Strathprints Institutional Repository

Rudd, Susan and Catterson, Victoria and Mcarthur, Stephen and Johnstone, Carl (2011) Circuit breaker prognostics using SF6 data. In: 2011 IEEE power and energy society general meeting. IEEE Power and Energy Society General Meeting PESGM . IEEE, New York, pp. 1-6. ISBN 9781457710018 , http://dx.doi.org/10.1109/PES.2011.6039599

This version is available at http://strathprints.strath.ac.uk/37466/

Circuit Breaker Prognostics Using SF$_6$ Data

S. E. Rudd, V. M. Catterson, *Member, IEEE,* S. D. J. McArthur, *Senior Member, IEEE*
and C. Johnstone

Abstract—**Control decisions within future energy networks may take account of the health and condition of network assets, pushing condition monitoring within the smart grid remit. In order to support maintenance decisions, this paper proposes a circuit breaker prognostic system, which ranks circuit breakers in order of maintenance priority. By monitoring the SF$_6$ density within a breaker, the system not only predicts the number of days to a critical level, but also incorporates uncertainty by giving upper and lower bounds on the prediction. This prognostic model, which performs linear regression, will be described in this paper, along with case studies demonstrating ranking breakers based on maintenance priority and prognosis of a leaking breaker. Providing an asset manager with this type of information could allow improved management of his/her assets, potentially deferring maintenance to a time when an outage is already scheduled.**

Index Terms—**Circuit breakers, Prognostics and health management, Condition monitoring, Maintenance.**

I. INTRODUCTION

PROGNOSTICS can be considered the ultimate aim of condition monitoring, giving a prediction of the future health and remaining life of an asset [1]. With accurate forecasting of degradation, maintenance can be planned in advance of failures, and potentially deferred to a prearranged outage.

Thus far, condition monitoring is mostly used for fault diagnosis and health monitoring. Moving from diagnosis to prognosis requires new models of fault progression, in order to assess not only the presence of faulty behavior, but also the trajectory of degradation. This will become more of an issue with smart grids, which are anticipated to have more monitoring and automated control than current networks. Control decisions may take account of plant health, while wider monitoring will produce more data for analysis. Data mining [2] will be a useful tool for uncovering previously unknown relationships between plant health and prognosis.

Circuit breakers are a prime example of an asset where prediction of future health can benefit maintenance planning. Circuit breakers are required to operate correctly in the presence of a fault, and maintenance is scheduled when it is estimated the breaker may fail to operate. Currently this is performed on a number-of-operations basis, but condition monitoring could be used to estimate the probability of correct operation. Maintenance can be scheduled when this probability falls too low.

Predicting future performance based on current condition requires a prognostic model of breaker health deterioration. To gain an insight into the circuit breakers condition, and potential prognosis, informative parameters must be monitored. One example of an online circuit breaker monitoring equipment is Alstom's CBWatch-2 [3], which constantly monitors a variety of measurements from the circuit breaker, including: opening and closing time of contacts; density of SF$_6$; arc duration and number of operations. This paper describes how data mining of CBWatch-2 data was used to build prognostic models for a number of a utility's SF$_6$ breaker fleet. The resulting models of degradation are integrated into a prognostic architecture, which ranks the breakers in order of maintenance need.

This paper will first highlight the authors' perspective of prognostics and how it is utilized in other fields. Section III will describe the various parameters used in condition monitoring of circuit breakers, highlighting key parameters that can be applied in both condition monitoring and prognostics. Section IV will discuss how these parameters can be employed to predict a critical SF$_6$ density level for a circuit breaker, with section V providing a substation case study of ranking the breakers based on maintenance priority. Section VI will demonstrate a case study of the prognosis for a leaking circuit breaker. The direction of future work will be outlined in section VII, and section VIII concludes the paper.

II. PROGNOSTICS

A prognostic system must be able to give a prognosis, or prediction, about the length of time before some event occurs. In the case of health monitoring, prognostic systems should give some information pertinent to maintenance timescales, such as remaining useful life (RUL), or time to failure (TTF).

