementation purposes because its mathematical properties make it straightforward to use. For example it is monotonically increasing which makes it impossible for spontaneous improvement to be accidentally modelled, and it only relies on two parameters, shape and scale, thereby making justifying the inputs more straightforward.

Updating the degradation forecast

The exponential curve has proven suitable for short term forecasting. However the approach of using a single exponential curve has limitations for long term forecasting due to a number of factors. One is that the initial estimate of condition degradation may be discovered at the time of last inspection to be an under-estimate or over-estimate. In reality there are different deterioration rates for different items of the same type such as a particularly bad environment that a switch is in or a poor standard of manufacture. These “hidden” factors can be approximated by giving an item a deterioration rate in keeping with its previous pattern of behaviour so after inspection it makes sense to move the asset to a different degradation curve path based on experience as shown in figure 2.

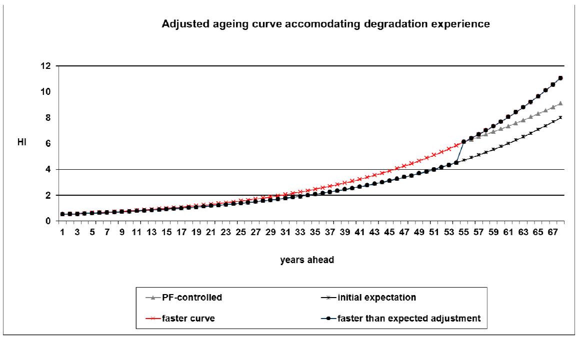

Figure 2. Updating degradation curves from experience

Controlling the degradation forecast

Another feature of the exponential curve that it is difficult to control is the escalating acceleration effect so it may be necessary to modify the curve at its extremes, or use an alternative curve with more terms such as a cubic. A simpler solution is to use PF interval concepts to modify the shape parameter so that the curve is controlled near its end of life to produce a better forecast of time to failure. This second modification is also illustrated in figure 2.

Basis for using several curves

The idea of using more than one curve in this way is consistent with delay time modelling concepts which in turn are founded on P-F interval reliability theory [3]. A delay time model is based around the P-F curve where P is the point where a potential failure can be detected and F is where the functional failure occurs. The points P and F divide an item’s condition into three states. The Delay Time model describes a two-stage failure process in which faults become visible in the first stage at a point u, and these visible faults then cause eventual failure in the second stage. The “Delay Time” is the window of opportunity of duration, *h* for preventing failure and is the time between the point *u* at which a defect leading to failure can first be detected and the point of failure itself. In order to avoid catastrophic failure F can be defined as moving into the worst state that an item can be in and in which replacement must occur.

Hence the Delay Time Model has the three states (0, u), (u, u+h) and (u+h, ∞) as shown in Figure 3.

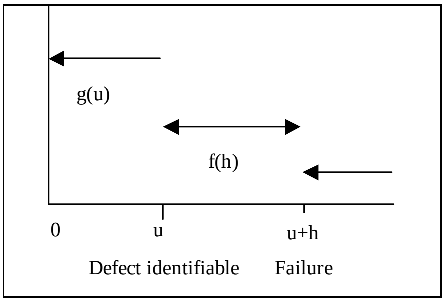

Figure 3. Delay time modelling concepts

Degradation forecast error

The trade-off is of model simplicity against forecast accuracy and so we expect forecast error in the models. A particularly relevant issue is that our forecast only cares about what condition banding an asset is in now but not on how long it has been there. For example an asset which has only just began to suffer surface corrosion will be forecast to make a transition to its worst state at the same time as another asset which has had visible surface corrosion for many years, even though in practice it is more likely that the second asset will reach the worst state first. More complex models which manage time spent in a state, such as semi-Markov models, are more accurate but computationally intensive and also subject to greater parameter uncertainty. An example of this particular issue might be becoming apparent now that we have the benefit of having a few years’ worth of data for distribution switchgear. Figure 4 compares two degradation forecasts for year 5 made a year apart as illustration. Early results are beginning to indicate that the middle category items possibly stay there for a longer period than previously forecast. On the other hand the poorer category items may degrade to the worst state faster than forecast. More data is needed before a firmer conclusion can be drawn though and it is also quite difficult to isolate where the revised estimate is due to natural deterioration as opposed to other factors like inspection subjectivity and data quality improvements.

