Increasing the Adoption of Prognostic Systems for Health Management in the Power Industry

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Effective asset management benefits from accurate information about the current health and expected future health of each asset. This information can be supplied by diagnostic and prognostic systems respectively, utilizing data from condition monitoring systems and inspections to derive status and likely future behavior. However, new prognostic techniques can face difficulties when transitioning from research tool to industrial deployment.

Within the power industry there are two main drivers to improve asset management. First, the safety of personnel and members of the public may be compromised by a failure in service, so maintenance aims to pre-empt such failures. Secondly, more accurate prediction of future degradation can feed into a more efficient maintenance program, reducing costs through appropriate delay of repair and replacement. These drivers prompt a cautious interest in prognostic tools, countered by some reticence within traditional utilities to adopt new and relatively unproven technologies.

This paper identifies issues which may hinder the deployment of prognostic techniques within the power industry. It considers two examples of diagnostic systems (for rotating plant within nuclear stations, and for power transformers) which progressed past the research prototype stage to deployed demonstrator systems, and one example of a prognostic system (for HV circuit breakers) which has not yet made that transition. Drawing lessons from these experiences, the paper extracts key factors which link the deployed systems, but are missing from the third.

The paper concludes that structural issues are the main differentiators, including automated access to data, clear and concise user interfaces, and working with the engineers who will ultimately use the system. Trust in the algorithm is also important, and the paper outlines the techniques selected for the case study applications, with discussion of selected results. Once engineers are able to integrate prognostics into their processes, it naturally contributes to asset management strategy.

1. Drivers for diagnosis and prognosis in the power industry

Analysis of asset condition in the power industry is desirable to ensure safe and economical operation. It can also be a regulatory requirement for the asset class in question, with a number of disciplines requiring formal explicability of the decisions taken by asset managers. The examination of a wide variety data sources, often on a low-level basis, necessitates the development of automated techniques to avoid the problems of "data overload" on engineers. Intelligent systems have seen notable success in a wide variety of engineering maintenance and reliability applications, including the monitoring of rotating plant (Jardine et al., 2006), power transformers (Saha, 2003), aerospace (Borguet and Léonard, 2009) and nuclear reactor cores (West et al., 2012). The major advantages of improved condition monitoring techniques include the reduction of unplanned failures, consequently leading to increased availability, and deeper insight into the operating characteristics of assets. Many systems are of a complexity that negates the possibility of full physics-based understanding, therefore any component or process-level reasoning (knowledge-, model- or data-driven) can be argued to be worthwhile.

Asset diagnostics seeks to provide decision support regarding fault detection and classification. With the success of diagnostic applications across a wide variety of areas, an increasing interest has developed in the topic of prognostics (Schwabacher and Goebel, 2007). Prognostics encompass techniques inferring future modes of operation, fault prediction and reasoning about the remaining useful life (RUL) of plant. From an asset management perspective, the benefits of a successful prognostic system are clear. A combination of successful diagnostics and prognostics makes possible advances in condition-based asset management regimes, allowing engineers to schedule maintenance and operation more effectively. This in turn would reduce costs, through appropriate deferment of asset replacement or removal of needless maintenance, as long as the cost of a prognostic system does not outweigh the possible savings.

1.1 Other industries
Prognostic approaches have seen success in other disciplines. Many of the developed systems are reliant on adequate failure data in order to create the necessary predictive models, affecting which industries can attempt prognostics. With the relative difference in adoption between industries, it is useful to consider existing prognostic techniques when planning for the application of such approaches to a new domain.

The large volumes of available data in the aerospace industry, along with the often critical nature of reliability in this sector, have allowed for noted progress (Batzel and Swanson, 2009, Saxena et al., 2008). Both defense and commercial aerospace have seen extensive developments, with application to both structural analysis (Roemer et al., 2005) and aircraft engine systems (Kallappa and Hailu, 2005). The nuclear industry in the US has recognized the need for prognostics as part of their Light Water Reactor Sustainability program (Coble et al., 2012), though much of this is still in its infancy. Electronics has also seen a number of key research outcomes in recent years, with physics of failure models seeing success due to the wealth of first principles knowledge at the component level. The study of 'life consumption' (Ramakrishnan and Pecht, 2003) in particular would find application in the experienced duty cycle of systems beyond electronic components. While electronics systems may traditionally be considered simpler to model than power assets, successes in the aerospace industry mean prognostic techniques should not be discounted for power engineering any longer.

2. Case study diagnostic systems

Some success has already been achieved with deployment of diagnostic systems for power asset monitoring. This section details two such research prototypes.

