

USING STRATEGIC MODELS IN ELECTRICITY DISTRIBUTION INVESTMENT PLANNING

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ABSTRACT

This paper draws on practical experience of quantitative strategic modelling in the long-term investment planning process at CE Electric UK. It combines theoretical and practical examples to suggest how proven approaches can be employed within the industry. There are now many models, methodologies and decision support tools available to assist asset management planning processes. The wisdom needed in distribution network operators (DNOs) lies in the art of determining to what situations different models can be legitimately applied and how to utilise the results. Decision support relies on models that answer the right questions; fit engineering parameters appropriately; and on managing the risk of uncertainty in forecasting.

INTRODUCTION

DNOs in the UK invest tens of millions of pounds annually into refurbishment and renewal of their asset bases to ensure the continued distribution of electricity safely, reliably and efficiently. Condition driven expenditure can form approximately half the overall investment made by the electricity distribution sector. CE Electric UK aims, in line with good practice asset management, to link investment decisions to the outcomes that are sought, so that investment options are appraised and balanced overall within the context of a range of diverse business success factors such as network performance, safety targets, legality, and regulatory integrity.

The process of making good investment decisions relies upon quantitative decision support methodologies. The development of such tools in use within electricity distribution networks has taken place in the context of asset management (AM) developing within the industry over the last 15 years and being seen as an important discipline across other infrastructure sectors [1]; and of generalised business experience of quantitative modelling in strategic investment decision making. This experience includes techniques such as Monte Carlo simulation, sensitivity analysis, decision trees with conditional and probabilistic branching for handling sequences of decisions, and mathematical programming for optimisation [2]; and is boosted by improved systems for electronic capture and storage of historical data [3][4]. Given the amount of choice it is appropriate to give careful consideration to the selection of appropriate models.

SELECTING THE APPROPRIATE TOOLS

It is essential to have clarity about the particular investment question being posed before the selection of the most appropriate tools to support the specific investment decision making process can be assessed. Applying the wrong techniques can be wasteful, and costly to an organisation.

General considerations

A number of general considerations are required in identifying which models can be fitted to different asset base classes along with what questions are most suited to the different approaches. For example, they need to be workable and reasonably accurate. Results need to be relevant, which requires knowledge of what the benefits of the model are in terms of what they do and whether their outputs answer the questions that are being asked. It is also desirable that modelled outputs are transparent, communicable, auditable, sustainable and repeatable. Aspects of assessing suitability of models include:-

- Engineering credibility of model for asset categories;
- Capture of population characteristics such as variance;
- Availability of required engineering input parameters;
- Robustness of results in terms of margins of error;
- Accuracy given assumptions and simplifications;
- Trade-off between model complexity and benefit;
- Relevance of results and where they can be applied.

Specifically for strategic analysis, models need to be flexible enough to successfully identify key drivers and to capture different possible scenarios, that is, to be capable of running repeated experiments with varied input parameters.

Long-term and short-term modelling

Whilst short-term planning decisions are concerned with the detail of what assets to invest in, long-term planning questions are concerned with issues such as:-

- Overall size and shape of investment going forward;
- Management of changing trends in future investment;
- Deliverability and smoothness of funding progression;
- Controlling risk over the entire planning period;
- Benchmarking and comparison of investment options;
- Balancing of investment within business priorities;
- Checking present planning decisions against forecasts.

Robust planning decisions for the short to medium terms (5 to 10 years) rely on the provision of sound estimates of the value of each investment option and associated risks. The decision outcome is the immediate implementation of the investment option for a named asset. Therefore the detailed

analysis for short-term decision support requires parameters with which a relative degree of certainty is associated. Deterministic methods using exact and detailed engineering data are a distinguishing feature of this type of tactical analysis although we need to handle uncertainty and imprecise data even at this end of the scale. For example most of the major system risk investment at CE Electric UK is appraised against a probability model at project level.