Prognostic systems differ in purpose from diagnostic systems. A diagnostic system aims to identify the presence of a fault, and may do this by classifying the type of fault (using knowledge-based or data-driven heuristic classification), identifying the faulted component (using model-based diagnosis), or simply highlighting that plant behavior has deviated from normal (anomaly detection, another form of heuristic classification). In all cases, the diagnostic system is making a judgment about the current state of the plant under study, and deeming it to be healthy or unhealthy based on current data.

In contrast, a prognostic system makes a forecast about the future state of the plant under study, based on current data. It may build on a diagnostic system; for example, a new fault diagnosis may trigger a recalculation of RUL in the prognostic system. However, the clear distinction between diagnosis and

prognosis is that a prognosis includes a forecasted timescale of deterioration.

Outside of the power industry, prognostics research is ongoing in some domains that can be characterized as having an inability to perform maintenance until the end of a duty cycle. This includes aerospace and marine applications, where maintenance and replacement is limited to time on the ground or in dock [4][5][6]. This limitation means that prognostic prediction is essential for efficient maintenance practices, and accurate prediction of the probability of completing the next duty cycle is used for fleet planning.

Useful discussion of the potential benefits of prognostics for the power industry is dependent on clear definitions of the capabilities of different types of systems. One particular framework for classifying and discussing prognostic systems is that developed at the University of Tennessee [7]. This splits prognostic systems into three types, outlined below.

Type I systems are the most basic, and model failure statistics about groups of assets. Instead of predicting the RUL of any specific asset, type I systems use the average lifetime and distribution of failures to make predictions about how many assets within the population will experience a fault within a given timescale. A common way of doing this modeling is using the Weibull distribution [1].

Type II systems give a "stressor-based prediction" [1], which combine the average component lifetime of a type I model with information about the environmental conditions experienced by a given asset. A type II system takes account of the different ways an asset can be used. For example, some circuit breakers are exercised frequently for switching operations, whereas others are expected to operate only to clear faults, and may remain unexercised for years at a time. These different environmental factors can exert different stresses on the breaker - one experiences regular, low level wear while the other experiences infrequent, high levels of wear - and consequently, one particular model of breaker could fail at different rates depending on whether it is used primarily for switching or fault clearance.

The type II prognosis is still reliability-focused, making predictions about the rate of failure within a group of assets. However, the prediction is more tailored to a specific asset than a type I prognosis, by factoring in the hazards or shocks the asset experiences from the environment.

Type III systems take a further step, by incorporating condition data measured from the specific asset. While a type II model assumes a particular environmental shock will place a certain amount of wear on the asset, type III models explicitly measure the condition to determine how damaging the environment is. The condition-based type III prognostic systems can forecast the likely RUL of a specific asset under study, based on the reliability of the asset group and specific feedback about the plant's current health.

Broadly speaking, type I prognostic systems are the tools of the asset manager, who must budget for replacements and maintenance across a fleet within a given timescale. Type I systems can forecast how many within the group will need corrective maintenance, but cannot say which units will be affected. In order to forecast the maintenance required for one particular item of plant, type II or type III prognostic systems are needed. Type III systems are generally preferable, as they

are most informed about the current status of the asset. Type II and III systems are also the most difficult to implement, as they require knowledge of the relationship between plant condition, shocks, and future degradation.

III. CIRCUIT BREAKER MONITORING

The monitoring of circuit breakers has been recognized as beneficial due to the valuable role the breaker plays in protecting the circuit from short circuits and overloads [8]. The monitoring of circuit breakers is usually split into the monitoring of its separate components, for example, gas mixture; mechanical parts; switching; contacts and control circuits. Part A of this section will briefly touch on commercial products for the monitoring of parameters that could highlight the state of a circuit breaker. By examining these products, and the present literature in this area, part B discusses the key parameters that could potentially indicate problems in the circuit breaker.

