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Li, Fengfeng, Cholette, Michael E., & Ma, Lin
(2016)
Reliability modelling for electricity transmission networks using maintenance records. In
Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015), Springer International Publishing, Tampere, Finland, pp. 397-406.

This file was downloaded from: https://eprints.qut.edu.au/99980/

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The final publication is available at Springer via http://dx.doi.org/10.1007/978-3-319-27064-7_38

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https://doi.org/10.1007/978-3-319-27064-7_38

Reliability Modelling for Electricity Transmission Networks Using Maintenance Records

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Abstract Maintenance decisions for transmission network assets (TNAs) require accurate reliability prediction. However, there are a large number of operating, design and environmental variables that potentially influence their reliability. This paper presents a new reliability prediction method for TNAs. Failure times were identified by extracting significant unplanned maintenance events for critical failure modes. A regression tree-based grouping analysis was utilized to analyse the influences by variety of factors on future unplanned maintenance. These results were then used to build the reliability prediction model allowing a decision maker to have an estimate of future unplanned maintenance requirements. A case study using real industry data was conducted to test the proposed reliability prediction model. The results demonstrate the feasibility of using this approach for TNA maintenance decision support.

Keywords – Reliability • Maintenance decision support • Regression tree

1 Introduction

Electricity transmission networks are a crucial part of the national infrastructure. Failure of transmission network assets (TNAs) can lead to significant consequences including: megawatt losses, regulatory penalties, and safety hazards. Despite their criticality, making informed replacement decisions prior to failure remains challenging, primarily due to the difficulty in assessing and predicting the dynamic condition of transmission network assets.

Decision-making can be supported by accurate reliability modelling for complex repairable systems which can assess and predict the future condition of

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TNAs. Reliability analysis and predictions can give decision makers nuanced information such as identification of likely network hot spots (i.e. areas that require more maintenance attention) and enable "what if" analysis.

However, reliability analysis and prediction is complicated by the fact that TNAs are linear assets (as opposed to discrete assets) which require specific modelling approaches for reliability and risk assessment. Additionally, the reliability prediction model needs to be based on actual data since the failure risk will not be uniform across the transmission network. There are many factors may influence the risk of failure. Structure characteristics (e.g. conductor type), voltage, load, and the operating environment (mechanical loading, wind, temperature, pollutants and humidity) are but a few examples of potential variables that can alter a section's risk profile, and these factors need to be accounted for in order to predict risks accurately.

This situation is further complicated by the fact that unambiguous failures are extremely rare. The majority of reliability analysis of TNAs treated outages as failure (Billinton and Kumar 1981, Amjady and Ehsan 1999, Yong and Singh 2010, Vaiman, Bell et al. 2012, Albert and Hallowell 2013). However, in many cases, outages are transient and the network is restored to service within a small time interval (often less than one minute). Also, avoiding long term outages are not the sole performance goal of network management. Safety and regulatory compliance are also important goals that are not captured by defining outage as failure. Therefore, outage data is of limited utility in providing significant maintenance events and costs for evaluating potential maintenance policies. Providing a workable definition of "failure" for TNAs represents a significant contribution of this work.

This paper details a new reliability prediction model for TNAs. Instead of using outage data, failure times are identified by extracting significant unplanned maintenance events for critical failure modes. A regression tree based grouping analysis was integrated with a reliability prediction model to analyse the influences by the variety of factors on future unplanned maintenance. A case study was conducted using real industry data to test the proposed reliability prediction model. The results demonstrate the feasibility the proposed approach for TNAs maintenance decision support.

2 Methodology

The decision support framework proposed in this study can be seen in Figure 1. The key contribution of this work is the definition and prediction of *maintenance triggering events* (MTEs), which we define as:

An event record (work order/notification) that requires immediate maintenance action due to network performance, safety, or regulatory compliance.

Essentially, an MTE defines an event that drives maintenance costs and risk and can be thought of as “failure” in a general sense. In this work, we use maintenance notifications and work orders to identify MTEs from historical records. However, these data contain *all* types of maintenance actions, including inspection and replacement, for every structure, equipment, or part for any reason. Since only some of these notifications trigger significant events, expert knowledge was employed to identify which of these events require immediate action. Despite the large number of notification and work orders, only a small subset of them constituted MTEs and experts were easily able to identify the relatively small number of notification types and priorities that would require immediate action.

