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Modelling Asset Management of Railway Overhead Line Equipment

P. Kilsby*, R. Remenyte-Prescott** and J.D. Andrews***

Centre for Risk and Reliability Engineering, University of Nottingham, University Park, Nottingham, NG7 2RD
**evxpk4@nottingham.ac.uk* **r.remenyte-prescott@nottingham.ac.uk* ***john.andrews@nottingham.ac.uk*

Abstract. The overhead line equipment (OLE) is a critical sub-system of the 25kV AC overhead railway electrification system. There is a need to evaluate OLE asset management strategies through a whole life cost analysis that considers degradation processes and maintenance activities of the OLE components so that the investment required to deliver the level of performance desired by railway customers and regulators can be based on evidence from modelling results. A Petri Net model is proposed to simulate the degradation, failure, inspection and maintenance of the main OLE components and to calculate various statistics associated with the cost and reliability of the system over its whole life. The Petri Net considers all the main OLE components in one model and can simulate both fixed interval and risk based maintenance regimes. To allow such processes to be modelled accurately and efficiently, High Level Petri Net features are used. The model developed is the first of its kind, in such detail, for OLE and the applicability of Petri Nets for modelling many processes on a large system, containing numerous components, is shown.

1. Introduction

Individual OLE component failures often result in system failure and delays of the timetabled train service. Therefore, it is imperative that inspection and maintenance of the OLE takes place in order to uphold system reliability. Network Rail (the British railway infrastructure provider) aim to maintain their current assets and correctly specify the assets to be installed in new systems, so that the required outputs, such as system reliability and line speed, can be achieved at the lowest whole life cost for the system (Skinner, et al., 2011). The whole life cost of an asset is composed of its acquisition costs, associated with its design and installation, and its ownership costs, associated with its failure and maintenance (British Standards, 1997).

The OLE is a sub-system of the 25kV AC overhead electrification system, which is Network Rail's preferred electrification system, representing 63% of the electrified network which contains over 5000km of railway. With such a large electrified network and many electrification schemes planned in the near future, substantial economic savings can be realised through specifying the OLE installation types and maintenance regimes that achieve the required outputs at the lowest whole life cost. Through modelling OLE component degradation and failure over the whole life of the system, whilst also taking into account the inspection and maintenance regimes, the expected whole life cost for a given OLE installation type and maintenance regime can be estimated. The results for different project options and maintenance regimes can then be compared.

Relatively little research into asset management and whole life cost modelling of OLE has been completed to date. Chen et al. (2007) used Fault Tree Analysis to evaluate the overall reliability of a section of electrified line (including OLE components and other assets in the power system). Ho et al. (2005) described a stochastic lifetime model for estimating failure and maintenance costs for a railway traction power system. A Monte Carlo simulation of the distributions describing the component lifetimes was undertaken taking into account fixed interval preventative maintenance and corrective maintenance after a failure. Min et al. (2009) employed a similar methodology to Ho et al. (2005), but during each preventative maintenance visit, different maintenance actions were considered (such as repair, replace, do nothing) that improve the component reliability by different amounts. A genetic algorithm was then used to find the optimum maintenance strategies with respect to the overall cost and system reliability. Such models can be used to estimate the reliability and cost of OLE components and evaluate the suitability of the preventative maintenance strategy. However, the methods used are relatively simplistic and therefore do not necessarily model all the processes that can be accounted for. Furthermore, instead of fixed interval preventative maintenance vists, Network Rail implement a risk-based maintenance strategy where OLE component maintenance is scheduled based on the condition it is found to be in during routine inspections. A more sophisticated methodology is required to model such asset management strategies accurately, so that all the main processes that influence the component and whole life cost of the system are accounted for.

This paper describes a Petri Net (PN) model that has been developed to simulate the degradation, failure, inspection and maintenance of OLE components. PNs are used to represent the behaviour of a system by modelling the concurrent or asynchronous events that occur. Since Carl Petri first developed PNs in 1962, due to their power and flexibility, PNs have been used to model many processes– including railway track asset management (Andrews, 2012). British Standards (2012) have a published standard for PNs where a detailed description of the approach can be found. Like Markov models, PNs are often used to graphically represent a state-based model with the different states (known as places) referring to different conditions of the system modelled. In addition, PNs can model more complex processes (especially if the framework is extended to include High Level PN features) and the transitions between places are not limited to occur at a constant rate and obey the Markov property. The flexibility of PNs makes them an ideal choice for accurately modelling the main processes that influence the operational cost and reliability of the OLE over the whole life of the system.