2.1 Rotating plant within nuclear power stations
In close partnership with EDF Energy UK, the University of Strathclyde have developed and continue to augment a decision support toolkit geared towards the analysis of rotating plant items within the nuclear generation context. The Rotating Machinery Alarm Analyst (ROMAAN) system, designed for diagnostics and monitoring of steam turbine generators and Advanced Gas-cooled Reactor (AGR) gas circulator units, is built on a knowledge base comprised of vibration-based diagnostic expertise (Todd et al., 2007) augmented with statistical self-tuning techniques (Costello et al., 2011). ROMAAN combines knowledge-based and data-driven diagnostics to provide a flexible and clearly explicable decision support function in the analysis of vibration alarms and modes of asset behavior. The major problem tackled by the system is the incidence of routine alarms in turbine generator operation; alarm instances that fire with no corresponding machine behavior change or damage. A rule base of heuristics was created in order to provide clear, crisp inference regarding alarm features from vibration data. Concurrently, a statistical tuning module (Costello et al., 2012) defines normality from machine data in order to optimize the inference procedure on a turbine-to-turbine basis.

This allows for accurate diagnostics to be made on alarm examples provided to the system for multiple machines. The system identifies any underlying behavior responsible for the routine alarm firing, and the tuning capabilities negate model initialization, which is often encountered when generalizing analysis across an asset family. Providing this inference procedure in an automated and verifiable manner is particularly powerful in the analysis of large volumes of alarms, which is a common scenario in the monitoring of multiple assets. A major success of the project has been the integrated software design and deployment process, with dynamics engineers involved with conception and development throughout. This has been a key mechanism for ensuring any deployed software is fit for purpose and relevant to the needs of the end-user. A prototype for the system was launched mid-2012, allowing engineers to interact with the toolkit and become more familiar with the aims and processes of the system.

2.2 Power transmission transformers

Power transformers are a key component of the transmission network, with a failure in service potentially destroying the transformer and surrounding equipment, or even harming personnel or members of the public. Since transmission transformers are often bespoke, design and manufacture of a replacement can take many months or years, during which time the network as a whole is less resilient to other failures.

A widely accepted approach to transformer monitoring is dissolved gas analysis (DGA), where ratios of gases dissolved in the transformer oil are used to diagnose the presence of faults (Saha, 2003). Oil can be sampled either off- or on-line, with the levels of key hydrocarbons and other markers measured. However, the diagnostic ratios are set for new transformer oil, and do not account for the presence of markers due to historical events. For this reason, DGA should be coupled with an element of anomaly detection for transformers with historical problems or simply a long service record.

Two particular transformers on the UK transmission network were reaching the end of their design life, and the utility desired to keep them in service while minimizing the risk of failure (Catterson et al., 2009). Over 50 sensors were installed to gain an extensive picture of the health of both transformers. The sensor set included external temperature and vibration at various points on the transformers, internal oil monitoring (dissolved gases and moisture), and current and vibration of auxiliary systems (pumps and fans). In addition, the environmental conditions were monitored with a weather station and 3-phase transformer load currents. Measurements were recorded to a third party data warehouse every five minutes, which provided access via both a web site (for engineers) and a web service (for automated systems).

A multi-agent system was designed and deployed to perform on-line analysis of this data. There were two types of analysis implemented: Conditional Anomaly Detection (CAD), in order to identify anomalous transformer behavior while reducing false positives (Catterson et al., 2010); and DGA, in order to present engineers with a familiar, commonly understood diagnostic to complement CAD.

The system ran for 14 months, the first two months of which were used as training data for the anomaly detection. During the remaining 12 months, 21 anomalies were detected. Further analysis showed these to be due to sensor or logging errors, rather than transformer behavior. No change of transformer state was detected during this period, and the two transformers were decommissioned at a time suitable to the utility, rather than due to faults (Catterson et al., 2010).

3. Case study prognostic system

In comparison to transformers, circuit breakers are generally less costly to replace. However, they play a critical role in the protection system, operating rapidly to clear faults. There is a growing interest in on-line monitoring of breaker health, especially parameters such as the density of SF_6 gas, which is used to break current by extinguishing the arc generated under high current flow conditions. If SF_6 density drops to a critical level, termed the lockout level, the breaker is no longer guaranteed to extinguish the arc at its rated current. Such a breaker is considered to be in a failed state. This section describes a prognostic system for identifying decreases in gas density, and predicting time remaining until the lockout level is reached.

3.1 Prognostic algorithm

A one-box system for circuit breaker monitoring was installed on 11 transmission breakers. This system records multiple parameters, including daily SF_6 gas density, calculated from measured gas pressure and ambient temperature. The first stage of SF_6 analysis is to determine whether or not a leak exists (diagnosis), followed by prediction of RUL for leaking cases (prognosis). In the case of a leak, SF_6 gas density decreases in a generally linear fashion, and therefore linear regression was chosen as the model.

