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Beyond Traditional Asset Management

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HubNet is a consortium of researchers from eight universities (Imperial College and the universities of Bristol, Cardiff, Manchester, Nottingham, Southampton, Strathclyde and Warwick) tasked with coordinating research in energy networks in the UK. HubNet is funded by the Energy Programme of Research Councils UK under grant number EP/I013636/1.

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- Development of a mega-grid that would link the UK's energy network to renewable energy sources off shore, across Europe and beyond.
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- Progress the use of power electronics in electricity systems through fundamental work on semiconductor materials and power converter design.
- Development of new techniques to study the interaction between multiple energy vectors and optimally coordinate the planning and operation of energy networks under uncertainty.
- Management of transition assets: while a significant amount of new network equipment will need to be installed in the coming decades, this new construction is dwarfed by the existing asset base.
- Energy storage: determining how and where storage brings value to operation of an electricity grid and determining technology-neutral specification targets for the development of grid scale energy storage.

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Beyond Traditional Asset Management

1 Introduction

The traditional approach to asset management relies on time-based planning, where intervention, repair, and replacement are scheduled according to time in service. This has significant advantages, such as allowing maintenance to be carefully planned to fit within a tight outage schedule. However, the desire to avoid a failure in service leads to conservative estimates of asset lifetime, meaning that assets may be refurbished or replaced well before their true end of life.

An alternative approach is to take more of a condition-based decision on maintenance, where intervention is scheduled when inspection or monitoring data indicates a deterioration in asset health. This can reduce unnecessary asset downtime, since a time-based programme is likely to result in outages when the asset is still in good condition, but a condition-based approach only results in outages when condition dictates it is necessary. It can also maximise useful life in service, and minimise annual costs. But it places considerable requirements on the asset management programme, as it needs ample condition data and a good understanding of the drivers for asset aging in order to realise the cost savings. While this is feasible for certain assets, condition monitoring itself is a field of active research [1].

This is set within the context of other changes to networks and utility practice, such as the increasing use of smart grid technologies. Future power networks can be expected to have more online monitoring and available computing resources, which increases the potential for condition monitoring through online data analytics [2]. However, smart grid technologies introduce automated control of aspects such as power flow [3-7], voltage [8-12], and dynamic rating of cables [13-15] and overhead lines [16-19], which all mean that network assets are being operated in new ways. These changes will have unprecedented effects on the aging and deterioration of these assets, and therefore historical experience may not be fully applicable [20].

This paper considers some of the key drivers for change in asset management of power network assets. It reviews the on-going regulatory changes which are encouraging transmission and distribution network operators to evaluate their current practice, then draws out some of the areas which may need to be addressed as a result. It discusses the advances in asset management which are currently being studied or proposed as enablers of improved procedures, as well as some of the new technologies and applications which require a change. It concludes with some common themes for utilities to consider, as they transition from previous asset management practice to the future.

1.1 Scope of this paper

The focus of this work is to survey the current landscape and assess the future direction of the stewardship of assets within electrical utilities in the UK. The terms asset health and asset condition refer to the ability for an asset to perform its intended function, while the lifetime or remaining useful life capture the expected time until the asset reaches a functional failure, at which it can no longer perform as needed. Criticality refers to the importance of a given asset within the network, i.e. the impacts (system, safety, environmental, etc.) of that asset ceasing to function. Asset management may be defined as the process of decision-making about assets: what to monitor, how frequently to inspect, when to intervene, and what maintenance to perform. These questions are fundamentally about balancing the costs of intervention against the likelihood and expected consequences of asset deterioration and failure, trading off the relative risks of all options. The goal of a successful asset management plan is for the organisation to utilise its assets to meet its business needs in a sustainable, cost-effective manner.

The core focus of this paper is the technical methods and means of asset management within electrical networks. Many of the measures and metrics which inform an asset management strategy are based on research and experience of risk in other sectors, such as financial risk management [21] and risk in safety systems [22]. Some specific tools from these domains include Modern Portfolio Theory [23], which considers how to allocate spending across alternatives, such as the optimal portfolio of funds to invest in. Quantitative approaches to this include unbounded stochastic processes [24] and backward stochastic differential equations [25], while qualitative frameworks are less robust, but can be easier to elicit [26]. The interested reader is directed to these other sources for an economic perspective on asset management.

