Dynamic Maintenance Based on Criticality in Electricity Network

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Abstract

The need to prioritize maintenance activities and investments based on asset criticality and associated risk is seen increasingly as important in industry. However, proper use of criticality in developing maintenance strategies and plans is still at a nascent stage in most organisations. A review of industrial practices showed that criticality is considered as more or less a static quantity that is not updated with sufficient frequency as the operating environment changes. This paper examines an electricity distribution network operator (DNO) to show the need to model the changing nature of criticality and ensure an optimal maintenance strategy and plan, aligned to business needs. A Real-time Criticality Based Maintenance (DCBM) methodology is proposed to identify factors affecting and influencing changes to criticality, monitor and update asset criticality and exploit the dynamic criticality to optimise maintenance decisions. Asset criticality was calculated using network performance, safety, environmental integrity, maintenance cost among other factors as the consequence categories for asset failure. The criticality for each asset (such as transformer circuit breakers, busbars etc.) is calculated as a weighted sum of the impact of supply loss on each of the consequence categories. Variations in some factors such as electricity demand influences changes in asset criticality with time and therefore criticality is modelled as a dynamic process, which is a function of time in addition to other factors. A comparison between an existing and a reviewed maintenance plan is shown where there are considerable variations in criticality over time. The performance measure used for the maintenance plan is based on the utility network reliability (quality of service) which is measured in terms of Customer Interruptions (CI) and Customer Minutes Lost (CML). standard service levels for DNOs are given in the UK's Office of Gas and Electricity Markets (OFGEM). The result showed improvement in availability mainly due to reduction of the duration of scheduled outages and short interruptions.
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1 Introduction

For the past decades, maintenance management techniques have been through a major process of metamorphosis, from focusing on periodic overhauls to the use of condition monitoring, reliability-centred maintenance and, most recently to, risk-based maintenance methodologies [1]. Criticality analysis, which is a first step to risk assessment, is a maintenance management tool which is crucial in making decisions on how to spend limited maintenance resources on those assets where it will do the most good [2], [3]. It becomes important to understand how crucial a piece of equipment/asset is to the bottom-line profitability of a business.

In risk-based investment programmes [4] [5], the risk associated to each asset is usually quantified for optimal maintenance decisions. As a first step to this, an analysis is usually conducted and an index is assigned to each asset indicating it criticality – a measure of the impact of its failure on business goals of an organization.

However, the criticality of an asset has been applied in a sense as though it is static and does not change with time. The long-time held myth is: "…we have just concluded our criticality analysis, we can now check that box …" Thus an inherent problem of criticality assessments is that they are static procedures that do not update as the operating environments and conditions changes [6], [7]. In order words, you can just "set it and forget it" and the maintenance strategy remains fixed once commissioned. But criticality depends on many factors which are volatile in nature; hence an asset's criticality will inevitably vary with time.

There's need to continuously monitor, review and update the criticality of assets to ensure maintenance objectives for the assets are aligned to business needs. Unfortunately, current criticality analysis techniques are only static procedures used primarily to identify initial maintenance strategies. Therefore current techniques cannot deal with the issues of real-time asset criticality. To illustrate the changing nature of an asset's criticality, we give a few examples.

1.1 Examples of dynamic criticality

Food processing facility: Take a simple example of a multi-product food processing plant with several production lines. Consider a scenario, as shown in Figure 1, where one production line is used to produce a more profitable product. If product A is considered a more profitable product then section 3 becomes a more critical production line than the

other since impact of its failure to the organisation is greater (assuming other variables are equal) [7]. A change in production schedule for the lines will result to change in criticality.

Again, if the utilization rate of section 2 (for example) is greater than that of the other sections for any product, then it becomes more critical. Therefore criticality of production lines depends on, and changes with, utilization rate and production schedules.
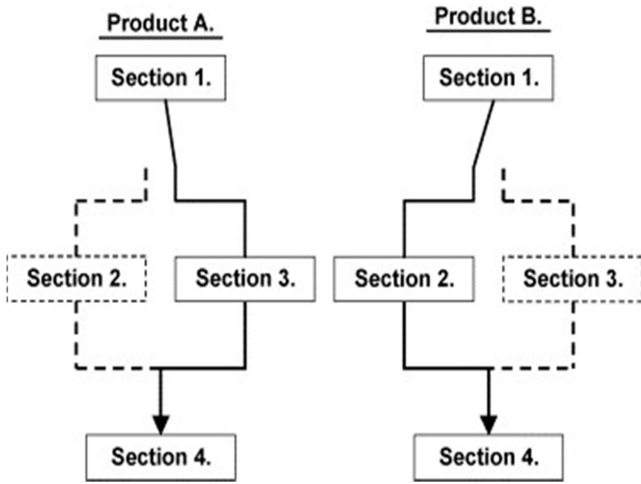