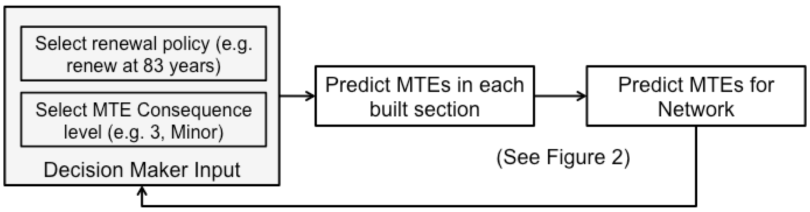

Figure 1: Decision support framework for transmission network assets

The remainder of this section details the construction of the reliability model for the prediction of MTEs, an overview of which can be seen in Figure 2. MTEs were identified from a sample of transmission network data. Subsequently, for each MTE the structures are “grouped” together according to the variables that influence the MTE statistics (e.g. coastline distance for corrosion MTEs) and a hazard model is fitted to the empirical hazard calculated from the data (Sections 2.1 and 2.2). The prediction of the expected number of MTEs is then conducted within each group and amalgamated into a total network MTE prediction (Section 2.3). Importantly, the amalgamation can be skipped and future “hotspots” can be predicted. Finally, the prediction of the effects of different maintenance actions is addressed by prediction the MTEs after maintenance action or by applying a maintenance policy for the prediction horizon (Section 2.4).

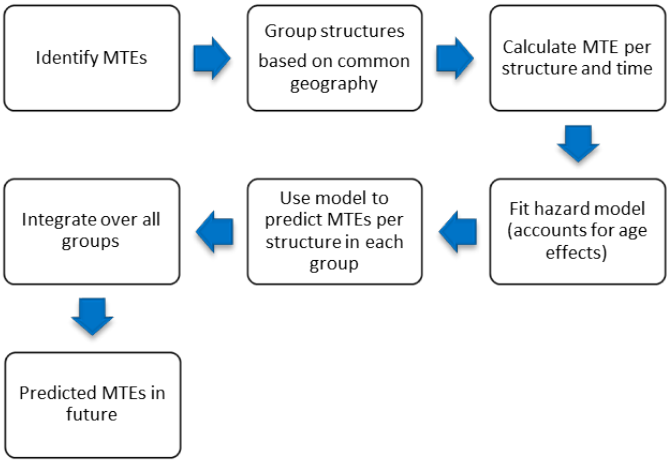

Figure 2: Overview of the MTE prediction methodology

2.1 MTE (Hazard) Rate Modelling

A discrete hazard-based modelling method was developed by Sun et al. (2008) for linear assets, where it was assumed that the lifetimes of assets followed a piecewise hazard function, which is given by

$$h(t) = \begin{cases} \lambda & , \ 0 \leq t < \xi \\ \lambda + \frac{\beta(t-\xi)^{\beta-1}}{\alpha^{\beta}}, & t \geq \xi, \alpha > 0, \beta > 1 \end{cases} \tag{1}$$

where λ is a constant failure rate, ξ indicates the wear-out point, $\xi = 1,2, \ldots$, α and β are the scale and shape parameters of the Weibull distribution, respectively.

We propose the use of (1) to model the *MTE rate*, which is defined as the number of specific failure mode MTEs in time period t per network structure, which is essentially a distributed hazard rate. Therefore, we set $MTE\ Rate = h(t)$. To estimate the model in Eq. (1), Non-linear regression is utilised to estimate the parameters λ, α and β and ξ using the empirical MTE. The Empirical MTE Rate is defined as the number MTEs per structure, per unit time which is obtained from the notification and work order data.

2.2 Grouping

The network contains a number of built sections. These built sections and their constituent segments (structures, conductors, insulators, etc.) can follow different degradation processes (i.e. have different parameters in in their hazard models). While analysis is ideally conducted for an individual structure, the number of

MTEs for an individual structure is normally insufficient for any meaningful statistical analysis. To compromise between data availability and specificity, lines with the same or similar characteristics are grouped to form an analysis population. In this study, a non-parametric decision tree technique, Classification and regression trees (CART) is used to split data into homogeneous groups by examining all independent variables. The selection of significant variables was conducted using expert advice and trial and error.