2. System Description

Live conducting wires, insulators and supporting equipment installed along a railway line are collectively referred to as OLE. The main OLE components are shown below in Figure 1. Structures support all OLE components by raising them above the track. Registration equipment is attached to the structures via insulators that separate the live components from Earth. The contact and catenary wires are attached to, and aligned by, the registration equipment and the contact wire is suspended below the catenary wire by droppers. The train's pantograph rubs against the contact wire to obtain the traction power. These components exist at each structure and repeat along the entirety of an electrified line. Since the span between structures is typically about 50m, the total number of OLE components on a line is considerably large.

Figure 1. The Main OLE Components

Network Rail undertake a risk-based maintenance strategy for the OLE whereby an individual component maintenance is scheduled based on the condition it was found to be in during routine inspections. Network Rail have developed standards that describe the maximum time that maintenance must be completed by for each component defect or degradation to reduce the risk of failure. However, since maintenance engineers are responsible for many OLE components and obtaining access to and isolating the line is often logistically constrained, the components requiring maintenance in the same area are scheduled to be maintained at the same time. The size of such an area is dependent on the access to the line. In this study it is assumed that maintenance of components in an area of approximately 2 miles in length can be undertaken during the same visit. The main inspection regimes are low level walking inspections and high level intrusive inspections (assumed to be undertaken every 28 days and every 2 years respectively for high speed lines). Some component defects, such as seized fittings on the registration equipment, may not be easily identifiable during a walking inspection, and therefore they are revealed during the high level inspections only. Service affecting failures are revealed sooner, by the power supply tripping or by alerts from rails users, such as train drivers.

3. Development of a Petri Net model for OLE

The PN models the degradation, failure, maintenance and inspection processes of all of the main OLE component types (shown in Figure 1) that have a significant influence on the whole life cost of the system.

3.1 *Basics of the Petri Net Model*

The PN contains places that describe the conditions of the different OLE components studied and the transitions move tokens between these places to model how the components can degrade and fail and be inspected and maintained. The PN is stochastically timed and a Monte Carlo simulation is used to evaluate it. Stochastically timed transitions exist such that, after becoming enabled, they fire after a time that is based on probabilistic distributions that describe the times to reach states of failure or degradation for the component. Such distributions can be found by analysing real data. However, due to lack of high quality data, exponential and Weibull distributions have been assumed. For illustrative purposes in this paper, the firing times for inspection and maintenance transitions are fixed and based on times stated by Network Rail's maintenance standards.

3.2 *A Whole System Analysis*

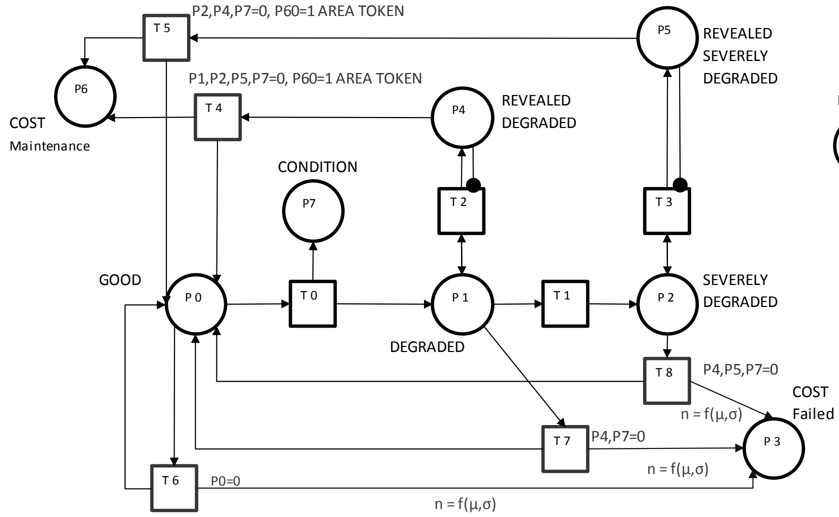
The OLE system consists of many different components that the maintenance regimes often address at the same time. Therefore, a holistic approach is used whereby all the main components that influence system reliability are considered in the same model so that the interactions between the different components can be modelled. The fact that the degradation of one component may influence the degradation and failure rates of other components is not considered in this study, since such relationships are difficult to determine and quantify accurately with limited data. Instead, the interactions between different components are modelled by considering common intervention actions. This is primarily done by scheduling the maintenance of different components to occur at the same time, if the components are known to require maintenance. Opportunistic inspection of nearby components after failures and during maintenance actions is also modelled. The PN developed is hierarchical, with a different sub-net describing the degradation, failure, inspection and maintenance processes for each of the OLE component types studied. The different sub-nets are then linked together through the interactions, described above, for the whole system analysis.