Figure 1: **Varying criticality in a production line** [7]

Power generating unit: Electricity demand varies seasonally. For example throughout the week, demands are usually less at the weekends, and throughout the day demands will be less at night. Consider a power station with an installed capacity of 600 MW(e), made up of five 120 MW(e) generating units. Assuming 3 of the sets are used for base load (non-varying demand) and the other 2 are expected to provide 'spinning reserve' to meet up with the peak demand. At nights, or weekends, when demands are low, the generating units for spinning reserve will become less critical compared to peak load periods.

The implication of this is that the consequences of failure associated with each individual asset are influenced by several factors. According to [4], for example, Network performance impact will be driven by the number of customers, or the amount of load, that is affected by the failure of the asset, similarly, the environmental impact may be dependent upon the proximity of the asset to environmentally sensitive areas (such as water course).

2 Dynamic Criticality based Maintenance (DCBM) Model

The proposed DCBM methodology aims to exploit the dynamic nature of asset criticality for setting the right maintenance plan for each asset based on its current criticality. There are three main components of the DCBM methodology, which are all linked interactively as shown in Figure 3. The algorithm for the implementation of this model is given in Figure 2.
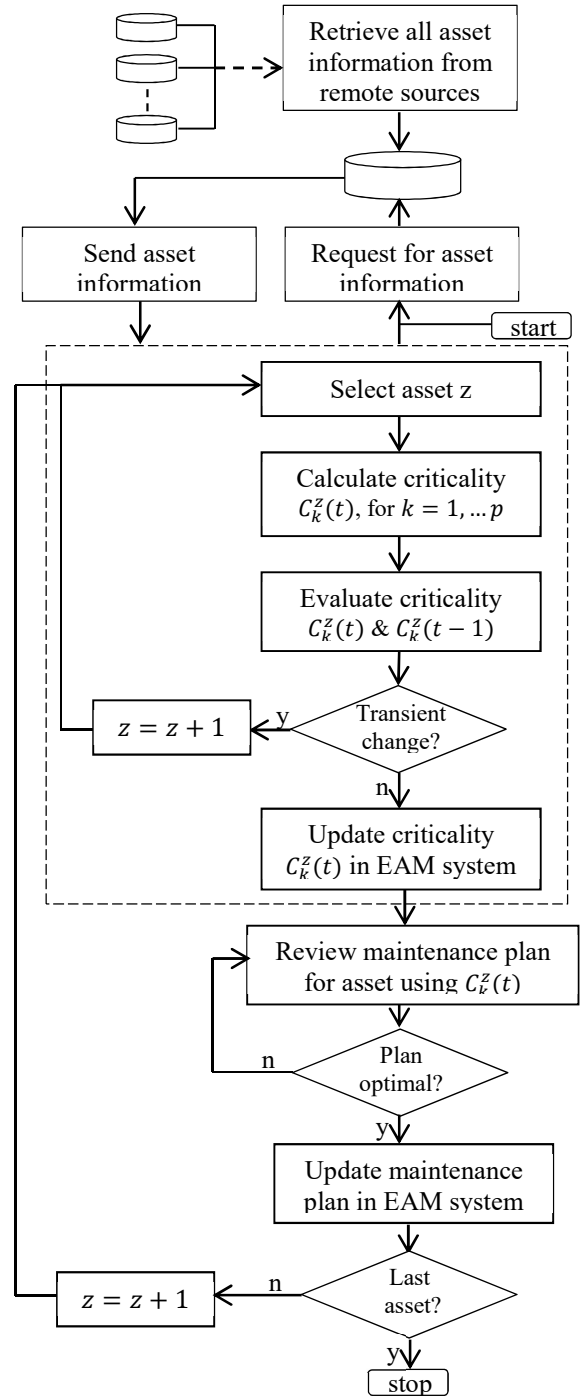