2.3 Prediction of Future Maintenance Triggering Events

Under the assumption of minimal repair, which is appropriate when one repairs a small part of a large system, the expected number of MTEs of type p for each Structure *i* for the time (age) interval [0, *t*] is given by:

$$H_{i,p,g}(t) = \begin{cases} \lambda t & ,\ 0 < t < \xi \\ \lambda t + \frac{1}{\alpha^{\beta}} \cdot \left[(t-\xi)^{\beta}\right], & t \geq \xi, \alpha > 0, \beta > 1 \end{cases} \tag{2}$$

and the expected number of MTEs for each structure *i* in group g, over the age interval $[t, t + \Delta t]$ is given by the difference between $H_{i,p,g}(t)$ and $H_{i,p,g}(t + \Delta t)$,

$$MTE^{s}_{i,p,g}(t, t + \Delta t) = H_{i,p,g}(t + \Delta t) - H_{i,p,g}(t) \tag{3}$$

where structure *i* is located in group g. The expected number of MTEs for each built section $j \in g$ over the time interval $[t, t + \Delta t]$, $\widehat{MTE}^{BS}_{j,p,g}(t, t + \Delta t)$, is given by

$$\widehat{MTE}^{BS}_{j,p,g}(t, t + \Delta t) = \sum_{i \in j} MTE^{S}_{i,p,g}(t, t + \Delta t) \tag{4}$$

where $i \in j$ (in a slight abuse of notation) indicates the structure *i* belongs to section *j*. The expected number of MTEs for each network section $j \in g$ between dates T_1 and T_2 can be computed as

$$MTE^{BS}_{j,p,g}(T_1, T_2) = \widehat{MTE}^{BS}_{j,p,g}\left(T_1 - build\ date_j, T_2 - build\_date_j\right) \tag{5}$$

where $build\ date_j$ indicates the build date of built section *j*. The total expected number of MTEs between dates T_1 and T_2 is given by

$$MTE_p(T_1, T_2) = \sum_{g} \sum_{j \in g} MTE^{BS}_{j,p,g}(T_1, T_2) \tag{6}$$

where $j \in g$ (slightly abusing notation again) indicates the built section j belongs to group g.

2.4 Evaluation of Replacement Policies

To use the MTE predictions for decision support (as proposed in Fig. 1), we propose presenting the decision maker with an expected number of MTEs for two types of replacement policies: Age-based and threshold-based. In age-based replacement, a built section is replaced when it reaches a certain age during the planning horizon T. Different cut-off ages can be specified for each different group g. In a threshold-based replacement policy, a built section will be replaced when its predicted number of MTEs reaches a certain value ($threshold$). For instance, if $threshold = 20$, the predicted numbers of corrosion MTEs of three built sections are greater than 20 in 2015, then these built sections will be replaced at 2015 based on the threshold-based replacement policy.

3 Case Study

The proposed reliability prediction model was applied to the prediction of corrosion maintenance events for an electricity transmission network in Australia. Using the available data and expert analysis, significant corrosion maintenance notifications were identified for further analysis. It was found that the distance from the coast has a strong influence on the corrosion MTE rate. The MTE rate decreases as the costal distance increase until approximately 100km inland. Through data grouping analysis (Section 2.2), the transmission line system is classified into three groups, $\text{AveCoastDis} \leq 6\text{km}$, 6km<$\text{AveCoastDis} \leq 55.48\text{km}$, and $\text{AveCoastDis} > 55.48\text{km}$.

Figure 3-5 show the empirical and fitted corrosion MTE rate as a function of age for the three groups. It can be clearly seen that TNAs closer to the coast have higher corrosion MTE rates. Using the methodology in Section 2.3, we can prediction the number of corrosion MTEs in each calendar year, based on the (clearly non-uniform) age of the different assets. Figure 6 displays the expected number of corrosion MTEs (computed using Eq. (6). Prior to calendar year 0, the MTE number are known and displayed as bars, but after year 0, the MTE values represent predictions. The information can be disaggregated to display a geographical distribution of the MTEs (as shown in the bottom two plots in Fig. 6).

