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A Gaussian Process based Fleet Lifetime Predictor Model for Unmonitored Power Network Assets

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***Abstract*—This paper proposes the use of Gaussian Process Regression to automatically identify relevant predictor variables in a formulation of a remaining useful life model for unmonitored, low value power network assets. Reclosers are used as a proxy for evaluating the efficacy of this method. Distribution network reclosers are typically high-volume assets without on-line monitoring, leading to an insufficient understanding of which factors drive their failures. The ubiquity of reclosers, and their lack of monitoring, prevents the tracking of their individual remaining life, and, confirms their use in validating the proposed process. As an alternative to monitoring, periodic inspection data is used to evaluate asset risk level, which is then used in a predictive model of remaining useful life. Inspection data is often variable in quality with a number of features missing from records. Accordingly, missing inputs are imputed by the proposed process using samples drawn from an advanced form of joint distribution learned from test records and reduced to its conditional form. This work is validated on operational data provided by a regional distribution network operator, but conceptually is applicable to unmonitored fleets of assets of any power network.**

***Index Terms*—Remaining Useful Lifetime, Asset Fleet, Gaussian Process, Non-Stationary Lifetime Modes**

I. Introduction

As low carbon technologies (LCT) continue to be embedded in electricity distribution networks, their operating complexity is increasing beyond their original design specification with new fault types emerging. Automation equipment such as reclosers can protect network assets from the consequences of failures but at the expense of additional complexity brought about by remote monitoring and communications. Observability of existing assets on power distribution networks is low, which can result in their true condition being obscured. New automation assets are no exception: distribution networks are extensive, with many thousands of low value assets installed, making condition monitoring financially unviable. However, the condition of these assets still needs to be understood from a fleet management perspective – questions around annual replacements, regional replacements and asset family lifetimes can only be informed by data but aside from routine testing, this is not economic to obtain at regular intervals.

A solution is to harness routinely collected maintenance data as the predictors for a lifetime model. However, using test data for this in the conventional sense [1][2] has challenges: 1) many recorded parameters are incomplete due to the complexity and economics of operational practice. Therefore, a model must be capable of working on partial input data. 2) Assets are not homogenous and may work under differing operating and environmental conditions; differences such as brand, location, frequency of use and weather condition, vary widely even for the same type of asset. This can result in different lifetime failure modes, and the need to identify these modes. Previous research has investigated multiple failure modes of assets [1]; however, regular monitoring was undertaken in this instance. 3) The parameter recordings are not obtained at a regular interval, and testing is apparently randomly scheduled, or at least scheduled according to maintenance resource availability.

In [3] the maintenance procedures of low value distribution circuit breakers were used to inform utility wide fleet health metrics by building probability densities of test data and relating the resulting performance modes to known failure mechanisms. In [4] it was also identified that accommodating multiple failure modes was essential, not for the diagnosis of faults but capturing the aging processes that are underneath them. In [5] an implicit metric based on continuous vibration data is used to evaluate the Remaining Useful Life (RUL) of a rotating machine which addresses dynamic lifetime problem due to non-steady state duty cycle. [6] uses a Weibull Mixture proportional hazard model to calculate the failure time probability density of each failure mode. This model assumes each failure mode has the same form of distribution but different parameterization, which is influenced by condition. Monitoring data and lifetime data are used to estimate distribution parameters (each failure mode is modelled as a product of the baseline hazard rate and deduced from the lifetime distribution and the covariate function), then if the cumulative value is over a threshold, the component is assumed to have failed. In [7] a range of power system equipment

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Figure 1: Actuating components on a three phase pole mounted auto-recloser.

inspection data are used to predict the failure rate, which resolve the bias from the conventional average reliability model in an economical way; a follow on study [7] [8] developed a condition assessment method for reclosers with condition data. Additionally, conventional lifetime estimation for low-value assets normally consider physics based models, such as [9] [10], which are impractical for large asset fleets. However, none of these worked on end-life anticipation with raw periodic inspection data, typically the only data available on such assets, and consequently did not have to address the problem of missing test values.

For power distribution networks, this paper proposes a novel analytic approach to manage fleets of unmonitored, low value assets, with reclosers used as proxy asset for method validation, using periodic inspection data rather than an online condition monitoring system [11]; in particular, the contribution includes: A RUL estimator for pole mounted reclosers based on annual inspection data. This accommodates multiple lifetime modes identified within a fleet of recloser assets which rules out the use of conventional lifetime distributions. A Gaussian Process Regression model with an Automatic Relevance Determination kernel is proposed as the predictive model which automatically selects predictor inputs from maintenance data and provides an RUL confidence level which can be used to rank assets within a fleet according to risk. The model is validated on archived recloser data gathered in the field.

This paper is organized as follows: the next section gives an overview of recloser assets used in power distribution networks, how these work and the consequence to operators if they perform sub-optimally. Following this, the data accrued during routine maintenance operation is described along with the challenges it presents to lifetime estimation models. The key barriers are multi-modal lifetimes, which motivates the need for the next section to cover the application of mixture models to lifetime distributions. The paper concludes with a reflection on how the contributed technique and models like it are essential for unmonitored assets on extensive regional power infrastructure.