Figure 2: **RCA Algorithm**

2.1 Real-time criticality analysis (RCA) algorithm

The mathematical model for the RCA algorithm is supported by the following notations:

k: $1, ..., p$ Consequence categories for asset failure

i: $1, ..., n$ Influence factors per consequence category k

j: $1, ..., m$ Levels of possible effect of asset failure for any influence factor i

e_{ij}:   Effect j for any influence factor i

w_i: Weights (contributions) assigned to i by experts, with $\sum_{i=1}^{n} w_i = 1$

v_{ij}:   Fractional value of effect j for influence factor i

M_i: Maximum level of admissible effect for influence factor i, with $M_i \leq m \quad \forall i$

z: Asset number

u_{ij}^z Retrieved effect level j for failure of asset z

The algorithm comprises the following steps, which are explained in detail below:

2.1.1 Step 1: Data acquisition and analysis

Data capture, data sharing and data standards have a very important part to play in driving improvement in the overall performance of an asset [8].

Some of the challenges relating to the effective use of data are: the 'right' data, data quality, data quantity and data sharing.

The first step in the dynamic criticality process involves the retrieval of all relevant data for calculating asset criticality. This can be achieved in either of two ways: data can be passed each time there's a change in any of the monitored/measure parameters or whenever the algorithm request for data. For the DCBM model, the algorithm uses a standardized request for text or number to pull data into the intermediate database each time before calculating criticality. This way, the decision makers can control when, or how often, they want criticality updated.

Most of the information needed by decision makers are often located in the different disparate sources. Some of the information sources will include:

* Maintenance management systems
* Financial records
* Condition monitoring system
* Production schedules
* Health and safety regulations

With recent advances in IT, the physical location of a database is no longer important. Remote data access architecture is adopted for the DCBM methodology. The different databases are dynamically linked and current information is retrieved by the criticality algorithm for analysis.
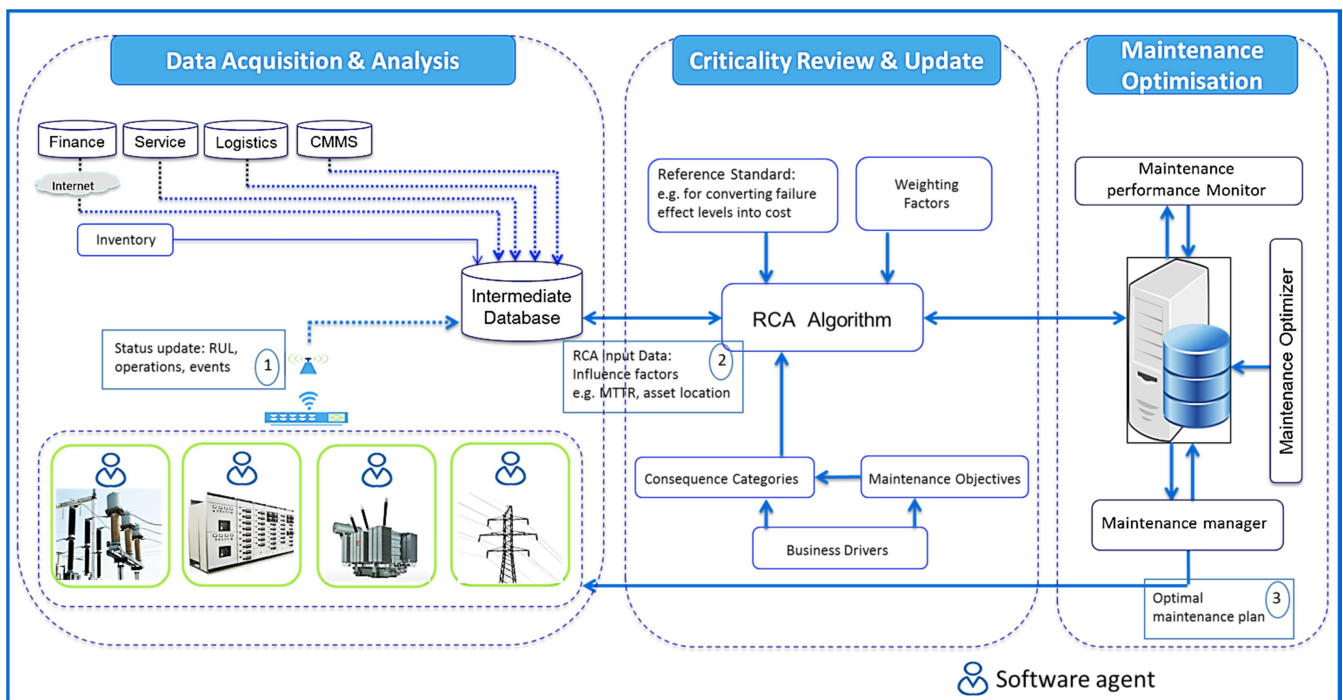

Figure 3: **Conceptual Model for DCBM**

The technical challenges involved include:
- knowing what data to ask for
- knowing where to get the data
- Using either a pull (retrieve data on request) or a push (data passed frequently) approach.