For each breaker, data was split into blocks of 50 data points (equating to 50 days), and linear regression using least squares was performed on each block (Rudd et al., 2011). This generated standard straight line equations, with the slope parameter m characterizing how gas density changes over time.

First pass diagnosis considered a prediction window of around one year (350 d). If the breaker was expected to reach the lockout level within this window, it was diagnosed as potentially leaking. If predicted failure was over one year away, it was considered to be noise in the data causing a decreasing slope, and not a true indicator of an SF_6 leak. This diagnosis was implemented by thresholding on m.

A prognosis of RUL was made by calculating the time at which gas density would equal the lockout level. This can be presented visually by extending the regression line until it crosses the lockout threshold, as shown in Figure 1. It can be seen than the data is relatively noisy, and statistical approaches were investigated for quantifying the resulting uncertainty (Rudd et al., 2011). The simplest of these was to calculate upper and lower bounds on the predicted RUL by shifting the regression line by one standard deviation in both directions (Figure 1). This gives a window of anticipated breaker failure, the width of which indicates the level of certainty in the prediction.
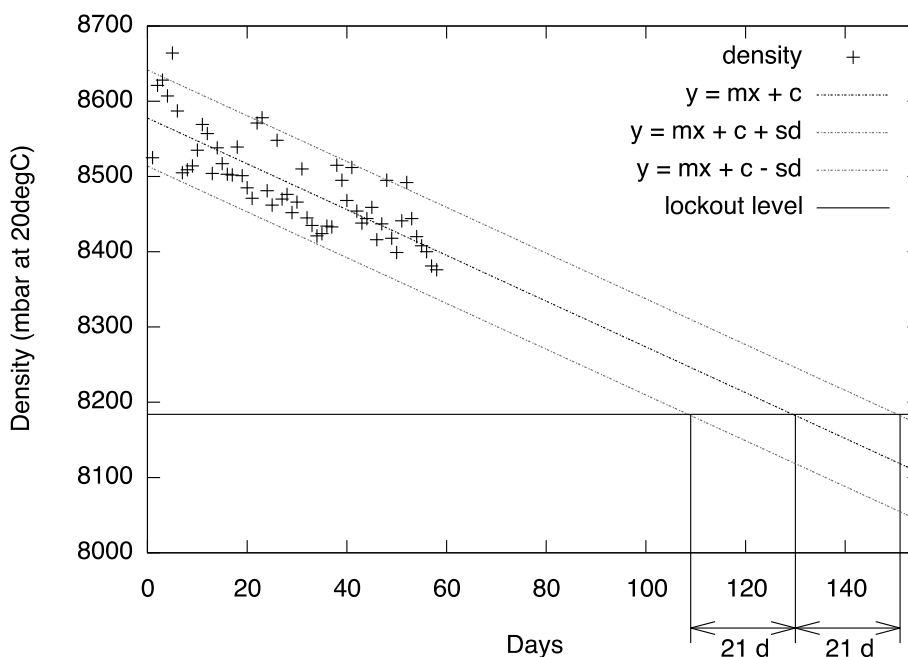
Figure 1: Regression line projected forward until lockout, with visual bounds on uncertainty.

Results from one representative block of data for each asset are shown in Table 1. This shows two breakers diagnosed with a potential leak, one of which shows an RUL of 52 days, and the other with 336 days. Given the high standard deviation of this last case, it was concluded to be not leaking. Ultimately, the utility replaced circuit breaker 11.

Table 1: Results of circuit breaker diagnosis and prognosis

Circuit breaker	RUL (days)	Diagnosis	RUL window (days)	Final conclusion
1	4624	No leak	n/a	No leak
2	2640	No leak	n/a	No leak
3	2575	No leak	n/a	No leak
4	1860	No leak	n/a	No leak
5	1550	No leak	n/a	No leak
6	1317	No leak	n/a	No leak
7	1114	No leak	n/a	No leak
8	760	No leak	n/a	No leak
9	733	No leak	n/a	No leak
10	336	Potential leak	±176	No leak
11	52	Potential leak	±8	Lockout in 46–60 days

3.2 Issues with deployment
The approach detailed above was developed as a software system, which would rank the circuit breakers in a substation according to how urgently they required maintenance, based on the RUL calculations. This system was demonstrated to project partners, and agreed to be a useful tool for the partner utility (Rudd et al, 2011). However, there are some issues which have delayed progress towards an online prototype, even although all partners are keen to demonstrate this technology in the field.
The main delay has been accessing data on-line. The development system utilizes spreadsheets downloaded directly from the one-box system, and is therefore currently an off-line tool. The utility was very supportive of allowing University access to the system, and granted site visits and credentials for remotely accessing one unit. However, a proprietary software tool was needed to connect to the unit, requiring a particular version of Windows without the latest security patches. This was incompatible with the University's IT policy. Further, remote connection to this unit by utility engineers in the past had put the

unit into a failure state, necessitating a site visit for rectification. University researchers were reluctant to connect to this unit regularly, knowing that it may generate extra maintenance for the utility engineers.