Longer range investment planning horizons (20+ years) similarly require sound estimates of future investment requirements to be provided. However the outcome for a long-term decision is not generally investment in named assets. Rather it is the establishment of an asset management strategy for the asset population under consideration. This might be, for example, a resolve to increase investment in a particular asset class in order to reduce risk, improve performance, enhance environment, or simply maintain current performance and risk levels.

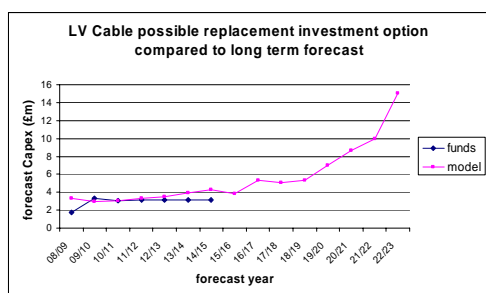


Figure 1: Checking planning decisions against forecasts

Figure 1 shows how short-term investment profiles derived from detailed analysis of named investment options can be viewed against modelled forecast profiles. In this example a simple birthday model, which replaces assets when they reach nominal lives assigned to them, is used to forecast the scale of requisite investment in low voltage (LV) cable replacement. The chart shows that whilst present investment levels are in line with the modelled forecast, a significant increase in funds might be expected in the future as the high volume of cables installed during peak network expansion years reach old age. Thus an asset management decision might be made to manage the possibility of the expectation being realised.

Long-term decisions have to handle the possibility of various different futures and the parameters involved in long range forecasting involve uncertainty. Because of this, probabilistic approaches typically underpin many of the quantitative methodologies for strategic analysis. Quantitative analytical and simulation based probabilistic models, supporting decisions under uncertainty, are well established in power systems. Monte Carlo simulation is used in long-term investment forecasting for asset renewal at National Grid. [5] Probabilistic approaches have been used to support large scale strategic studies concerning future low carbon generation scenarios [6]. Maintenance

interval decisions are commonly supported by probabilistic techniques [7]. The experience of the regulator Ofgem using a probabilistic survivor model [8] to assess asset renewal investment forecasts in the next distribution price control period (DPCR5) should be interesting.

Case study – models for asset renewal

The choice of model can make a significant difference to the forecast and it is important that model parameters adequately describe the underlying engineering problem.

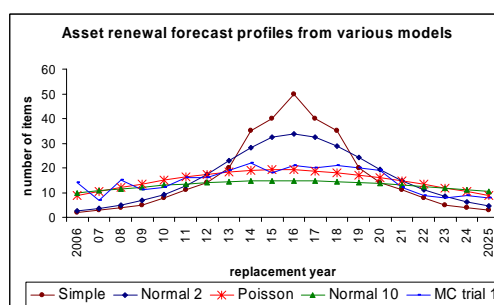


Figure 2: Modelling scale and shape of investment

Figure 2 shows the investment profiles resulting from a number of different asset renewal models for an asset category with a nominal life of 45 years and a given installation profile. One profile comes from a simple birthday model with a single asset life. Three profiles come from an analytical survivor model with different distributions around the asset life, i.e. two Normal distributions with standard deviations of 2 years and 10 years respectively; and a Poisson distribution. The last profile comes from a survivor model implemented as a Monte Carlo simulation using a Normal distribution with a standard deviation of 6.7 years.

There is clearly variation in the results from the different models. The simple output mirrors the peaky shape of the installation profile but this profile is smoothed by the use of distributed asset lifetimes in the other models. The models which use a Normal distribution can control the standard deviation parameter so that the results for an asset life with small variation approach the simple result whilst for wide variation the peak is considerably reduced and smoothed. The shape of the Poisson distribution cannot be controlled and is approximately a Normal with standard deviation set to the square root of the nominal life. Whilst the analytical models only output one average answer, each Monte Carlo simulation produces a different answer. Thus it can produce a range showing extremes as well as the average answer.