2 Current Practice

Within Great Britain (GB), utilities work within a regulatory framework that encourages efficiency in asset management through controls on spending. As part of the RIIO-ED1 price control period (2015 to 2023), all GB Distribution Network Operators (DNOs) have committed to addressing network reliability through improved procedures for asset management [27-38]. At the same time, there has been a commitment to standardising many of the asset management practices across utilities, which has led to the publication of the Common Network Asset Indices Methodology [39]. With this process now firmly underway, the Transmission Owners (TOs) have begun a similar attempt to standardise practice. A consultation is in progress on defining a common set of Network Output Measures (NOMs) which can be used for calculating asset risk [40]. This section discusses the impact of these efforts.

2.1 Common Network Asset Indices Methodology

A typical approach to asset management is to rank asset health on a fixed scale, so that different types of deterioration and defects can be compared against each other in terms of impact on overall asset health. Typically, each utility has their own internal method of converting condition data, inspection reports, family history, and so on into a health index value. Differences in the health indexing methodology mean that comparisons across utilities can be hard to make.

Since the RIIO-ED1 price control links the spending of each utility to their risk portfolio, there is a need to compare the performance of each utility. Risk is derived from the probability and consequences of an asset failure occurring [41]. The probability of failure is inferred from the discrete scale health index of the asset, while the consequences can be calculated based on the financial impact of a failure in service. Therefore, a standard method of calculating health indices and cost of failure will make it easier to compare the asset risk of one utility against another.

All GB DNOs have contributed to the Common Network Asset Indices Methodology [39]: a document specifying how to calculate both probability of failure and cost of failure for particular types of asset. At the moment, the Methodology covers assets such as switchgear (LV up to 66kV), transformers (11kV up to 132kV), overhead lines (poles, fittings, conductors, and towers, from LV up to 132kV), and cables (33kV to 132kV). A number of assets are explicitly excluded from the methodology, including batteries, pilot wires, and cable tunnels.

The cost of failure of an asset is determined by four factors: the financial cost (covering replacement of assets and labour), the safety consequences, the environmental consequences, and the network performance consequences. The probability of failure is also derived from four factors: two environmental (location and duty), one family-related (reliability modifier), and one specific to the condition of the asset (health score modifier). The cost of failure is indexed on a scale of four criticality bands, C1 to C4, where C1 is the lowest criticality (smallest cost). The probability of failure is indexed on a scale of five health bands, HI1 to HI5, where HI1 is the lowest chance of failure.

These indices can be calculated for every asset, to determine a snapshot view of the risk profile of the asset portfolio. More powerfully, the risk profile over time can also be examined. The consequences of a failure are expected to stay relatively static, but the health of assets is expected to deteriorate over time. The methodology assumes that age, environment, and duty have the strongest impact on rate of deterioration, and therefore calculations of future risk are determined by these factors plus the current health of the asset. The health score modifier is used to adjust the rate of aging in specific cases, if condition data indicates that an asset is aging faster or slower than expected.

The methodology has been developed to integrate current practice at different utilities as much as possible, to avoid requiring significant changes in process. Certain parameters for use within the health score modifier are suggested, such as dissolved gas analysis (DGA) for transformers, but are not required by the methodology. The process of converting raw measurement values or inspection observations into condition criteria bands is somewhat subjective, although guidance is given in the Methodology's appendices. There is no guidance given about which parameters should be measured on or offline, what should be included in inspections, or how frequently data should be collected to ensure an up-to-date understanding of asset risk.

The Common Network Asset Indices Methodology was approved by Ofgem on 1st February 2016.

2.2 Condition Based Risk Management

One tool which can be used to implement the Common Network Asset Indices Methodology is EA Technology's Condition Based Risk Management (CBRM). Originally developed in 2002 in close collaboration with Electricity North West [42], CBRM quantifies asset risk as a monetary value, by combining the probability of failure with the consequences of failure. CBRM can be used to model risk in various ways, such as identifying the optimal replacement year for an individual asset which minimises risk, or maximises the health index profile of an asset population, or optimises the total risk before and after asset replacements [42]. CBRM works with the cost of failure and health index bands as specified in the Common Methodology, but has an internal representation of health on a scale of zero to 10. It contains a model for projecting an asset health index forward in time, according to an exponential function [43].