2.1.2 Step 2: Criticality analysis

This step involves calculating asset criticality using current (not just historical) information. The algorithm selects one asset type at a time and calculates the criticality of all consequence areas for that asset, i.e. $C_k^z(t)$, for $k = 1, \dots p$. The criticality of consequence category k for asset z (e.g. safety criticality for pump), is given as:

$$C_k^z(t) = \sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}^z(t) v_{ij}(t) w_i$$

Where j is the current effect level information retrieved $v_{ij} = e_{ij}/e_{iq}$, with $q = M_i$ and $j \le M_i$, and $v_{ij} = 1$ for $j = M_i$ and $\forall i$.

The change in criticality is evaluated at this stage using the previous asset criticality $C_k^z(t-1)$ and current asset criticality $C_k^z(t)$. A volatility test is conducted to check if change in criticality is simply a transient change. If the scale and frequency of the change is above a predetermined threshold, then the maintenance plan for that asset is reviewed.

2.1.3 Step 3: Maintenance decision and optimisation

This step involves making decisions on what maintenance action to take based on the change in criticality index. The magnitude of the criticality change could mean, for example, that the frequency of the preventive maintenance plan be increase. It could also mean a change in the inspection schedules of another dependent asset.

While the use of criticality for maintenance strategy is still at a nascent stage, a more challenging task is to optimise the maintenance strategy using changes in criticality. The problem lies in knowing what maintenance task/activity that should be removed or added to the maintenance plan or how frequent should it be done.

Although Markov decision processes have been used extensively to model maintenance decisions, dynamic Bayesian Networks (DBN) seems to be gaining prominence for addressing maintenance issues [9]. For DCBM methodology, the change in maintenance decision, as a result of change in criticality is modelled using Bayes theorem, which uses conditional probabilities. DBN consists of two networks: a prior and a transition network [10]. The prior network can represent the initial value of asset criticality.
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3 Application of DCBM to electricity distribution network

3.1 Description of the Distribution Network Operator

Company A is a Distribution Network Operator, taking electric power from the National Grid and distributing it at lower voltages to business and domestic customers. The company is licensed to distribute power to over 3 million homes and businesses on behalf of the supply companies. The major assets for the distribution network consist of:

- 83,000 kilometres of overhead lines and underground cables
- 155,000 pole & ground mounted transformers
- 105, 000 substations

We consider a section of the network. The capacity of the substation is known to be 32.5 MVA. Each of the three transformers has an average load of 7.5 MVA. In the event of failure of one busbar, the estimated time to transfer load is 1 hour. The mean time to repair the failed circuit breaker is estimated to be 24 hours. Total number of customers connected to the circuit is 750, with each of the three busbars serving 250 customers.

3.1 Criticality review process

The following example shows how the dynamic criticality of an incoming transformer circuit breaker for three-busbar substation will be determined and updated. There are mainly four consequence categories considered for the network, which are safety, environmental, financial, and network performance. The network performance criticality for the circuit breaker is used for this example.

The criticality review team determines the different levels that failure of an asset can have on business goals, based on each criticality influence factor. This is shown in Table 1 for this example.

The interpretation of Table 2 is as follows: a circuit breaker functional failure affecting less than 50 customers (as presented in Table 1) will attract an estimated penalty cost of £ 1,544. As another example, a MTTR of more than 24 hours will cause a potential cost of £ 1,084.8 per customer hour loss.

Criteria to measure severity per influence factor			
Influence factors	**Customer load** (fed directly via asset z, in MVA)	**MTTR** (duration of repair work, in hours)	**CI** (number of customers affected)
Effect levels per influence factor	≥ 50	(OO)	≥ 500
	$\geq 20 \leq 50$	$\geq 12 \leq 24$	$\geq 200 \leq 500$
	$\geq 10 \leq 20$	$\geq 6 \leq 12$	$\geq 50 \leq 200$
	≤ 10	≤ 6	≤ 50

Table 1: **Failure effect levels**

OO: out of order; **CI:** customer interruption; **MTTR:** mean time to repair.
With $[M_i] = 4, 3, 4$ as maximum level of admissible effect for each influence factor