A. Condition Monitoring Packages

A number of commercial products are available on the market to monitor a variety of parameters that depict the condition of the breaker. Examples of these include Hathaway's CBT 200/400 portable circuit breaker test kit [9] and BCM200/200E online breaker monitor [10], INCON's OPTImizer+® [11], Doble's TDR9000 [12], InuoSys Solutions Pte Ltd's BSM1000 [13] and Alstom's CBWatch-2 modular circuit breaker monitoring system [3]. The parameters that are generic to most units include:

- Mechanism:
  - o Opening contact times of the mechanism.
  - o Closing contact times of the mechanism.
- Gas:
  - o Temperature of SF_6.
  - o Pressure of SF_6.
- Main contact wear:
  - o Arc duration.
  - o I^2t.

It should be noted that software and/or alarms are often associated with these commercial products, informing the engineer if certain issues arise. Most of the commercial products shown above are only concerned with diagnostic capabilities, where parameters are measured to indicate the present condition of the circuit breaker and invoke alarms if it diverges from the expected. However, the CBWatch-2 system has a software counterpart that provides a diagnosis of the circuit breaker faults and also utilizes the SF_6 data to inform a RUL timescale. The system described in this paper is concerned with prognostics and differs from the CBWatch-2's prognosis by not only providing a time to critical level and ranking the circuit breakers based on this prognosis, but also by indicating boundaries of upper and lower limits of the prediction. Furthermore, it is intended to form part of a combination of useful parameters in an overall prognostic architecture.

B. Useful Parameters

Research regarding automated analysis of circuit breakers has been conducted since 1969 [14] to optimise maintenance and improve safety of personnel and the environment. The general consensus of a literature review performed by the authors revealed that a combination of parameters should be utilized to indicate the health of the breakers [15][16][17], with the IEEE C37.10.1 guide [8] offering a variety of ways to measure these parameters. The main focus of the literature is that the opening and closing times, the SF_6 pressure and I^2t are useful parameters that indicate mechanical wear, SF_6 leakage and interrupter erosion, respectively. These parameters were also highlighted from the commercial products in part A.

Since an indication of the overall health of a circuit breaker is dependent on a union of monitoring techniques, the aim is to create a prognostic architecture that ranks circuit breaker condition using a combination of all these useful parameters. However, for this paper, we focus in detail on the SF_6 data and the creation of a prognostic module for SF_6. Further work will expand this architecture to incorporate other parameters for an improved prognosis.

The density of SF_6 within a circuit breaker is important to ensure the correct operation of arc extinguishing. Cigre reported that 40% of minor faults and 7% of major faults are as a result of gas leakages in SF_6 circuit breakers [18]. These leakages could not only have an impact on the arc extinguishment, restricting the potential of the asset, but also have environmental impacts. For these reasons, data mining techniques [2] were utilized during this research on CBWatch-2 recorded SF_6 data for condition monitoring and prognostic purposes.

IV. PROGNOSTICS USING SF_6 DATA

Examining the SF_6 density level of a circuit breaker provides an insight into the condition of the asset. If a circuit breaker has an SF_6 density below a certain level the circuit breaker may not be able to extinguish an arc, and will therefore require maintenance in the form of a top up of SF_6. This paper proposes a method to project this condition monitoring data to predict a time when a circuit breaker may reach such a level, known as lockout, based on its past and present SF_6 levels. This information would provide the asset manager with prior warning of a critical level of SF_6 density, allowing the safe delay of maintenance to a planned outage, removing perhaps unnecessary outages.

SF_6 density data from the CBWatch-2 commercial product was used in this research from 3 substations of 9, 12 and 15 circuit breakers, from 2002 to 2007. Each day, at midnight, the density of SF_6 in each circuit breaker was recorded, along with a timestamp, the ambient temperature and the current in pole A. Samples were taken at midnight to remove external parameters, such as the sun's rays, which could have an effect on the density of SF_6.

The overall aim of the prognostic system was to provide the asset manager with a list of circuit breakers in each substation ranked by their maintenance priority. This ranked list would highlight the number of days to lockout, along with an uncertainty providing upper and lower limits of this predicted time frame. Before such a system could be created, data mining was employed to identify if a relationship existed when sampling the SF_6 density.