While CBRM can be a useful way of managing the methodology, it does not help to overcome the subjective aspects identified above (i.e. assigning condition criteria bands, how frequently to collect data, or what method to use for data collection).

2.3 Network Output Measures

The need for risk management across the asset portfolio applies to transmission as well as distribution. The GB Transmission Licensees are currently undertaking a similar process to that recently completed by the DNOs, in order to develop a common methodology for assessing asset risk as part of the RIIO-T1 price control period (2013 to 2021). A draft Common Network Output Measures (NOMs) Methodology [40] was submitted in January 2016, for which Ofgem requested modifications. At the time of writing a revised version will be published imminently, which is expected to include a more theoretical underpinning than the previous draft.

The broad aim of instituting NOMs is to monitor long-term risk management of the asset portfolio. The network redundancy inherent at the transmission level means that underinvestment in asset management would take years to create a clearly detectable network reliability issue, but at that point the cost of intervention would be much higher than if investment were steady and targeted. As a result, the NOMs are metrics which aim to capture risk and performance in such a way as to incentivise appropriate and efficient asset management.

The assets covered by the Common NOMs Methodology include circuit breakers, transformers, reactors, overhead lines (conductors and fittings), and underground cables. Towers are included only for Scottish Power Transmission and Scottish Hydro Electric Transmission. All assets of these types are assigned a health index ranking from AH1 to AH5, where AH1 represents the lowest probability of failure. Assets are also assigned a criticality ranking on a scale of C1 to C4 (C1 being the highest, in contrast to the CNAIM), which is derived from safety, environmental, and system impacts, with financial impact of failure being added as a requested amendment.

While the Common NOMs Methodology is very similar in output to the Common Network Asset Indices Methodology, it has a number of unique challenges:

- The number of assets at higher voltage levels is smaller than at distribution, and in particular there are generally fewer units of a given design family in service, therefore there is less of a historical portfolio from which to derive statistics and calibrate the model.
- Failure in service at transmission is even rarer than at distribution, as utilities aim to remove assets from service before a point of failure is reached. This hazard censoring means that there is greater uncertainty about when true end-of-life would be reached, and therefore how much service life remains in current assets.
- The greater levels of redundancy at transmission improves the system reliability, but can also make it harder to calculate the impact of an asset failure on the system reliability.
- Generally, there is more data of a higher quality recorded about transmission asset health. Integrating this data into appropriate models is a welcome, but difficult, challenge.
- Many sources of data are available which relate to transmission asset health, but the original purpose of such data is not for Asset Management. For example, work orders and operational data have a clear relationship to asset condition, but aligning such data with typical condition monitoring data in a robust manner can be difficult.

However, transmission has the distinct advantage of generally higher levels of online monitoring than at distribution, which can give higher confidence in the assessment of an asset's current health index.

3 Implications of Current Practice

While transmission and distribution utilities work on harmonising and streamlining their asset management methodologies, there are some areas not covered by these efforts which can still impact the outcomes. In particular, uncertainties from various sources can affect parts of the asset management process, while not being explicitly captured within the methodologies.

3.1 Uncertainty in the data

The initial assessment of asset health is critical to predicting its life in service. There are two key parts to this judgement: how to convert raw measurements and inspection observations into condition criteria, and how certain of a health index value the utility can be, given condition criteria. The first is highly dependent on the type of data collection, while the second can be mitigated with regular data collection. Frequent updates will allow true changes in condition to be differentiated from outliers and noise in raw measurements, bringing greater certainty in the health index score.

Data quality can be assessed on five axes [44, 45]:

- Completeness: are any parameters missing?
- Timeliness: is all data up-to-date?
- Validity: is the data formatted correctly and conforming to domain rules?
- Consistency: do related records conflict?
- Accuracy: does the data reflect the true situation?

Low data quality on any of these axes will impact the certainty of the health index, and hence the confidence in the risk profile and risk projections derived from the data. The ISO 55000 standard for asset management includes record keeping and data quality within its scope [46]. But ISO 55000 places the onus on the utility to justify the level of data quality appropriate for its decision-making, rather than prescribing a particular approach.