Secondly, the proprietary tool was designed for engineer use, not automated system use, and could not be programmatically induced to download data on a regular schedule. This meant any automated asset analysis still required an engineer to perform the data access, reducing the practicality of such a system.

There are also challenges with presenting the output of the system to engineers. Attempts to quantify the uncertainty in the RUL prediction can lead to wide windows of possible failure. While the width of the window can be taken as an indicator of the certainty of the prediction (for example, an RUL prediction ±5 d may be considered more certain than an RUL prediction ±15 d), engineers without expert understanding of linear regression are less likely to draw this inference. The graphical presentation of training data, regression line, and upper and lower bounds was found to be far more intuitive than presenting simply the outcome, e.g. RUL of 52±8 d.

Future work is expected to result in a prototype deployment of this system. However, the source of the data for such a deployment is unlikely to be the one-box system originally used for data collection. Once the data access issues have been robustly solved, researchers will promote the prototype more widely within the utility to increase the number of engineers interested in the prototype. This will increase the number of potential users, and hence the amount of feedback which can be given on the software.

4. Discussion

The case studies reported here show two examples of diagnostic systems which progressed from research concept through to deployed software prototype, and illustrate the benefits of automated data analysis for plant health monitoring within the power industry. The case study prognostic technique, in contrast, was shown to generate prognostic information about circuit breakers which the utility agreed would be beneficial to asset engineers, but as yet has not progressed past the stage of off-line proof-of-concept software. Analysis of these projects suggests that certain structural issues are just as important as the accuracy of any technique being proposed. This section highlights some of these issues, which should be resolved before future prognostic systems are likely to progress towards deployed prototypes.

Presentation: In delivering any potential prognostic metric for examination by the end-user, some thought is required regarding the way in which this information is presented. Given the often statistical nature of prognostic calculations, any system output will need to communicate the corresponding uncertainty or limits of the model to the engineer utilizing the decision support. This was attempted for the circuit breaker case by visually representing both the prediction and uncertainty bounds.

Data: In cases such as that described here, access to data is a great challenge. However, it is not just access but also the quality and type of data which is important. For many areas of condition monitoring, one of the main obstacles facing the adoption of effective prognostic methods will be in the availability of labeled condition data. To generalize condition evolution from a training set for a particular asset class, the selected approach needs to consider the scope to which it purports to supply useful decision support and whether this is possible with the information available. Some application areas may simply not have the available data or tacit knowledge to attempt to build an accurate model of degradation. This is true where the nature of the assets themselves dictate the impossibility of an observable failure (nuclear reactor cores, for example, represent a non-replaceable structure). Numerous publications refer to the problem of 'censored' or 'suspended' data, and there is discussion surrounding ways in which to circumvent any problems where the quality of available data is in question (Heng et al., 2009).

Buy-in: Clearly, there must be support within the utility for the project, and specifically from the engineers who will be working with the prototype system. These engineers can assist with development by suggesting the preferred placement of information and order of tasks. As a simple example, the diagnostic threshold for leaking circuit breakers is calculated using the m slope parameter, but presented to engineers in terms of a time prediction. This type of task-specific knowledge can be difficult for system designers to identify unless a close relationship is built with the asset engineers.

Algorithm: Finally, the engineers must have confidence in the algorithm itself. This can be difficult to gain, especially with intelligent system techniques which do not offer straightforward ways of presenting their output. This was a challenge for the transformer diagnostic system, which implemented conditional anomaly detection (CAD): a novel statistical approach to capturing relationships between asset condition and environmental parameters. The widely-recognized and understood DGA algorithms were implemented alongside CAD, giving engineers not only the new probabilistic interpretation, but also the more familiar traditional approaches to diagnostics. In cases where an anomaly was detected, engineers could examine individual parameters and DGA analysis in order to decide on the meaning of the anomaly.

5. Conclusions

By presenting three case studies of power industry applications, this paper highlights the successes of diagnostic systems and the challenges for prognostics systems in this field. The ultimate goal is to develop a prognostic system which accurately predicts future health of key assets, to help deliver safe and economic operation by enabling condition-based maintenance. The selection of appropriate techniques in order to build trust in the asset life prediction is most important, but the accuracy of the technique alone is not enough to ensure deployment within industry. On-line access to the right type of data is key, coupled with asset degradation knowledge where such expertise exists. Presenting the conclusions of a prognostic system must be considered carefully, in consultation with the engineers who will be end users of the system, since the level of uncertainty in a future prediction can be hard to quantify and visualize. In short, the deployment and in-service use of the prognostic system places equally important requirements on system development as the technique itself.

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