Failure Analysis Informing Intelligent Asset Management

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Abstract

With increasing demands on the UK's power grid it has become increasingly important to reform the methods of asset management used to maintain it. The science of Prognostics and Health Management (PHM) presents interesting possibilities by allowing the online diagnosis of faults in a component and the dynamic trending of its remaining useful life (RUL). Before a PHM system can be developed an extensive failure analysis must be conducted on the asset in question to determine the mechanisms of failure and their associated data precursors that precede them. In order to gain experience in the development of prognostic systems we have conducted a study of commercial power relays, using a data capture regime that revealed precursors to relay failure. We were able to determine important failure precursors for both stuck open failures caused by contact erosion and stuck closed failures caused by material transfer and are in a position to develop a more detailed prognostic system from this base. This research when expanded and applied to a system such as the power grid, presents an opportunity for more efficient asset management when compared to maintenance based upon time to replacement or purely on condition.

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Declaration Statement

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Chapter 1: Introduction

In the late 1990s the partners in the Joint Strike fighter program, headed by engineers from the United States Air Force, began a project to revolutionize the way that combat aircraft were maintained [1]. Previous efforts had been primarily focused on automated diagnosis of certain aircraft components such as engines [2] offline at the point of maintenance. The new plan was to integrate diagnostic systems into the aircraft itself, communicating with the ground in order to inform maintenance crews of any faults existing in the aircraft's systems. In addition to this feature this data was also going to be used to improve the efficiency of maintenance and keep the aircraft in a ready state for longer by using the diagnostic data to predict the time of life remaining in the aircraft components. This concept represented one of the first major commercial applications of Prognostics and Health Management (PHM), the science of diagnosing an incipient fault and estimating the dynamic time to failure. As a result of this seminal work the technology has become widespread in the aerospace industry, being fitted to airliners and military aircraft.

Prognostics and Health Management (PHM) is a fairly broad term for a number of different technologies that aim to accomplish the same goal: to estimate the current health of a system and to attempt to predict the time until the remaining useful life. To that end PHM has two main objectives:

1. Diagnose the system to determine when it is deviating from its normal operation (calculating current system health).
2. Analyze the deviation from normal operation and trend that divergence towards a failure threshold in order to compute the remaining useful life.

These objectives can be conducted in a number of different ways using techniques such as statistical analysis, physics of failure modelling, fusion of both modelling and statistics and the use of specially designed materials that fail a fixed time ahead of the main device.

Recently the potential of this technology has become apparent to industries outside of the aerospace industry such as in the electronics industry [3]. However, PHM has not seen as much adoption in the power industry. Due to the ageing of the power network infrastructure and new challenges relating to dynamic rating and extension of the network to remote locations as a result of increasing renewable generation there is a need to move from reactive-based maintenance and traditional condition monitoring approaches to a more predictive and holistic asset management system. To achieve good uptake of PHM the technology must be reliable and it must also be cost effective to cover the expense of developing the system.

To demonstrate the suitability of PHM methods to power network assets, an electromechanical device - power relay, is studied via a Failure Mode Mechanism Effect Analysis (FMMEA). Power relays are a common device within almost every industry, from small 5v switches used in telephone relays to 100KV power system disconnectors. The relay investigated within this research is the Barnbrook Systems 24V British Rail type relay. These are small, desktop size relays that are typically deployed in transport applications and are suitable for inclusion within a laboratory rig for characterisation. The relay contacts are also small enough to be analysed using standard laboratory equipment available within the Microsystems Engineering Centre (MISEC).

The objective of this experiment was to design a series of tests that would reveal the most common relay failure mechanisms. The analysis of the generated data would then be focused on identifying precursor data that indicates the various failure mechanisms. Failure mode analysis was conducted and a design of experiment was created, along with a bespoke experimental rig to instrument the relays and conduct the testing. Informing the Design Of Experiment was the focus on future practical implementation of a PHM supported asset management network. The premise of this future implementation is that smart front end sensing, sensors capable of data processing, would transmit information as opposed to large volumes of data. The intention of this asset management approach is to limit the volume of data generated by an asset management system. The difficulty presented by big data is that centralised asset management can become to challenging based on the process of data mining and transformation that is required. The end result being that near to real-time monitoring and adaptive measures cannot be implemented. With respect to the monitoring technology, over sampling of assets places demands on the operational life of the monitoring unit, the communications network as well as the power management. Hence there was a focus on identifying data capture parameters that would be reasonable to expect from low power microcontrollers embedded within these monitoring units.

Along with online monitoring within the experimental rig, post-failure analysis was also conducted to investigate the cause and process of failure within sample relays.

The structure of this dissertation consists firstly of a review of the literature surrounding PHM and the power sector in general in Chapter 1. It also includes a section discussing the benefits of PHM when applied to the power sector. Chapter 2 covers the construction of power relays and the work done in the area of relay failure to this point. Chapter 3 covers the premise of the relay failure experimentation and the experimental setup. Results of the experiment are detailed in Chapter 4 and analysed in Chapter 5. Finally, the conclusions of the report are summarized and future work detailed in Chapter 6.

Chapter 2: Review of Literature

In this chapter a review of literature relating to the challenges presented to the global power sector are provided along with discussions of previous work focused on power relay analysis.

The case for advanced Prognostics and Health Management (PHM) in the power sector

The smart grid principle is defined by the International Energy Agency as “an electricity network that uses digital and other advanced technologies to monitor and manage the transport of electricity from all generation sources to meet the varying electricity demands of end-users” [4]. This has presented many opportunities for advanced condition monitoring and prognostics systems in the power sector. The modern electricity grid still operates based on design requirements laid down in the mid 20th century [5]. The majority of the network operates unsupervised (in particular the low voltage network), the electricity being transmitted blind and the assumption made that the consumer is receiving that electricity (although some steps are being made by installing demand side management and visibility at the consumer level). At the same time the demand for electricity in western countries is trending ever higher (see Figure 1) [6].

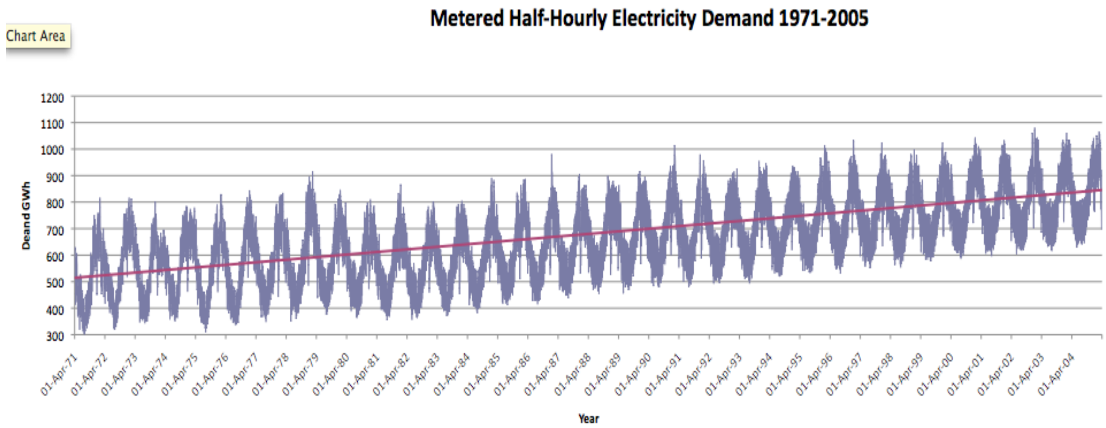


Figure 1: National Grid Demand Trend '71-'05

Over the last fifteen years there have been serious disruptions to the power grid in Europe, Asia and America [7-9], which have had serious economic impacts. Given the highly industrialized nature of modern economies and their dependence on a constant supply of electricity, any loss of power can bring all economic activities to a halt. The science of Prognostics and Health Management (PHM) presents some interesting possibilities to improve the economic, environmental and security of supply issues that plague the power network by enhancing maintenance policies and asset management.

One of the most severe blackouts to have occurred in the last twenty years was the 2003 Northwest US-Canada blackout [7]. Due to a lack of system visibility and a very serious IT system failure the system operators lost situational awareness of the power grid in their care. In the hours leading up to system collapse the operators were unaware of the severity of the situation that faced them. An unfortunate combination of a grid with limited monitoring, IT failure and an ill-timed power plant failure meant that the Northeast power system collapsed. This resulted in economic damage estimated at between $4.5bn and $10bn across manufacturing, service and government industries [10]. It is becoming more and more important to industrial power customers to ensure good power quality and reliability, such as for centralized data servers [11]. These are critical elements of Internet infrastructure that are absolutely dependent on the power grid to maintain their operation.

More recently, in July 2012, India suffered the world's most widespread electricity grid failure, which at its worst extent had isolated almost the entire Northern, Eastern and North-Eastern Electricity grid. The Ministry of Power report of August 2012 [9] identified several key factors in this failure. The first was that the Indian power operators had mis-scheduled a series of major outages and had severely weakened key inter-regional power interconnections (to the point where the only line supporting regional interconnection between the Northern and Western regons of India was one single 400KV line). This lead to severe overloading and tripped the line. However, on neither on the 30th or 31st of July was a fault actually observed in the system, indicating a clear lack of system visibility. The lack of available telemetry data crippled the observability and state estimation of the Indian grid and prevented the load dispatch centres from shedding load effectively. The committee recommended a major overhaul of outage management procedures and of network visibility infrastructure (both of which are in keeping with the smart grid principle).

A key driver of grid development, and particularly the idea of the smart grid, is therefore, to improve the security of electricity supply to ensure that such large-scale failures of the power system do not reoccur. The smart grid concept consists of improving the information capture and usage of the grid, to create a system that collects and reacts upon prevailing conditions rather than on a set of assumptions[12, 13]. To this end asset management and grid reliability sit at the very heart of the concept, and these are elements that condition monitoring and PHM can assist with.

While the failure of the US grid was only partly due to the failure of components in the grid the blackout which affected Sweden and Denmark in the same year was caused by faulty components in both the transmission network and the generating stations themselves [8]. The grid was already weakened due to a series of scheduled maintenance actions (the 400KV lines to Germany and Poland were undergoing inspection for instance). A failure in a steam valve at Oskarshamn nuclear power plant caused the grid to lose a major element of its generation capacity. Another fault then occurred when a bus bar disconnector suffered thermal induced mechanical failure and collapsed into another bus bar assembly. This faulted both lines and disconnected a further 1.75GW of capacity from the grid. The loss of this capacity caused a voltage collapse and subsequent failure of the grid in the South of Sweden and East of Denmark. Had the system operators been aware of the condition of the substation bus bars or the Oskarshamm steam valve. Condition monitoring and prognostic analysis of the steam valves in the nuclear power station could have predicted the potential failure of the steam valves in advance, while even a basic condition monitoring of the disconnector assembly might have identified the overheating issue that caused the failure.

The world's power networks represent an ageing infrastructure with limited monitoring, another significant challenge affecting Western power grids. As an example, the US power grid currently has an average Large Power Transformer (LPT) age of 40 years with 70% or more being over 25 years of age. In addition, replacing these transformers would take six months of lead time and require between $2.5 and $7.5 million dollars per transformer, depending on the rating [14]. The demand for such transformers reached a value of $1 billion during 2010, demonstrating the enormous cost to utility providers of this asset expansion and replacement even in a single year.

Due to the increase in renewable embedded energy these ageing assets, throughout the distribution and transmission networks, adding load to devices in excess of their original design specifications. Large scale renewable generation projects have added their own burden to power networks, where significant funding has been required to extend and reinforce the power network. Examples of this occur in Romania and China, where the majority of renewable resources are located in areas of low demand and must be transported to the major population centres [15, 16]. This requires significant investment in strengthening the transmission backbone to support the new power generation. For instance, the Beauly-Denny 400KV transmission upgrade from the Scottish Highlands to the Scottish Lowlands is designed to provide a gateway for renewable power generated in the wind rich North of Scotland [17]. This scheme has a capital cost of £600m. Aside from the large capital costs, Beauly-Denny suffered from strong local opposition to the potential aesthetic and ecological damage that it would cause to the local environment [18].

In parallel to the policy of investing in the network to support the integration of renewables, another example being the £730M Western isles connector, another policy is to assess means of deferring network upgrades. An example within the UK is the Thames Valley Vision [19]. Germani et al of Ontario Hydro conducted a study in 1986 using probability based design techniques to determine whether a certain substation required up-rating [20]. The 40-year repair costs were determined to be significantly less than the upgrade would have been for very little extra risk. Upgrade deferment is therefore very desirable when the existing equipment can fulfill the same role.

There have been proposals to further enhance this approach to upgrade deferment by using appropriate condition monitoring and PHM in the literature [21, 22]. This approach has the advantage over the single time study of providing a dynamic assessment of the asset remaining useful life and performance by collecting operational data in real time and applying it to the appropriate statistical or physical model. At any time the optimal balance between performance and RUL can be struck to optimize the usage of the system. Given that the ability to monitor a device using a smart sensor (such as the stick-on sensors developed by Georgia tech) can be achieved for as little as $45 dollars per sensor [23] plus the development costs of the prognostics system, the use of this monitoring technology could be used to reduce the replacement costs of large and expensive assets (such as transformers).

A good example of this technology is in the field of dynamic line rating (DLR). There are a number of test studies available in the literature that detail the planning, implementation and capacity gain benefits for a DLR equipped line [24-28]. By studying the local weather conditions or the sag of the line it is possible to predict its capacity (which might be significantly higher than the line's static maximum rating). This defers the upgrade of the power lines by several years and potentially saves a large sum of money through better utilization of the existing infrastructure.

Integrating PHM systems can also aid in the intelligent scheduling of maintenance, helping to reduce the mean time to repair (MTTR) and schedule repairs at the most economically and technically viable time. In this vein, a compelling economic argument comes from the defence sector. Banks, Reichard and Drake make the case for the use of PHM in a heavy vehicle battalion[29], targeting the vehicle batteries. Given that current batteries are generally considered unreliable, if a battery fault is detected the entire vehicle battery system is replaced. A comparison between increasing the designed-in reliability of the batteries with implementing a battery prognostics system shows that that the prognostic approach is competitive. The proposed system has both economic savings and also improves the availability of the system, particularly at the most critical times (when the vehicle is in combat).

The savings from this methodology can also carry over to the power sector. Nilsson and Bertling [30] used two case examples of single turbines and large wind farms to show what would make a condition monitoring system viable compared to existing corrective maintenance methods. It was predicted that if the CM system was able to convert 47% of corrective maintenance to predictive maintenance, or increase availability by 0.43% then the CM system was economically viable. Similarly Tamilselvan, Wang and Wang [31] predict in turn that a maintenance strategy which was informed by a Prognostics and Health Management (PHM) system has a significant economic advantage over an approach only informed by the present condition of the system. This study also makes an interesting point in factoring in the carbon dioxide emissions 'cost' in the economic argument for PHM. There are a number of studies and reports that describe the approximate carbon dioxide and other pollutant emissions of existing thermal power stations and how they might be displaced by wind [32-34]. If the Department of Energy and Climate Change (DECC) DUKES (Digest of UK Energy Statistics) 2011 estimate is taken for coal CO2 production then for every MWH of renewable energy produced, 912g of CO2 are displaced for a coal plant or 392g are displaced for a gas plant. If a wind turbine is out of commission for maintenance then the less environmentally friendly fossil fuel plants must take up the load. It is therefore desirable from an environmental viewpoint to keep renewable energy source availability as high as possible (which PHM and CBM can assist with).

Another area where condition monitoring and prognostics may come into their own is in the maintenance of offshore systems. There is a trend towards offshore power in the United Kingdom, given the enormous energy potential available in UK territorial waters. DECC predicts that 18GW of offshore wind generation could be deployed by 2020 and up to 40GW deployed by 2030. Tidal and wave are also predicted to be a substantial addition to the generation mix, with up to 27GW potentially installed by 2050 [35]. All of these systems present a unique challenge in that they all require subsea grid interconnections. The cost of repairing this infrastructure is extremely high. This activity is also extremely sensitive to the weather. Poor weather conditions in the North Sea can last for weeks and delay repairs to cables. Every day that the renewable energy generators are disconnected represents a loss to the company in revenue and an increase in generation from fossil fuel sources. When these interconnections represent a significant contribution to the generation mix their loss can have serious implications for security of power supply. It is therefore not only desirable, but also necessary to be able to predict faults and locate them rapidly in order to minimize economic and environmental impact.

In summary PHM and CBM techniques can potentially provide advantage to the power sector in the following categories:

- **Economics** through improved maintenance procedures, asset management and upgrade deferment
- **Adaptability** through improved integration of distributed generation into the grid.
- **Reliability** through greater system availability and early warning of potential failures
- **Environment** by ensuring that critical renewables projects remain operational and able to displace traditional fossil fuel driven power plants

A brief overview of PHM technologies

Prognostics and Health Management (PHM) is a fairly broad term for a number of different technologies that aim to accomplish the same goal: to estimate the current health of a system and to attempt to predict the time until the system fails (calculation of remaining useful life). In that respect the PHM system has to fulfil two objectives [36]:

1. Diagnose the system to determine when it is deviating from its normal operation (calculating current system health).
2. Analyze the deviation from normal operation and trend that divergence towards a failure threshold in order to compute the remaining useful life.

Generally these are implemented in one of four ways: a Physics of Failure (PoF) model, a statistical model, canaries or combinations of all three (known as fusion prognostics). The methods of meeting objectives one and two are summarized in the table below:

	Diagnostic System	Prognostic System
Data driven PHM	Statistical comparison & classification of historical training data and current data.	Trending of feature divergence towards known failure condition.
Canaries	Component designed to fail with the same mechanism as the monitored component but earlier. As canaries fail damage can be estimated.	Trending of canary failures combined with knowledge of product failure rates allows estimate of component life.
Physics of Failure driven PHM	FMMEA to create stress & damage model. Use of model to estimate level of component health	Trending of extracted damage level to failure threshold.
Fusion prognostics	Use of both statistical and physical failure models to identify anomalous behavior.	Independent predictions of failure merged using data combination techniques.

Data driven prognostics

Data driven prognostics requires a number of different steps and techniques to reach a conclusion on the remaining useful life of the system. This begins with extracting the relevant features of the system, then applying a statistical model to determine a measure of system health, and finally a statistical prediction of failure[36].

Feature Extraction

In order to determine if a failure exists the raw data has to be turned into something meaningful through the process of feature extraction. The choice of feature to extract is very application specific and has to be informed by past failure data. Some examples are given below.

Crossman et al identify several possible features that can be used to diagnose signal faults in automotive signals applications[37]. These include simple statistical data features such as the average of the signal, variability of which can indicate failure, up to much more detailed signal analysis such as wavelet transform energy. This is an analysis of how much energy is contained in the detail coefficients of a signal subjected to a wavelet transformation.

Wavelet analysis is an important signal processing technique, as it can extract both time and frequency data from a signal (for instance how frequency varies through time). This is useful in instances where a fault is characterized by a frequency which changes in time, such as in a generator, exemplified by Kawada et al[38]. In this case if the rotating blade is hitting the generator casing it exhibits a vibration frequency, but one that has a relevant time component as well.

Another novel example of feature extraction application is in the diagnosis of heart problems in human foetuses [39]. One of the main indicators of a heart problem in a foetus is an increase in the variability, acceleration or deceleration of a heart rate. This is something easily spotted by a trained medical professional but an automated monitoring system has to actually extract these features to identify the existence and nature of the problem.

Statistical features can also be very powerful indictors of defects in a material. An interesting application of statistical feature usage comes from the realm of lumber processing [40]. This has quite a similar nature to diagnosis of problems with machines as flaws in the wood have a distinctive characteristic, and any machine vision system inspecting the lumber has to be able to identify the existence and nature of those ‘faults’ in the wood. By using statistical measures such as mean, standard deviation, variance and Grey Level Co-Occurrence analysis it’s possible to compare the inspected wood sample to a master and determine their correlation. If that measure exceeds a ‘good’ value then that piece of wood can be accepted.

Diagnosis and Prognostics

The next stage of the process is to attempt to classify the extracted features and make an assessment of the current system health, and how much life remains. The diagnostic systems main objectives are to analyse the features that have been extracted from the raw sensor data and determine whether these features are anomalous given the expected behaviour of the system. The prognostics system then observes how the system features change and then trend that towards a failure point.

One method of determining system health and trending the remaining useful life is to apply the Markov Chain principle to the system. A Markov Chain is a system consisting of a variety of states that does not exhibit system memory. The transition between states depends only on the current state and not on the previous states. Generally the system state is not observable, so Hidden Markov Models (HMMs) are normally used. In this case a probability distribution exists both for which state the system is currently in (PS) and which state the system is going to transition into given the current observations (PT), as shown in Figure 2.

This lends itself very well to the diagnostic and prognostic process[41]. HMM type approaches have been used in a number of different applications: Geramifard et al developed a methodology of predicting health state of a CNC cutter (based upon how worn the cutting head is) using a single HMM model [42]. This concept was extended by the same authors using a semi-Markov model which takes into account the time in each state when predicting a state change [43]. The new HSMM algorithm developed has advanced diagnostic accuracy over the HMM and also has accurate prognostic capability.

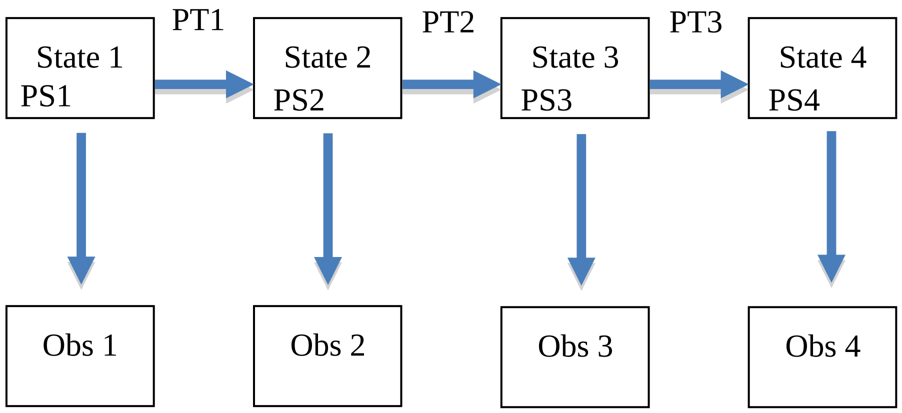


Figure 2: Hidden Markov Model states

Another extension of the HMM method is in using the Mix of Gaussians and Hidden Markov Model method presented by Tobon-Mejia et al [44]. In this system a large set of MOG-HMM models are developed from the training data and the system is continually updated to determine the best model fit to the observed data. The current state is identified using the Viterbi algorithm and then the shortest and longest state path is identified to attempt to determine the pessimistic and optimistic failure times (given the times in state that are learned from the training data). These are used to compute the remaining useful life.

The second main method of data driven prognostics consists of using an Artificial Neural Network (ANN) to help classify data into damage states and predict the resulting system degradation.

ANNs are loosely based on the biological nature of the human or animal brain. They consist of a structure of input elements, hidden processing elements (artificial neurons) and output elements, illustrated for one of the more common types, a feed forward neural network, in Figure 3. A good description of ANNs is given in [45]. Each artificial neuron has a summation of weighted inputs from other inputs of artificial neuron layers. These are then introduced to some function and output to the next set of outputs of artificial neurons. The neuron function and the interconnect weightings are ‘trained’ by the designer to produce correct outputs. This is normally done by providing the network with a problem training data set and n answer and adjusting the weightings repeatedly until that answer is achieved (supervised learning), or providing the network with a large amount of training data and then adjusting the weightings until some convergence criteria is achieved (unsupervised learning).

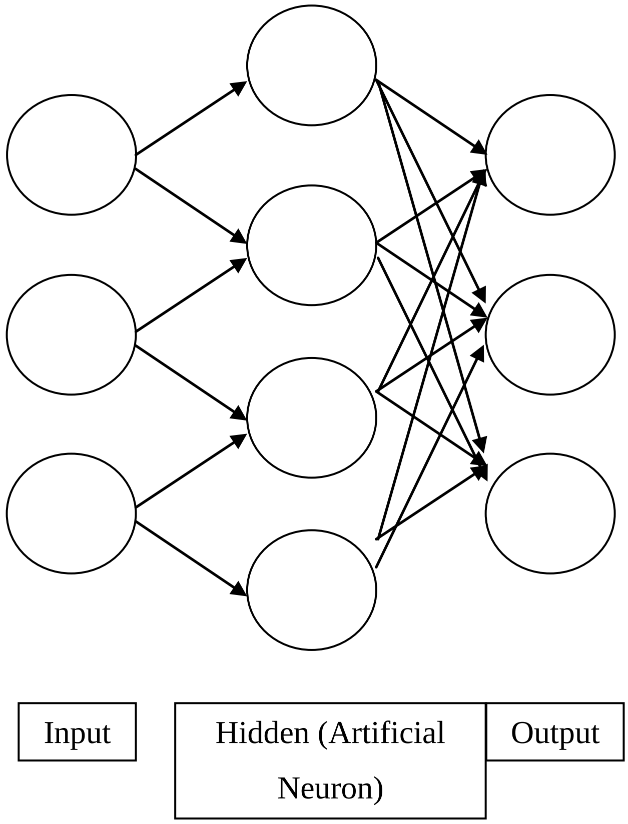


Figure 3: Feed Forward Neural Network Structure

Artificial Neural Networks have seen extensive use in a number of areas, from business management [46], modelling IT costs relating to their business benefits, to agricultural science [47], modelling the drying kinetics of parboiled rice. More recently they have started to see use in diagnostic and prognostic systems. Lall et al made use of a wavelet transform combined with a neural network to classify the type of failure experienced by a Package on Package electronics design[48]. Asmai et al made use of regression analysis of data from an industrial autoclave to determine the system failure probability and artificial neural network to extrapolate those failure probabilities towards a time of failure [49].