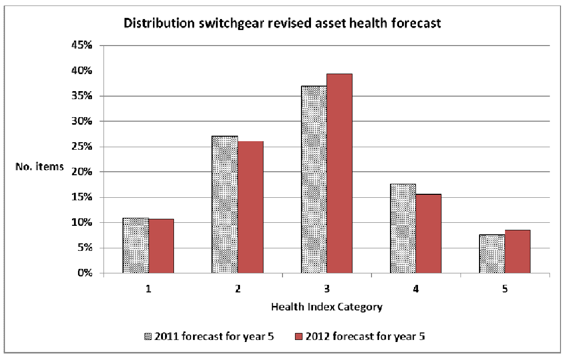

Figure 4. Distribution switchgear forecast

UPDATING MODEL PARAMETERS

Learning drives the next model iteration so there is a continual need to monitor and update parameters according to actual experience. This can take time for the following reasons. Firstly the degradation forecast curve parameters are uncertain and there is no rich source of electricity distribution asset condition histories. This is due partly to the fact that electronic condition data collection and storage is relatively recent; and partly to data "censorship" in terms of assets being removed for safety reasons well before failure. It will be many years before we have condition histories covering the whole lives of electricity network assets and the end of life patterns may never be fully known. Secondly, as well as forecasting error due to uncertainty in the degradation curve, there is uncertainty in the starting conditions from which the forecast is made. This is associated both with the input data and with the health index parameters. These too need constant re-evaluation but again the models, and even the data collection requirements in some instances, are recent innovations. The drive to use enabling technology in electricity distribution asset management has only been in the last two decades [4].
Thirdly it is worth stressing the point that the models are of the degradation of external condition ratings as an indicator of internal deterioration, rather than of internal deterioration itself. Therefore the model will capture observed degradation of condition but will be missing unobservable internal processes. Take wood poles for example; the onset of internal decay and the rate of deterioration will vary depending on unquantifiable factors, such as the quality of the original treatment. It is not practical, if at all possible, to model such parameters. Also, deterioration results from a variety of causes apart from the ageing process and is influenced by external events. Research and experience in these areas can throw up the possibility of extending the model to incorporate new information and discoveries.

Updating the forecast curve's parameters

As more years' worth of experience comes in the suitability of the forecasting curve parameters can be re-evaluated although it is noted that asset importance and type dictates inspection frequency, which can vary from months to years. In some cases, notably overhead lines, suitably comparative data may only be collected for some assets a few times over its lifetime. In other cases such as cables, for a variety of reasons condition data is not collected pro-actively so closing the loop in terms of forecast versus actual degradation is that much more challenging.
This paper has discussed already how each year the forecast curve's parameters are re-attuned to its current health index. But beyond this is the question of the quality of the shape and pace of the expectation curve in general. That is, the underlying parameters of the entire forecasting model might need updating. For instance, the few years' worth of distribution substation switchgear degradation experience indicate a potential need to update the ageing curve parameters but we are still in early days to be able to say so definitively or to say how it should be done.