Criteria to measure severity per influence factor			
Influence factors	**Customer load**	**MTTR** (Per customer hour)	**CI**
Penalisation cost per effect level (in £)	62,474	Nonadmissible	16,984
	28,248	1,624	12,352
	12,274	1,084	6,176
	4,284	542	1,544

Table 2: **Cost per effect level**

Parameter	**£ (at 2012/2013 prices)**
Costs of CML	£ 0.38 (£22.60 for one customer hour lost)
Costs of CI	£ 15.44

Table 3: **Conversion reference standard** [11]

Criteria to measure severity per influence factor			
Influence factors	**Customer load** (Weight: 35%)	**MTTR** (Weight: 25%) (Per customer hour)	**CI** (Weight: 40%)
Weighted fractional effect level	35	100	45
	15.8	25	32.7
	6.8	16.7	16.4
	2.4	8.3	4

Table 4: **Weighted severity level**
With maximum severity $MS = 100$

Day	**Customer load (MVA)**
Monday	10.04
Tuesday	10.80
Wednesday	10.58
Thursday	10.37
Friday	10.20
Saturday	8.32
Sunday	8.10

Table 5: **Daily load on percent of weekly peak** [12]
With a weekly peak of 10.8 MVA

The effect levels for the influence factors can be expressed in both qualitative and/or quantitative terms. This must be translated into quantitative terms (e.g. cost) to get the severity of each influence factor for calculating criticality of consequence category. This conversion must be based on certain contract which must be honoured by all users, stakeholders and operators of the asset. An example of such contract is shown in Table 3 below, which is used in the derivation of Table 2 from Table 1.

In order to determine the weights assigned to influence factors, various considerations were taken into account such as, the impact on each factor on the consequence categories, the importance of factor considering contracts and standards, etc. A major challenge of assigning weights is that it usually contains subjective judgements form experts in the review team.

For a consistent judgement, analytic hierarchical process (AHP) can be used. According to [2], a major advantage of AHP approach is that both qualitative and quantitative criteria can be included in the classification scheme. In our example, the weights assigned by the experts to the influence factors, using AHP, is equal to $[w_i] = 35, 25, 45$.

3.2 Data retrieval and criticality analysis

Table 1 – 4 can be stored as look-up tables for the criticality algorithm. These tables can be manually updated by the review team as contracts, regulations, market structure, or working environment of the asset changes. Influence factor information for asset z is retrieved from the disparate sources to an intermediate database.

When failure of an asset occurs, data concerning effect levels can be retrieved and captured in the variable u_{ij}^z. This variable, which is a matrix of $n \times m$ elements, is Boolean with the following values:

$$u_{ij}^z = \begin{cases} 1, & \text{when } j \text{ is the effect level the failure of asset } z \text{ for influence factor } i \\ 0, & \text{otherwise} \end{cases}$$

The Tables 5 show the weekly variations of electricity consumption/demand on each of the bus-bars. Note that other factors such as MTTR and number of connected customers could change over time also, but we focus on customer load variation in this example to demonstrate dynamic criticality of the circuit breaker.

Considering $z =$ circuit breaker, where $[k] =$ safety, environmental, financial, network performance

For $k =$ network performance

$$[i] = \text{Customer load, MTTR, CI}$$

With MTTR $= 24$ hours; weekly peak customer load $= \frac{32.5}{3} = 10.8\ MVA$; Customer load on Saturday $= 8.2\ MVA$ and CI $= 250\ customers$

$$u_{ij}^z = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$v_{ij}.w = \begin{bmatrix} 35 & 100 & 45 \\ 15.8 & 25 & 32.7 \\ 6.8 & 16.7 & 16.4 \\ 2.4 & 8.3 & 4 \end{bmatrix}$$

$$C_k^z = \sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}^z v_{ij} w_i$$

$$C_k^z(sat) \quad 2.4 + 25 + 32.7 = 60.1$$

$$C_k^z(tue) = 6.1 + 25 + 32.7 = 64.5$$

The network performance criticality for the circuit breaker on Saturday (for week under consideration) is 60.1. A plot of the network performance criticality for the week (monitored) is shown in Figure…
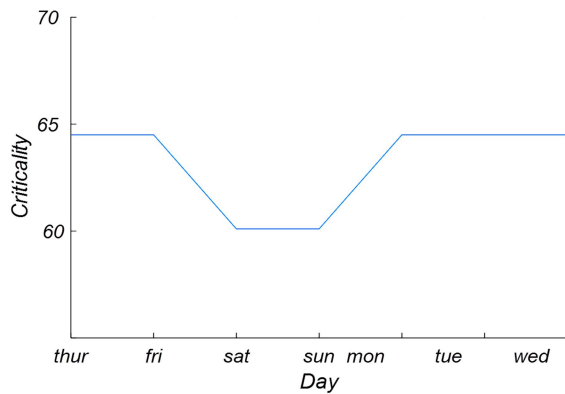