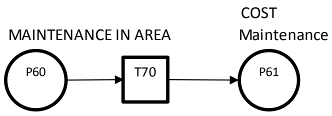
3.3 *High Level Petri Net Features*

The PN developed is a High Level PN, with features that add further functionality to standard PNs to enable the processes in the system to be modelled more accurately and efficiently. Multiple different token types that can exist in the same place are used to represent different instances of each component type in the area studied. The tokens can also contain information regarding their location and scheduled maintenance times. The transitions then have different modes, so that the different token types can be modelled concurrently. A function can exist within a transition arc in order to fire a specific number of tokens to a place according to this function. Further information about the implementation of PNs containing different token types and transition modes can be found in documentation for High Level PNs (British Standards, 2010). This study used reset arcs, which make the marking of the token type in their connected place equal to a specific value, regardless of the initial marking. When tokens may exist in multiple places at the same time, reset arcs are useful for clearing them from certain places without the need for multiple transitions, so that the PN can be more concise and efficient.

3.4 *Example Sub-Net for an Insulator*

For each component, there exists a good or working condition of the component (denoted by P0 in Figure 2). In addition, there exists a condition where the component has degraded to the extent that, according to Network Rail's maintenance standards, maintenance should be undertaken (P1). For example, for insulators, the standards state that maintenance should be undertaken when signs of minor damage are present, i.e. when less than 3 sheds are damaged. Similarly, the component condition can deteriorate further to be severely degraded (P2). Finally, a component can also be in a failed condition (P3), which causes an interruption of the timetabled train service and delay costs are incurred. There are also places that represent the revealed degraded and revealed severely degraded condition of the components (P4 and P5 respectively), since changes in component condition are not known until after an inspection has been undertaken. A number of places are used to collect statistics, such as the number of maintenance actions in a year (P6) and the duration of time a component stays in a degraded condition (P7). P60 represents maintenance as being undertaken in an area and is linked to every sub-net. P61 records statistics associated with the number of maintenance visits and isolation costs for the maintenance area.





Transition	Parameters	Source
T0	Weibull β=1.5, η=29200 days	Assumed
T1	Weibull β=3.0, η=3650 days	Assumed
T2	28 day inspection frequency	Standards
T3	28 day inspection frequency	Standards
T4	maximum = 730 days	Standards
T5	maximum= 7 days	Standards
T6	Exponential λ=0.000018 per day	Assumed
T7	Weibull β=3.0, η=14600 days	Assumed
T8	Weibull β=3.0, η=1095 days	Assumed
FUNCTION	Lognormal μ=8.95, σ=2.46	Data Analysis
T70	0 days (instantly after maint.)	n/a

Figure 2. Insulator Sub-Net (Transitions with reset arcs list the places that are reset next to them)

Degradation transitions (T0 and T1) describe the process of degradation from the good state to reach the degraded and severely degraded states. Inspection transitions, T2 and T3, describe an inspection where the two states of degradation are revealed, at which point maintenance is scheduled for the component.