Plotting all the available data on a scatter plot of sample day versus SF_6 density highlighted a linear relationship between the two parameters during a leakage of SF_6. Fig. 1. shows an example of the linear relationship for a subset of the data, where the subset was taken from between two presumed top-ups. From this discovery linear regression [19] was used to predict the day (plus or minus the uncertainty) when the SF_6 density would reach a lockout limit.
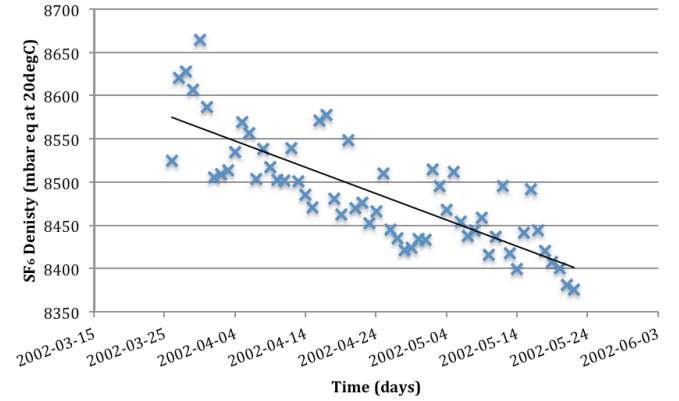

Fig. 1. Linear Regression of SF_6 Density

Using the data in Fig. 1, the calculated linear regression equation can be seen in (1).

$$y = 8577.6 - 3.0412\,x \qquad (1)$$

Rearranging (1) allows the number of days (x) to be calculated when an assumed lockout limit (y) of ≈ 8200 mbar occurs. This can be seen in (2), where it is predicted that the lockout limit will be reached on day 126. Assuming 24/05/02 (the final sample day) is today and knowing that there are 58 samples in the dataset, the number of days from today to a lockout is 68 days i.e. 126-58.

$$x = \frac{8577.6 - 8194}{3.0412} = 126 \qquad (2)$$

Since the SF_6 density fluctuates between sample reading, it is beneficial to calculate the uncertainty; displaying an upper and lower limit of the number of days to lockout. Two approaches were examined to provide this information. The first involved calculating the standard deviation (sd) of the density and plotting new functions from the data based on the equation $y = mx + c \pm sd$. By taking the data in Fig.1, these boundaries can be seen in Fig. 2, where the standard deviation in y is 60.36. Calculating the number of days until lockout from the final sample results in 68 ± 21 days.
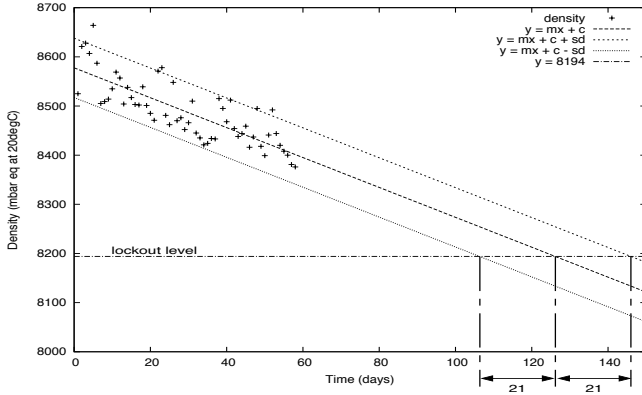
Fig. 2. Projecting the density leakage to predict when a lockout level will be reached, providing upper and lower bounds on prediction based on the standard deviation of the density.

An alternative approach to uncertainty was performed taking into consideration the uncertainty of the slope and the uncertainty of the y-intercept. Equations to calculate these were taken from [19] and can be seen in (3) and (4) respectively.

$$(\Delta m)^2 \approx \frac{1}{\sum(x_i - \bar{x})^2} * \frac{\sum(y_i - mx_i - c)^2}{n - 2} \qquad (3)$$

$$(\Delta c)^2 \approx \left(\frac{1}{n} + \frac{\bar{x}^2}{\sum(x_i - \bar{x})^2}\right) * \frac{\sum(y_i - mx_i - c)^2}{n - 2} \qquad (4)$$

where $\bar{x}$ is the mean of x, n is the number of samples, m is the gradient of the slope and c is the intercept of y.