3.2 Uncertainty in the deterioration model

Some asset classes such as transformers have historically been studied in detail, due to their relatively high cost and criticality to the network. Others have had less intensive modelling and analysis, such as towers. As a result, the precision of deterioration models cannot be expected to be the same across all asset types.

Further, some external influencing factors are well-understood, such as the effects of a coastal location on assets, while some assets deteriorate more rapidly than expected for unknown reasons. A larger population of assets may be expected to lead to a more accurate model, but there may be order of magnitude differences in the population sizes for different assets. Manufacturer and model may have a strong impact on expected life in some situations, due to known type faults. Finally, new technologies such as HVDC and new insulating materials introduce assets to the network with no (or limited) operational history, meaning the data simply does not exist which could be used to construct a deterioration model. In such cases, experimental work gives some indication of what to expect in the field, but ongoing research is needed to validate and build confidence in the results [47].

The common methodologies described above tend to reduce or avoid some of this nuance. Aging is modelled as an exponential function in all cases, in the expectation that older assets have a higher probability of failure. While the Common Network Asset Indices Methodology allows aging to be adjusted by location and reliability factors (accounting for coastal and family effects, for example), years in service still tends to dominate the model predictions.

For all these reasons, there can be significant levels of uncertainty in the deterioration model for an asset.

3.3 Uncertainty in the risk profile

The risk profile assists with decision making about interventions. For example, if a particular maintenance action can improve health by two index points, the effect on the overall risk profile can be calculated to determine whether or not the intervention is cost-effective. Alternatively, if a maintenance programme can retain health at its current index for a year, the effect on the risk profile in five years' time can be examined.

The asset risk is calculated from its probability of failure (health index) and consequence of failure (criticality index). Since both indices are discrete values with crisp boundaries, assets must be classified into a specific category (e.g. HI3, CI2). Since there is uncertainty in the source data, there is some uncertainty in the categorisation. Of 500 assets classed as HI3, there will be some nearer the HI2 boundary and some nearer the HI4 boundary, and potentially some small number which have been misclassified as HI3.

When applying maintenance effects to the risk profile, these nuances may be lost. In addition, not all maintenance actions are successful. The expected outcomes of a particular intervention will not always be met, and yet this uncertainty is not generally included in the analysis. It may be beneficial to give a best case/worst case analysis, or a probability-based risk profile, when considering the effect of maintenance. The general literature on risk management may also be informative here.

4 Future Look

Within this context, utilities are aiming to increase network reliability through improved asset management. New technologies and methods can be used to address particular sources of uncertainty within the current process, with the effect of increasing confidence and accuracy of asset lifetime predictions. This section surveys particular areas where this is possible.

4.1 Improved Prognostic Modelling of Asset Deterioration

Prognostics is the field of making predictions about future asset health, based on current health and a model of expected deterioration [48]. Within the asset management practice of utilities, the deterioration model used to predict future asset risk is a prognostic model.

Assets are expected to age through time and usage and eventually reach a point of functional failure, where they can no longer adequately perform their intended function and are considered to have failed. Certain fault types do not lead to immediate failure, and it may be possible to continue operating the asset for some time after the inception of the fault and before functional failure occurs. By predicting the time at which some threshold of condition will be reached (either functional failure, or some warning level prior to failure), utilities can plan appropriate maintenance, replacement, or repair.

As discussed above, standard approaches such as the Common Network Asset Indices Methodology assume that all deterioration fits to an exponential curve. While this may be true of specific failure modes, there are particular assets and fault types where a more precise model of deterioration is known or can be developed. The creation of specific models for specific situations can give more accurate predictions about remaining useful life (RUL) of an asset. Accordingly, there is room to reduce maintenance costs and improve asset availability with less conservative RUL estimations.

Prognostics has been under study for some time in other fields, such as aerospace [49, 50] and nuclear power generation [51-54]. For power asset condition monitoring, prognostic models have been developed for circuit breakers [55], power transformers [56], and cables [57, 58]. To date, in all of these domains the techniques and models have been selected on a case-by-case basis, without an underpinning design approach or justification for the chosen method. It has been recognised that a methodology for design of prognostic systems would be beneficial [59], by simplifying and speeding up the design process, and allowing lessons learned in one domain to more easily translate to another.