Assessing benefits of modelling approaches

Whether it be for short-term or long-term decisions, it is important to assess whether the effort required to build and run a probabilistic model is worthwhile. Models designed to capture future uncertainty may involve generating random numbers in thousands of simulations or they may

require a complex set of parameters for defining the random distribution and variance. Complex parameters might be hard to assess, for example deciding which of the distributions producing the results in figure 2 are the most suited to the engineering properties of the asset class.

It might be the case that simpler models are preferred on the basis that it is easier to manage uncertainty for models with simple parameters. For example the output illustrated in figure 2 from a simplistic asset renewal model has a transparency to the size of the peaky installation problem but this is hidden within the input distributions in the other models. At CE Electric UK the practice has been to prefer to know the size of the problem and apply smoothing to the outputs. The smoothed investment option is then risk managed against the unsmoothed forecast so that any asset service life extension (beyond its nominal life) is clearly visible. Meanwhile the engineering suitability of this approach is validated by the real world experience of diversity in asset lifetimes.

Another consideration is that the situation to which the model is being applied is not necessarily worth the cost of the greater complexity. If the decision relates to major asset renewal funding priorities going forward then the cost of obtaining the modelled outputs is more justifiable than for a decision, say, about the replacement of back-up batteries on a particular line due for refurbishment, given in particular the low cost and also the finite service life of such assets. As a general rule the suitability of the model depends on the circumstance to which it is being applied. So in some cases there might even be a rationale for applying complex degradation forecasting techniques to short-term decision making, such as in the case of safety critical assets with multiple failure modes. Conversely a long-term decision for an asset class with a known and certain degradation path may only warrant a simple approach.

Primary and Distribution network assets

In terms of the total asset numbers for the low voltage (LV), high voltage (HV), extra high voltage (EHV) and 132kV networks, the number of primary (EHV and 132kV) assets is less than 20,000 whilst distribution (LV and HV) assets on the other hand number hundreds of thousands. The smaller number of primary assets includes asset categories which are safety critical and hugely expensive to replace whilst the larger number of distribution assets includes categories which are not safety critical and/or are relatively inexpensive to replace. Therefore detailed complex modelling may be suitable for some of the primary asset categories but not necessary for the sheer volume of such distribution assets. These may be better suited to simpler general population based models. For example it is probably not worth carrying out the same detailed forensic evidence based analysis of asset life in the case of say HV pole-mounted switchgear compared to ground mounted EHV switchgear because the consequences of failure vary widely in these two cases. The sheer volume of distribution plant makes replacement costly so trends need to be

modelled. Where high volume or physical difficulty in reaching assets prohibits full data collection it can be enough to derive population statistics from age, condition and fault information for smaller samples of the population. In the case of very expensive or safety critical assets the complexity of a simulation model might be desirable to identify the extremes of expenditure that might be required.

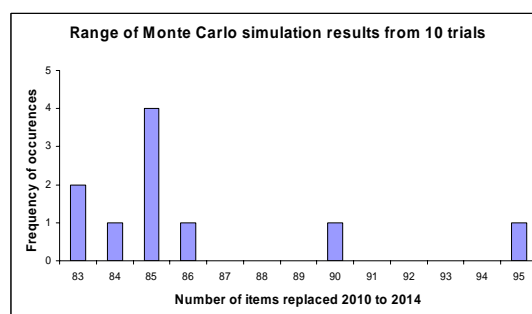


Figure 3: Identifying extremes in results

Figure 3 shows a frequency distribution of the numbers of items forecast for replacement during the 2010 to 2014 period using the Monte Carlo simulation model for the case study shown previously in figure 2. It is based here on 10 experiments but in practice 100s of trials are ran. The chart shows that whilst the most frequent case was for 85 items being replaced, in one case 95 items needed replacing.