From (3) and (4) new lines can be drawn providing the upper and lower bounds based on uncertainty. The equations of these lines can be seen in (5) and (6) respectively. These alternative boundaries can be seen in Fig.3. From these bounds the time to lockout from the final sample is 68 + 10 or 68 − 8 days.

$$\text{upperbound} = \frac{y - (c - \Delta c)}{m + \Delta m} \qquad (5)$$

$$\text{lowerbound} = \frac{y - (c + \Delta c)}{m - \Delta m} \qquad (6)$$
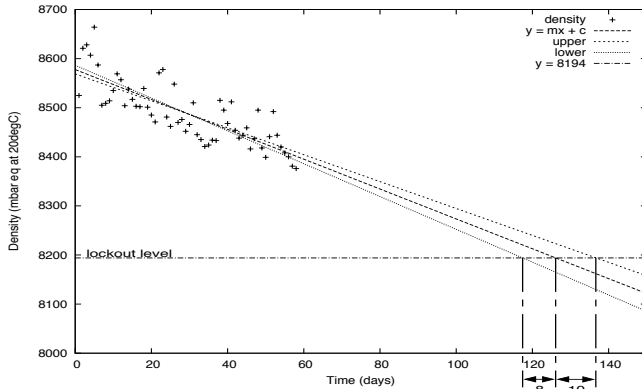
where y = lockout value.

Fig. 3. Projecting the density leakage to predict when a lockout level will be reached, providing upper and lower bounds on prediction based on the uncertainty of the slope and the y-intercept.

Further examination of the data revealed that the time of year had an effect on the recorded density of SF_6, with higher density corresponding to higher summer temperatures. Clearly this is an artifact of the measurement process, as the density of gas in the sealed container cannot increase unless it is refilled, and these slight summer increases are not due to refilling.

The recorded density is calculated within the CBWatch-2 monitoring system from measurements of temperature and pressure, using the Beattie-Bridgeman equation [20]. This equation links pressure, temperature, and density with five empirical parameters tuned to the gas in question. The Beattie-Bridgeman equation is one of a number of real gas equations of state, which are more accurate than the ideal gas equation of state given certain conditions (such as within a given range of pressures).

However, the seasonal fluctuations in recorded SF_6 density indicate that inaccuracies exist with this approach. Equations of state assume steady-state conditions for temperature, pressure, density, etc., whereas the presence of a leak would invalidate that assumption.

An alternative real gas equation of state, the virial equation, links pressure and temperature with empirical parameters, removing the need for density calculation. The empirical virial parameters for SF_6 are available from the literature [21][22]. Using measurements of ambient temperature, the virial equation can be used to calculate pressure residuals; that is, the difference between the expected pressure for a given temperature, and the measured pressure. The linear regression can then be applied on the resultant residual to project for a prognosis, as described previously.

V. SUBSTATION CASE STUDY

The overall aim of the prognostic system, described in this paper, is to rank the circuit breakers at a substation based on their maintenance priority, in order to allow the scheduling of maintenance to when an outage is already planned. This section will demonstrate the output of the created system by using data from a subset of the aforementioned datasets. The input to the system examines 11 circuit breakers in 1 substation from 13/05/07 to 20/08/07. For each circuit breaker the system performs linear regression and ranks the circuit breakers based on their predicted number of days to lockout, assumed to be $\approx$ 8200 mbar. Uncertainty, giving upper and lower bounds, calculated by the two methods shown in section IV are also included in the output. The linear regression and the ranking can be performed every n days, where n is predefined by the engineer. Table 1 shows an example of the output after the first 50 days of data.

The data used in this example was composed of circuit breakers with relatively stable levels of SF_6. Fig. 4 shows an example of a circuit breaker's dataset, with the other datasets showing similar distributions. As seen in Fig. 4, the data could be described as relatively stable with a slight decrease in density, as well as large fluctuations between samples. It is thought that this slight decrease in SF_6 might be the resultant of a small leak.