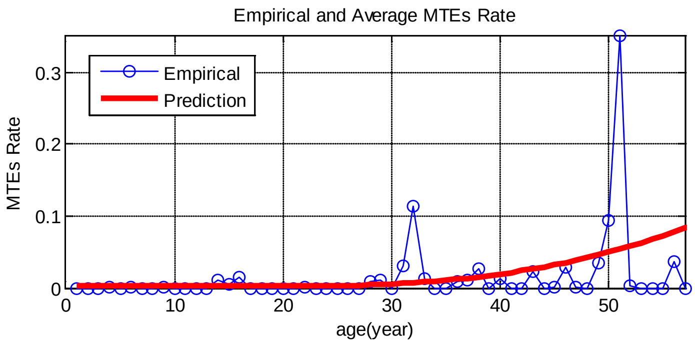

Figure 3 Prediction of significant corrosion MTE rate for $AveCoastDis \leq 6km$

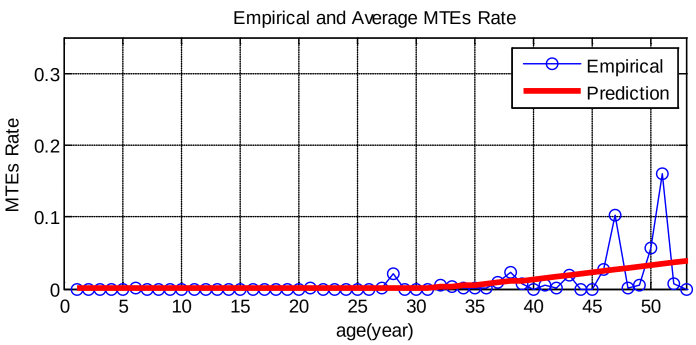

Figure 4 Prediction of significant corrosion MTE rate for $6km < AveCoastDis \leq 55km$

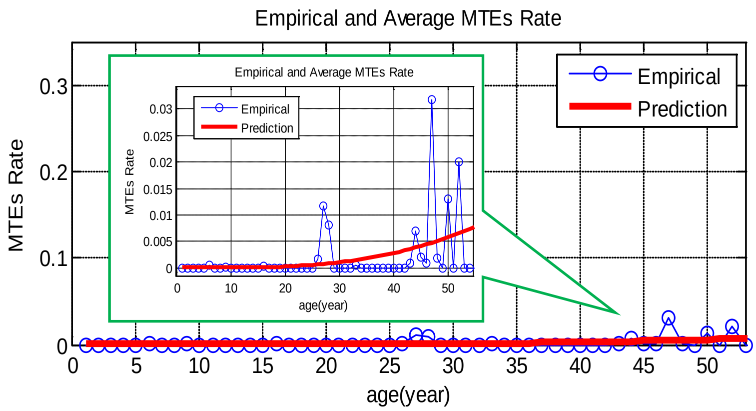

Figure 5 Prediction of Corrosion (Level 3 & 4) MTE for $AveCoastDis > 55km$

3.1 Prediction of Notifications under Repair Policies

In this section, the MTE prediction methodology is used to evaluate the effectiveness of different repair policies. The prediction of the effects based on age-based maintenance policies for the predicted MTEs is demonstrated in this section. The threshold for replacement age can be different for each group and the policy demonstrated is as follows: Group (1): $\text{AveCoastDis} \leq 6\text{km}$, replace when age >60 years; Group (2): $6\text{km} < \text{AveCoastDis} \leq 55\text{km}$, replace when age >65 years; Group (3): $\text{AveCoastDis} > 55\text{km}$, replace when age >65 year. Figure 7 shows prediction of average number of significant corrosion MTEs for each calendar year under the different policies.