To that end, the Assisted Design for Engineering Prognostic Systems (ADEPS) methodology has been proposed [60]. This splits the process of development into four stages:

- **Identification and prioritisation of the fault modes**. Not all fault modes will lead to asset failure, meaning that some are inherently more critical than others. Since prognostic modelling is time-consuming and may require collection of specific data, this stage ensures that the potential benefits realised by the prognostic model will offset the investment, by selecting only the highest priority faults for modelling. This is achieved through model-based safety assessment (MBSA) and criticality analysis, which together provide a design-centred decision making framework to identify critical fault modes in complex engineering systems [59].

- **Prognostics model selection**. There are a vast number of techniques which can be used to model degradation in components. These can be broadly classed as data-driven, model-based, or hybrid (data-driven and model-based). A decision framework has been developed with ordered design questions, which can guide the system designer to select an appropriate technique for the specific application [61].
- **Verification of the prognostics requirements**. Since predictions are inherently uncertain, verification of the results of a prognostic system is essential for building trust in its output. Even more so than for diagnostics, some method must be employed to give confidence that the predictions are reasonable and accurate within certain bounds. Historically, formal verification techniques have been used for the verification of safety-critical systems [62]. These techniques can also be applied to assess the performance of a prognostic system, and to ensure it will meet the design requirements [63].
- **Update of the asset health state**. ADEPS can integrate multiple independently developed prognostics prediction models for different fault modes to evaluate the effect on the overall asset health state [60].

By utilising the ADEPS methodology, it is anticipated that prognostic systems can be developed with higher certainty of success. A prognostic model created in this way should reduce the uncertainty in deterioration of an asset over time, thus improving the accuracy of risk modelling.

4.2 Reuse of Data from Other Sources

One way of addressing uncertainty in data is to aggregate various related sources of data together. With more measurements and parameters indicating the status of an asset, there should be more certainty in its current state of health and rate of aging. This concept has been shown through work on data fusion [64] and ensembles of classifiers [65], and would also be beneficial to the accuracy of risk modelling.

Generally speaking, sensors and data collection infrastructure are installed on networks with a particular project in mind. The cost-benefit case has to be made for online monitoring of a particular asset, in terms of the potential savings gained by postponing maintenance while avoiding a failure, versus the initial investment in infrastructure. However, additional benefits can be derived from data once multiple related sets have been gathered. The potential benefit of this combination of data can be hard to quantify. Yet the move towards smart grid technologies, with more monitoring and automation, make the reuse of existing data more feasible than ever before [2].

There are two potential sources of these additional datasets: existing projects within the utility, and publicly available data. In the first category, data collected for one purpose could be utilised for additional condition monitoring purposes. Some examples include:

- Trip coil current monitoring, which would be installed primarily to indicate circuit breaker condition. This can also give secondary information about the health of the batteries [66].
- Power quality monitoring, which would be installed primarily to monitor harmonics from a network delivery perspective. This can also provide context for interpretation of partial discharge patterns [67].
- Network operational data, which primarily indicates the state of the network. This can also indicate dynamic loading on assets, which can affect lifetime predictions [13-15].

Installation of monitoring and data collection systems can be a significant cost, so gaining as much information from existing sources of data as possible is advisable.

Public data may not relate directly to the asset condition, but may be very comprehensive in recording the circumstances and environment the asset is operating in. Simple examples are weather information, including ambient temperature, solar radiation, rainfall, and wind speed and direction, which may be gathered from a public meteorological mast instead of requiring the installation of sensors at every substation.

To take full advantage of these datasets, a utility would need to undertake an exercise to list possible data sources, both within the utility and in the public domain. Once the list has been developed, the relationships between various datasets can be enumerated, and the potential benefits of aligning and mining those sources identified. This could be considered a "bottom-up" approach: looking at what data is available and the potential links. Traditionally, projects are developed "top-down" with a particular goal in mind (e.g. transformer thermal monitoring). The bottom-up approach is likely to identify relationships and cost-benefits that would not be considered by taking a top-down approach.

These two approaches have parallels with dependability analysis techniques, with the bottom-up approach mirroring Failure Modes and Effects Analysis, while the top-down approach mirrors Fault Tree Analysis [68].