TABLE 1
RANKED OUTPUT OF CIRCUIT BREAKERS FOR MAINTANENCE PRIORITY

Order of Maintenance	Circuit Breaker	Number of days until lockout from last sample (x)	Bounds based on standard deviation of density	Bounds based on uncertainty of slope and y-intercept	
				Lower	Upper
1.	X505	336 days	x ± 49 days	x - 115 days	x + 319 days
2.	X205	733 days	x ± 55 days	x - 263 days	x + 867 days
3.	X130	760 days	x ± 79 days	x - 343 days	x + 2741 days
4.	X705	1114 days	x ± 83 days	x - 510 days	x + 4920 days
5.	X330	1317 days	x ± 69 days	x - 539 days	x + 2750 days
6.	X105	1550 days	x ± 89 days	x - 734 days	x +10828 days
7.	X305	1860 days	x ± 167 days	x - 1174 days	N/A
8.	X905	2575 days	x ± 140 days	x -1508 days	N/A
9.	X605	2640 days	x ± 139 days	x - 1541 days	N/A
10.	X405	4624 days	x ± 208 days	x - 3131 days	N/A
11.	X610	No leak, the regression slope is positive			

As seen in Table 1, there are a few circuit breakers that have N/A beside their upper bound calculated from the uncertainty in slope and y-intercept. This is due to the calculated uncertainty of the slope being greater than 100%, meaning that the slope would now be positive and the density increasing. This should not be the case since no refill has occurred and therefore is suggestive that no leak exists.

Table 1 also shows one circuit breaker where no predicted lockout time is calculated, X610. This is due to a positive slope being calculated during linear regression for this circuit breaker, meaning that the recorded density during this sample period is increasing. This also indicates that no leak is present. It should be noted that a positive slope is not expected in relation to the density's behavior and in this case it must be due to measurement error or as an effect from the ambient temperature.
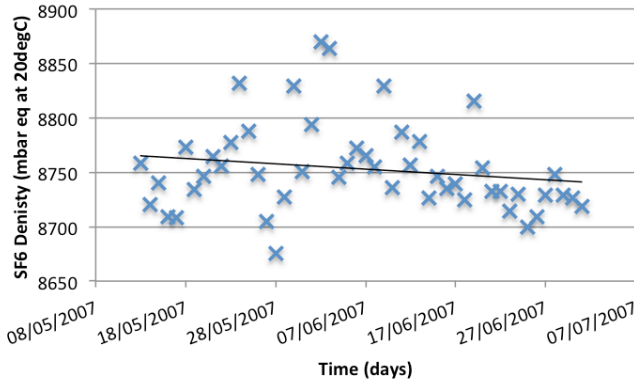

Fig. 4. 50 days of SF$_6$ density data for circuit breaker X705.

VI. CIRCUIT BREAKER CASE STUDY

This case study will demonstrate the output of the prognostic system using data from a circuit breaker that is definitely leaking SF$_6$. Taking the dataset from Fig.1, the SF$_6$ module performed linear regression on the data every 20 days. It should be noted that this is a moving window of 20 days across the dataset, meaning that 3 subsets of the data are examined individually:

    1.   From 1 to 20 days
    2.   From 21 to 40 days
    3.   From 41 to 58 days.

The length of time in this window is always a trade off between a quick and accurate prognosis. This number was investigated by performing prognosis with varying sample sizes. 20 days was found to be amongst the quickest and most accurate results. However, the prototype allows the moving window number, as well as the sample size of the data, to be easily changed if a more accurate solution is discovered with further research.

The results of this examination can be seen in Table 2. The reason for the change in the predicted time to failure across the subsets is due to the greater variance of samples in the second subset. Taking into account the temperature effects in further research should reduce this variation.

TABLE 2
PROGNOSIS OF CIRCUIT BREAKER

Day	Number of days until lockout from last sample (x)	Bounds based on standard deviation of density	Bounds based on uncertainty of slope and y-intercept	
			Lower	Upper
20	52 days	x ± 8 days	x - 13 days	x + 22 days
40	68 days	x ± 12 days	x - 23 days	x + 62 days
60	44 days	x ± 8 days	x - 17 days	x + 10 days

Comparing the bounds in Table 2 with the bounds in Table 1, a lower standard deviation and uncertainty in the slope is present when there is a leakage. This means that when a leakage occurs there appears to be less fluctuation between samples/days and fewer outliers, creating a narrower range of predicted time to critical level. An open research question that arises from the results in Table 2 and also Table 1 is which uncertainty method should be used when trying to predict an accurate time to failure.