The Self-Organizing Map (SOM) variant of the artificial network has also seen use in the diagnostic domain of data driven prognostics. This consists of a grid of nodes that sit in a feature space. By using competitive learning the weightings of each node can be adjusted as the training algorithm is iterated over training data sets. The rough training operation consists of testing the weights of each node, choosing the best matching unit, then moving that node to the location of the training data (usually moving its neighbouring nodes as well). At the end of the training cycle the SOM grid should approximate the distribution of the data, with strong data clusters represented by each segment of the grid. The SOM can then identify clusters of data in the feature space that represent different classification regions (such as different speech elements)[50]. Lall et al made use of a self organizing map in this manner to diagnose an electronics test board which was subjected to drop testing [51]. The SOM training was able to identify map classification regions to the appropriate input data. By observing how far the input data is diverging from the healthy data cluster the damage type propagation can be assessed.

The last type of data-driven prognostics system covered here is the Support Vector Machine (SVM). The SVM operates by attempting to divide clusters of data which represent a given system condition using a hyperplane either using a linear or non linear methodology depending on the separability of the data with the widest margin possible between classified regions, shown in Figure 4. The closest data to the hyperplane decision boundary are known as the ‘support vectors’ and define the location and orientation of the hyperplane vector. These are the critical data points that would change the position of the decision boundary if they were removed. Once the optimal decision boundary is found the SVM can then classify an extracted feature and detect potential anomalies [36].

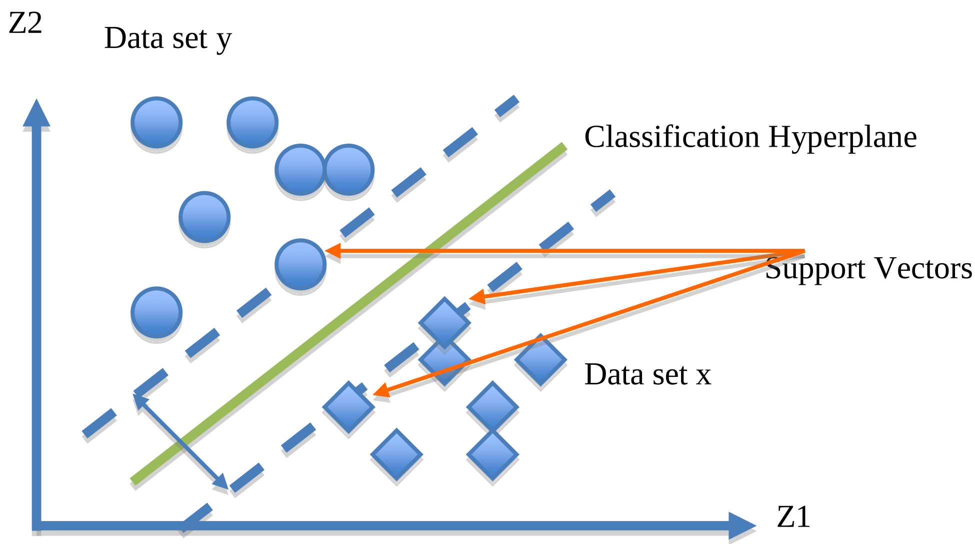


Figure 4: SVM classification of data

Support Vector Machines are frequently used in the diagnostic domain, as anomaly detection, due to their good classification performance. Xiong et al made use of a slight variation on the SVM (the Least Squares Support Vector Machine) to detect anomalies in orbiting spacecraft. This attempts to reduce the computational intensiveness of the algorithm by using linear equations to solve the equation rather than complex quadratic equations [52].

De Padua Moriera et al extend this technique into the prognostics domain by prognosing failure in aircraft engine bleed valves [53]. Several statistical features were extracted from each of three sensor data vectors. These were used to produce a degradation index based on the assumption that data within x days before a failure were unhealthy and data within x days of replacement was healthy. This training data was applied to a sample set of data and was shown to accurately predict the replacement requirement of the component.

Physics of Failure Prognostics

The second primary prognostic technique is the Physics of Failure model. Physics of Failure is a well-established design technique, which aims to enhance the reliability of a product through understanding the chemical, mechanical, thermal or electrical mechanism that leads to product failure [54].

This consists of using detailed knowledge of a component's physical breakdown mechanism to determine the level of damage done to the component and trend the damage towards a failure threshold[3]. In order to determine the underlying failure mechanisms of the device a Failure Effects, Mechanisms and Modes analysis is performed[55]. This consists of determining failure modes, ways in which the system can fail to meet its intended function, their effect on the system and the physical failure mechanism that underlies them. Underlying failure mechanisms can be ranked according to severity and frequency of occurrence and the most severe and/or frequent can be chosen for investigation. If the appropriate physical model for that failure mechanism is known then the parameters (failure of that model can be monitored and the physical model used to track damage accumulation in the component).

The first step after the FMMEA is to perform accelerated testing on the device to determine how the physical damage accumulated is related to the failure precursor parameters. For instance, Celaya et al [56] conducted accelerated ageing tests on a MOSFET by repeatedly power cycling the device to force a die detatch thermal stress failure. The drain-source resistance was then identified as a valid failure precursor and was monitored during the accelerated testing to characterise its relationship with the failure mechanism. From this a method of extrapolating the remaining useful life of the device based on an exponential model based on the change in drain-source resistance and a bayesian tracking algorithm has been developed[57].

Once the precursor parameters have been established a model has to be developed to determine the level of system damage, which is then trended towards a failure threshold. A number of different models are used in the literature. In [57] the drain-source resistance was found to have an exponential failure characteristic, and so an exponential model given in Equation 1 could be used to model Rds.

$$R = \alpha(e^{\beta . t} - 1)$$

Equation 1: Example of an exponential failure equation

Where α and β represent the curve fitting parameters.

Similarly Hua et al examined the failure of large area solder substrate attachments under thermo-mechanical load [58]. A variation of the Coffin-Manson law was used to model the damage accumulated by the solder interconnects over a number of strain cycles. This particular model is useful for failure mechanisms such as thermal loading, which is applied in a strictly cyclical manner (heating and cooling cycles). The Coffin-Manson law has the following form:

$$N_L = \frac{L}{a(\Delta\varepsilon_a)^b}$$

Equation 2: Coffin-Manson Law

Where N_L represents the lifetime of the product in cycles, L represents the length of the solder interconnect in mm and Δεp represents the change in plastic work per cycle. The two other parameters a and b are empirically derived constants. This generalized law can be applied to the specific Δεp equation that relates to the particular plastic strain of the material. Hua et al used this equation to make a prediction of the expected in service lifetimes of solder interconnects used in railway traction control systems.

In [59] Mathew et al work through the entire process for designing a PoF based prognostics system for a high power LED application. Failure modes and their associated failure mechanisms are identified. These are prioritised according to their severity, their rate of occurrence and their ease of detection. Once the main failure mechanisms are identified then damage accumulation models are constructed for the main failure mechanisms.

Canary Prognostics

Often used as an alternative method or extension of PoF based prognostics are canary prognostics. A canary is a device that has the same failure mechanism as the system being monitored but with an increased failure rate. This device is co-located with the main device so that it is subjected to the same environmental and operational loads [36]. Each canary device has an acceleration factor associated with it, which is the ratio of canary failure time to system failure time. This acceleration factor creates a ‘prognostic distance’ between the canary failure distributions and the main system failure distribution as shown in Figure 5. By using several canaries with different prognostic distances it is possible to trend the failure of the canaries to determine the failure of the system [60].

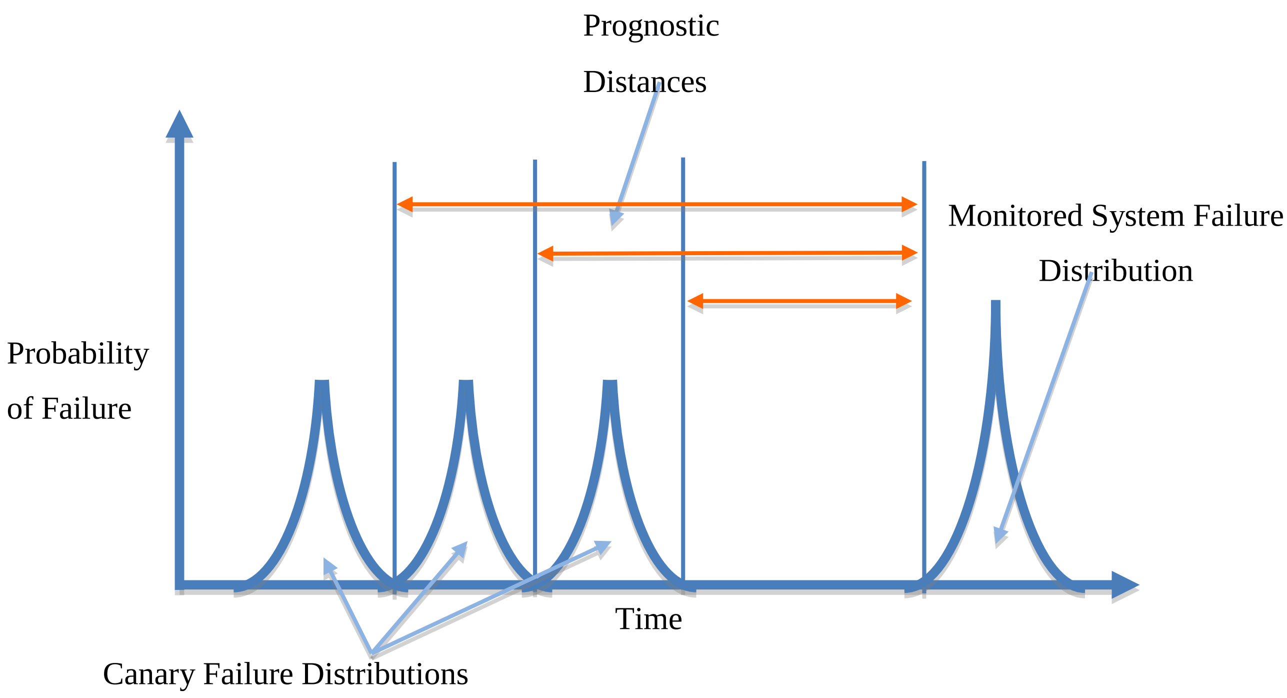


Figure 5: Canary Prognostic Operation

This approach has been used in a number of different applications, such as to diagnose ball solder joints on printed circuit board cards by Mathew et al [61]. A set of resistors was emplaced on a printed circuit board alongside a ball grid array mounted integrated circuit. This was subjected to temperature cycling to determine the prognostic distances between resistor-mount failure and the failure of the ball grid array. A larger resistor with a 20% solder pad surface area was found to give a good prognostic distance for failure of the ball grid array.

Fusion Prognostics

Fusion prognostics are the final method of prognostics that will be looked at in this section. Fusion prognostics is the process of making failure predictions based on several different methods of prognostics and combining the data into a diagnosis and RUL prediction, such as described by Cheng and Pecht [62]. In their methodology an FMMEA is conducted to determine the appropriate parameters that must be modelled and to aid in the construction of the PoF models. Data driven techniques are used to identify anomalous system behaviour based upon the extracted system features. This is then used to isolate the relevant parameters that are abnormal, which are fed into the Physics of Failure models to define the failure point and establish a RUL prediction (where PoF models are available).

In this particular methodology either the PoF model or historical data are used to define and predict system failure. Another method of fusion prognostics consists of making a number of independent RUL estimates and then unifying them into a single and accurate RUL prediction. Rosunally et al made use of this technique in [63]. The aim of this research is to predict the degradation of the wrought iron structures aboard the heritage cargo ship Cutty Sark. As the ship has important historical value its preservation is considered extremely important, however invasive testing and monitoring is not acceptable. As such the team makes use of parrot and canary devices, PoF modelling and Malhalanobis Distance analysis and fuses their predictions to make preliminary failure predictions. These are fused together by feeding the predictions, along with time variables, into a Bayesian Network, which can combine the various predicted failure probabilities into a single measure, which can then be trended towards failure and a final RUL measure made.

The fusion approach has seen other applications within the literature. Yinjiao et al propose the use of this particular approach in prognosing the failure of battery units [64] by analysing multiple failure mechanisms and using a combination of data driven and physical modelling methods to gain a state of charge and RUL estimate.

Current applications of CM and PHM in power systems

Nuclear Power Stations

One of the key areas where PHM technology has made inroads into the power sector is in the maintenance of nuclear power plants [65]. Existing nuclear power stations are undergoing life extension reviews and new generations of nuclear power stations are expected to live beyond their sixtieth year. Due to the inherent risks involved in nuclear power and the age of the equipment being operated, good condition monitoring and prognostics becomes critical to the safety and efficient operation of the power station.

One monitoring technology that is in early stages of development is the use of acoustic techniques to detect and characterize damage to plant components. Experimentation has been performed by Meyer et al at Pacific Northwest National Laboratory [66] to characterise the use of acoustic emission detection and guided ultrasonic testing on pipe cracking tests. This method uses the physics of failure approach to track crack growth based on Paris' law. The key findings of this indicated that guided ultrasonic testing could discriminate between crack lengths, however this would require correlation with other methods (such as passive acoustic emission testing), since the specific crack modes may alter the generality of the equation. Dong-Hyun et al have used a similar method, using a network of transducers, to detect and localize the noise generated by leaking steam from cracked pipes in a thermal power plant [67]. The authors have not yet proposed advancing the system into the prognostic domain, however the use of acoustic emissions to track fatigue damage has been demonstrated for aerospace applications [68].

Another avenue for improved asset management within nuclear power stations is the application of sensing and prognostics to the cabling of the power station. Wang et al made use of Joint Time-Frequency domain reflectometery to identify areas of core insulation damage to Cross Linked Poly Ethylene (XPLE) cables, and showed that this could track the degradation of the cable under accelerated testing conditions [69]. This technique is based on the concept that damage to the insulating material of the cable or the shielding will result in an impedance mismatch at the fault location. This creates a point at which a transmitted waveform can reflect back to the transmitter. Reflectometry-based techniques, normally in the time domain, have also seen extensive use in higher voltage power cable fault finding and diagnostics [70-72].

Generating Sets

More generally there has been a great deal of interest in the condition monitoring of generators since the 1960s. Systems such as those described in [73] consist of sensors monitoring the generator temperatures to detect overheating and partial discharges to detect electrical failure. Since the late 1980s the reliability of condition monitoring has improved significantly and is now considered to be a reliable and trustworthy source of maintenance information for generating sets [74].

This condition monitoring approach has seen extension into the prognostic domain with research conducted at both the system level [75] and at the induction machine component level [76]. At the component level, Batzel and Swanson created a prognostics system for wound rotor failure in airborne synchronous generators. Their Failure Mode and Criticality Analysis identified field winding shorts and rectifier diode failure as key failure modes, and generator transfer characteristic as a potential precursor parameter. This was tracked using a kalman filter to produce a RUL estimate.

One particular application of prognostics for generators that is receiving interest is in the maintenance of wind energy converters (WECs) [77]. Given the relative inaccessibility of these sites and their associated high repair costs PHM becomes an attractive proposition.

A number of different condition monitoring approaches have been proposed for wind turbines and their constituent components. These have included vibration monitoring of the gearbox [78], the wind turbine blades [79] and the turbine bearings [80]. As an example of this on-line diagnosis approach, Liu et al made use of a novel wavelet based variation of the Support Vector Machine to diagnose faults in roller bearings with a high degree of accuracy [81]. Further, systems that analyze the entire WEC and determine the potential for failure across multiple components have been designed [82]. The SeeByte system uses sensor and diagnostic conclusion fusion techniques to attempt to diagnose a system based on the assumption that models, information and sensors are not completely reliable, with the aim of greater diagnostic accuracy.

Some research has been conducted into moving these concepts into the prognostic domain. Nayak and Stepanovic have performed initial work into model-based prognostics for turbine blades, conducting the fault analysis and mathematical modelling for the blades [83]. Gearbox prognosis research has been performed by Abouel-seoud et al in [84] with the aim of diagnosing gearboxes using acoustic emission monitoring. The acoustic signal is captured by a microphone and then filtered using a wavelet transform and extracting the signal kurtosis measure from the filtered signal. By trending this kurtosis against the probability of failure a remaining useful life estimation of the gearbox can be calculated. Tian et al made use of Artificial Neural Network based prognosis to determine the RUL of machine bearings [85]. By training the ANN with a mix of failure and suspension (data from devices pulled after displaying abnormal behaviour) an accurate, generalised life prediction method was developed.

Transmission and Distribution Equipment

Transmission and distribution equipment, frequently sited in remote or inaccessible areas, present a particular asset management problem for the electricity transmission industry.

High voltage circuit breakers are an area of interest to the electrical industry, as their operation is critical to the everyday running and protection of the power grid. A failure of a circuit breaker can stop a fault being isolated correctly, and allow it to propagate through the network.

In order to accomplish any sort of diagnosis, the circuit breaker must be heavily instrumented in order to detect the widest range of failures possible. Kayano et al [86] describe the proposed architecture, IT and communications infrastructure for installing condition monitoring systems at Brazilian substations, with an emphasis on transformers and circuit breakers.

Fazio et al developed a diagnosis method for circuit breakers by utilising an acoustic sensor to detect vibrations in the circuit breaker [87]. These measurements were processed using a wavelet transform and the resulting traces could be compared against the expected healthy baseline vibrations to determine presence and type of error. Other methods of diagnosing faults with circuit breakers have been proposed in the literature, covering a diverse range of techniques including fuzzy logic based diagnosis [88], Dempster-Shafer theory [89], Hilbert-Huang transforms [90] and wavelet packet decomposition informed neural networks [91].

Compared to work on diagnostics for circuit breaker devices, there has only been a limited amount of work done in extending these diagnosis frameworks into prognostics systems. Rudd et al have made some progress towards this goal by constructing a prognostics and asset management system for circuit breakers [92]. This system makes use of a commercially available condition-monitoring package, but uses the acquired data to predict and trend the pressure of the breaker’s sulphur hexafluoride gas atmosphere. While the system results for a leaking circuit breaker appear promising, the error margins for the technique’s current iteration are very large when the system is in normal operation.

Transformers are also an important element of both transmission and distribution networks and have received significant work on fault diagnosis. There are a number of different faults that can affect a transformer, and one of the key predictor of faults in a transformer (such as bushing failure) is partial discharge activity [93]. The primary method of detecting partial discharges within transformers is using the UHF electromagnetic waves developed when electricity flashes over a small cavity in the insulation [94]. Generally this method consists of an RF antenna with the appropriate frequency response connected to a suite of acquisition hardware and signal processing equipment [95, 96]. This can extract the PD signals from noise, using techniques such as the Hilbert-Huang transform [97], and plot them relative to the phase of the main electrical voltage to determine PD type and severity.

Acoustic emissions can also be used to identify partial discharge within a transformer. When the insulation cavity discharges part of the energy released is propagated as an acoustic vibration, which can be detected by an appropriately positioned sensor [98, 99]. It has been shown that various different types of partial discharge activity associated with different faults can be distinguished by using this method [100]. Theoretically a network of sensors can also adequately locate the source of the PD emissions within the transformer structure; however the propagation path of the sound wave is not always in a straight line from the source. As such this technique has been used in combination with other techniques such as direct electrical measurement to produce more accurate results [101].

Regardless of the method of PD detection in a transformer unit, the issue causing the abnormal readings must be diagnosed. A wavelet decomposition informed fuzzy logic neural network can be used for this purpose, when trained using historical fault data for each PD location [102]. This provides a probabilistic measure of where the fault may lie in the transformer.

An alternative method of expert system diagnosis can also be used to diagnose the PD location in the transformer. An expert system is a type of decision-making algorithm that aims to mimic a human expert's decision-making process when coming to a conclusion. The system described in [103] begins with a set of rules that relate to the statistical patterns that various partial discharges can create in the detection system (in this case from the UHF monitoring method). From there the system has higher order sets of rules which form a decision making process from the interpretation of the sensor's raw data up to a decision on where the most likely system fault lies.

Once again extending the monitoring of transformers into the prognostics domain has seen less work than diagnostics of their most common failure causes. One interesting method makes use of offline testing parameters to determine a 'health index' of the transformer by using an Artificial Neural Network [104]. While this doesn't provide a direct remaining useful life measure, it does make a qualitative assessment of the transformer's health state using measurements already included in standard transformer testing, providing a single measure that can be trended towards failure.

Another proposed method is to use an entirely statistical method of failure prediction. This consists of collecting the failure data on an entire population of transformers and then making use of Bayes' theorem to generate a hazard rate for the remaining transformers of that type [105]. As this system operates at a very high level above the individual transformer it can only make broad probabilistic assessments of the number of failures of a certain type of transformer that might be expected in any given year, however it does allow for new information to change the expectations of failure. This should eventually bring the probability of failure in line with the actual failure rate of the transformers, allowing better control of asset replacement. It does not, unfortunately, give an indication of *where* in the network a transformer might fail, and as such is not effective for informing preventative maintenance.

Lifetime prediction has also been simulated using physical modelling. Wouters et al made use of a physical model of thermal insulation breakdown in order to simulate the remaining useful lifetime of transformers in service [106]. With the installation dates and locations of each transformer on the network each transformer on the network was modelled and their approximate insulation RULs. This generates a failure distribution for the transformer population on the network. This technique appears not to have been extended beyond the simulation stage at the present time.

Implementation of a PHM informed smart grid

In order to actually benefit the smart grid it is necessary to discuss the ways in which PHM can be integrated to support operational decision support of the assets within the smart grid structure. There are three main factors that allow the effective deployment and integration of PHM based asset management systems, they are as follows:

1. Intelligent sensing systems able to perform initial data analysis.
2. Integration of the sensing systems into a network-wide asset management system.
3. Use of the network asset management system to improve the system level planning and operation of the grid.

Intelligent Sensing Systems

One of the major issues with the grid pointed out in an earlier section was that certain assets have problems with maintenance due to remote location or hostile environment (such as under the sea or in remote rural areas). As a result there is typically a problem with communications between the sensor modules and the base station. Data capacity is extremely limited in situations such as subsea, when acoustic modems are frequently necessary, and as a result it is hard to return the quantity of data generated by prognostic sensor arrays back to the host computer. Therefore it makes sense to attempt to reduce the quantity of data sent back from the monitoring system and attempt to instead provide smaller quantities of more relevant information. To do this the sensor requires some communication data processing ability in-situ that can provide the conversion from raw sensor data to useful prognostic information. This is known as smart or intelligent sensing.

An intelligent sensing system is loosely defined as a combination of sensor system logical computing element (programmable logic or a microcontroller) and communications system which can translate the data from the sensors into more useful information and communicate it back to a base station [107]. Generally there are several layers of abstraction in a sensor based computing system, shown in Table 1.

High level decision making based upon collated information
Optimization of collected data to improve information content
Basic signal processing to improve data quality

Table 1: Layers of abstraction in an intelligent sensor

These layers of abstraction are normally performed in the microcontroller that is paired closely with the sensor. An example of this type of sensor in action is given by Figueroa et al [108]. The smart sensor proposed by this team at the John Stennis space centre consists of a transducer connected via several possible connection types (for instance RS232, I2C or SPI) to a microcontroller. The microcontroller communicates back to the base station via Ethernet. This form of setup uses cheap buses and inexpensive microcontrollers that can perform basic digitization and signal conditioning prior to higher level processing in the host computer.

One of the key elements of smart sensors is their ability to communicate back to a base station. Given that for PHM applications a large number of sensors must be used, the sensors will likely require the ability to communicate wirelessly back to the base station. This is both to avoid large amounts of wiring and to provide communication in places where wires would be intrusive or impractical (such as in subsea applications or in rotating machine sensing).

The technology and architecture needed to implement networks of smart sensors has already been proven. Al-Ali et al give an overview of sensor networks of this type [109], presenting the idea of smart sensors connected in clusters, via Bluetooth or similar wireless standards. These clusters have a primary node that is able to access wider networks to communicate data back to a control station, as well as provide services and applications that make use of that particular local network of sensors. This control station is tasked with managing the communications between several different cluster control nodes, as well as providing system level use of the information generated by the networks of sensors.

An additional problem also comes into play when considering sensors that have to be distributed around a substation or other area of interest. Wireless sensors require on board or localized power sources in order to operate effectively. In areas that are remote and spend long periods of time unmanned these sensors require the ability to operate for extended periods without replacing batteries. In especially remote areas or applications it may not be possible to replace batteries at all. As a result sensor designers have begun to move towards ambient energy harvesting devices for smart sensor implementations.