The firing time of a maintenance transition (T4 and T5) is calculated by considering whether any other components (of any type that can be grouped for maintenance) have been scheduled for maintenance in the same area. Note that rules are implemented in the code that runs the model and are not depicted in the example PN. If other maintenance is due to occur before the maximum delay allowed for the component defect type (for an insulator, 2 years if degraded, and 7 days if severely degraded), then the maintenance of the component is undertaken earlier, i.e. with other planned maintenance in the area. Otherwise, the maintenance is planned according to the maximum time in the standards. The date that this maintenance is due to occur is recorded, so if other components are found to require maintenance, they are scheduled to be maintained at the same time. Maintenance returns components to the good condition (P0), for insulators a like for like replacement is undertaken. The maintenance transition reset arcs clear all other instances of the relevant token type from any of the other places it could have moved to (due to further degradation and inspection). A reset arc also sets the marking of the corresponding area token type (that represents the area that the maintained component is in) in P60 to be equal to 1, to signify that maintenance is underway in the area. T70 will fire, once all the maintenance transitions that were scheduled to occur in the same area have fired, and statistics related to the number of maintenance visits and isolation costs for the area are in P61.

There are 3 failure transitions (T6, T7 and T8) that represent component failure from each of the component conditions that are modelled. When the component is in a good condition, failure will occur primarily due to random processes, such as bird strikes. When the component has degraded, there is an increased chance of failure due to its degradation. Due to lack of available data, downtime is not considered in the analysis. Instead, the cost of failure is used to account for different failure severities since data containing the delay costs due to failures of the different component types was available. A distribution of failure costs was found for each component type (the lognormal distribution provided an appropriate fit). When a failure transition fires, the cost of the failure is sent to P3, which records the failure statistics. This is done using an arc with a function that samples the failure cost from the lognormal distribution of failure costs for an insulator, and fires the cost to P3. It is assumed that all the different failures for an insulator are revealed and have the same distribution of failure costs. The failure transitions fire the cost to P3 and also fire a token back to the good condition as the component is replaced after failure.

The distributions of time for degradation (T0 and T1) and failure (T6, T7 and T8) can be found by performing survival analysis of historical maintenance and failure data, as carried out by Meier-Hirmer et al. (2006) for the OLE in France. Due to limitations in the data, some of the parameter values for Weibull and exponential distributions are assumed in this paper, as shown in Figure 2. Nevertheless, Weibull distribution represents wear-out failures in this study, since an increasing hazard rate was observed in the data and the characteristic life was estimated using the data. Exponential distribution represents random failures, such as bird strikes, and a constant hazard rate is assumed for T6.

3.5 *The OLE System Petri Net*

A sub-net has been developed for each component type considered in this study. Each sub-net contains a different token type for each instance of the component in the area studied, and each transition has a different mode for each token type. Figure 3 shows an overview of how the different sub-nets interact in the system PN. The maintenance of components in the same area is scheduled to occur at the same time (apart from maintenance of structures). When maintenance is undertaken, the line needs to be isolated and the work undertaken by the maintenance team. Therefore, all the maintenance transitions fire a token to a sub-net that models this process (P60, T70 and P61 in Figure 2). Additionally, when maintenance of a component takes place, the adjacent component degradation will be revealed by a detailed inspection, therefore component maintenance transitions also fire a token with location information to a sub-net that models this process immediately after the maintenance transition has fired. Similarly, after the component fails, a low level inspection of the nearby section of line (roughly 1 mile) takes place immediately afterwards.