VII. FUTURE WORK

The SF$_6$ module described in this paper is intended to form part of an overall prognostic architecture for the ranking of circuit breakers based on maintenance priority. Fig. 5 shows the proposed architecture of this system, highlighting a combination of modules that have the potential to provide an enhanced insight into the condition and prognosis of a circuit breaker. Further work will focus on the creation of these additional modules, along with their corroboration, to provide a ranked list of maintenance priorities.
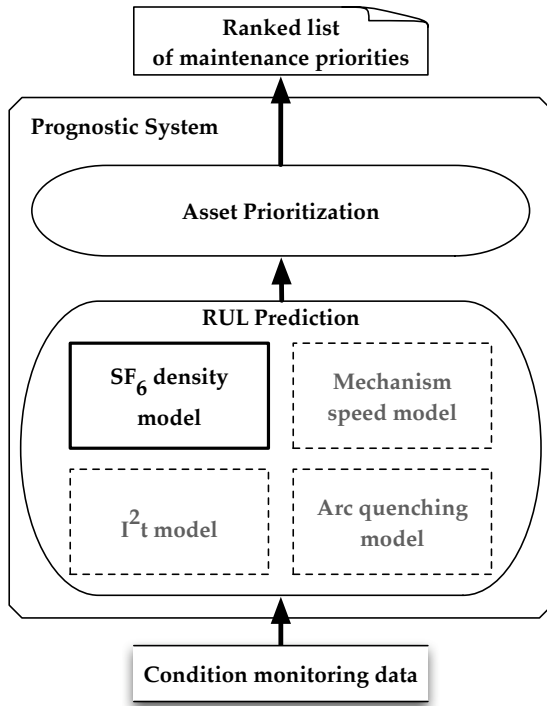
Fig. 5. Prognostic system architecture

VIII. Conclusions

This paper has described how condition monitoring data can be used in a prognostic system to rank circuit breakers for maintenance priority based on their recorded SF_6 density. During data mining, a linear relationship between SF_6 density and time (days) was exposed when examining the leakage of SF_6. This led to using linear regression as a basis for prognostics, predicting the number of days when the SF_6 density within a breaker would reach a critical level, known as lockout.

In order to provide the asset manager with upper and lower bounds around the anticipated lockout time, the uncertainty of the predicted time was investigated through two different methods. First, by examining the standard deviation of the SF_6 density in a dataset, upper and lower bounds of a predicted day could be calculated. Second, the uncertainty of the slope and the uncertainty of the y-intercept in the linear regression equation were determined, and utilized, to predict alternative boundaries of the number of days to the critical level.

The paper then provided a case study of the prognostic system using a dataset from a substation. Here the circuit breakers were ranked in order of their maintenance priority. Finally, a further case study was examined using data from a leaking circuit breaker, identifying a lower standard deviation and uncertainty in the slope when a leakage occurs. Providing the output displayed in these case studies to an asset manager could assist their maintenance decisions, potentially deferring maintenance of the circuit breaker safely to a time that was already planned.

IX. Acknowledgment

X. References

[1] J. B. Coble, "Merging Data Sources to Predict Remaining Useful Life, An Automated Method to Identify Prognostic Parameters", University of Tennessee PhD Dissertation, 2010.

[2] A.J. McGrail, E. Gulski, E.R.S. Groot, D. Allan, D. Birtwhistle, T.R. Blackbum, "Data mining techniques to assess the condition of high'voltage electrical plant", Cigre Paris, WG15.11 paper, 2002.