There are a number of different techniques to energy harvesting. One method with promise is small scale photovoltaic combined with either battery or capacitive energy storage [110]. This has the advantage of having a high power density at the point of collection, however it does suffer from sensitivity to conditions and evidently its application in dark conditions would be minimal. However, it presents interesting possibilities for external use (such as tower mounted transformer monitoring). A second method, also using natural forces to develop harvestable energy is the wake galloping instability harvester [111]. This system makes use of a fixed cylinder to cause aerodynamic turbulence upon a movable cylinder placed behind it. The second cylinder is cyclically displaced by the turbulence from the leading cylinder and the motion can be converted to electrical energy by use of a simple permanent magnet generator. This system is again condition dependent, but it does offer reasonable power generation and could potentially be used in situations where strong airflow is likely (such as near substation air circulation inlets, or on assets in higher altitude areas). The last technology covered here is the use of electromagnetic systems to harvest AC power from conductors[112]. The system proposed uses a sheath of multi-layer magnetic material around the conductor allowing for the induction of current from the changing AC conductor magnetic field. This is perhaps the most suitable harvesting system for certain power applications as it does not rely on climatic conditions for good performance and can consistently supply 10mW of power over long durations. By paring this with energy storage and power efficient sensors monitoring could be conducted more or less indefinitely.

Application of the techniques and principals described above to smart grid sensors has been relatively slow until recently, where several implementations have been developed. Erol-Kantarci and Mouftah[113] propose a method of installing wireless sensors throughout a substation and then using a small autonomous vehicle to perform radio frequency power delivery to the sensors as they begin to run low on battery. This method has some attractions. Firstly, it frees the sensors from the limitations of being located near an available harvestable power source of sufficient capacity to drive the sensor. Secondly, this system allows for operation even when the power system has failed, since the sensors can continue to have their batteries recharged for as long as the autonomous robots are operating. However, it does add in expense and installation time to the facility being monitored. It also relies upon the sensors being installed in an environment that the autonomous vehicles can operate within.

Moghe et al propose a different solution to the problem, utilizing the techniques described above to produce a rapidly deployable and robust sensor network for smart grids[23]. The sensors described take the form of 'stick on' packages, which can be rapidly glued to assets and carry a variety of sensor payloads. A harvester, consisting of a wound core designed to collect power from nearby conductor magnetic fields, and a transformer to step the voltage up to that required by the sensor hardware, powers these sensors. The sensors communicate back to their base station using the Zigbee standard and report in every ten minutes. The sensors are backed up using an ultracapacitor (similar to that described in [110]) so that they can continue operating for two hours after loss of power.

These sensors fit the requirements outlined above for smart grid capable sensing. They are self-powered (which makes them ideal for remote monitoring), able to continuously harvest energy as long as they are close to a conductor and they are easily deployable into a wireless sensor network. They also resolve a key issue, which is that expensive sensor hardware and installation would likely deter utilities from installing monitoring systems in a widespread manner. By developing a low cost and low deployment overhead sensor the cost of the system can be reduced. The main disadvantage to this sensor architecture is the dependence on proximity to a current carrying conductor, however given that most grid electrical equipment operates close to high current conductors this does not present a huge issue, at least for distribution and transmission level monitoring. Under low voltage network conditions it might become necessary to use other methods of energy harvesting, such as the wind or PV methods, to power the sensors should the harvestable energy from the LV conductors be insufficient.

Integration of smart sensors into the smart grid asset management system

One of the key tasks after adequate sensing technology has been developed and deployed is to integrate it within an appropriate asset management framework. The lowest level of this above the smart sensors will be the condition assessment and RUL prediction tools that are described previously. These tools produce a set of data about individual assets that then needs to be integrated together to provide a holistic view of a system's condition. This allows greater comparative visibility of assets within similar areas or of similar purpose. By having this visibility it is possible to identify areas of concern such as a particular type of asset that has units approaching RUL, or a particular substation that is experiencing unusual wear on machinery. These can be addressed through appropriate maintenance action.

In order for the system to take place a reasonable hierarchy of systems must be developed in order to handle the large number of individual condition monitoring systems that a comprehensive asset monitoring system will require. The proposed structure of this asset management system is given in Figure 6.

At the lowest level of the proposed structure are the smart sensor devices that capture data and perform basic signal processing and feature extraction. These communicate back to base using Zigbee or another wireless transmission protocol in a meshed network of wireless sensors.

Immediately above this is the diagnosis and life prediction level. This level is the point at which anomalous behaviour is identified and located; and where the main algorithms that relate extracted features to remaining useful lifetime are executed.

Depending on the application these levels can potentially perform more or less signal processing and feature extraction. In extreme cases the smart sensor level might completely subsume the life prediction level. For instance, in areas that have limited communication bandwidth (such as subsea) the smart sensor can be programmed to execute simplified RUL and diagnosis models in order to provide the maximum of useful information back to the main asset management system.

At the third level is the substation control level. This level manages the interaction of a group of different monitoring in a commonly accessible local area. This may be a substation facility (hence the name) or it might be another such collection of assets such as segments of a subsea cable. The substation level monitoring is required to handle alarms raised by monitoring systems and prioritize them in order of importance, depending on state of fault and criticality of the faulty subsystem. The priority system should also take into account the temporal proximity of failures. Failures that occur within a short time period of the other should be given similar priority weighting (and consequent repair at the same time) in order to improve maintenance efficiency. The substation monitors then generate alarms or maintenance updates which are dispatched to the level above.

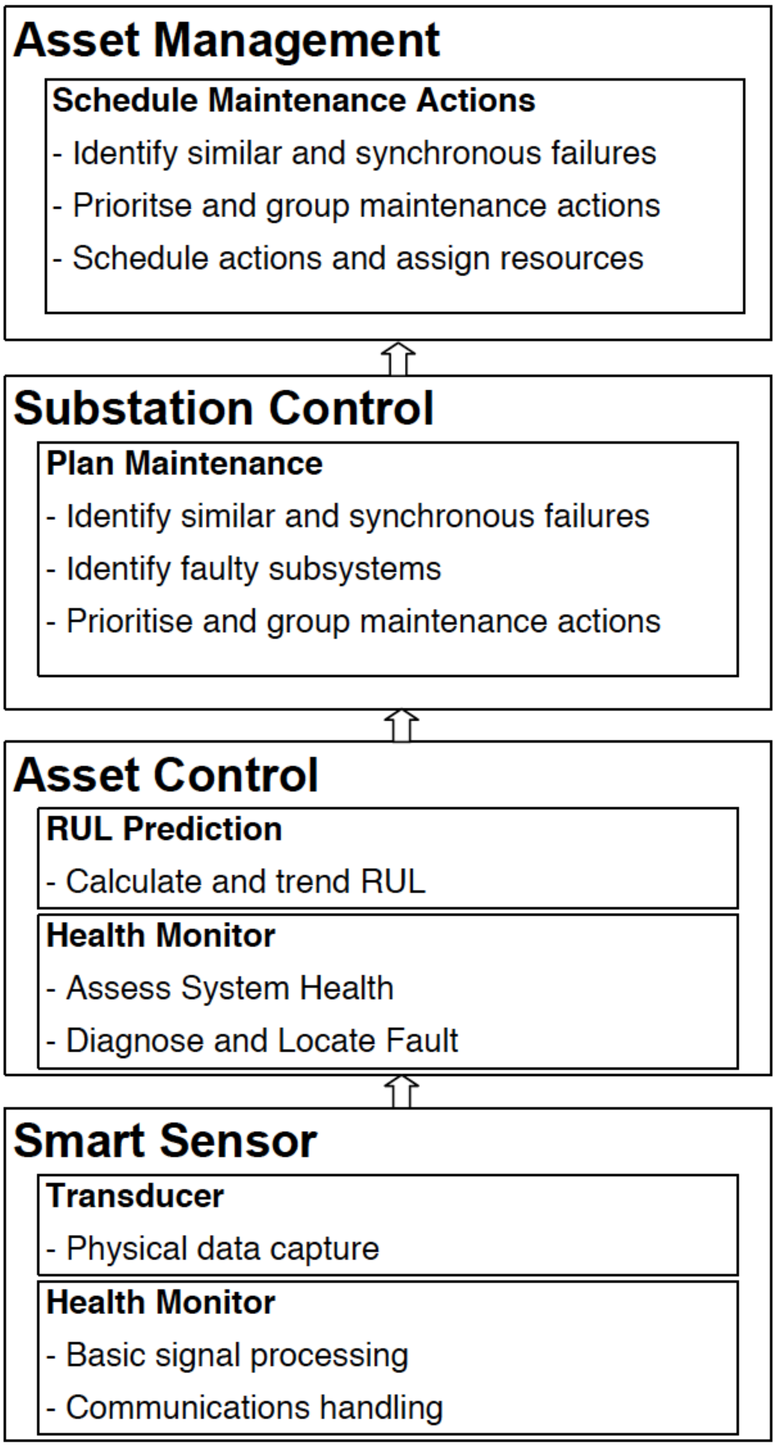


Figure 6: Combined asset management system

The final top level is the system-wide asset management system. This system accepts input from all the local clusters of monitoring systems throughout the network. This level has an index of available maintenance assets and maintenance updates and alarms from monitoring systems. It is responsible for the deployment of assets to rectify these issues in a timely and efficient manner. Since these maintenance reports contain prioritized maintenance lists with associated RUL the asset management system can perform similar tasks to the level below (only on a larger scale). Potential and current failures that are grouped both temporally and geographically can have grouped maintenance actions to make better usage of maintenance teams. Additionally, decisions can be made with regard to predicted external factors. These might include lead-time or replacement parts, weather conditions, seasonal accessibility, other scheduled maintenance actions and availability of external contractors. These factors can be combined with the times to failure to produce master priority lists of assets that require attention, along with potential maintenance actions and asset assignments that can be presented to utility maintenance management.

By making use of this more holistic system, rather than scattering monitoring systems around in a manner that lacks integration or centralized management, maintenance assets can be made more effective use of and maintenance actions can be more effectively scheduled around each other to ensure grid stability is maintained. This system also ensures that maintenance actions restricted by external factors (such as the requirement to replace north sea cables during seasonal breaks in the normally adverse weather) are performed within their associated time windows by tracking lead time and availability factors that affect them and assigning maintenance at an appropriate time.

Finally, once adequate monitoring is in place it is possible to capture system and intercomponent dependencies, which cause faults to propagate through the system. This can inform better system design in the future which can minimise these propagating faults.

Improving the overall operation of the grid using intelligent asset management

Once a comprehensive asset management system has been developed it must be integrated into the wider smart grid concept. How can asset management influence the smarter grid and vice versa?

The first, and key principle is that the smart grid must inform the asset management as much as the asset management informs the smart grid. The interaction between the two entities is extremely important. Intuitively it can be seen that events within the asset management system can affect the higher level system planning however it is also true that events at the system planning level can also affect the asset management.

The example of dynamic line rating was brought up in a previous section to illustrate the use of condition monitoring to inform the grid power flow and rating management. By extending this to a more comprehensive asset management system the effect on the lifetime of the overloaded asset can be both estimated using the established RUL model and also predicted during operation. In addition to this, there are benefits when predicting how grid actions can affect the reliability of systems of systems. For instance a substation consisting of transformer equipment, transmission lines, switchgear and breakers. When a change is made to the rating of one of the pieces of equipment in the substation the dynamic RUL can be calculated for both the asset in question and also connected assets. This allows for a balance to be struck between performance of the substation and all the associated substation components.

There are other areas where this interaction between the higher-level grid and the asset management system is beneficial. One of the key drivers of the smart grid is to make the power grid more resilient to faults and allow it to self-heal. Jia et al identify a number of different criteria that tie into this principle [114]. Equipment condition monitoring is identified as a key factor in allowing the grid early warning of possible fault, informing the higher level ‘policy making’ layer of areas of concern. By introducing prognostics into the calculus it may be possible to identify these areas of concern further in advance and prime backup and recovery systems to deal with them.

A combination of all these different factors can be imagined if a hypothetical scenario is considered. A substation consisting of PHM enabled systems reports that a transformer is approaching, but not yet at, the limit of usable life. The asset management system schedules a maintenance action and then updates the self-healing system with the news that a transformer is approaching RUL and may not be completely reliable. The self-healing system may then elevate the alert level for that fault location. It can analyze the local grid and determine the effect of a failure of the transformer the alert refers to and take appropriate measures to ensure stability in the event of a fault, such as creating and seeking authorization for automatic fault isolation schemes. Additionally, the distribution planning system of the smart grid can flag the transformer and its associated substation as being a potential issue and can make the decision whether or not to shift power to other routes. If demand-side management systems are available it may also make the decision (should the transformer be close enough to wear-out) to temporarily reduce load in order to preserve operations until maintenance assets are available as well as requesting that any distributed generation systems (rooftop solar PV and Wind) activate and top up their power storage.

If a fault does occur with that transformer then the self-healing system can check through its lists of alarms and rapidly identify the cause of the fault. It can then begin executing its contingency plans to isolate the fault and pass the information onto both the asset management system (to schedule an emergency maintenance action) and to the distribution planning system (to inform customers of an outage and to mitigate any effects such as isolated power stations).

To conclude, this chapter has reviewed the state of the art in PHM, has summarised a number of issues that affect the smart grid and the manner in which condition monitoring and PHM techniques can be applied to the system in order to address them.

Chapter 3: Theory and Construction of Relays

This chapter will give a brief overview of the technical theory of the operation of an electromechanical relay and give a description of the anatomy of the Barnbrook BV416 relay selected for this experiment. These relays provide allow for representative experimental analysis on a piece of small electrical equipment, allowing for experimental practice to be developed and to provide preliminary development for automated diagnosis development.

Basic principles of operation

In the most basic form the components of the relay are shown in Figure 7.

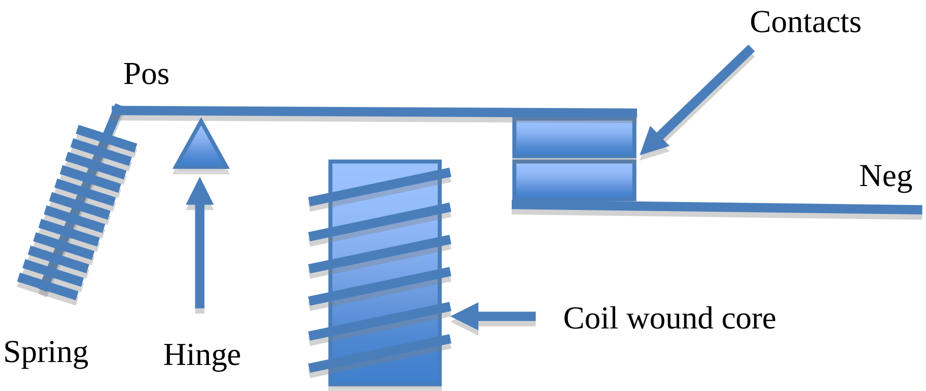


Figure 7: Diagram of basic electromagnetic relay

Electromagnetic relays are very mechanically simple devices that take advantage of the principles of electromagnetic attraction created from an energised wire wrapped around a ferrous core. When a current is passed through the wire a magnetic field is established with a force vector aligned parallel to the armature. This is used to attract a magnetic strip on a sprung armature that completes a circuit through a contact surface. The sprung armature returns the relay to an initial position once the magnetic field has been released [115].

Relays can come in a variety of different designs and configuration. We will concentrate on the parameters and features of sprung armature/magnet based designs in this section for concision's sake and because the relays tested in the experiments are of this configuration.

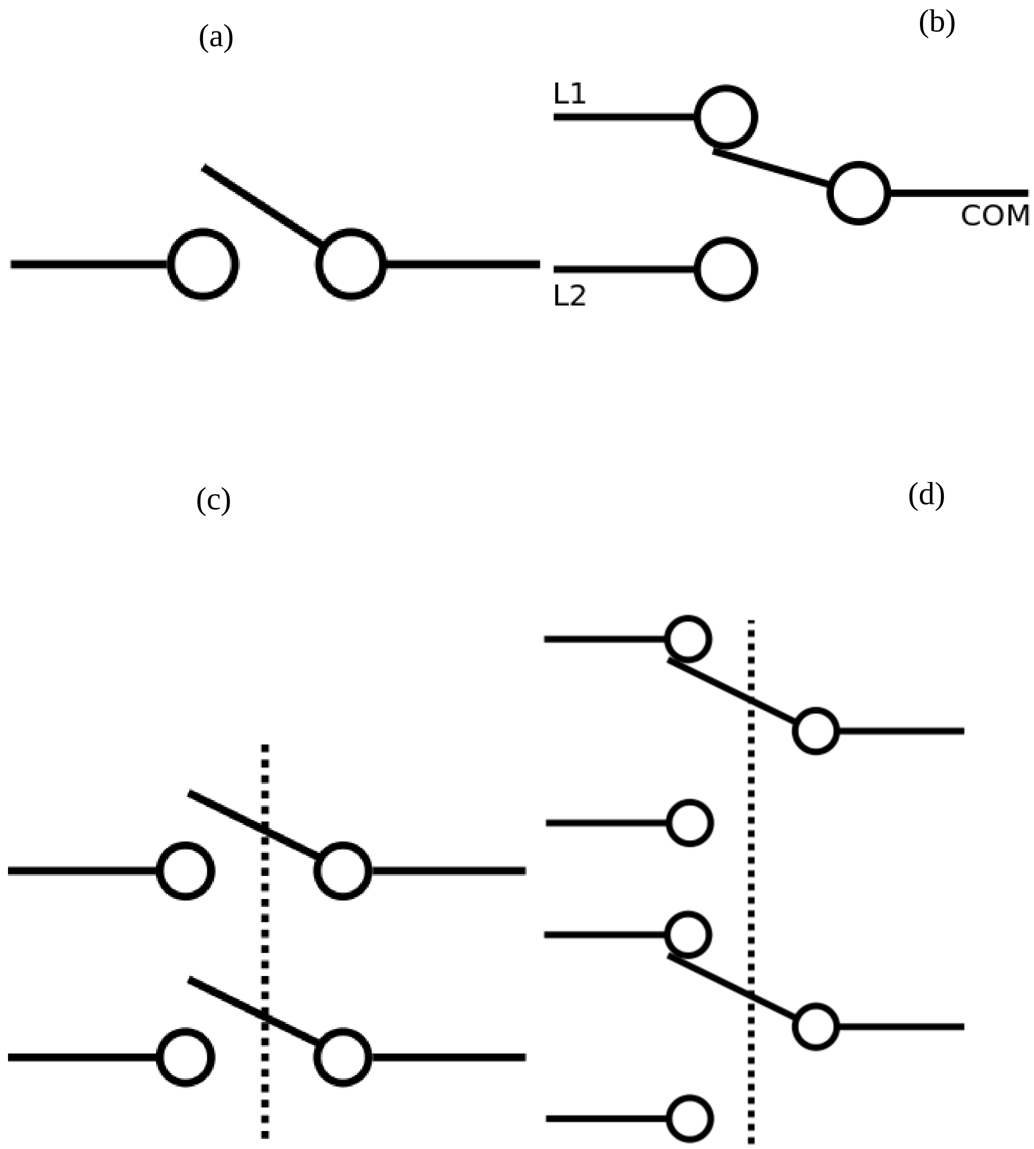


Figure 8: Various armature switching types

The armatures can have a number of different switching configurations that affect their operation under open and closed conditions. The most basic configuration is single pole single throw (SPST), shown in Figure 8(a). This is a simple relay with one closed state and one open state. Single pole double throw (SPDT) relays operate in a similar manner to the SPST relays, however they have two on states, with each position of a relay controlling a separate circuit (Figure 8(b)). Double pole single throw (DPST) (Figure 8(c)) relays are two switches operated in the same actuation (the two armatures move together). From this the actions of double pole double throw (DPDT) relays are intuitive, consisting of two double throw relays that operate in tandem as shown in Figure 8(d).

Each relay has a different set of characteristics that define its operation. These include the pull in and drop out voltages that the magnetic coil requires to both pull the armature towards itself and release it; the maximum voltage and current that the contacts can handle under inductive and resistive loads; the expected lifetime of the relay and the open and close times.

Typically the main form of life degradation for a relay of this type comes from the electrical erosion of the relay contacts. This follows from arcing that occurs between the contacts. As the contacts break apart or close together the distance between the contacts reduces to the point where the electrical field between the two contacts exceeds the breakdown voltage of the air and an arc is instantiated. Material transfers along this arc and is dispersed in several manners [116]. In the initial phase ionized metal particles bombard the cathode plate and transfer materials from the anode to the cathode. As the arc gets longer gaseous ions from the ionized air also begin to impact the cathode surface and impart energy. This energy ejects material from the cathode, causing it to erode. The material is deposited on the anode and into the surrounding area of the case. Finally, the high temperatures incident on the contact surface from the arcing cause the metal to melt and fluidic and electrostatic forces eject the droplets from the surface. The material transfer and erosion eventually causes the contact to either fail open, as the contact surface erodes away, or fail closed as a contact bridge is formed.

Construction of the BV416

The relay used in this experiment is the Barnbrook BV416 railway standard relay. This relay is primarily used in transport applications but makes a good system development testbed due to its desktop size, ease of disassembly and manageable voltage and current demands. It is an armature type relay, representative of the majority of industrial electromechanical relays.

The relay consists of a hermetically sealed closed unit containing a quad array of relay armatures. Essentially the relay is a quad pole double/single throw design, with the top two armatures in double throw configuration and the lower two armatures in single throw configuration. All four armatures act together to provide four possible circuit paths. A disassembled relay is shown in Figure 9.

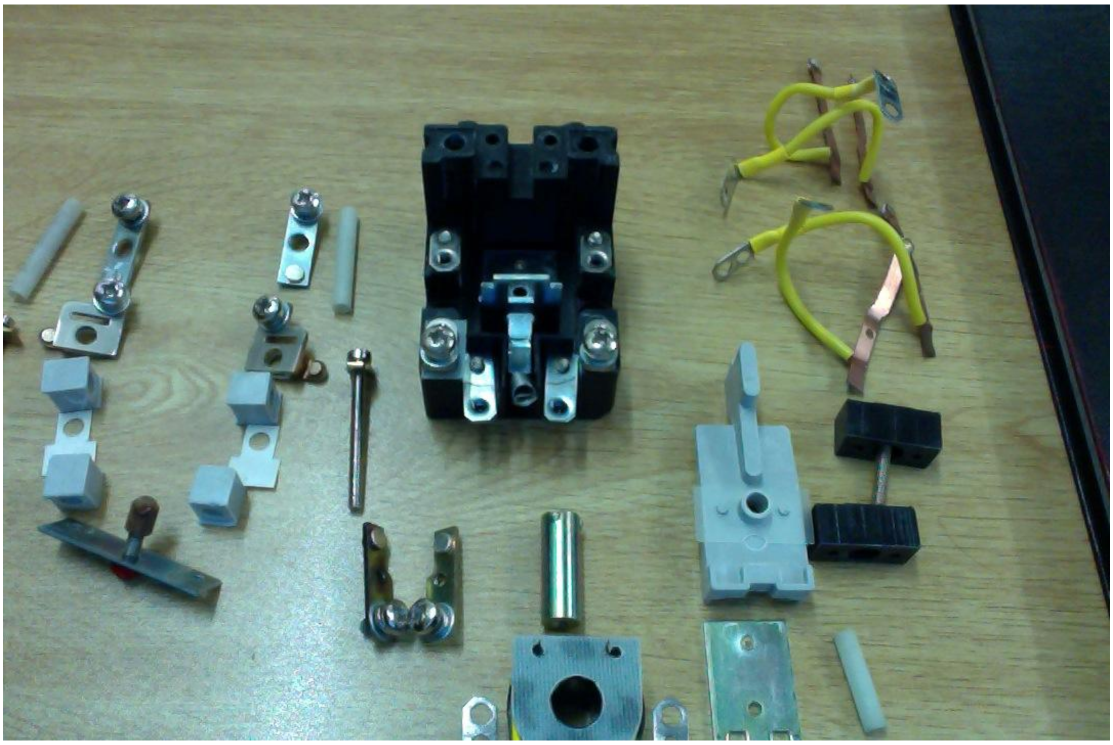


Figure 9: Disassembled BV416 Relay

The relay armatures consist of brass connectors and armatures with a Silver Cadmium Oxide (90 Ag, 10% CdO) contact riveted to the end, shown in Figure 10. Each contact is coated with a thin gold layer, bonded to the AgCdO substrate with nickel, to improve the electrical connection on close. The counterpart contact is riveted to another brass receiving plate mounted below the armature. The four armatures are attached to a plastic plate with steel backing and hinged at the rear of the unit. A stainless steel spring provides a counterbalance force to the armature to return the assembly to the open position on release of the magnetic field. The coil is soft iron with a brass spacer installed between the top of the core and the armature assembly to reduce the relay overshoot.