Figure 4: **Change in network performance criticality for circuit breaker**

4 Discussions

The use of criticality ranking for assets is quite understood for many organisations. But such rankings are usually not documented as part of the maintenance strategy [13]. Although the use of assert criticality for planning maintenance is still at a nascent stage in practise, it is important to examine the findings and benefits of the proposed methodology in this paper.

This methodology is still at an initial stage of development, hence there are no clear rules on how to use the changes in criticality index to review maintenance plan for the asset. Ideally one would predict that changes in criticality of circuit breaker, for the period of time as shown in the result from previous section, would result in some maintenance actions. Such action could be increase/reduction in inspection period. Thus the methodology provides handy information that is invaluable to maintenance managers for making informed maintenance decision for their assets in order to achieve overall business profitability of the company.

5 Conclusion and further work

- Most organisations do not yet use criticality for planning maintenance strategy for their assets.
- So far in both literature and practise, criticality has been understood and used in a static sense. Therefore current criticality analysis techniques cannot deal with the dynamic nature of asset criticality.
- The criticality of an asset is dynamic due to changing operating environment and conditions; hence it should be updated with sufficient frequency to ensure a maintenance plan that is aligned to business needs.
- Dynamic criticality based maintenance methodology has been introduced as a method to monitor, review and update the asset criticality over time and use changes in criticality to review maintenance plan.
- Although this method is still at infancy stage, it promises to be a useful maintenance management tool.
- Further work is required in the model architecture and will be reported in future publications.

References

[1]   F. I. Khan and M. M. Haddara, "Risk-based maintenance (RBM): a quantitative approach for maintenance/inspection scheduling and planning," *J. Loss Prev. Process Ind.*, vol. 16, no. 6, pp. 561–573, Nov. 2003.

[2]   A. Crespo Márquez, P. Moreu de León, A. Sola Rosique, and J. F. Gómez Fernández, "Criticality Analysis for Maintenance Purposes: A Study for Complex In-service Engineering Assets," *Qual. Reliab. Eng. Int.*, p. n/a–n/a, 2015.

[3]   J. Moubray, "Maintenance Management: A New Paradigm," 2014. [Online]. Available: http://reliabilityweb.com/index.php/articles/maintenance_management_a_new_paradigm/.

[4]   P. Pschierer-barnfather, D. Hughes, and S. Holmes, "DETERMINATION OF ASSET CRITICALITY : A PRACTICAL METHOD FOR USE IN RISK-BASED INVESTMENT PLANNING," in *Network*, 2011, no. 1013, pp. 6–9.

[5]   P. Pschierer-barnfather, D. Hughes, and S. Holmes, "Condition-based risk management of physical assets within the electrical power sector," in *CIRED*, 2009.

[6]   R. Smith, "Equipment Criticality Analysis," *Analysis*, no. 6, pp. 1–20.

[7]   W. J. Moore and A. G. Starr, "An intelligent maintenance system for continuous cost-based prioritisation of maintenance activities," *Comput. Ind.*, vol. 57, no. 6, pp. 595–606, Aug. 2006.

[8]   C. S. Alliance, "Engineering Asset Management: Issues and Challenges," in *Cambridge Service Week Workshop on the Future of Asset Management*, 2012, p. 15.

[9]   S. Rengaraja, "Impact of lifecycle information availability on maintenance decisions and performance," 2008.

[10]   R. B. Camci, F., Chinnam, "Dynamic Bayesian networks for machine diagnostics: hierarchical hidden Markov models vs. competitive learning," *IEEE*, 2005.

[11]   Network Asset Indices methodology Working Group, "DNO Common Network Asset Indices Methodology," 2015.

[12]   "The IEEE Reliability Test System-1996. A report prepared by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee," *IEEE Trans. Reliab.*, vol. 14, no. 3, pp. 1010 – 1020, 1999.

[13]   A. Kelly, *Maintenance strategy*. Elsevier, 1997.