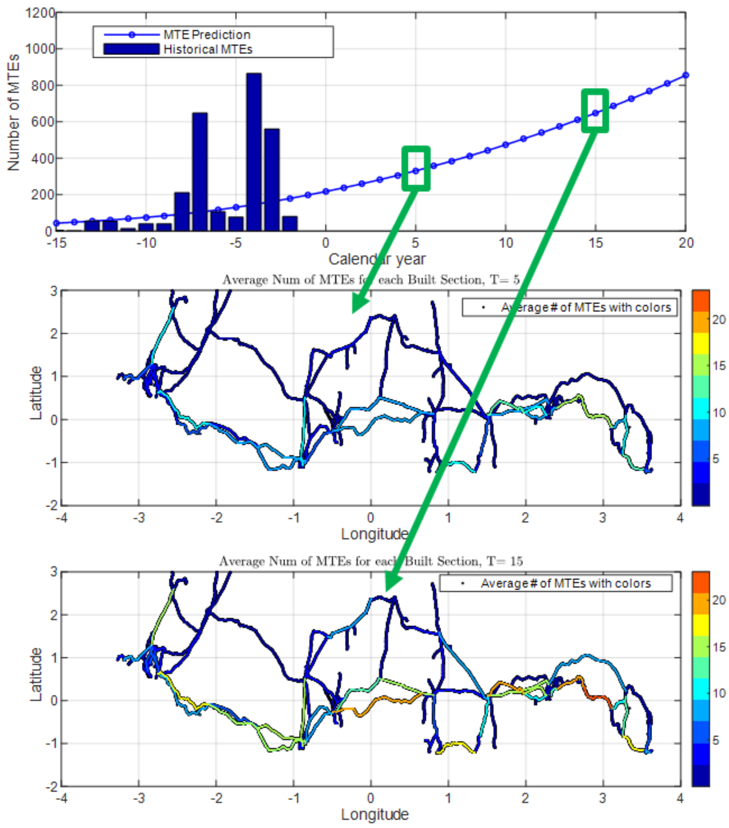

Figure 6 Prediction of Average Number of significant corrosion MTEs with calendar year (Top), the prediction of significant corrosion MTEs for each TNA section at T=5 yrs (Middle) and T=15 yrs (Bottom)

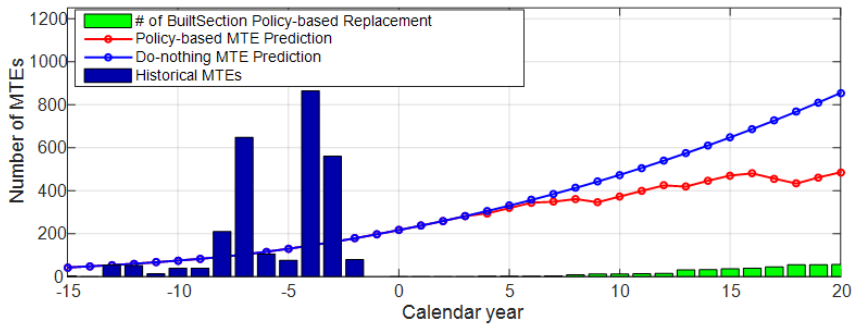

Figure 7 Prediction of Average Number of Corrosion MTEs (Level 3 & 4) with calendar year using age-based replacement policy

Instead of replacing on age, one can utilise the prediction of the expected number of MTEs, i.e. if the expected number of MTEs for a built section exceeds a threshold, the built section will be replaced. For corrosion MTEs, the results of this policy for two different thresholds can be seen in Figure 8 ($threshold = 10$). We see that the threshold-based policy has a similar number of MTEs, but far fewer replacements over the time horizon.

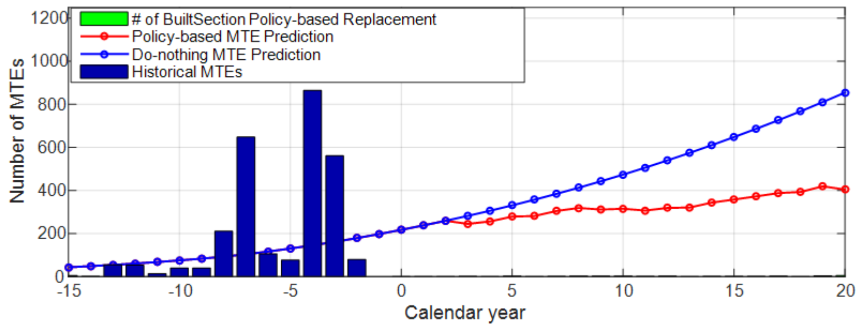

Figure 8 Effects of corrosion MTEs prediction based on the threshold-based replacement policy ($threshold$=10)

4 Conclusion

Electricity transmission networks are long-life, reliable and linear assets, which require innovative reliability modelling approaches to support maintenance decisions. This paper details a methodology that extracting significant unplanned maintenance events for critical failure modes, termed Maintenance Triggering

Event (MTE), and introduces a new reliability prediction model for their prediction. A regression tree based grouping analysis is integrated with the reliability model to analyse the influences by variety of factors on future unplanned maintenance, where it was found that age and geography have significant effects on particular corrosion MTEs. These results were then used to build the reliability prediction model allowing a decision maker to have an estimate of future unplanned maintenance requirements.

Though only corrosion maintenance event prediction was demonstrated here, this model is also capable to predict future unplanned maintenance requirements for other failure modes. Two different replacement policies have been integrated with the model and it was demonstrated how maintenance actions can be evaluated in the framework. A case study was conducted using real industry data to test the proposed reliability prediction model. The results demonstrate the feasibility and benefits of using this approach for TNA maintenance decision support.

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