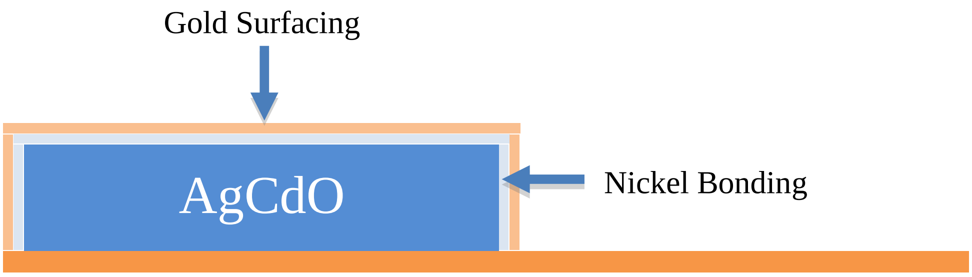


Figure 10: Armature Structure

The BV416 has the following series of characteristics, drawn from the datasheet and empirical testing, which define the operation of the relay [117]:

Characteristic	**Value**
Pull In Voltage	15V
Drop Out Voltage	5V
Maximum Contact Current	16A Resistive, 2A Inductive
Nominal Operating Voltage	24V
Lifetime (expected using MIL-STD-416)	1 million operations
Opening Time (measured)	30ms
Closing Time (measured)	20ms

These characteristics are used as the baseline from which we drew our experimental parameters.

Recent work in the field

There has been a significant amount of work on the degradation of electrical contacts over the last 20 years, with a significant amount of work focusing on the physical mechanisms and characteristics that define these types of ageing.

Hasegawa et al [118] present a series of interesting results when testing a set of low current telecommunications relays that illustrate the typical effects of material transfer and also investigate the transition from material transfer to erosion phase. They noted that after a certain period of time and as the arcs get more intensive the relay moves from transferring material between contacts to predominantly eroding material away from the contacts.

The mechanics of the make and break phases of the contact operation have also been shown to be slightly different. Several research teams have looked into the specific physics that underlies the erosion and material transfer of the contacts in these two phases. Swingler and McBride investigated the physics of the break arc, identifying phases where material transfers anodically, cathodically or is vaporised and ejected from the contact area during break [116].

Jemas et al [119] performed their own analysis of the make and break arcs and the associated material transfer caused. They found an interesting phenomenon where under certain low current conditions the aggregate direction of material flow was from cathode to anode, while at higher current flows this transfer flow was reversed. This is due to the make and break arcs having the same transfer direction (anodic) at low currents, while at higher currents the make arc not only reverses material transfer direction but also becomes more dominant.

In terms of physical modelling of these phenomena Swingler and McBride developed a model based on physical calculation of the power dissipation of the arc, the power flux density of the arc and the heat transfer that results to determine the volume of material eroded and displaced by the arc[120].

There has been some recent work in the field of electrical contact reliability using diagnostics and prognostics. This work is varied, but usually involves the standard practice of identifying diagnostic parameters and then measuring and predicting based on that identified parameter.

Yao et al [121] measured the static resistance, bounce time and maximal resistance value over time to drive a fuzzy logic based prediction algorithm that predicts the reliability of the contact. This technique is effective but computationally and measurement intensive, requiring very fast measurement and a lot of data, which may not be possible in embedded applications.

Xuerong et al [122] made a more complex study of the problem by taking several variables as precursors to several possible failures and then using a statistical model to trend to failure. The variables consisted of over-travel time (the time between contact being made and the armature coming to rest), the rebound time and a correlative combination of several other variables. This is designed to predict bridging, erosion and contamination related failures. The statistical model is based on a simple regression with regard to a set of captured data and an alternative physical model was also developed that could also predict the reliability of the contact. These models are accurate, but again are data intensive and require measurements that may not be possible in a hermetically sealed case, such as the over-travel time (which requires knowledge of the stopping point of the armature, not just the time that the electrical contact is made). While this type of high complexity model might be appropriate for single relays in, for example, space travel or subsea applications it is less suitable for mass deployment.

In summary, this chapter has covered the various manners of construction of electromechanical relays in general and the BV416 in particular, and has reviewed the literature regarding the breakdown of electrical contacts within them.

Chapter 4: Experimental Methodology

This section covers the experimental method that was used to perform the acceleratd ageing of the Barnbrook relays. It describes the design of experiment and post-failre analysis.

Failure Mode, Mechanisms and Effects Analysis

A Failure Mode, Mechanisms and Effects Analysis (FMMEA) was conducted using information from literature, prior experience with this type of relay and from consultation with Barnbrook.

Failure Mode	Failure Mechanism	Failure Effect	Likelihood	Criticality	Repairable
Stuck Open	Contact arc erosion	Increase in resistance, eventual failure	High	High	No
	Contact contamination	Increase in resistance, possible insulator	Medium	Medium	Yes
	Clapper jam	Relay action stuck	Low	Medium	Yes
	Broken control line	Relay remains in present state	Low	Medium	Yes
	Bent armature	Relay may fail to open or contact	Low	Low	Yes
	Magnetic coil failure	Relay unable to operate, not repairable	Low	High	No
Stuck Closed	Contact bridge	Relay will not open	Medium	High	No
	Clapper jam	Relay action stuck	Low	Medium	Yes
	Spring failure	Relay not returned to initial state on magnetic field release	Low	Medium	Yes

	Broken control line	Relay remains in present state	Low	Medium	Yes
	Bent armature	Relay may fail to open or contact	Low	Medium	Yes
Maximum contact resistance exceeded	Contact arc erosion	Increase in resistance, eventual failure	High	High	No
	Contact contamination	Increase in resistance, possible insulator	Medium	Medium	Yes
Overlong Opening Time	Microwelding	Relay sticks closed then breaks open. Increases release time	High	High for safety critical application	No
	Spring degradation	Spring loses tension and applies less force to clapper, increases release time	Medium	High for safety critical application	Yes
	Spacer wearout	Relay pulled closer to coil, further traverse needed to open	High	High for safety critical application	No

Table 2: Failure Modes, Mechanisms, Effects Analysis for BV416 relay

From this analysis we can see that the most serious failures are those that have a high likelihood of occurring, a high criticality (i.e stop the relay from fulfilling its main functionality) and are not repairable.

Experimental premise

From the FMMEA it can be seen that there are a number of different possible failure modes and attendant mechanisms that must be considered. The primary failure modes that are not repairable or have serious critical effects regardless of the application of the relay tend to occur due to failures of the relay contacts and so it was decided that we would concentrate our efforts there. Barnbrook systems reported that they had seen returns from their customers reporting failure operating their relays at voltages at the high end of the rated voltage band and so it was decided to focus on tests with a fixed current and a varying voltage to determine if higher voltages provoked any particular failure mechanism.

We also considered it important to select an appropriate relay actuation frequency and data capture rate for the experiment. It was important to operate the relay slowly enough that small increases in the opening or closing time would not cause the relay to fail prematurely while at the same time operating quickly enough to conclude the test in a reasonable time. The rate of data capture also was chosen to conform to a reasonable rate that might be expected of a low power microcontroller in the field.

We decided that the condition for failure should cover the stuck open, stuck closed and unacceptable opening time failure modes, as these would indicate failure in a safety critical relay application (worst case operating scenario). As such it was decided to use the average current over each cycle to detect failures. If the waveform distorts from an initial 50/50 duty cycle then it is evident that something is occurring to distort the waveform. The failure of the relay through a full or partial failure to open or close would result in a change in the average current which is easily measured in real time. Additionally, the percentage change in the average current would allow us to choose a level of distortion of the waveform that would represent a change in the opening or closing times of the relay.

It is known from previous experimentation on relays that the BV416 style of relays are a resilient design and as such the experiment would require continuous long term operation of the relay in order to provoke a failure. As such it was important that the experiment was not disturbed during operation and that any experimental setup could be relied upon to operate for sustained periods of time. We also desired that the relay be isolated from any adverse environmental conditions that might exist in the lab where testing took place, such as particulate introduction.

Experimental Setup

To address the considerations presented in the previous section it was required to design the experiment carefully. The following section addresses the manner in which the experiment was conducted.

Physical Components

In order to address the isolation issue we decided to run the experiment within an isolation chamber. The chamber was comprehensively cleaned with methanol prior to use in order to ensure that any particulates present in the chamber were removed. The relay was contained within the isolation chamber along with the data acquisition equipment and its attendant power supply. This had the added benefit of reducing the access to delicate equipment that could disrupt the operation of the relay or the data capture. The power supplies and resistor used for the experiment were retained outside the case for ease of access along with the test PC. Power and USB cables were brought into the case through existing access holes with electrical tape seals. This was not a perfect environment seal, however the fact that the relay itself sits within a sealed case and the very small size of any holes into the case meant that we were confident that the seal was good enough for the purposes of this experiment. Figure 11 shows the experimental setup.

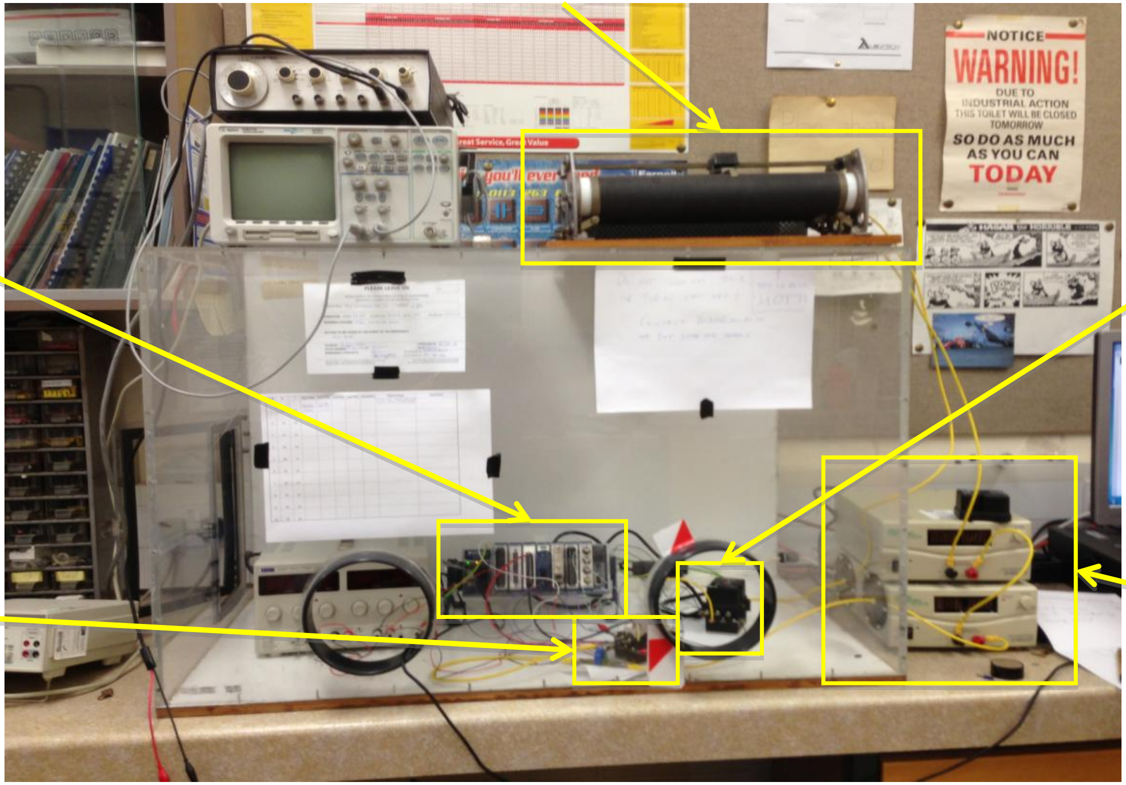


Figure 11: Experimental Setup

To allow variable voltage levels to be used a variable switch mode power supply was used to drive the circuit (two 15V, 40A rated supplies connected in series) and a 4ohm 2KW rated variable resistor was used to provide load. To take into account thermal loading of the resistor changing its resistance qualities the resistor was allowed to heat up prior to the experiment commencing. Since the resistor is variable it is inevitable that it has a parasitic inductance due to the coil design. Previous literature has shown that inductive loads have an effect on the arcing duration across the contacts. This is due to basic inductor theory, where an inductive load will discharge energy stored in a coil on cessation of the applied voltage, related to the difference in current relative to time. As such it is important to characterize the value of inductance for each experiment. This characterization was performed after each experiment and the resulting inductance values were found to be between 35 uH and 54 uH. This is likely to slightly increase the length of the arc that can be sustained on open or close compared to a purely resistive sample, however given the very small value of inductance we believe that this is unlikely to seriously affect the outcome of the test.

As the relay was being left unattended for long periods of time a safety cut-out relay was installed in the circuit which was set to open at the conclusion of the test when a failure was detected, an error occurred or the test stopped. This measure removed any possible health and safety risk from a hot resistor being left on for extended periods should the relay fail closed.

Data capture was performed using a National Instruments Compact DAQ data modular data acquisition unit interfaced to the test PC running NI LabView via a USB connection. Figure 12 shows the graphical user interface (GUI) that displays and stores the captured data.

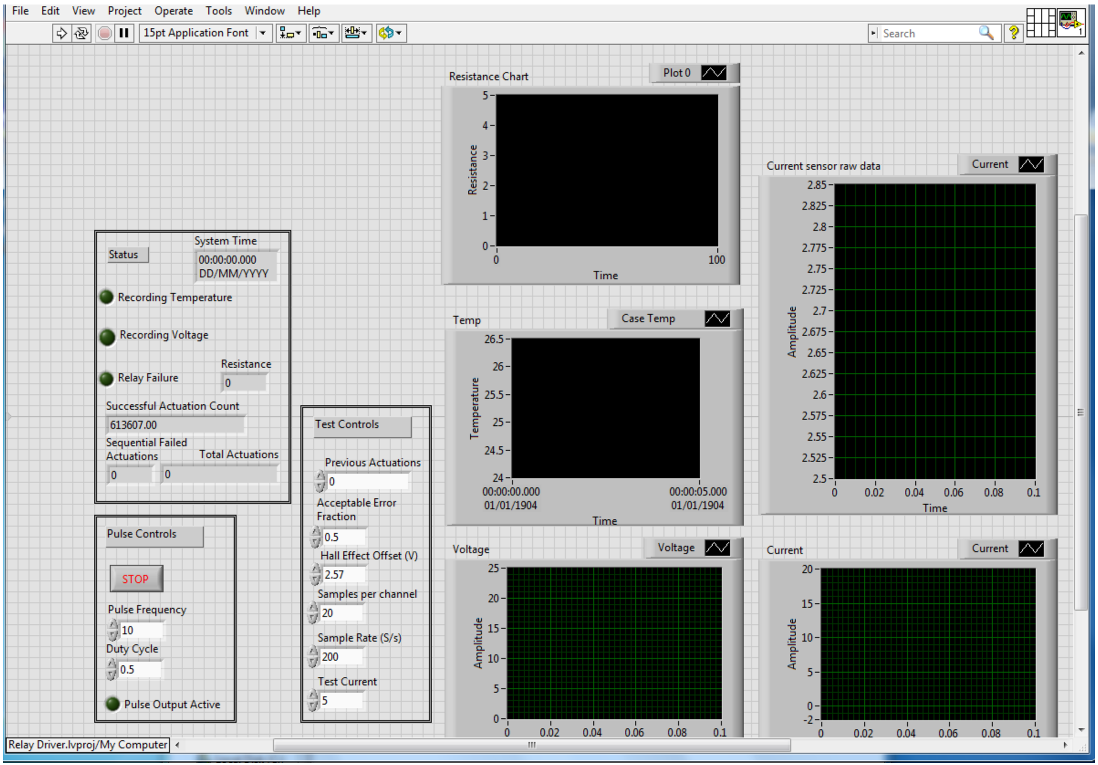


Figure 12: LabView GUI

Experimental Stimulus and Data Capture

In order to drive the relay at a reasonable rate, and leave enough time between actuations to accommodate ageing related increases in open and close time. The initial open and close times of the relay were found to be around 30ms. Therefore a pulse repetition frequency of 5Hz was chosen for the square wave driving the relay in order to allow 70ms of spare time to absorb increases in either the open or close time.

The relay was loaded with a closed current of 10A at a voltages ranging between 20V and 30V in 2V increments.

Voltage and Current was captured through an NI voltmeter and LEM Hall effect current sensor respectively at a rate of 100S/s for an event resolution of 10ms. Temperature was captured using two thermocouples, one inside the case and another outside in the isolation chamber at a rate of 1S/s. The low data rates were chosen in order to reduce the size of the data sets collected over long period ageing tests (4 million cycles plus) and prevent them becoming unwieldy to analyse. This also was in line with our intention to prove that valuable information can be extracted from low data rate and inexpensive condition monitoring systems for retrofit application to commercial relay systems.

Figure 13 shows the timing diagram for the relay actuation cycle. The 24V rising edge that drives the relay is also routed to the CompactDAQ data capture channels where it is used to trigger the capture of 20 samples of data at 100S/s (one cycle). As this is a high-accuracy timing signal and can be assumed to reach the relay at the same time as the data capture card it can be used to determine the approximate open and close times of the relay in post processing.

The condition for failure we chose for the test was a 30% deviation (upwards or downwards) from the expected average current value across the whole waveform. For the tests chosen this indicates a rise in the average current to 6.5A or a drop to 3.5A. This would indicate an increase in close or open time by double (from 30ms to 60ms) and would also identify stuck open or stuck closed failures. To remove short duration transient faults we decided to introduce a requirement that at least 200 sequential actuations would have to have 'failed' in order to classify the relay as non-functional.

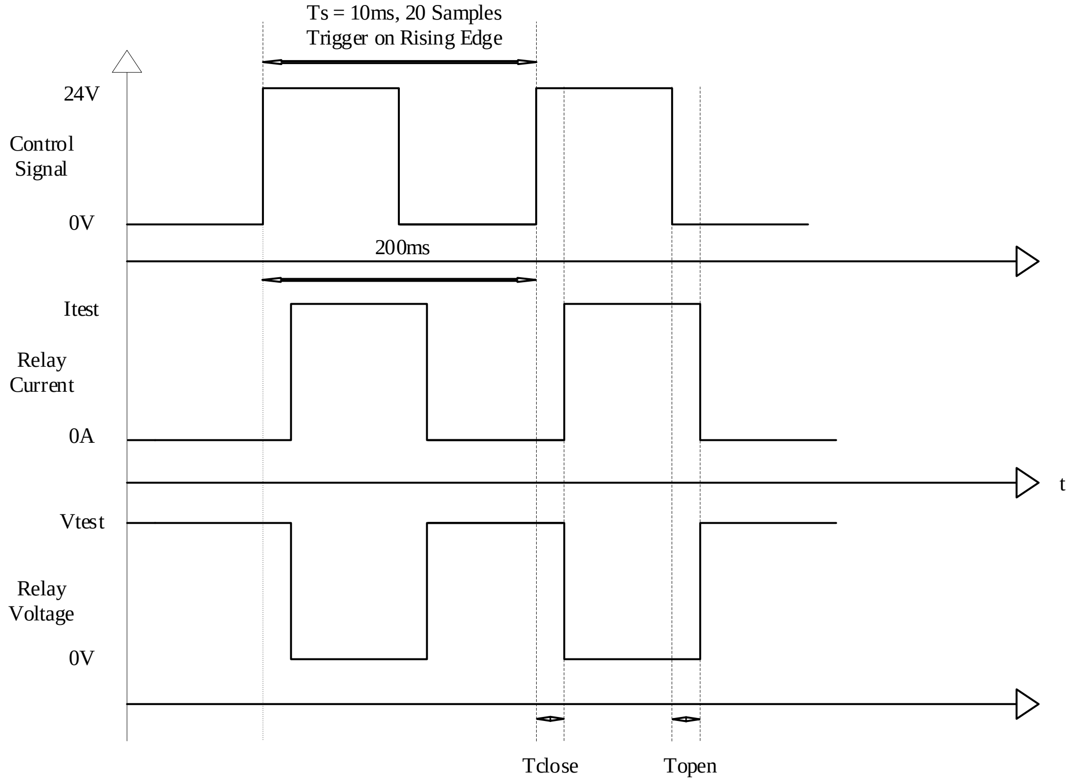


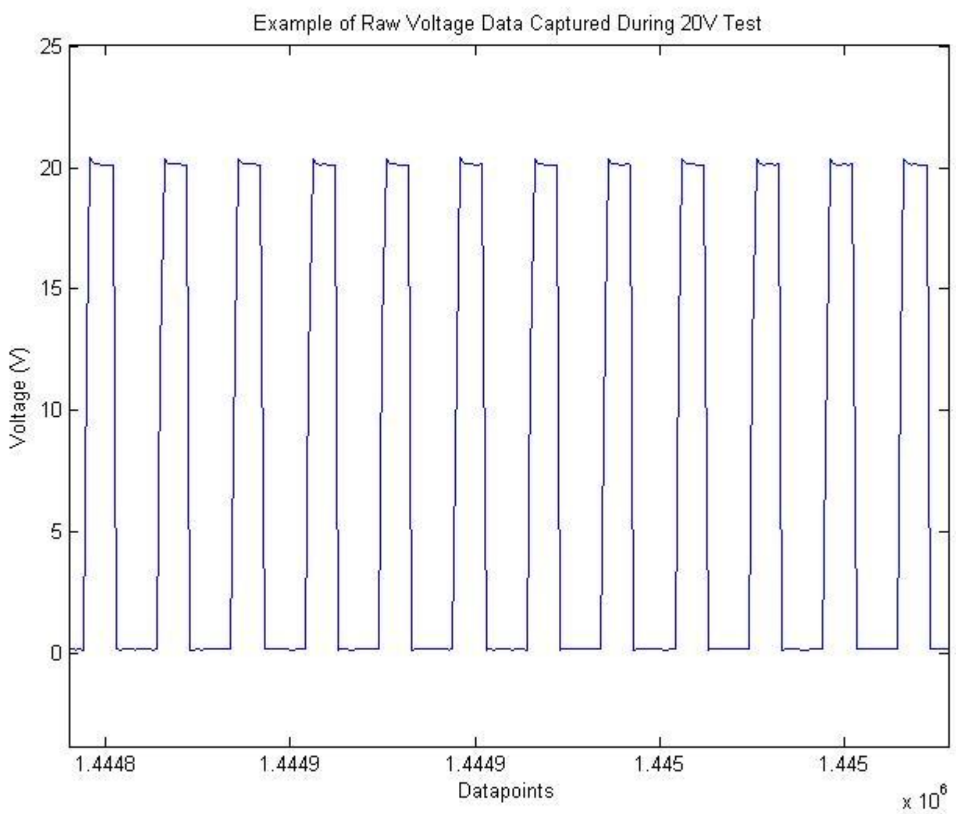
Figure 13: Timing diagram for relay operation

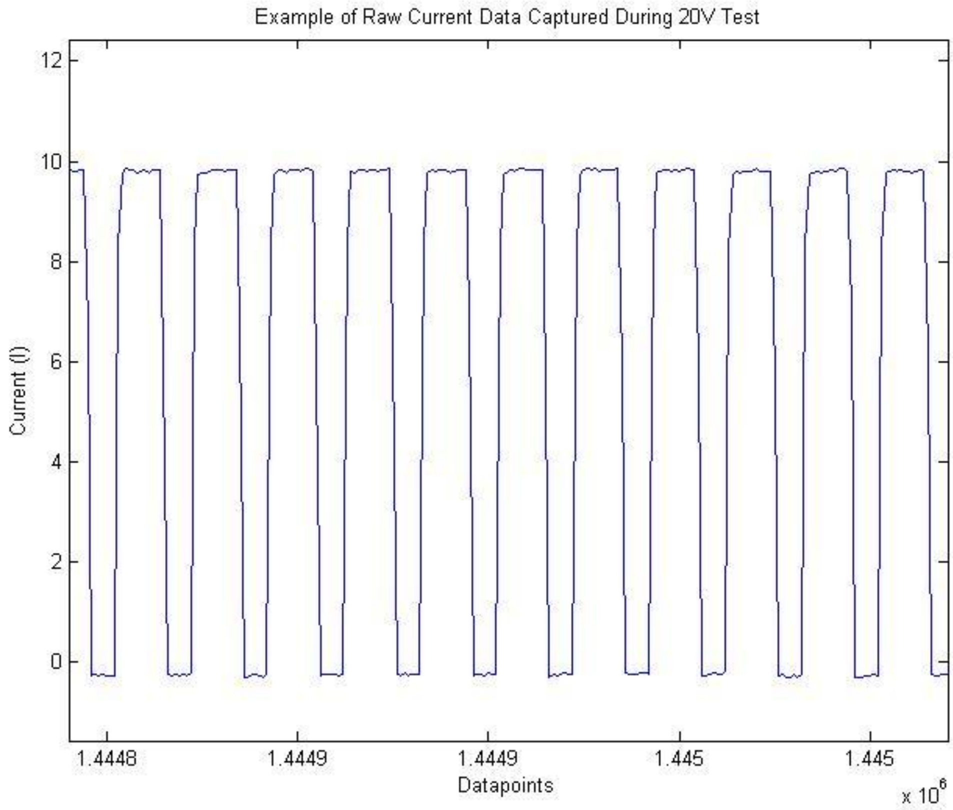
Chapter 5: Experimental Results

This section covers the results obtained from the accelerated ageing testing of each of the six relays. We present a sample set of raw data captured from the relays during operation, tabulated results of the experiments, surface profiles and case example data.

Typical Data Example

Figure 14 shows an example of the typical data captured by the voltmeter, ammeter and temperature sensors.