Input data and HI model parameter uncertainty

Questions of data quality generally and of subjectivity in condition inspection measures have already been extensively discussed in the research. There has also always been the trade-off between the relative merits of using an overall index, which is the choice made at Northern Powergrid, or of using the separate component measures. This has been extensively discussed in research literature.
"The use of an index (like PCI) to define pavement state causes some concern because it is an aggregation of specific distress measurements. Maintenance requirements and therefore costs are more directly related to these components of the index. It is also possible that future pavement conditions might be more accurately predicted from the components of the index …(but) there could be an enormous amount of work involved …" [5].
Data uncertainty is managed in the company via annual data updates and constantly seeking better data sources. For instance we have recently been able to use more in-depth partial discharge analysis in place of basic readings provided from annual inspections, where it is available.
Updating the health index model parameters and methodology is also a continual process for us. For example we have taken advantage of having more plentiful and detailed plant condition information in recent years to implement a methodology change that supplements a fairly age driven health index with the option of using a more purely condition driven value. We have also added new condition points to the models where appropriate to do so. Meanwhile reliability judgements about our various plant types are regularly updated as more information comes through from failure investigations, dangerous incident notices and national equipment defect reports. By exception ad-hoc assessments, such as conductor samples and PURL tests (portable ultrasonic rot locator) for overhead assets, provide an additional quantifiable view of asset health, which can in turn be factored into the current and future health forecasts of similar assets that may not have been similarly assessed.

Unforeseen effects on asset condition

Some assets suffer a sudden shock to health because of unpredictable random events such as third party damage, damage caused by the weather and the environment, and damage caused by birds, animals, and insects. Other assets in apparently good health fail because of problems not detected by the health index model's condition indicators.
Managing this problem involves two aspects:- i) designing suitable processes for updating results to reflect operational experience; and ii) understanding the bounds around average forecasts through probabilistic techniques or from use of scenarios that cover unforeseen eventualities.

Processes for handling the non-modelled realities include careful and auditable evidence-based analysis of reasons for unforeseen failure; and recommendations for improved techniques to capture these in the model where possible. To consider the random events the degradation curve needs to be regarded as an average curve existing within a range. It has been demonstrated that, for long-term forecasting in particular, a probabilistic spread of curves such as those shown in figure 1 might be more appropriate [6].

APPLYING THE RESULTS

Condition based risk models should be fully transparent and comprehensible in terms of their underlying engineering sense, reflecting established and well understood engineering terminology and classifications. They need to be defendable under scrutiny and results need to be communicable at a wider business level. In applying the results the limitations imposed by uncertainty, in particular for long term forecasting should be acknowledged, understood and managed. The regular updating of the model described in this paper contributes to such management.
In applying the results it is not unreasonable to assume that the assets showing the poorest overall condition can be forecast to be doing badly a few years ahead. The problem is about how good the longer term forecast is for the assets currently in moderate health. At Northern Powergrid modelled outputs are used to provide a priority list of potential candidates for the short to mid-term investment pipeline [7]. These models can also support asset management policy decisions, such as determining at what health it is optimal to refurbish or replace in terms of minimising cost whilst satisfying safety/reliability constraints [8]. For longer term strategic decisions such as the scale and shape of investment the outputs also provide decision support but with full awareness that “we can never expect to predict what will happen with absolute confidence” [9]. Thus the outputs are regarded as indicative rather than as absolutely definitive answers. Overall we conclude that, with the level of certainty around the outputs fully understood, our models provide useful investment decision support in the production of robust business plans and are powerful tools in the decision making process.

FUTURE CHALLENGES

Increasingly attention is turning in electricity distribution networks to building consequences of asset failure into the models. This allows risk-based investment decisions that consider criticality as well as asset health. Some risk models show a health and criticality matrix where the riskiest assets are those in the worst health / highest criticality corner of the matrix. Others calculate composite overall risk values formed from the probability of asset failure (health-based) multiplied by consequences of that failure [10]. Typically consequences for network performance, environmental, safety and financial consequences are assessed.

Building risk models requires care and attention to engineering detail and uncertainty continues to be a challenge. Firstly there are difficulties with determining failure probability due to issues like electricity distribution network failure data being censored by assets not being allowed to fail; and asset specific complications such as failure recording for very small sections of underground cable [11]; and overhead line inter-dependencies meaning absolute failure may be caused by one of many component parts each having in turn its own functional failure rate. Secondly the value of the consequence is determined from considerably complex underlying factors. For example behind a safety consequence are assumptions about probabilities of death or serious injury, and debateable judgements about the cost of such incidents. Risk models in other industries, such as civil infrastructure, are complex and have been developed over many years. We expect the same to be true for the electricity industry.

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