Finally, there could be significant benefit in data sharing between utilities. The common methodologies mean that data collection and storage are becoming more harmonised, since the outcomes must be reported in a common way. The sharing of success stories and good practice as well as more negative outcomes in a more open manner could lead to benefit for all.

4.3 Better Tools for Visualisation and Exploration of Data

Trends such as more data capture, online monitoring, and the linking of related data will automatically increase the size of datasets that engineers must manage. As the volumes of data relating to asset management increase, improved tools will be needed for visualising, handling, and exploring data. The ultimate goal of online monitoring is to convert high volume streams of raw sensor measurements and data points into actionable information, relating to asset health and lifetime.

The field of Big Data relates to applications involving high volume, high velocity, and high variety of data streams [69]. Within the domain of power engineering, some work has considered the implications of Big Data for power systems operation [70] and condition monitoring [71]. However, the types of data being collected from power networks to date do not tend to display the volume and velocity of Big Data in other fields [2]. Further, the variety of data is generally limited to technical network parameters.

This suggests that asset management datasets are not prime candidates for the application of Big Data tools and techniques at present. However, lessons learned from this field may indicate approaches and features to incorporate into asset management tools, which would assist engineers in asset decision-making.

It is already understood that segmenting datasets appropriately can derive better information, such as grouping together particular families and design types of asset. This has been hampered in the past by a general limitation on the amount of data available: some families with very small datasets must be grouped together with others to generate statistically significant results, even if it would be more meaningful to keep them separate. Better tools for visualisation and exploration of data are required to allow investigations into appropriate groupings and segmentation, with the aim of surfacing previously hidden relationships.

Further, there is a need for tools which allow the integration of expert knowledge with statistical data analysis. While patterns can be uncovered by data mining, the input of an expert engineer is valuable for determining whether or not a relationship is meaningful and useful. An example of a meaningful relationship is the link between transformer faults and dissolved gases, but human expertise can provide useful context to determine whether a detected fault is urgent, or can be explained by other factors. Further research is needed into methods of capturing expert explanation of data analysis, and allowing system to learn from expert feedback.

4.4 New Technologies for Inspection and Monitoring

The majority of condition data comes from inspection, with some from condition monitoring. Both are relatively expensive, and inspection is personnel-intensive. New technologies for data collection may be able to reduce the number of person-hours associated with inspection, with the added benefit of allowing automated data processing and decision support. In particular, there is scope for greater use of mobile hardware, drones, and satellite imaging. A description of the possible utilisation of these technologies for inspection and monitoring is provided below.

4.4.1 Consumer-Level Mobile Hardware

A high percentage of engineers carry smart phones and tablet computers with them everywhere, including to site. Instead of using bespoke devices for measurement and recording on site, these "commercial off-the-shelf" (COTS) devices can be utilised, as is beginning to happen in other industries [72]. As a stand-alone device, tablets and phones can be used to take pictures, record audio, and record accelerometer data.

Additional sensors could be developed to connect to the phone, increasing the capabilities, such as an infra-red camera. The internet connection of such devices can be used for sending data to a centralised database.

To exploit this, custom software would need to be developed for collecting and sending data from smart phones or tablets, and cyber security issues would be critical. However, this could be expected to reduce costs overall when compared with bespoke ruggedised hardware devices.

4.4.2 Drones for Asset Inspection

Overhead line inspections are currently done by helicopters that take high resolution images of the components of interest and use infrared cameras to detect hot spots in conductors [73, 74]. Recorded images and photographs are then examined by experts to determine the health state of overhead line components. However helicopters are not able to photograph some of the critical components and they are not able to access all areas due to environmental or land owner restrictions. Additionally, the speed of the inspection pass can lead to a lack of detail in many cases.

Some companies are starting to use drones for the inspection process [74]. Drones also take high resolution images, which are analysed afterwards by experts. Drones must currently be directed by personnel on the ground. Therefore, at present the main savings are in reduced numbers of crews sent to inspect areas of difficult access, and reduced need for personnel to climb towers to take a closer look at the components.