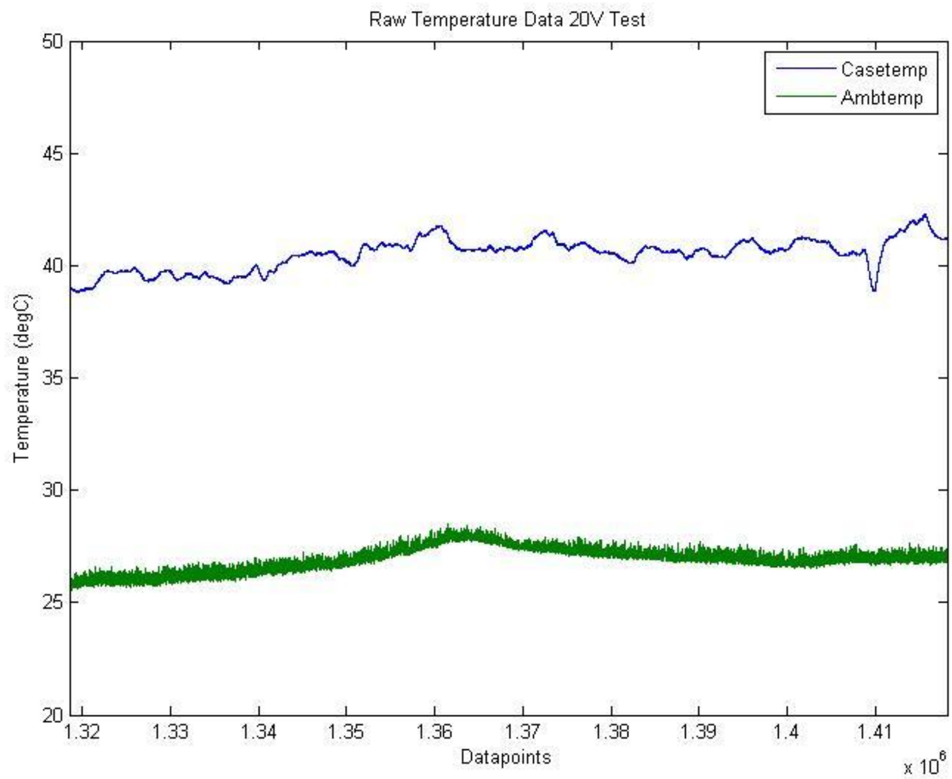


Figure 14: Typical Data

Test Results

Table 3 reports the experimental voltage, actuations reached and failure observations of the experiments.

Test Voltage (V)	Actuations prior to failure	Failure observation
20V	7.5 million	Contact Erosion
22V	4.8 million	Excessive Opening Time
24V	8.2 million	Contact Erosion
26V	4.3 million	Excessive Opening Time
28V	150,000	Pip and Crater
30V	98,000	Pip and Crater

Table 3: Results

Both tests that failed due to contact erosion (the 20V and 24V tests) lasted for a very large number of cycles prior to failure. The 22V and 26V test both failed due to an overly long opening time and failed in just over half the time of the fully eroded contacts. The 28V and 30V tests both experienced extremely rapid failures that were attributed to the formation of a pip-and-crater structure and subsequent bridging arc across the contacts.

Surface profile images

Figure 15 shows the topological profiles of the contacts with the contact surface size overlaid. It should be noted that the white light interferometer used is only able to profile surfaces that provide reflective enough surfaces to return strong interference fringes. Where the surface is not reflective or has too steep a gradient the interference fringes cannot be detected, as the light incident on the surface is not adequately reflected and appears as a black area. The results were filtered and smoothed after capture to remove spikes and improve image quality. The white rings represent the actual size of the contacts. It can be seen that in both the 28V and 30V test that prominent pips and craters have developed on the anode and cathode respectively. The 30V contact pair has an anode pip of 596 micron height, and a cathode crater of 140 micron depth. The 28V contact pair has an anode pip of 129 micron maximum height and a contact crater of 137 micron depth. the 20V test there has been significant wear that is concentrated towards the leading edge of the contact, but no real area of preferential contact erosion beyond that. Figure 16 gives the Energy Dispersive X-Ray Spectroscopy (EDX) equipped Scanning Electron Microscope (SEM) material analysis of prominent areas of damage on the contact surfaces. Particularly noteworthy here is the composition of the pip in the 28 and 30V test, which has a substantial amount of gold and nickel (the material bonding the gold plating to the Silver Cadmium Oxide base material).

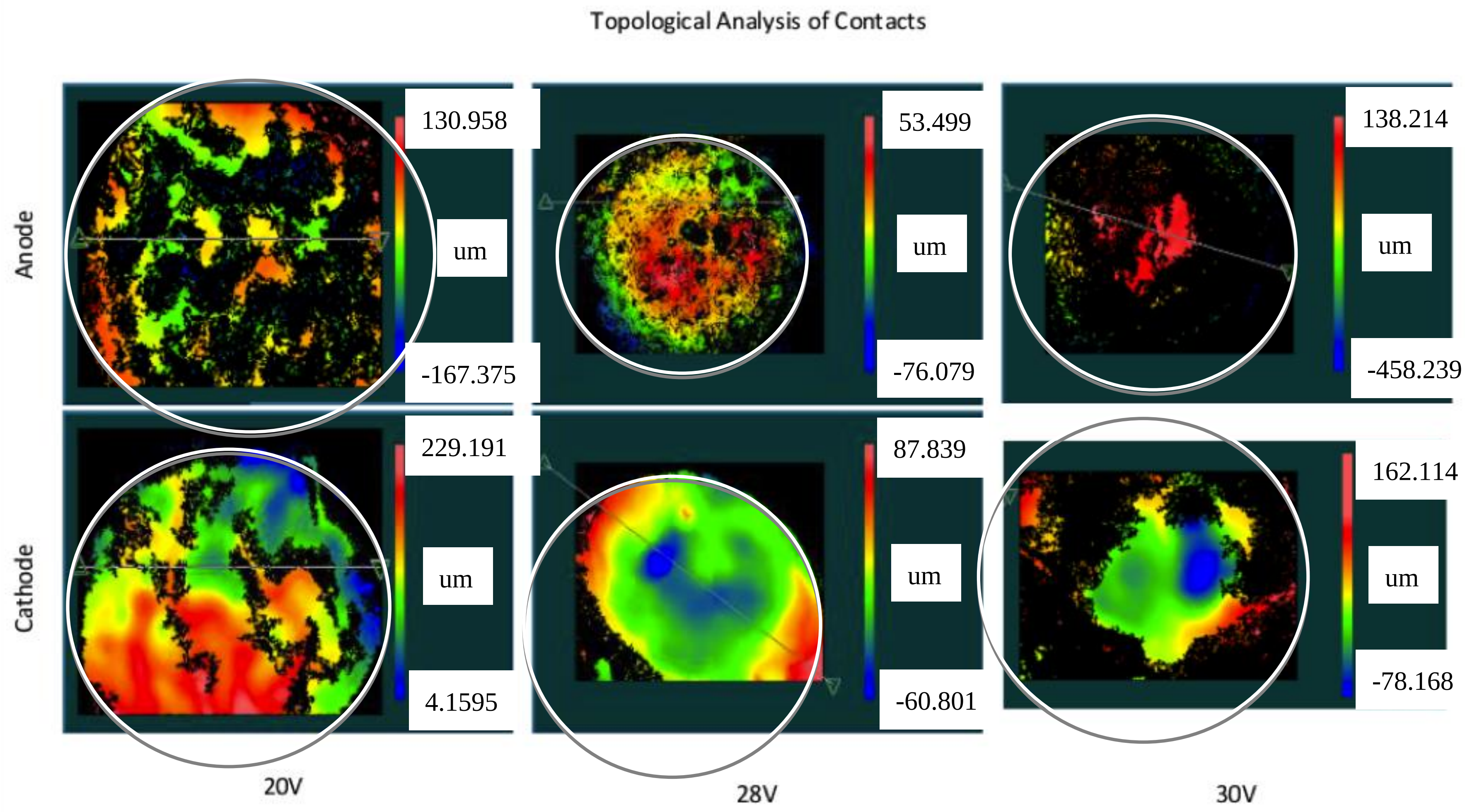


Figure 15: (a) 20V, (b) 28V, (c) 30V Anode/Cathode Topology

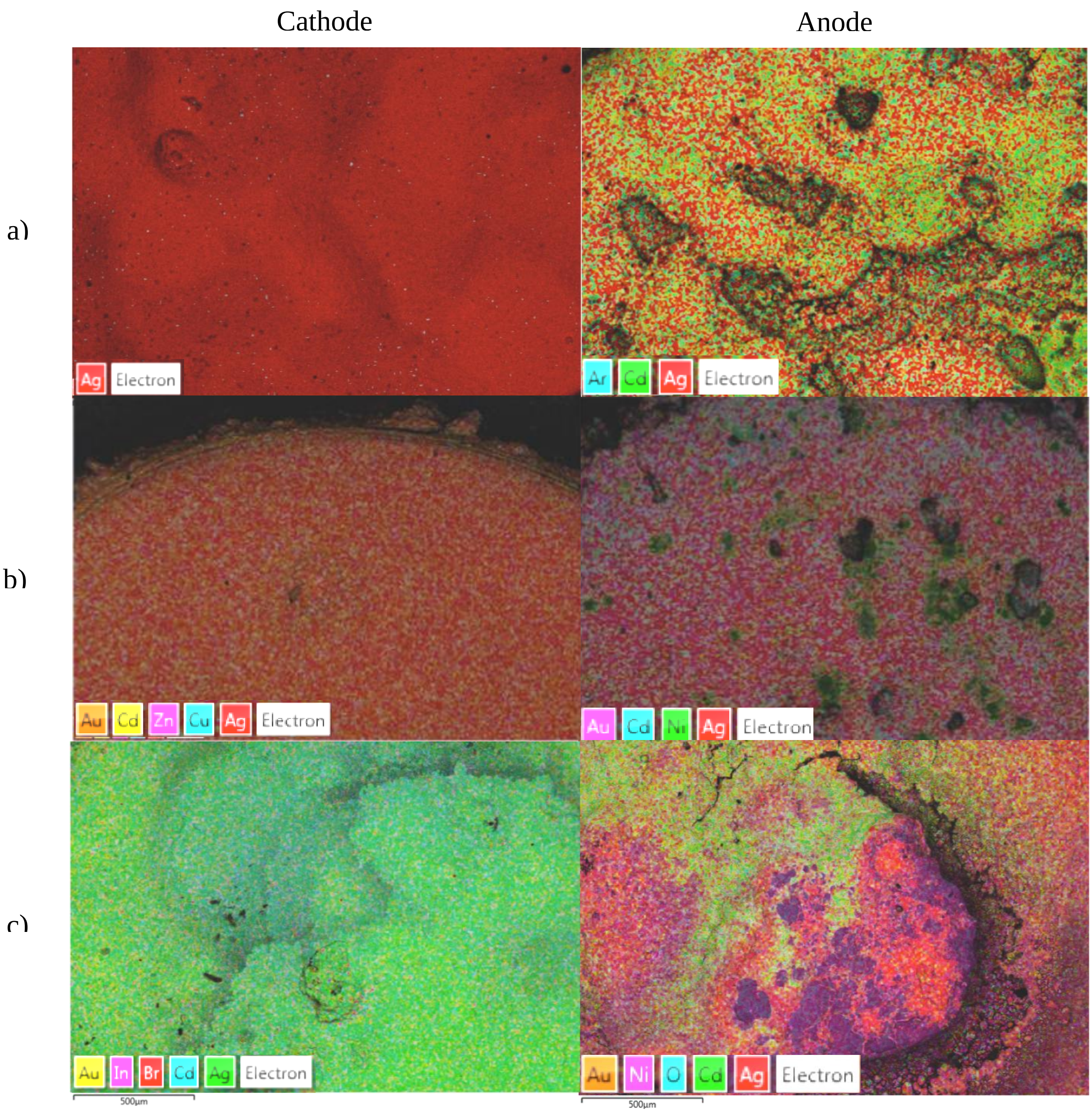


Figure 16: EDX Analysis of Damage Sites

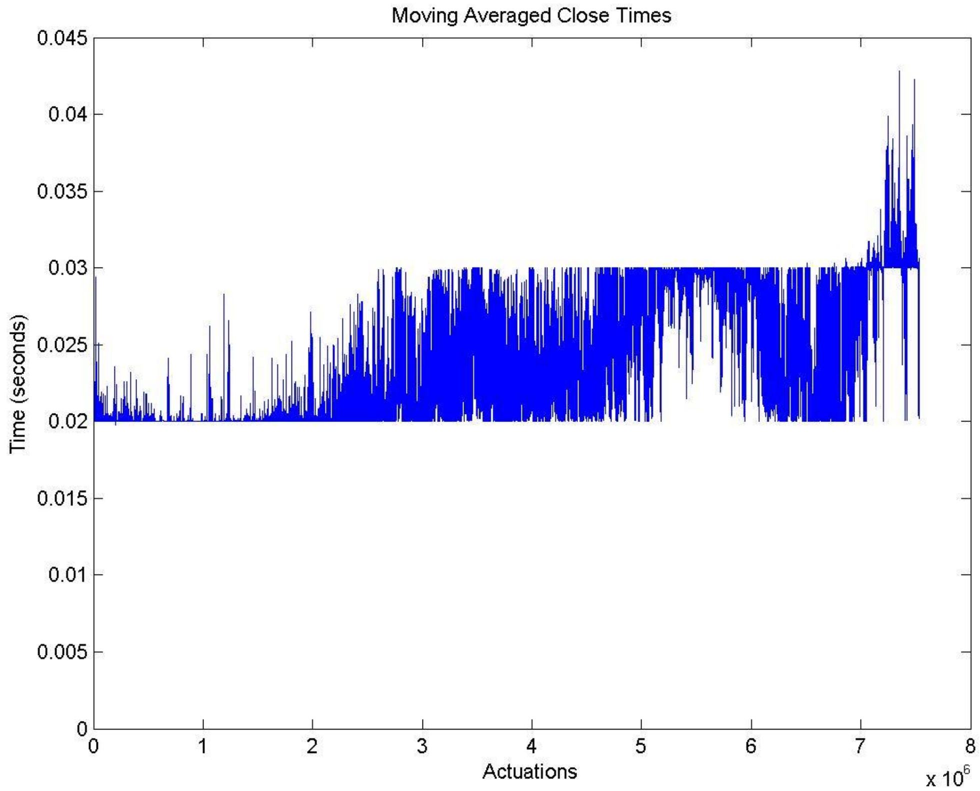
Extracted Features

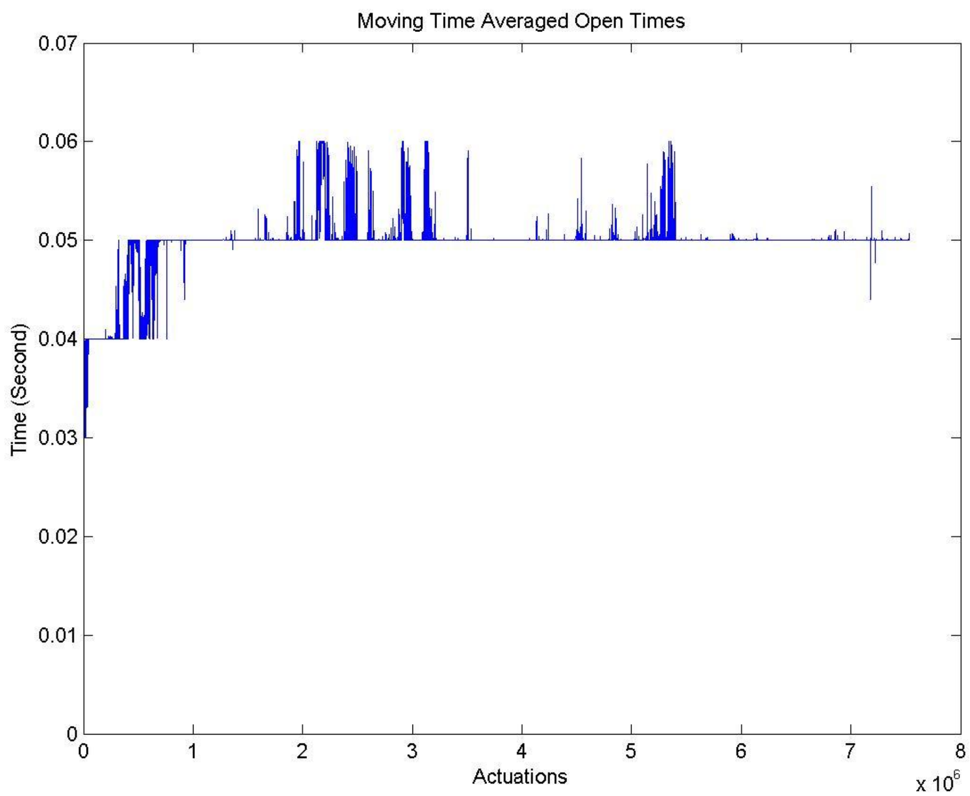
This section details the features that have been extracted from the tests for each relay: the open/close times, the differential temperature and the contact resistance value. The open and close times were derived for each actuation by comparing the expected open/close time index for a perfect relay with the actual time taken to reach an electrical state consistent with a relay being open or closed. In the case of a closing actuation, the time between the actuation signal and the voltage across the contacts dropping below 5V was taken to be the close time. For an opening actuation, the time between the actuation signal and the voltage exceeding 90% of the test voltage was taken to be the open time. Due to the sample rate that was chosen and the consequent maximum resolution of 10ms the data is noisy and difficult to interpret. As such a moving time average filter of 100 samples window width was applied to the resulting data set to highlight longer-term trends and remove transient increases or decreases in actuation time. There are cases where the raw open and close time data is instructive but this has been included in the relevant discussion chapter subsections.

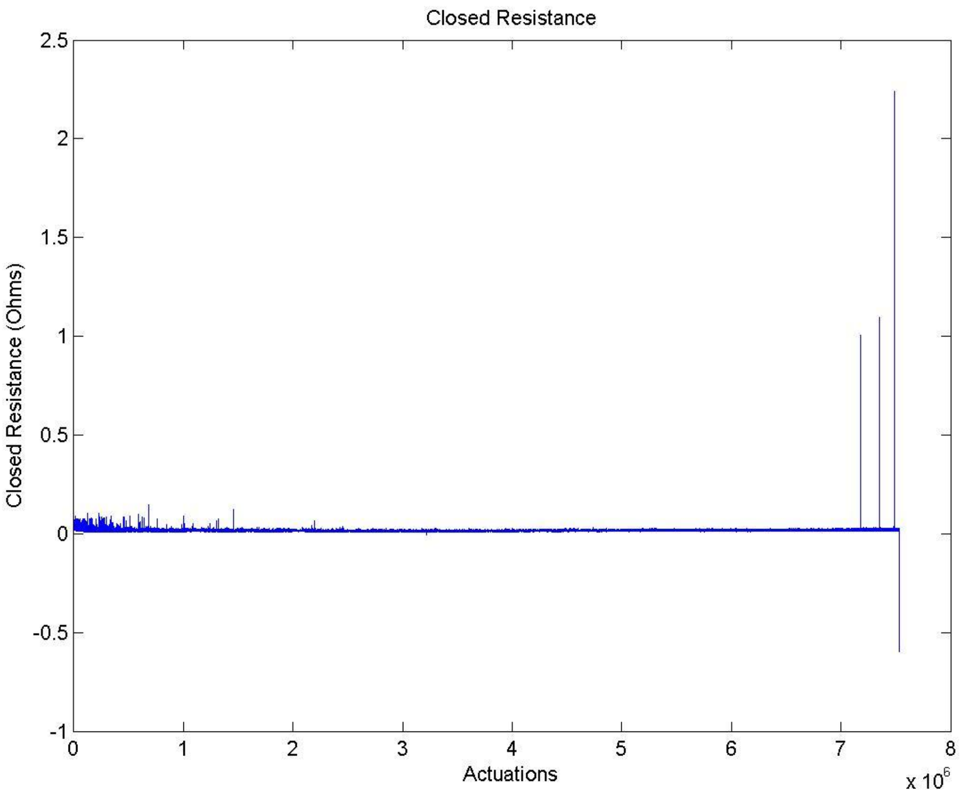
In order to attempt to remove the effects of day/night and room heating cycles on the temperature readings the differential temperature between the Ambient and Case temperature was calculated. This is presented alongside the calculated closed state resistance values for the contacts and was determined by taking the last three readings of voltage and current before the opening actuation edge, averaging them and applying ohms law. This served to mitigate the effects of a slow close time on the measurement and to even out small fluctuations in the measurement. A total failure to close also appears as a very large resistance spike, although this was only observed in the 24V test at the very end of the test.

Note that the 22V test suffered an experimental failure and around 450K failed to record. Examination of the relay revealed that it was still operational and was displaying behaviour well within expected parameters. It was therefore decided to continue the test and accept the loss of data, as valuable information could still be extracted from the test.

20V Test Results







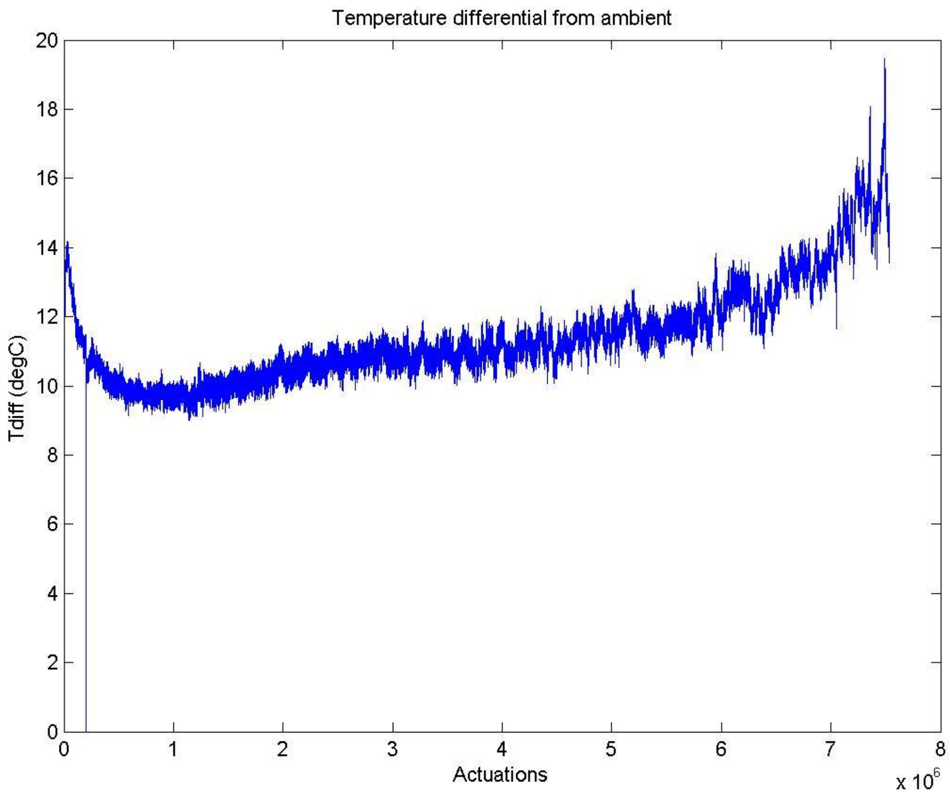
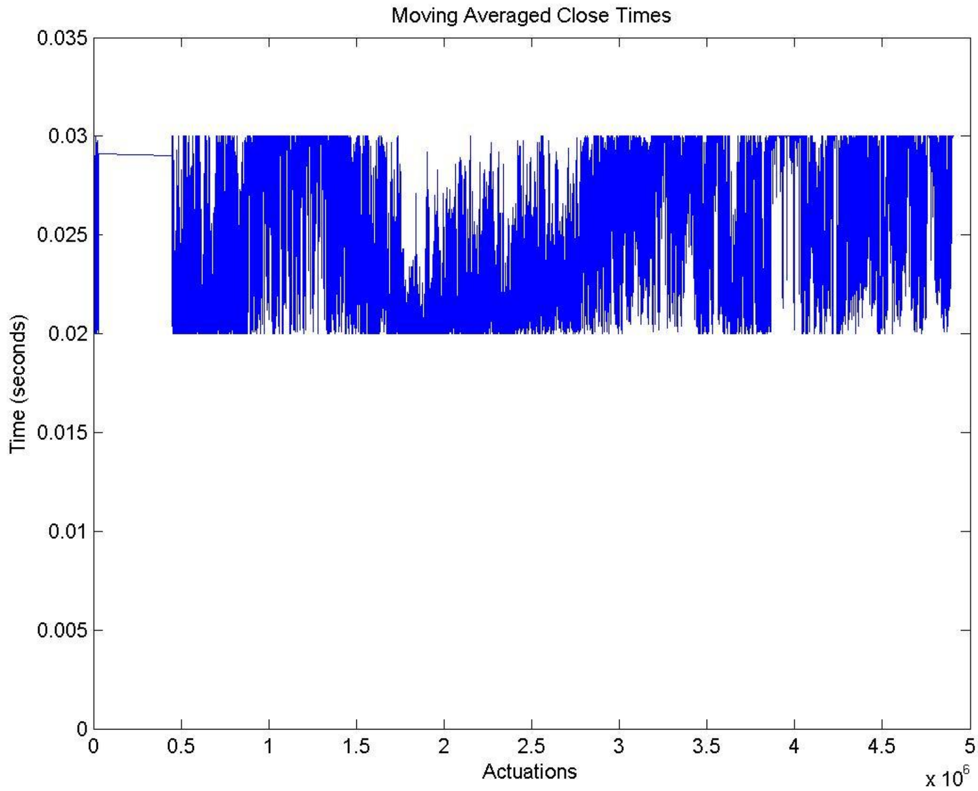
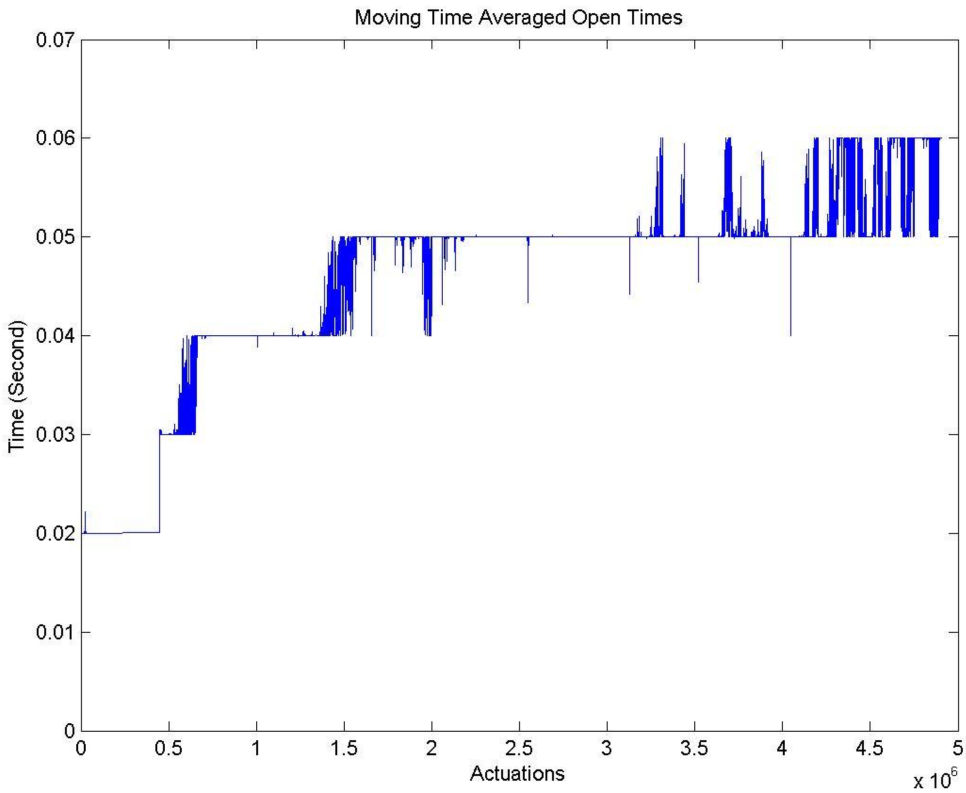