[3] CBWatch-2 Modular Circuit Breaker Monitoring System Manual. Available: http://85.91.240.105/netprint/PDFfinal/areva/savefile.asp?file=31617_Products-L3-CBWatch2-70649-V1-EN___loRes.pdf

[4] F. Peysson, M. Ouladsine, R. Outbib, J.-B. Leger, O. Myx, C. Allemand, "A Generic Prognostic Methodology Using Damage Trajectory Models", IEEE Trans. Reliability, vol. 58, no. 2, pp 277-285, June 2009.

[5] N. Gebraeel, J. Pan, "Prognostic Degradation Models for Computing and Updating Residual Life Distributions in a Time-Varying Environment", IEEE Trans. Reliability, vol. 57, no. 4, pp 539-550, December 2008.

[6] V. A. Skormin, V. I. Gorodetski, L. J. Popyack, "Data Mining Technology for Failure Prognostic of Avionics", IEEE Trans. Aerospace and Electronic Systems, vol. 38, no. 2, pp 388-403, April 2002.

[7] J. B. Coble and J. W. Hines, "Prognostic Algorithm Categorization with PHM Challenge Application", 2008 Int. Conf. on Prognostics and Health Management.

[8] *IEEE Guide for Selection of Monitoring Circuit Breakers*, IEEE Std. C37.10.1-1995, March 2001.

[9] CBT 200/400 Portable Circuit Breaker Test Kits Manual. Available: http://qualitrolcorp.thomasnet.com/compare/breaker-condition-monitors/hathaway-cbt-200-400-breaker-condition-monitor?&forward=1&itemids=1169+1170+

[10] BCM 200/200E On-line Breaker Condition Monitors Manual. Available: http://qualitrolcorp.thomasnet.com/item/breaker-condition-monitors/hathaway-bcm-200-200e-breaker-condition-monitor/bcm200?&forward=1

[11] OPTImizer+® Circuit Breaker Wear and Condition Monitor Manual. Available: http://www.franklinfueling.com/products/prs/op1.asp

[12] TDR9000 Circuit Breaker Test System Manual. Available: http://www.doble.com/products/tdr9000.html

[13] On-line Circuit Breaker Condition Monitor BMS1000 Manual. Available: http://inuosys.com/pdfs/Inuo-BMS.pdf

[14] Dy Liacco, T.E.; Kraynak, T.J., "Processing by Logic Programming of Circuit-Breaker and Protective-Relaying Information," *IEEE Transactions on Power Apparatus and Systems,* vol. PAS-88, no. 2, pp.171-175, Feb. 1969.

[15] Nelson, J.H., "Electric utility considerations for circuit breaker monitoring," *Transmission and Distribution Conference and Exposition, 2001 IEEE/PES* , vol.2, pp.1094-1097, 2001.

[16] Mladen Kezunovic, "Monitoring of Power System Topology in Real-Time," *Hawaii International Conference on System Sciences*, vol. 10, pp. 244b, Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06) Track 10, 2006.

[17] Sweetser, C.; Bergman, W.J.; Montillet, G.; Mannarino, A.; O'Donnell, E.J.; Long, R.W.; Nelson, J.; Gavazza, R.; Jackson, R., "Strategies for selecting monitoring of circuit breakers," *IEEE Transactions on Power Delivery*, vol.17, no.3, pp.742-746, July 2002.

[18] A. L. Janssen, W. Degen, C. Heising, H. Bruvik, E. Colombo, W. Lanz, P. Fletscher, G. Sanchis, "Final Report of the Second International Enquiry on High Voltage Circuit Breakers Failures and Defects in Service" (Working Group SC 13.06), 1994.

[19] G. L. Squires, *Practical Physics, Fourth Edition,* University Press, Cambridge, UK, 2001.

[20] Ch. Baudart, Y. Brassod, "CBWatch-2 Modular System User's Manual", Alstom, 2002.

[21] W. H. Mears, E. Rosenthal, J. V. Sinka, "Physical Properties and Virial Coefficients of Sulfur Hexafluoride" *Journal of Physical Chemistry, 73(7)*, pp 2254-2261, July 1969.

[22] J. J. Hurly, D. R. Defibaugh and M. R. Moldover, "Thermodynamic Properties of Sulfur Hexafluoride", *International Journal of Thermophysics*, vol. 21, no. 3, 2000.