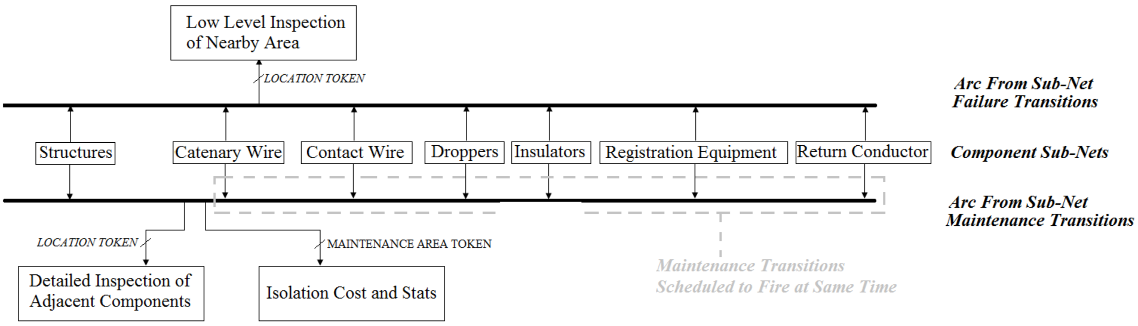


Figure 3. Overview of System Petri Net

4. Example Outputs of the Model

The model was used to simulate 100 years of operation of all the main OLE components in a maintenance area, which is approximately 2 miles long and contains 53 structures. The 100 year timeframe is chosen to allow the entire life cycle of most of the components to be witnessed (as OLE component lifetimes are typically between 40 and 80 years). The system PN developed contained 64 places, 69 transitions and 384 tokens (resulting in equivalent to 3746 transitions at runtime due to different modes for each transition). Using C++, bespoke software has been developed to perform the Monte Carlo simulation of the PN and collect various statistics. Each simulation was coded to be performed in parallel in order to reduce the run time. 100,000 simulations of the model were completed in less than 1 minute using a computer with a dual core Intel i3 processor. The mean yearly total maintenance and failure cost had converged in this number of simulations.

A number of output statistics, that express the system behaviour and various costs incurred over the 100 year period, were obtained. The statistics were found for each component type and for the overall OLE system in the maintenance area studied (by collating the different results). For example, in Figure 4, the left-hand chart shows the mean yearly maintenance costs of all the insulators in the area. The Monte Carlo simulation allows statistics, expressing the large degree of uncertainty associated with the costs, to be calculated, such as the inter quartile range of the total cumulative cost (comprised of inspection, maintenance and failure costs), as shown in the central chart. The right-hand chart shows that yearly failure costs are greater than maintenance costs for the system. The yearly maintenance and failure costs and failure rate increase overtime, as components age and degrade (and large scale renewals were not considered in this study). Note that the fluctuations between alternate years are due to the scheduling of the high-level inspections (modelled to occur every 2 years). Therefore, component degradation is only revealed every 2 years, and maintenance and component failures are more likely to occur every other year. With many of the initial failures being due to random failure or components with degradation that is revealed through a low level inspection (such as insulators), the failure rate does not fluctuate noticeably until after 40 years (see right-hand chart). After 40 years the components with degradation revealed through high level inspections (such as the catenary wire) are more likely to be in a degraded state and therefore more likely to fail.

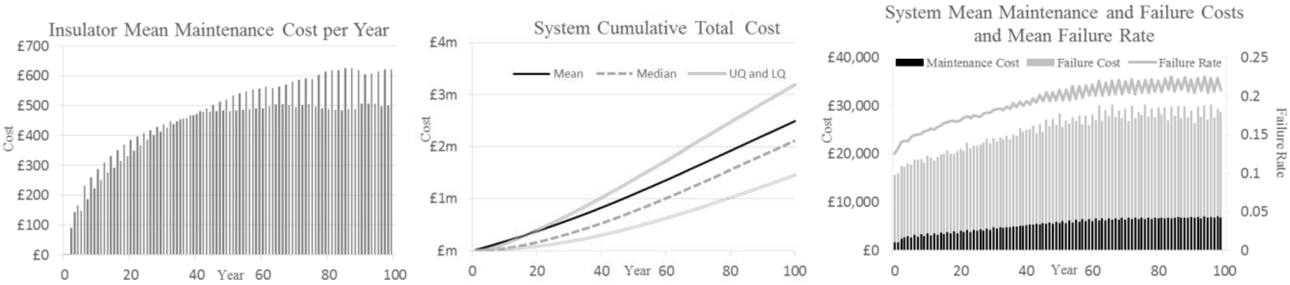


Figure 4. Charts Plotting Some of the Statistics Calculated.

5. Conclusion

This paper demonstrates how a PN approach can be used to evaluate the OLE asset management strategies through a whole life cost analysis. Degradation and failure processes are modelled for all the main OLE component types, whilst also taking into account the inspection and maintenance actions undertaken as part of a risk based maintenance regime. The whole system model considers a large number of components in a maintenance area and allows opportunistic maintenance and inspection to be modelled. The variety of statistics calculated can be used to support decisions on future maintenance requirements and to evaluate the component and system reliability over the whole life of the system. Further work could consider the influence different component reliabilities have on system reliability and whole life cost using a sensitivity analysis of the component degradation and failure rates. The PN could also be run in conjunction with a genetic algorithm to find the optimum inspection frequencies and maintenance strategies.

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