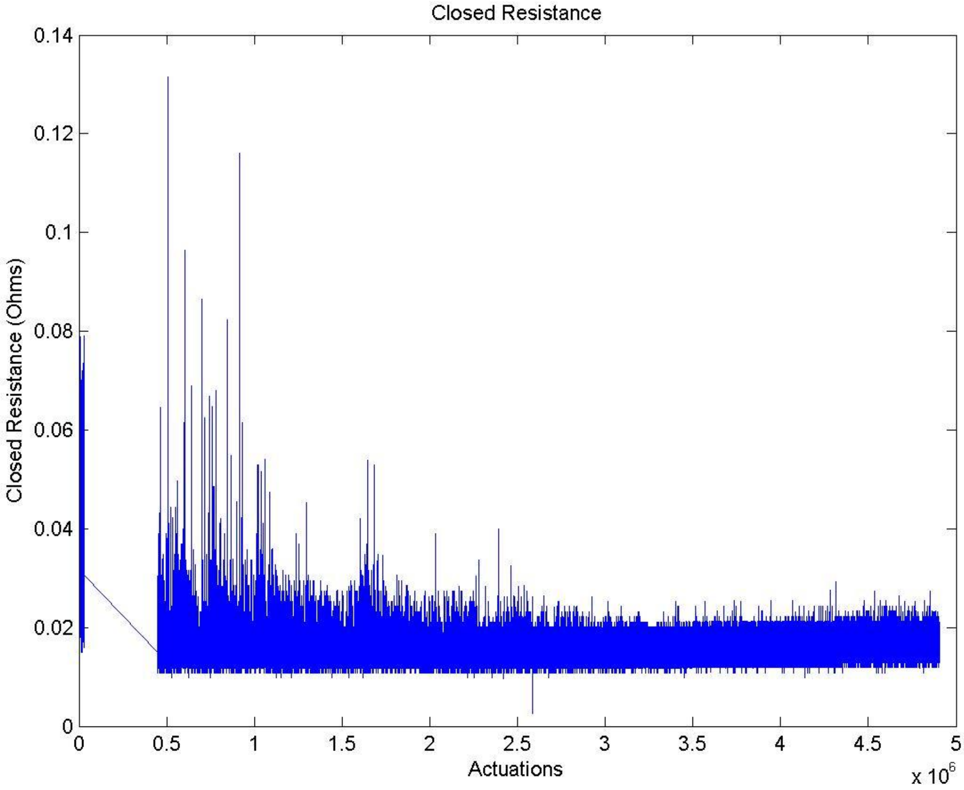
Figure 17: 20V Test Results

22V Test

Results







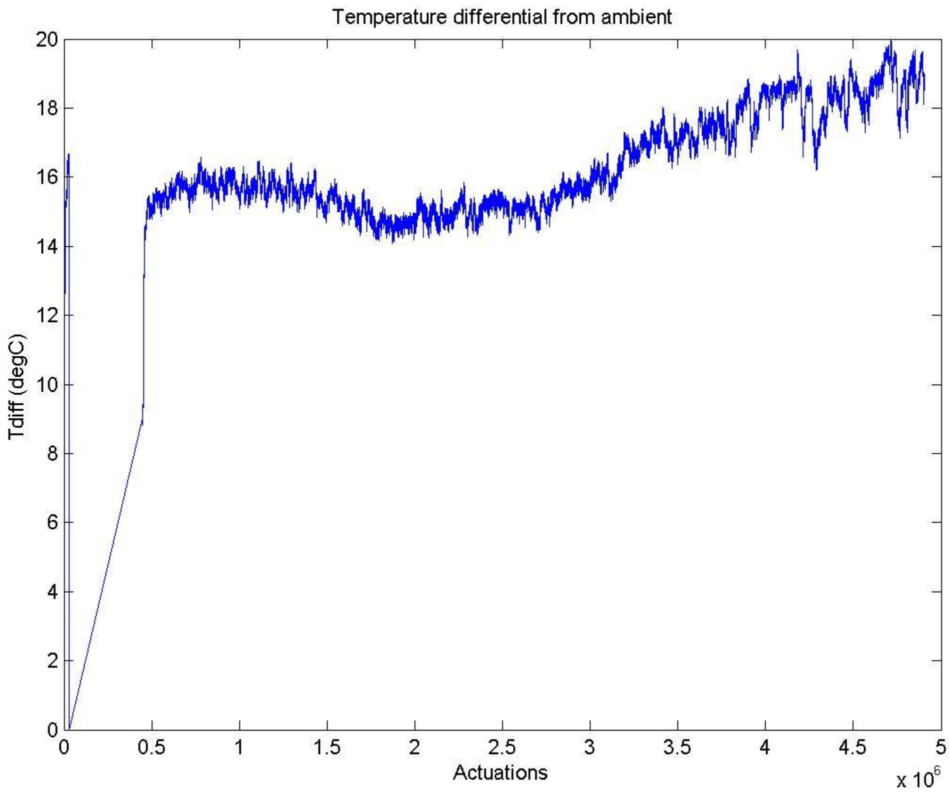
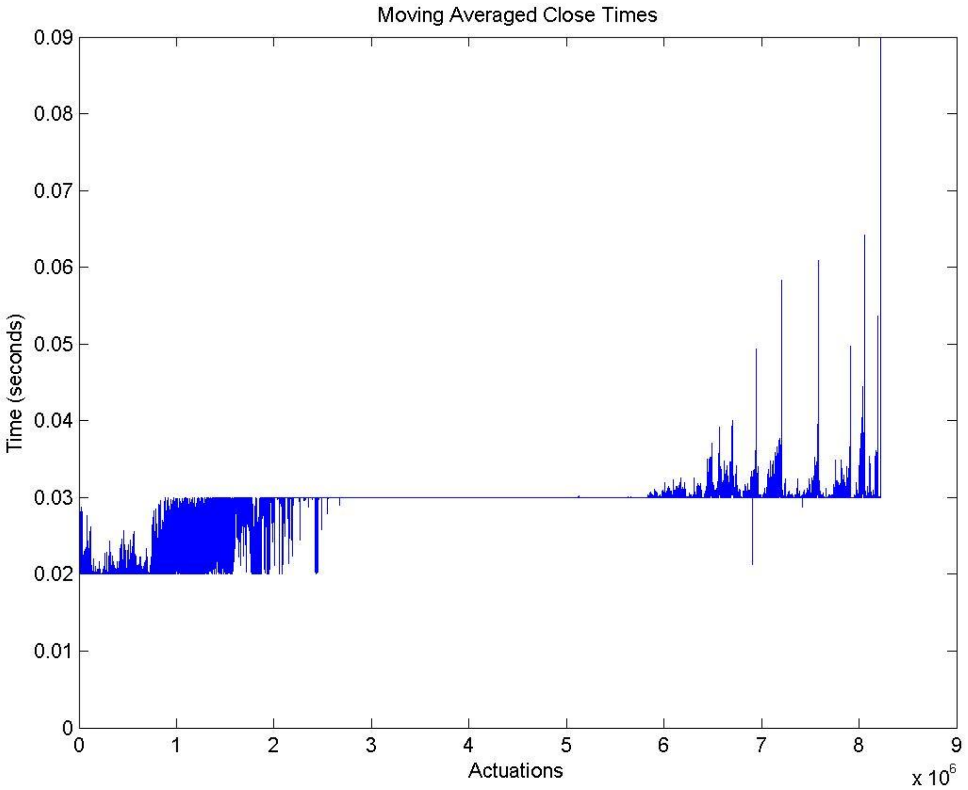
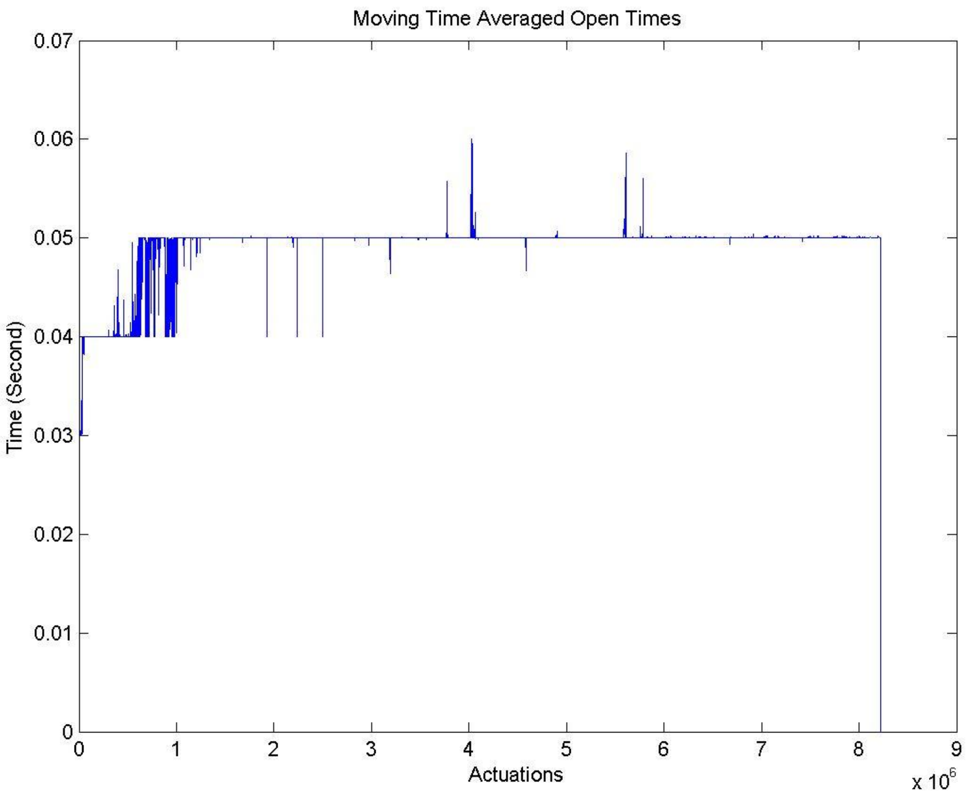
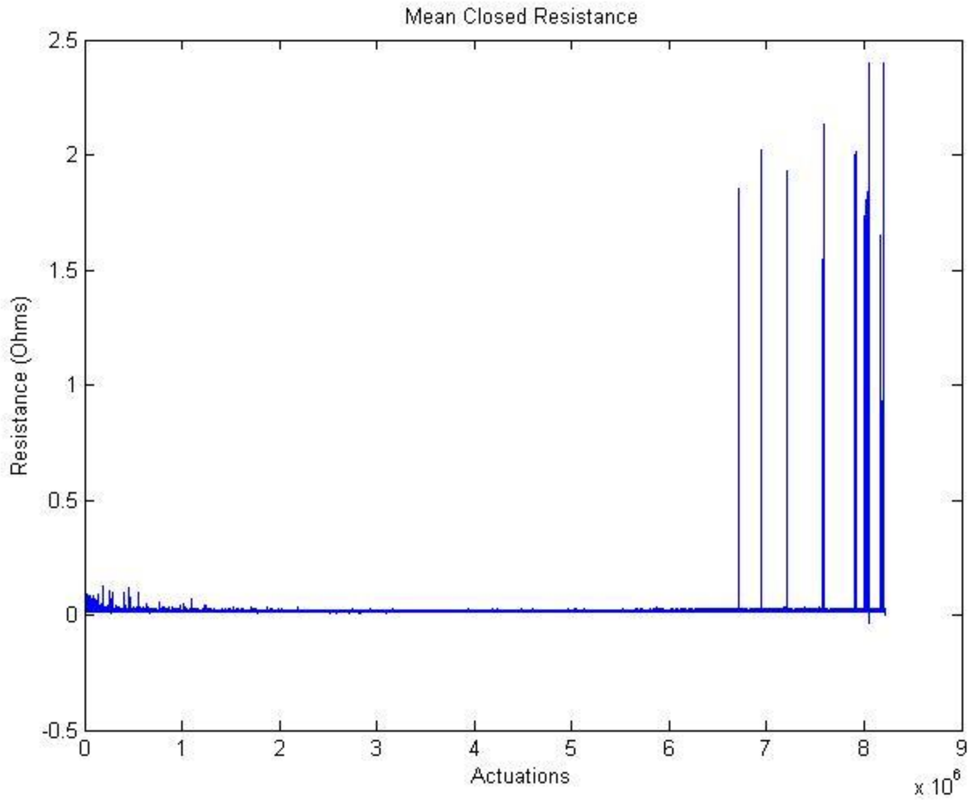


Figure 18: 22V Test Results

24V Test
Results







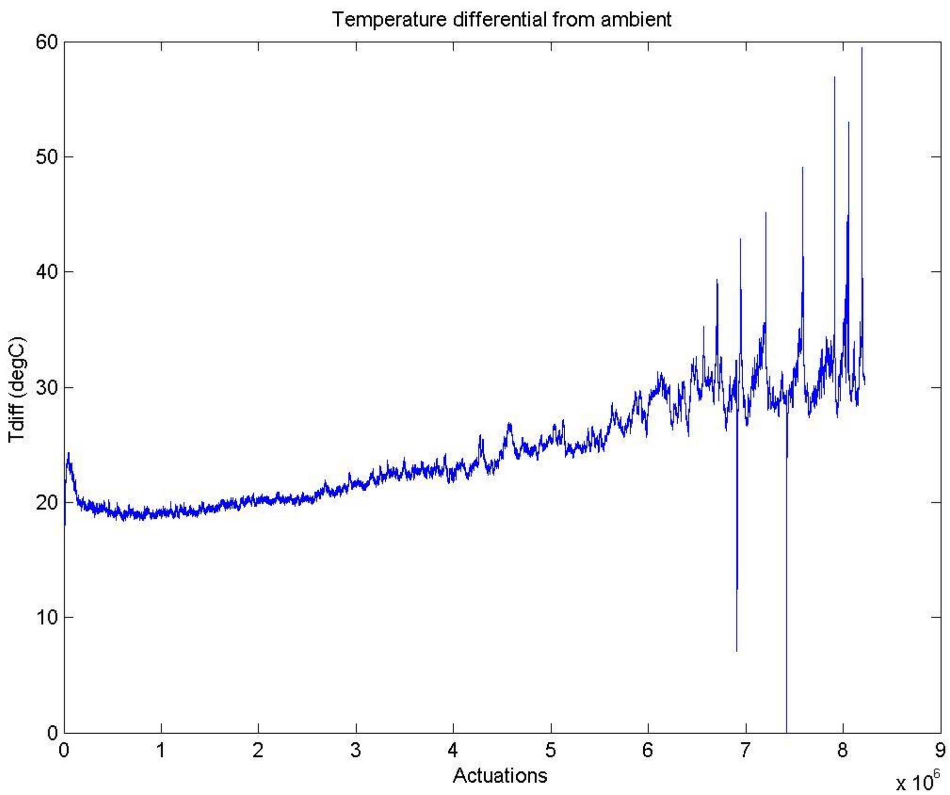
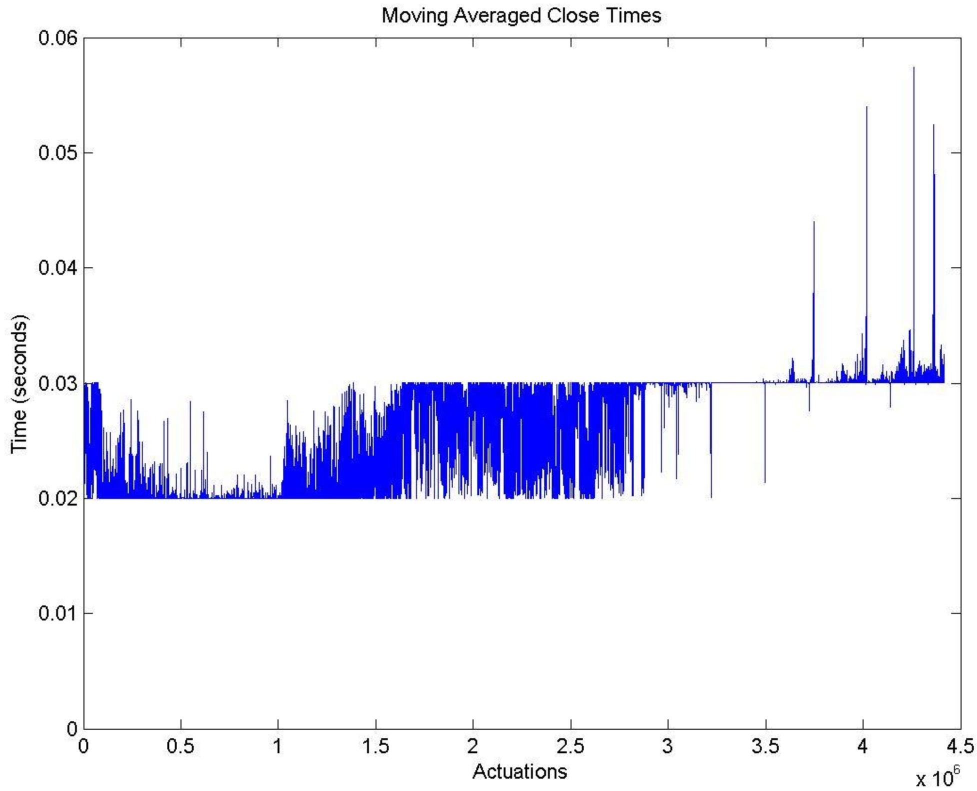
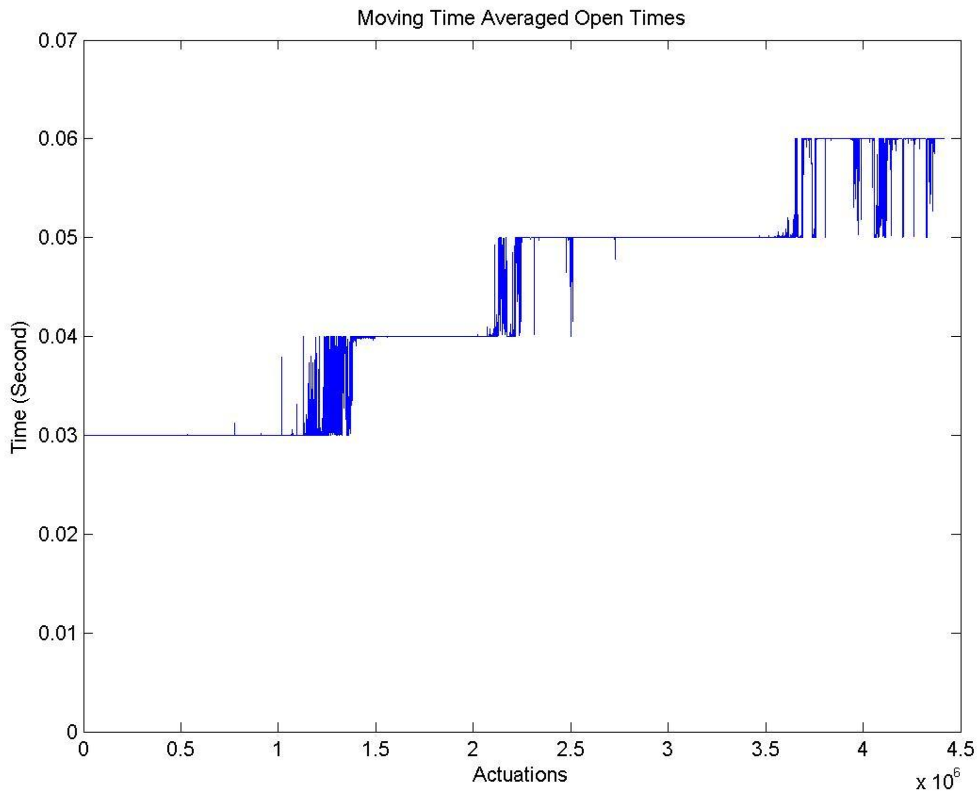
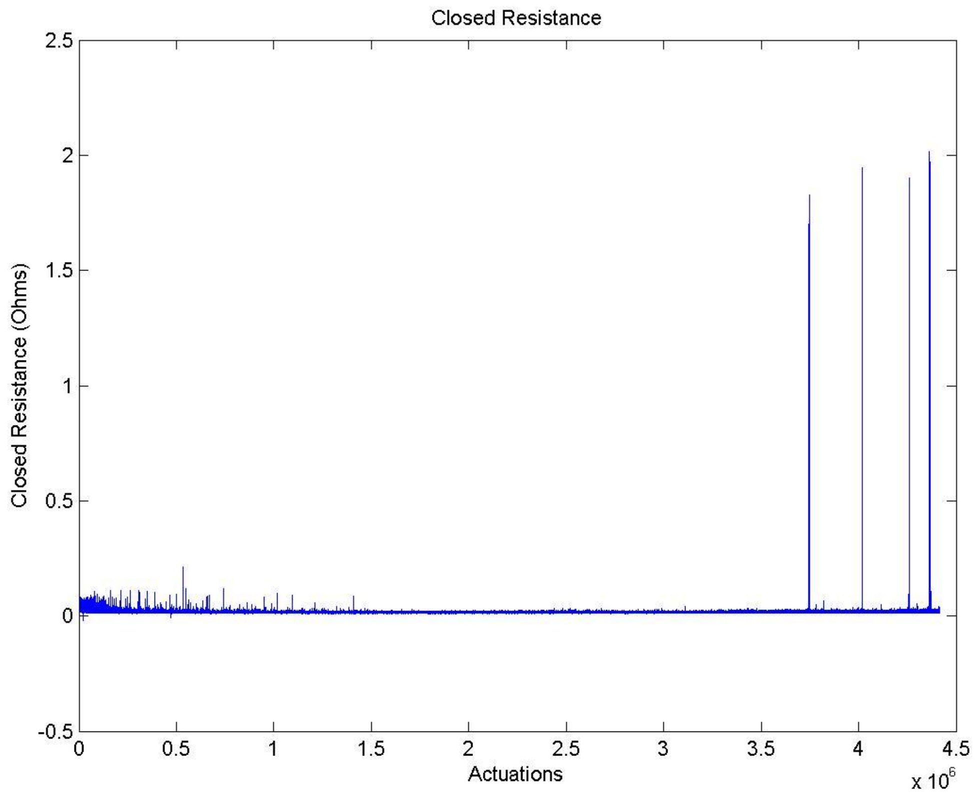