It is expected that drone technology and regulation will continue to progress, bringing greater potential for future cost and personnel savings (see for example [75]). Weight of the drone carriage is critical, but progress on sensor technology will allow the inclusion of additional relevant sensors, not just imaging. Improvements in data processing will allow automated analysis of inspection photographs and other sensor data, to locate and highlight birds' nests, corrosion, and other notable features.

Eventually, self-directed drones could be able to inspect an entire line without manual intervention, by automatically re-planning its route and data collection to take account of tree branches, birds, and other impediments. This is a significant research topic with both technical and policy challenges, however it would bring significant cost savings while decreasing uncertainty in asset management data.

4.4.3 Satellites for Data Collection

Satellites provide enabling technologies such as positioning and observation that are widely applicable across many sectors. In particular, Earth-observing satellites are currently acquiring data related to the atmosphere, agriculture, transport and transport infrastructure, and oceans. In one case, satellites have been shown to detect subsidence below the ground level within subway systems [76].

Satellite technology could support the inspection process of many of the assets present in the distribution and transmission networks. As one example, satellites could be used to detect hot spots in underground cables through changes to the Earth's crust and surface, providing a heat map of areas of interest for further inspection. Satellite imaging is expected to provide relatively course-grained information about potential faults and overheating. Therefore, after detection, a crew would be sent to perform a more detailed inspection of the area using infra-red cameras.

As another application, storm conditions can cause network faults which interrupt supply to customers. Satellite imaging would be one way of checking the integrity of substation assets without dispatching a crew to each site. Images could be analysed manually in the first instance, or automatic change detection techniques applied to highlight the most critical substations. In this way, maintenance efforts could be prioritised, and customer minutes lost minimised.

4.5 New Devices and Applications

Utilities have long experience of managing traditional network assets, such as transformers, cables, and overhead lines. However, changing usage of traditional assets and increased numbers of new devices can be anticipated, which will challenge conventional asset management in particular ways.

Electric vehicles have the potential for significant impact on networks, particularly at the distribution level. Studies suggest electric vehicles will not be evenly dispersed through the network, but instead will tend to be clustered in particular streets and areas [77, 78]. This will compound the effects of increased load on the network, changing the duty on traditional assets to such an extent that health index predictions may significantly underestimate the rate of aging. There is a need for tools which help to explore the impact of electric vehicles on particular areas of the network.

Dynamic rating of assets is one approach to managing increased loads [15]. Assets are loaded to stay within their rated thermal capacity, to avoid overheating or premature aging. However, environmental conditions can mean that the thermal capacity at a given point in time may be higher than its design rating, due to factors such as low ambient temperature, high wind speed, and low solar radiation. Dynamic rating of assets currently relies on a conservative standard model of asset health, without being tailored to a specific asset.

With an accurate model of health and remaining life, the appropriate rating for a given asset can be calculated more precisely, to maximise the rating while ensuring that the asset will not be excessively stressed. However, any uncertainties in the data and the deterioration model will also affect the ability to dynamically rate assets. Therefore the capabilities of dynamic rating systems are closely linked with asset management research.

The use of High Voltage Direct Current (HVDC) transmission is another method of adjusting to changing loads and power flows. This technology brings significantly different usage patterns for conventional assets such as cables, and devices with relatively limited operational experience such as power electronics converters [20]. This leads to high uncertainties in the types of data to collect for condition assessment, the types of failure modes to expect, and how to manage the long term risk of such a small and new portfolio of assets. Significant research is needed into appropriate asset management practices for these devices.

5 Conclusion

This paper has reviewed the current and emerging practices of asset management for transmission and distribution network utilities in GB. The regulatory framework has thrown a spotlight on asset management within the past few years, and the industry is working closely together to develop common tools and practices which allow comparison and validation of performance between utilities.

However, there are areas of practice which are not covered by the methodologies, where there is scope for significant innovation. In particular, improved prognostic modelling, reuse of data from different sources, better tools for data exploration, and innovative technologies for inspection and data collection can all enhance the reliability and accuracy of condition assessments and risk predictions. At the same time, new devices and technologies such as electric vehicles and HVDC drive innovation in asset management, since the previous regimes cannot be applied directly in the absence of historic operational experience.

In short, there is a good foundation for asset management in place in the industry, and the will from utilities and researchers to continue working together to improve.

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