Time and condition based considerations

There is not a straightforward relationship between age and condition for electricity distribution assets. Neither is there an understandable correlation between age and failure due to conscious intervention for the avoidance of failure. Sometimes therefore the models used might not be the best fit to the degradation mode of an asset. For example in the absence of reliable condition information, an age based model might be used with age acting as a proxy for condition. Ideally though, the model should fit the engineering qualities of the asset.

Condition driven degradation modes often have rapid deterioration occurring after a random shock causes the onset of a problem (which may or may not have occurred later anyway from ageing). Examples include partial discharge in ground mounted plant, corrosion from water ingress, and the propagation cracks in plastic insulation. In these cases the time spent in a condition state may also be important. Age driven degradation modes reflect cumulative effects from operating history and environmental factors for example, oil degradation from unavoidable increases in moisture levels, plastic degradation from continuous pollution, and galvanised steel corrosion which has known corrosion rates for different operating situations. Age based models have long been established within the electricity distribution sector. More recently, condition based approaches have also become more widely used. [9],[10] Models using condition data can be subdivided into treatment of degradation as a function of

a) age, b) of condition, or c) of both age and condition.

DECISION SUPPORT

The outputs from models are for decision support in asset management processes. They do not represent the final answer. It is important to be clear about the limitations of the models, the assumptions, and the sensitivities. For example the asset renewal birthday model is highly sensitive to small changes in asset life, with a significant impact in terms of delaying or bringing forward investment.

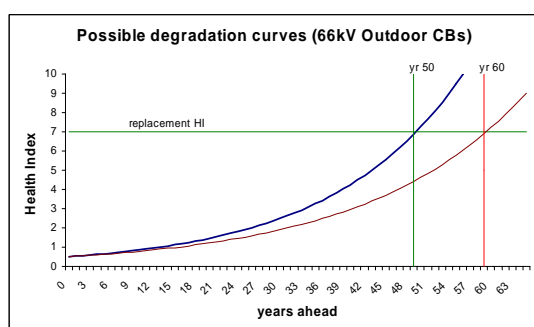


Figure 4: Sensitivity in deterministic models

Figure 4 shows the sensitivity of deterministic models in which small changes to the input parameters can lead to large variation in the output. The example is based on a model which provides a prioritized list for scheduling investment a few years ahead, based on the present condition of named assets combined with an ageing curve. If assets are to be replaced when they reach a condition state of 7 (on a scale of 1 to 10 where 1 is as new) then it can be seen that all the assets currently at a value of 5 will move en bloc into the replacement condition within 6 years, but a slightly gentler curve would delay the replacement decision. Therefore for long-term forecasting a probabilistic spread of curves might be more appropriate. [11]

Risk management is applied to the decision making process. For condition based models this assesses the risk of the proportion of items in the worst state for various investment options. For age based models the percentage remaining life of the asset base is generally calculated. At CE Electric UK we also employ a metric developed in-house which quantifies how long a given investment option is extending asset service life compared to the modelled output. It is a cumulative measure which allows risk assessment across the whole planning horizon and is based on a policy of replacing the oldest asset first, thus keeping close to reality.

FUTURE DEVELOPMENTS

Strategic modelling going forward faces a number of challenges. These include analysing the expected increase in information about asset age, condition, performance and serviceability and updating model parameters accordingly. There will be a greater emphasis on the whole asset life

cycle and a requirement to model associations and synergies between different investment drivers within the overall business. Models for the network as a whole are expected to become increasingly important for assessing the wider impact of investment decisions. Also a greater emphasis is likely to be placed on understanding the consequences in the absence of investment. Finally, better degradation information might pave the way for increased use of probabilistic approaches. Whatever happens, decision support will continue, as now, to rely on models that answer the right questions; fit engineering parameters appropriately; and manage risk of uncertainty in forecasting.

Acknowledgments

Other colleagues at CE Electric UK involved in developing the processes described: Iain Miller, Mark Drye, Phil Jones.

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