Figure 19: 24V Test Results

26V Test Results







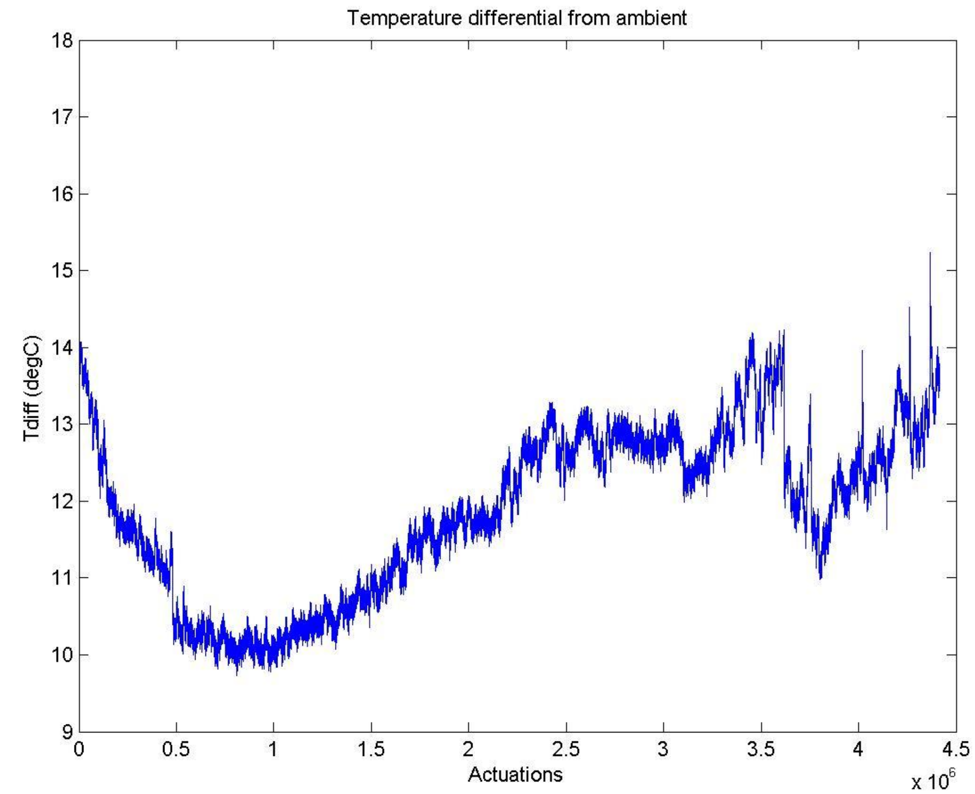
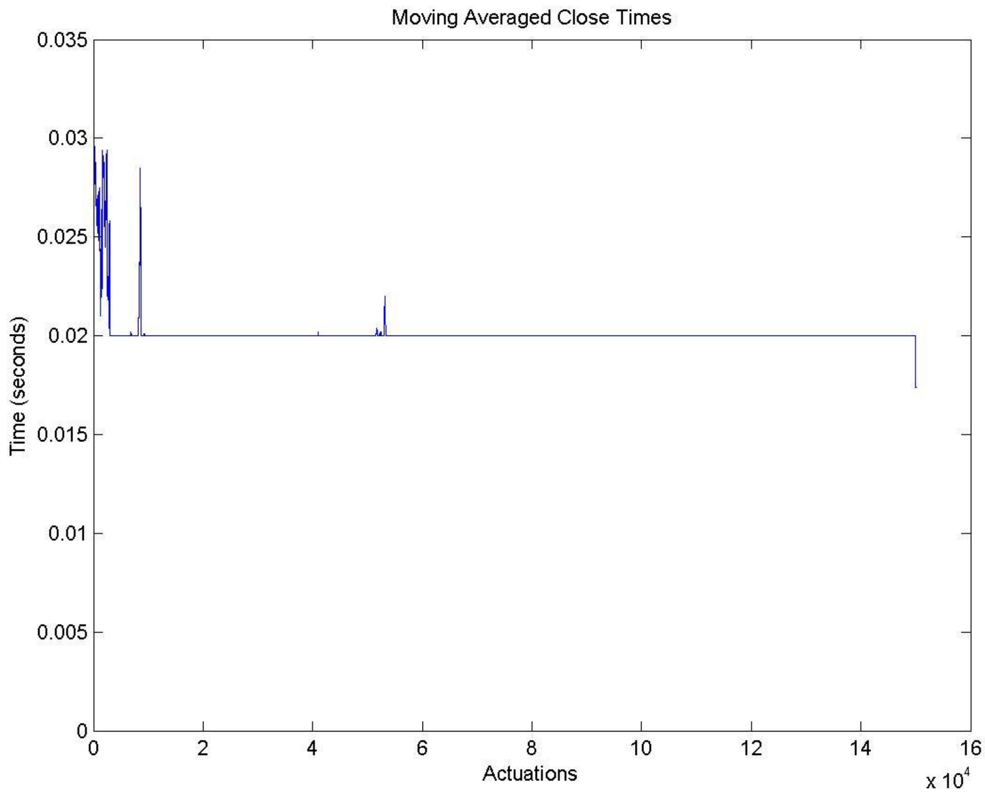
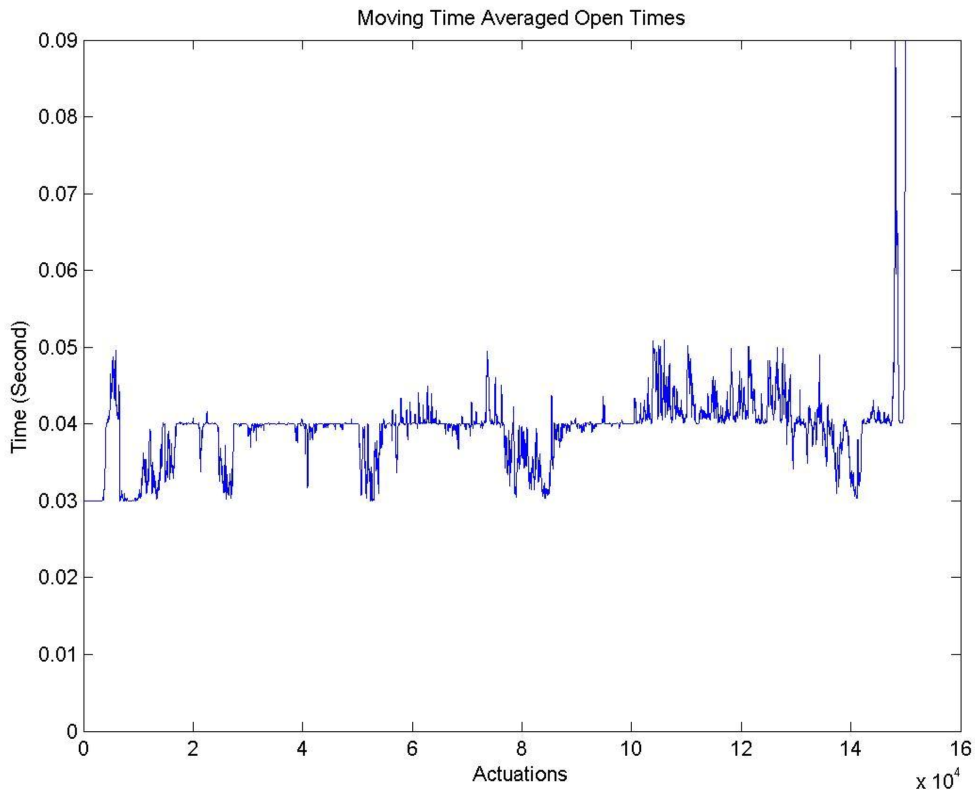


Figure 20: 26V Test Results

28V Test Results





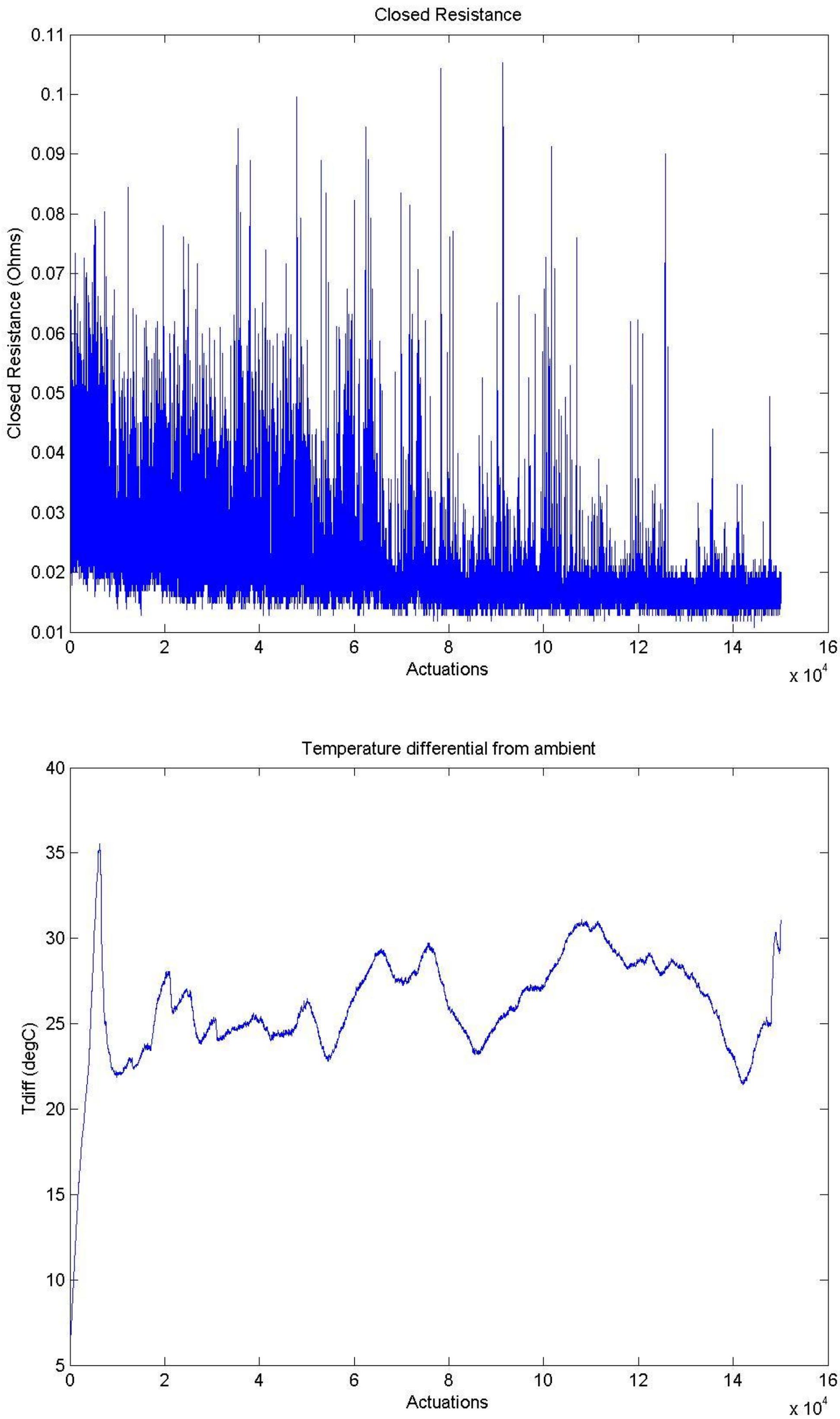
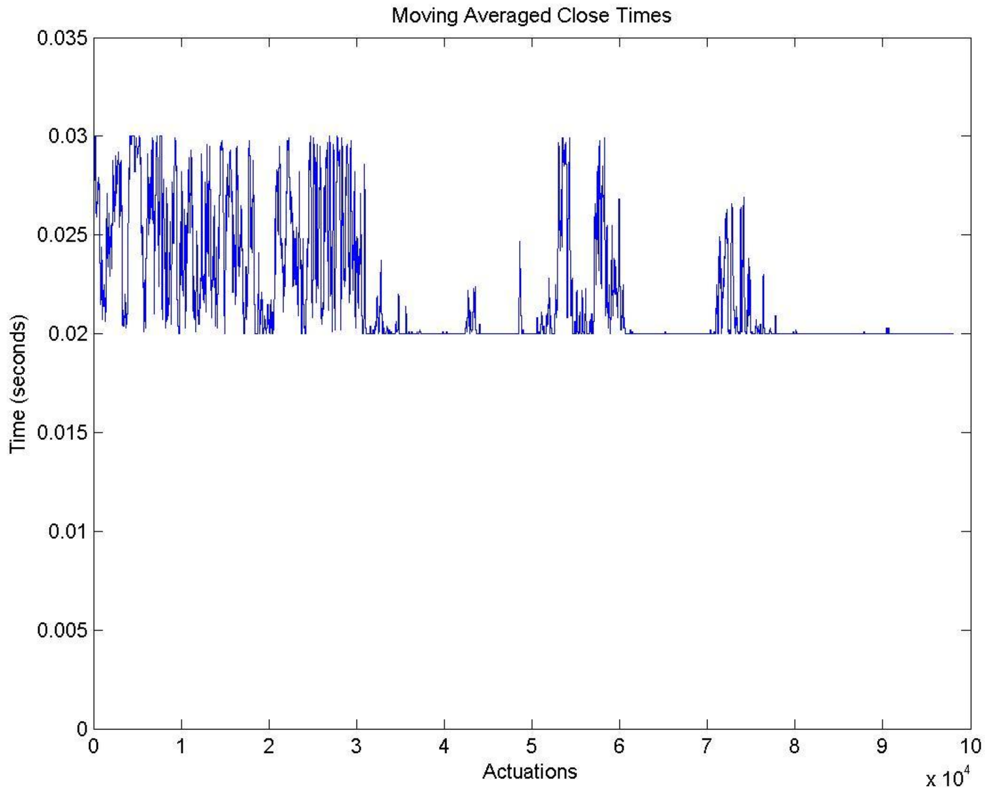
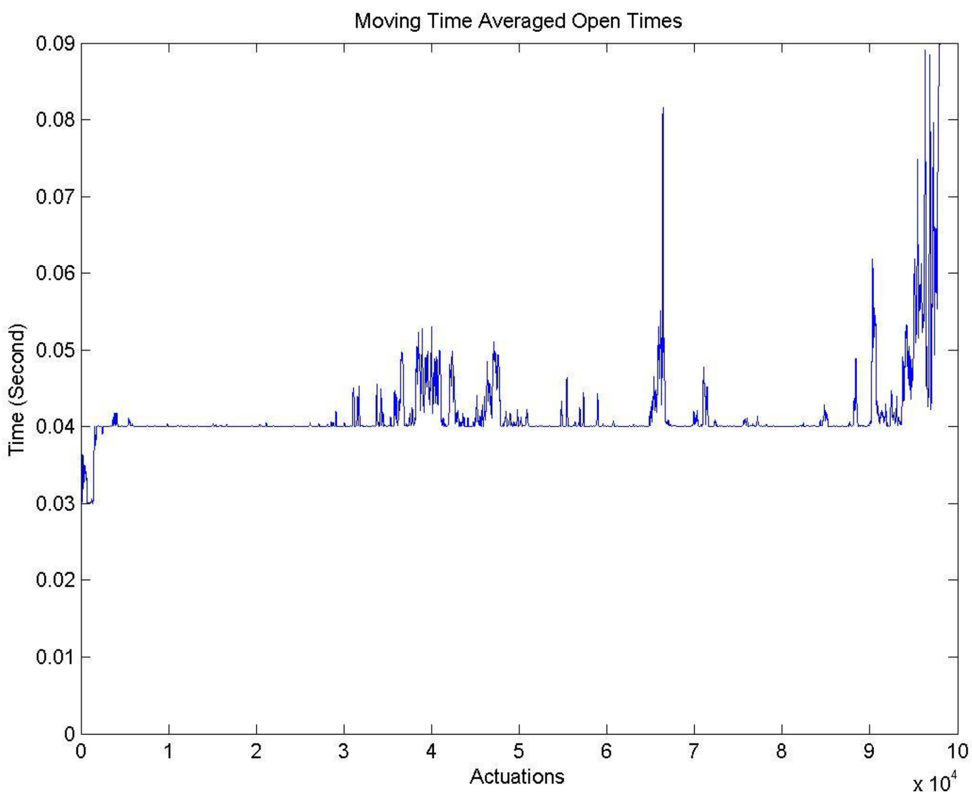


Figure 21: 28V Test Results

30V Test Results





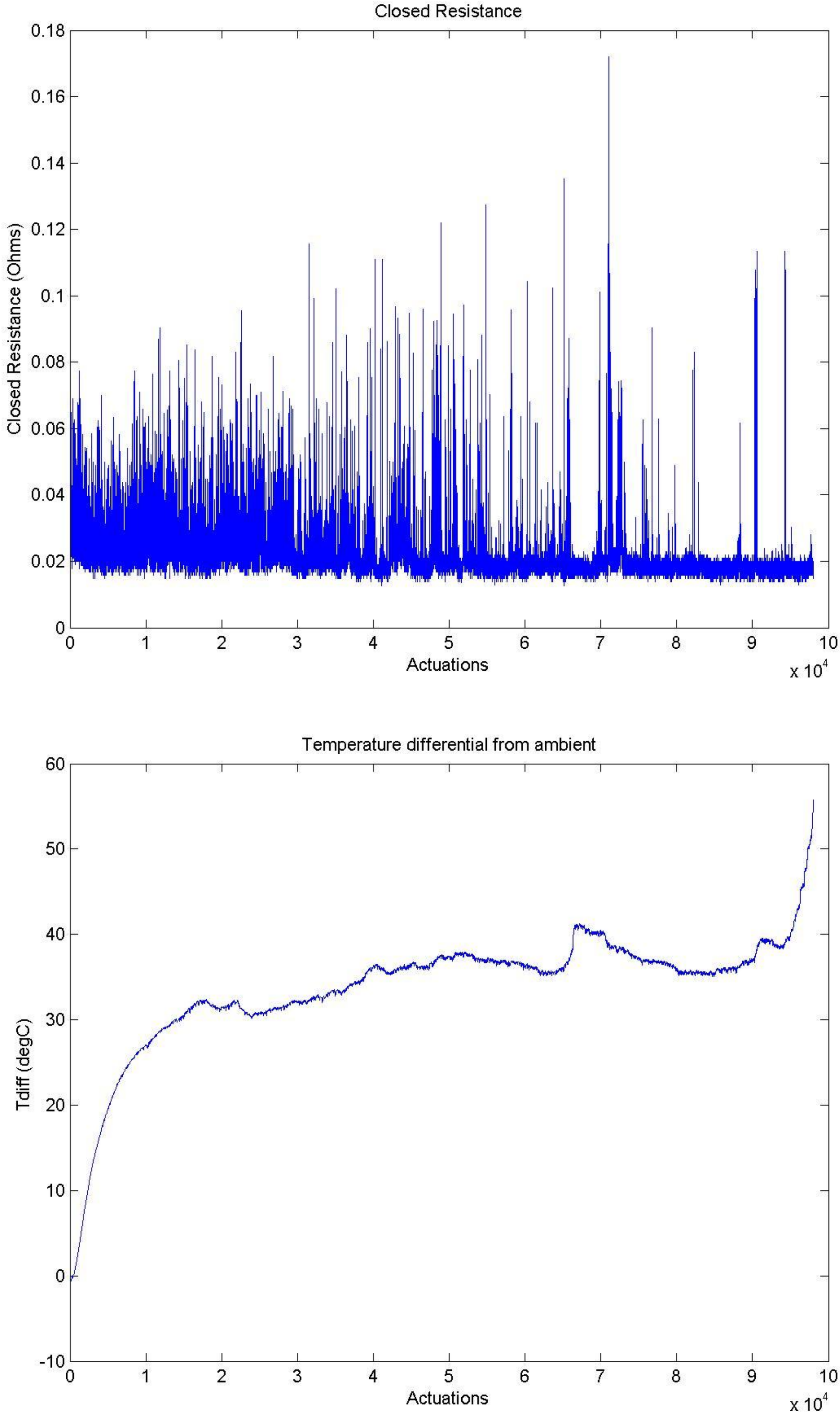


Figure 22: 30V Test Results

Chapter 6: Discussion of Results

In this section we discuss the results of the experiment and identify important features exposed by the experimental regime.

Stuck Open Failures

The most notable features extracted from the tests that resulted in stuck open failures are the abnormal spikes in resistance that occur in the last 1.5 million actuations prior to failure, and the reductions in averaged close times that occurs in the same period. Three of the relays tested displayed this behaviour, with two of them failing eventually from erosion. The 26V test eventually failed due to an increase in opening times; however it was displaying the same symptoms of failure as the relays that failed open. Examination of the relay contact surfaces of these relays reveals heavy contact erosion from arcing, to the point where a connection can no longer be achieved. The fact that these relays lasted significantly longer than relays affected by the bridging failure condition seems to correlate with Hasegawa's assertion that after a certain number of actuations the relay falls out of a "Material Transfer" phase and switches to an erosion phase (although significantly more tests would have to be done at single voltage levels to confirm this) [118].

It was suggested to us by Barnbrook that increases in contact resistance of ten times or greater would constitute a failure, however they had doubts about the validity of that measure, as this may indicate transient contamination of the contact rather than a true indicator of failure and often the relay would self-clear. Our observations suggest that this hypothesis is likely true as all relays suffering from erosion-based failure mechanisms displayed spikes in resistance that then dropped away. However, the spikes in resistance become more frequent and more intense as the relay reached the end of its life. Figure 23 shows these spikes occurring at 7.487 million actuations in greater detail.

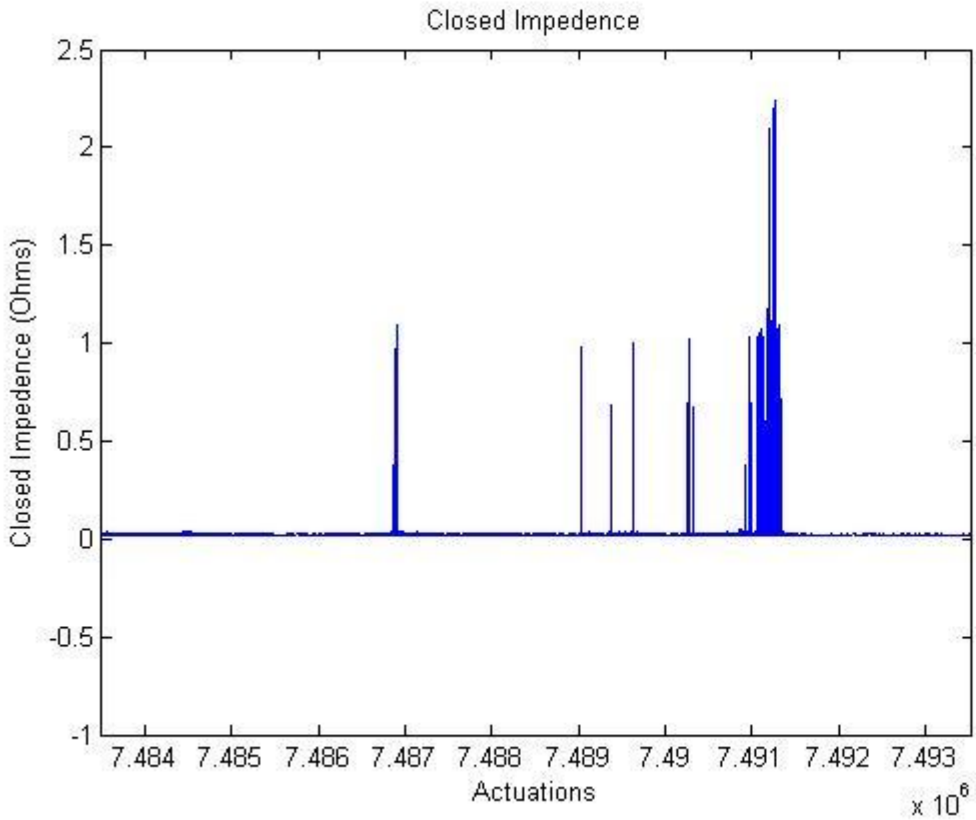


Figure 23: Periods of resistive activity at end of 20V life test

We believe that this is due to the underlying physical mechanism that, as the relay erodes, the contact area reduces significantly as the end of life approaches. This is intuitive, as it can be imagined that the amount of contact surface area that can physically make contact is reduced and therefore the probability of a 'clean' connection free of contamination and with good metal/metal contact is reduced. Figure 24a illustrates the contact when un-eroded and the chance of a good contact is very high. Figure 24b shows the contact in a state of partial erosion, still with a reasonably good chance of a good connection and Figure 24c shows the contact in a state where only a small amount of contact area is left, and as such the contact is barely able to contact and the chances of a good contact have dropped significantly. The surface profile images of the eroded contact support this conclusion, showing no particular areas of degradation, but showing a generally rough and cratered profile with only small ‘peak’ areas as likely sites of contact, as opposed to the smooth surface of a clean and undamaged contact.

Figure 25 presents the raw data gathered during a period of resistive activity in the 20V test. As expected there are times where the resistance increases due to a poor connection, however there are also moments where we assess that the bounce arc is not extinguishing correctly (likely due to the relay settling in position of poor contact, allowing the arc to continue burning).

There is also resistive activity across all the relays that survived beyond the first two hundred thousand actuation that we ascribe to the ‘wearing in’ process of the relay: where the gold and nickel plating designed to protect the SnCdO contacts is ablated away by the arcing process, creating an uneven contact surface that eventually evens out once the plating has been completely evaporated (at between 1.5 to 2 million cycles).

a) Uneroded Contact

b) Partially Eroded Contact

c) Heavily Eroded Contact

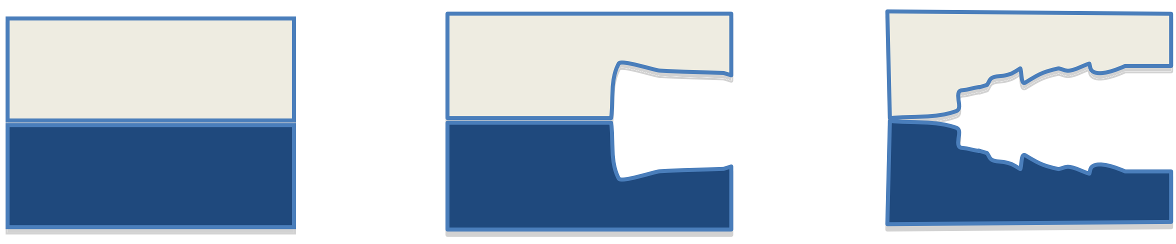


Figure 24: Contact Profiles with Erosion

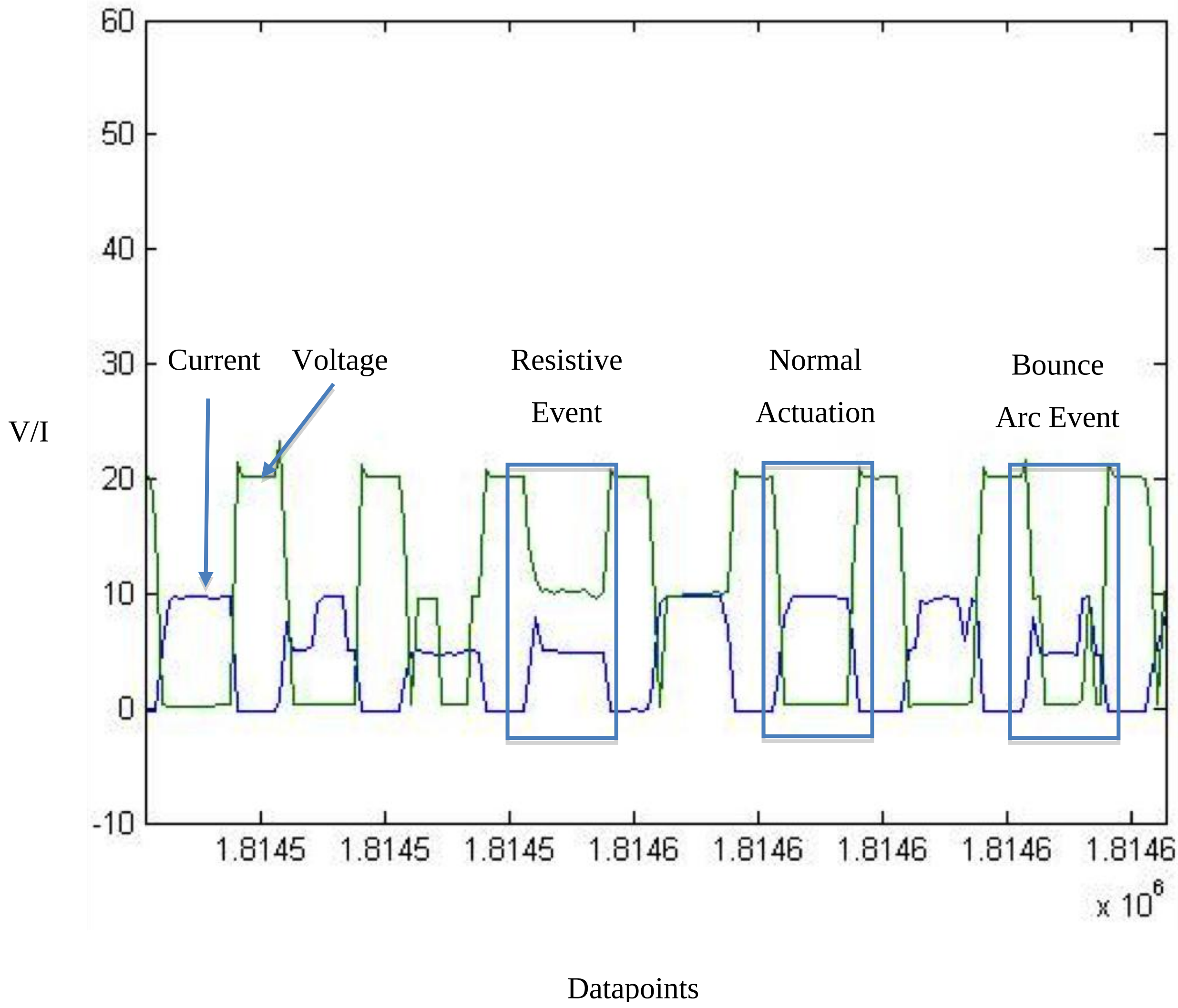


Figure 25: Actual Current/Voltage Data Showing Events

The changes in closing time are also worthy of note in the tests suffering from the erosion related failure. The moving time averaged (MTA) closing times of all relays that did not fail early due to material transfer showed a gradual increase in MTA closing time to a reasonably steady value of around 30-40ms range (greater accuracy is not easily obtained due to the discretisation caused by the 10ms sample period). In the relays that experienced erosion related failure the MTA closing times began to rise in spikes that coincide with the spikes in the mean resistance. This is likely to be due to the noted increase in bounce arcing activity and the increase in time taken to achieve a good connection between the two contacts increasing the amount of time for the voltage to drop below the 5V criterion set in the feature extraction algorithm for a 'closed' contact state to be recorded.

In the cases of the eroded relays the open times rose to the 50-60ms range and then remained there for the majority of the remaining test, with only a few increases above that level that were insufficient to trip the ‘unacceptable opening time’ condition.

The differential temperature dropped off in line with the resistance value, which is expected given that less energy is being dissipated in the case. However it then begins to rise with the increase in relay open time and the consequent increase in time that the relay is closed and sinking power. Finally the temperatures show sharp increases that coincide with the spikes in resistance value of the relay, suggesting that more power is being sunk into the relay and more energy is being released to heat the case.

It is our conclusion that the most relevant values captured that most accurately predict the state of the relay are the close times of the relay (averaged using a 100 point window MTA) and the average resistance value of the relay in the closed state.

Stuck Closed Failure

The relays that experienced a stuck closed failure failed extremely rapidly, each failing within 150 thousand cycles. Increasingly active break arcing, a consequent reduction in average open time and a sharp spike in case temperature characterize these failures. Two relays, both at the high end of the tested voltage range (28V and 30V) experienced failure in this manner.

Inspection of the relay surfaces using the interferometer testing and the SEM reveal a substantial pip and crater formation in these two relays. This correlates with the data obtained from the relay showing increasing arcing activity. The voltage across the relay is high enough to instantiate make and break arcing even early in the life of the relay, causing material transfer to the anode and building the pip. This creates a preferred point of arc impact due to the concentration of the electric field and means future material transfer is more likely to transfer to the pip. Jemas et al observed similar effects when testing various materials for 42V automotive relays [119]. They noted that at lower currents (including at 10A where our tests are operating) the transfer of material was anodic and also in the same direction for both make and break arcs, enhancing the flow of material between the two contacts and increasing build up on the anode. Our results suggest that this is also true for silver cadmium oxide contacts.

Another interesting feature that was observed in the elemental analysis of the relay was the composition of the pip. Mixed in with the expected silver cadmium mixture was a large amount of gold and nickel. The gold is the surfacing material applied to the contact while the nickel is used as an aid to bonding between the gold and the silver cadmium oxide. This composition implies that the formation of the pip is beginning from the very start of the erosion cycle, incorporating vaporised gold and nickel from the surfacing layer to create the initial pip, while further arcing into the primary AgCdO contact increases its bulk.

The most noticeable indicator that the relay is undergoing this type of failure are spikes in the opening time of the relay and associated increases in the average current across a cycle. Figure 26 and Figure 27 show the raw opening times for the 28V and 30V tests. The 30V tests shows incidences of arcing of varying lengths starting from 30k actuations, including moments where the actuation fails completely, as the arc persists for the entire 10ms duration of the open phase of the cycle. This arcing becomes more frequent and more severe over the course of the relay life until the relay fails completely, effectively carrying a current continuously. The 28V test shows significantly less sign of failure in opening times until it actually fails at 150 thousand cycles aside from some long opening time events at sporadic intervals. It does display a period of strong arcing at the start of the test. We also observed an unusual sound coming from the relay during this time period. It is not known precisely why the relay displayed this behaviour, as no other relays displayed arcing so early in their life. It is possible that the surface of the relay contact may have had pre-existing damage or contamination prior to testing which cleared after the arcing ablated the gold/nickel layer of the contact surface.

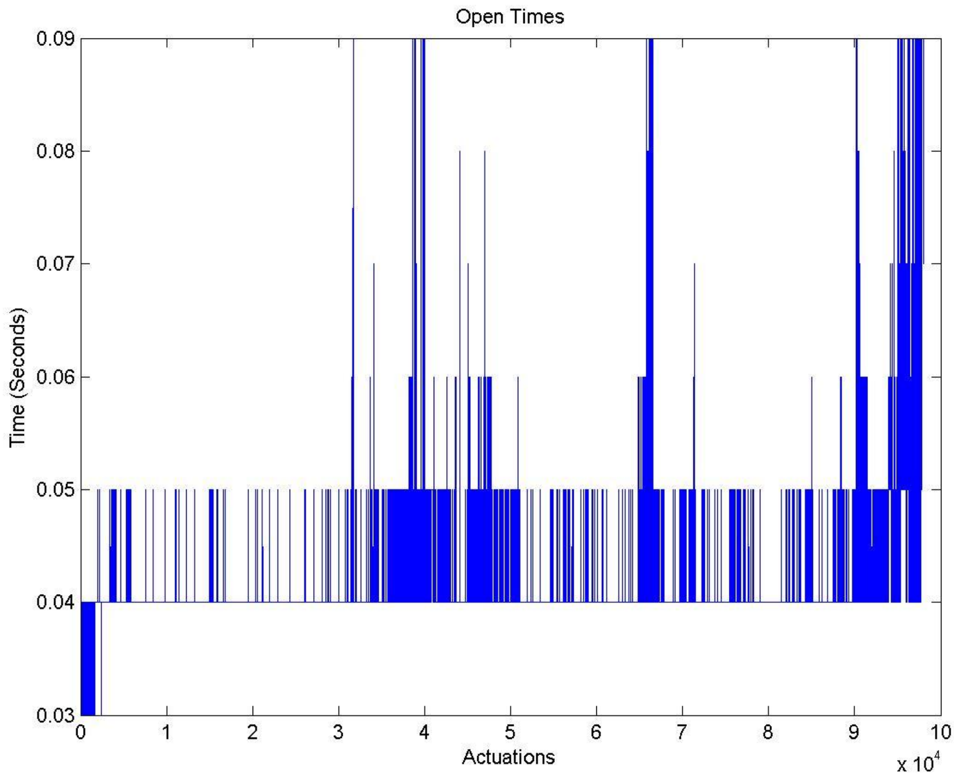


Figure 26: Raw opening times, 30V test

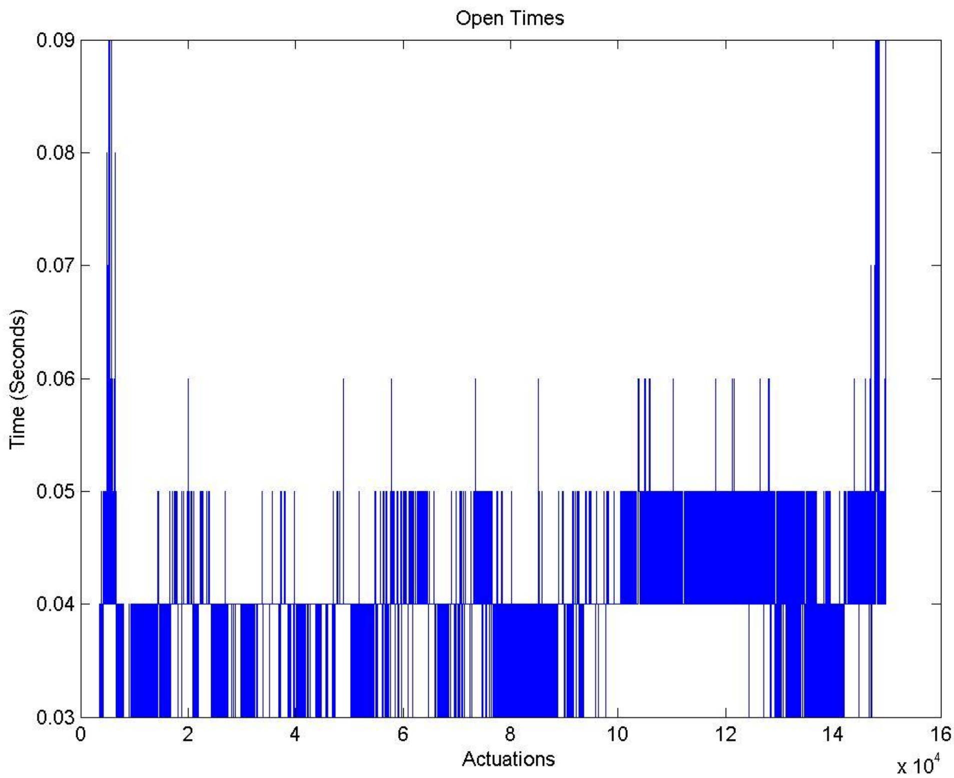


Figure 27: Raw opening times, 28V test

It is perhaps more constructive to look at the temperature readings in this case. Both sets of temperature differential graphs for the 28V and 30V tests show a substantially increased temperature (at least 5 degrees) over the tests that did not suffer from pip and crater failure. This is a good indicator of serious arcing occurring, however when the relay is in service the operation rate of the relay may not be sufficiently rapid to create noticeable rises in temperature. Certainly a high temperature would be a reasonable alarm signal for an operator to inspect and service the relay.

In conclusion this type of failure is detectable in advance as long as the relay displays the arcing characteristics detected in the 30V test. The opening times should be monitored for spikes in the raw opening times and overly high temperatures. More testing is required for this type of failure, however, in order to establish the precise statistical relationship between the spikes in opening time and the failure of the relay, as there are too few samples to be sure at this time.

Unacceptable Opening Time Failure

Several of the relays failed due to an eventual increase in opening time that exceeded the acceptable tolerances. These relays showed a gradual trend upward in opening time until eventually the average current exceeded the 30% tolerance set in the program (showing a 50% increase in opening time). These relays were still able to conduct current after a failure being indicated. Depending on the application this failure would be considered critical if the relay were being used in an application where response times were a major issue.

We believe that the source of this failure lies in two factors. The first is based on engineering insight from Barnbrook Systems. In their own testing they found that the spacer that lies between the magnetic coil and the armature plate was wearing down. This causes the armature to lie deeper in the magnetic field, and as such the coil voltage required to maintain a strong enough magnetic field to oppose the action of the return spring is decreased. This means that the length of time for the magnetic coil to demagnetize to the point where the armature is released increases and the opening time as a whole increases. This is a consistent degradation characteristic across every relay that was tested that lasted for more than several hundred thousand cycles. The relays experienced an increase from 30ms to 50ms between the start of operation and 1 million to 2 million cycles. This increase stabilized on several of the relays in the 50-60ms bin and continued to rise to failure in others.

The increase in opening time seen in the relays that did trigger this relay condition is hypothesised to be the result of contact welding at make. As the contacts come together they bounce and arc during the bounce. This arcing melts the contact material and causes the contacts to stick together. These contacts require force to allow them to release, and as such will increase the amount of time that the circuit will remain connected. We believe this to be consistent with our results, as this welding can clear while a mechanical failure cannot. For instance a weld could occur on three or four cycles, and then not occur again for several hundred, while a mechanical wear defect could not return to a 'normal' state. This can be seen in the 20V and 24V tests where the relay displayed short periods of >60ms opening time before returning to normal. Other relays experienced enough actuations with >60ms opening time to push the average current above the allowed value which we hypothesise is due to the degraded contact surface resulting in more welding.

An alternative hypothesis is that some of the relays have 'worse' spacers than the others, which degrade more before stabilizing and thus cause an increase in opening time, however we do not have the data to confirm this hypothesis one way or the other (more testing would be required). Based on the data that we have the relays remain stable for a long time before their opening times spike to >60ms compared to the rise to 50ms and as such it is thought that the welding hypothesis is more likely.

Predicting the mechanical wear should be relatively simple, as regression could be used to identify a trend in the opening time increase (assuming that the damage type follows a linear damage model such as miner's law). However the microwelding is harder to detect in advance, and only a condition warning would be able to be used that indicated the relay was showing opening time behaviour getting close to the slated failure time.

Chapter 7: Conclusions and Future Work

In conclusion this series of experiments aimed to prove that it is possible to identify relay contact failure precursors from low sample rate data related to a number of different possible failure mechanisms. We have shown that it is possible to detect signs of the impending failure of a contact due to erosion, consisting of resistance and closing time spikes using data captured at a low sample rate and using mathematical techniques that would be able to be implemented on an FPGA or microcontroller. These results also correlate well with results from previous research.

Stuck closed failures caused by material transfer were detected through the unusual spikes in opening times caused by arcing through the diminishing distance between anode and cathode. We have also identified a failure condition we believe is related to micro welding. This causes an unacceptable opening time failure of the relay within the constraints of the testing regime conducted.

With this in mind we believe it is very possible to extend this research into the development of a condition monitoring and prognostics system for the relays. Several challenges exist in this task.

Firstly, having identified the failure precursors within the relays, more sample datapoints must be obtained in order to obtain a statistical distribution of failure precursors across a large number of relays. We suggest that this be performed using parallel testing, testing multiple relays at once but modifying the testing equipment to extract the opening/closing times and average open/close resistance on capture rather than in post processing. This will cut down on the amount of data that needs to be stored (a significant issue that we found with the current testing equipment) and can act as an algorithm prototyping stage for eventual hardware implementation.

Secondly, the actual residual life algorithm must be developed. Within the data driven sphere of prognostics the statistical distributions of the precursors for each failure mechanism can be combined with the expected failure distributions to produce a hazard rate or failure probability which can be trended to a failure time. Alternatively, combination techniques such as using Mahalanobis distance to gage how far from normal the data points are, and then using predictive techniques such as Kalman filtering or Particle filtering to trend them to a probable failure time.

Given that the preparatory work done includes material analysis and a comprehensive FMMEA it would also be possible to develop a physics of failure model of the degradation of the contact, based on research performed into the amount of material transferred per cycle of the relay (knowing the voltage and current across the relay).

Thirdly, once an appropriate algorithm has been developed, appropriate hardware must be selected and the system partitioned appropriately. Given that these relays are frequently used in banks of multiple relays it would make sense to attempt to partition the system into two components. Firstly, a pre-processing system on a Field Programmable Gate Array (FPGA) or microcontroller, which extracts the features from each relay and prepares them in easily readable packets. Then a more powerful centrally based processor, which takes the data from these smaller motes over a wireless network, such as Bluetooth, and uses them to produce a remaining useful life estimate.

Examples of hardware that might be used are the Altera Cyclone V or Xilinx Spartan 6 FPGAs or a low power microcontroller such as a microchip PIC8 or PIC16 series MCU. Alternatively, for high criticality applications in areas with limited accessibility (such as in a power transmission substation) an entire SOC solution consisting of an FPGA and powerful ARM based processor such as the Xilinx Zync-7000. These are moderately low cost/low power devices that can operate as an entire combined and reconfigurable digital computer system with full integration between the system elements. Addition of a Solid State Drive (SSD) to the package would allow rapid capture of large quantities of data to an easily swappable backing storage device.

A theoretical system level diagram of such a system that the conducted research has informed is given in Figure 28.

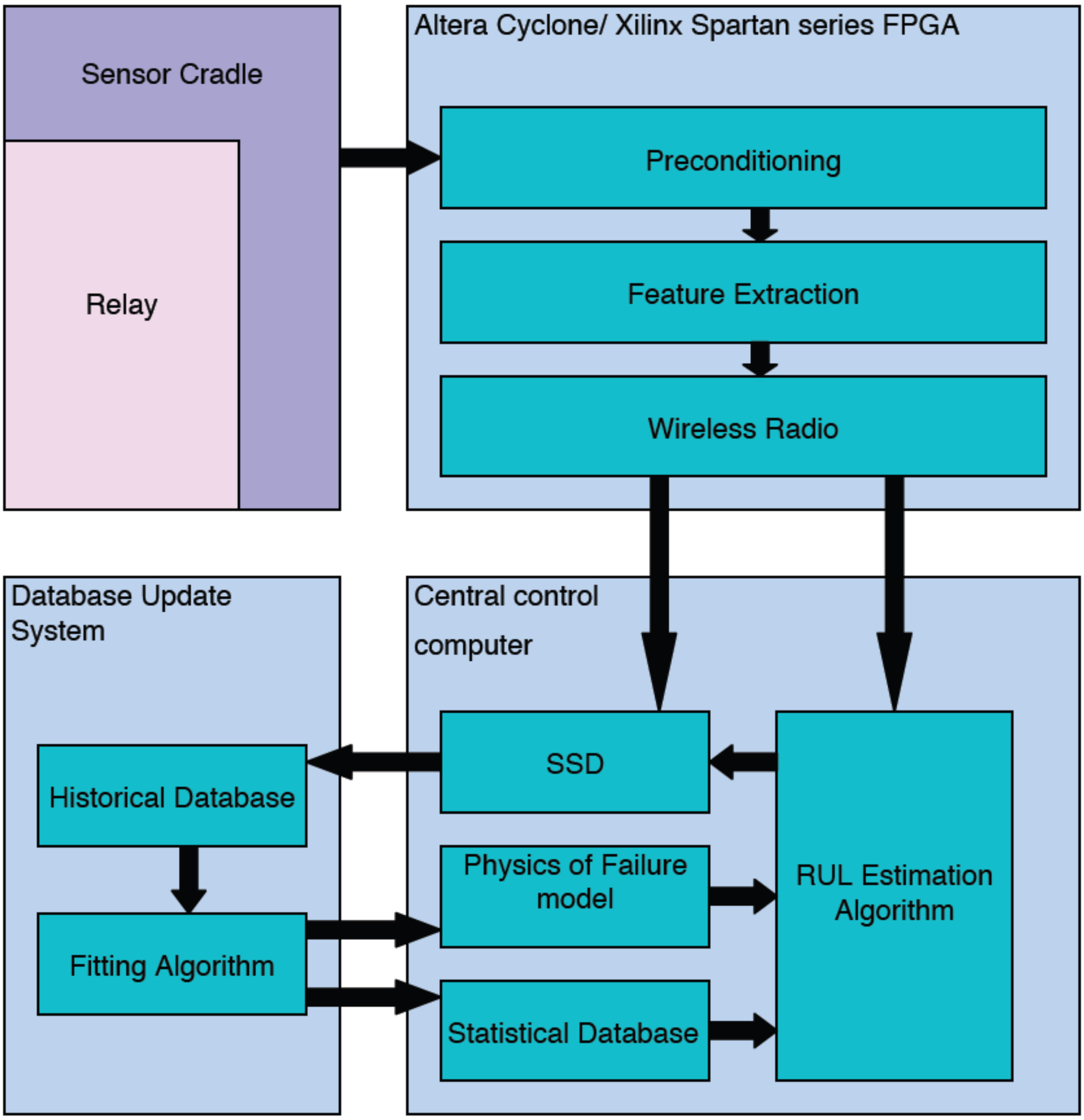


Figure 28: Theoretical prognostics system

In a much longer-term vision these small monitoring systems would be linked into a significantly larger asset management system that can make autonomous decisions as to the operation of the system, such as the ability to automatically schedule maintenance or to highlight issues to maintenance teams. There are issues with this, of course, particularly in terms of trust in automation in the industries concerned and the complexity of the decision-making system. Communication becomes a serious issue when dealing with monitoring systems in remote or hostile locations, especially when data rates are constricted. This requires intelligent partitioning of systems and a powerful central processing node that is able to process the information and then present it in a human-friendly manner to the system operators, who must be able to implicitly trust that the information is correct (through adequate study of and feedback of operator procedure).

Overall we believe that the aim of an integrated and adaptive asset management system is worth pursuing and that the techniques described in this document can be used to enable it.

List of Common Acronyms

ANN	Artificial Neural Network
CBM	Condition Based Maintenance
DECC	Department of Energy and Climate Change
DLR	Dynamic Line Rating
DoE	Design of Experiment
DPDT	Double-Pole Double-Throw
DUKES	Digest of UK Energy Statistics
EDX	Energy Dispersive X-Ray
FMMEA	Failure Mode Mechanism and Effect Analysis
FPGA	Field Programmable Gate Array
HMM	Hidden Markov Model
MISEC	Microsystems Engineering Centre
MoG	Mix of Gaussians
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
PD	Partial Discharge
PHM	Prognostics and Health Management
PoF	Physics of Failure
RUL	Remaining Useful Life
SEM	Scanning Electron Microscope
SOM	Self Organising Map
SPDT	Single-Pole Double-Throw
SPST	Single-Pole Single-Throw
SVM	Support Vector Machine
WEC	Wind Energy Converter
XPLE	Cross-linked Polyethelyne

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