II. Automated Reclosers

Reclosers are widely used in distribution networks which are designed to interrupt transient fault currents until they pass, then automatically reconnect their associated circuit. On a three-phase circuit there will be three sets of contacts within the recloser which can interrupt a fault current on any one of the phases. Figure 1 shows a typical three-phase recloser. Reclosers are often used in rural areas, which are served by overhead line (OHL) circuits which means that recloser units can be situated on a pole in series with the conductors [12]. The complete recloser installed on an OHL circuit is shown in Figure 2, which also shows the remaining components of the recloser mounted in a box mid-way up the pole the recloser is installed on. This contains a battery to power the recloser actuation mechanism that opens and closes the contacts, and the control circuitry for initiating trip and close operations.

A. General recloser operation

Reclosers serve two purposes: to allow current to pass under normal operation and to isolate current under fault conditions. This means that both their conductivity and insulation properties must be assessed as well as the assets ability to make the transition from conductor to isolator. Figure 3 shows the operation sequence of a typical recloser aligning the control signals with the behavior of the circuit current: recloser would be activated when the line current exceeds a preset threshold for

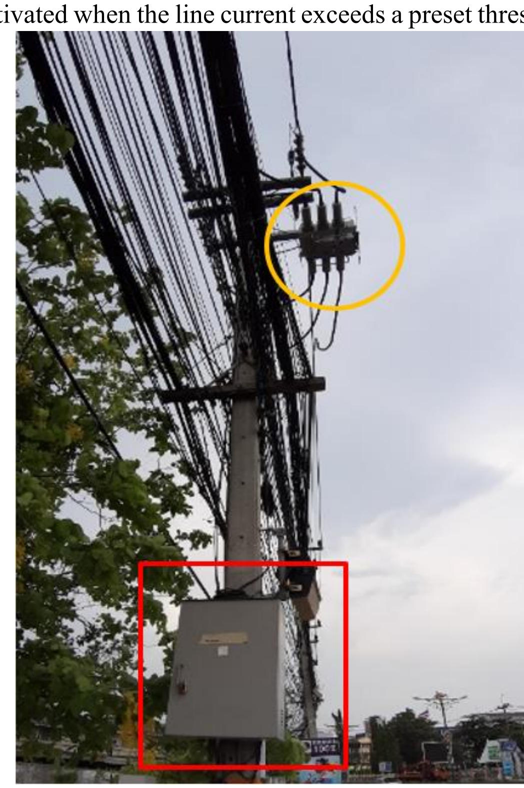

Figure 2: Three-phase pole mounted auto-recloser in situ. Highlighted are the recloser contact unit (upper) and the auxiliary components including the control circuit.

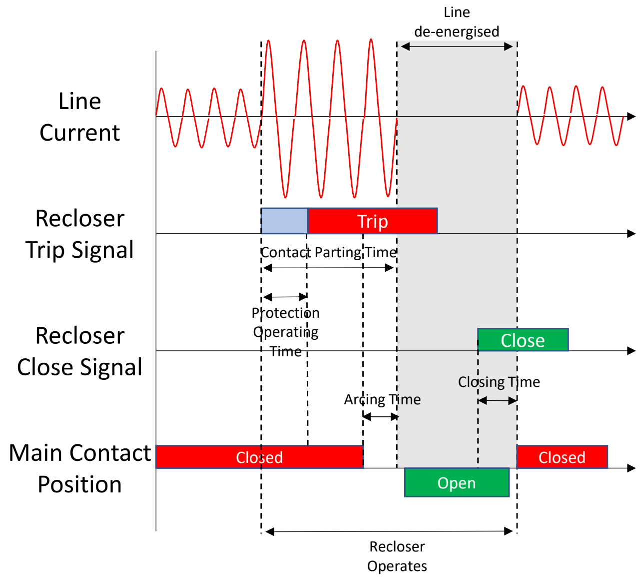

Figure 3: Simplified recloser operating sequence adapted from [13].

a short period – this may be invoked by an equipment fault, tree contact with an overhead line or a line-to-ground fault caused by an insulation failure; then the contacts will be opened, and the arcing will be extinguished. When the fault is cleared, the contact would be re-closed resulting in the associated circuit being re-energized. One feature of recloser operation is that if the fault has not passed, the contacts will reopen in an attempt to clear the fault again. After a set number of open operations within a given time period, the recloser will lock-out and require a manual reset on the basis that the fault experienced was not of a transient nature.

The recloser performance during these operations is dependent on the condition of a number of the subcomponents of the asset, such as controller and main switching device, meaning that failure modes can take a variety of forms. Consequently, tests carried out under routine maintenance are wide ranging in their scope.

B. Typical data resulting from recloser maintenance

For many utilities, the common test data gathered on reclosers includes contact resistance, insulation resistance, counter, timing test, failure reason and failure time [13]. These tests are elaborated upon in Table I. The number of recloser operations (or counts), and the times with which they take to execute are also carried out. As a matter of operational course, failure information and general observations tend to be recorded alongside these and provide useful context including failure reason, failure time, installation time and the manufacturer and model name.

TABLE I
PERIODIC INSPECTION DATA

PARAMETER	DEFINITION
Contact Resistance	The test is used to measure the voltage drop/resistance across the terminals of each pole
Insulation Resistance	The resistance to current leakage through and over the surface of the insulation material surrounding a conductor
Counter	Counter recording the trips since commissioning
Timing test	Times for contacts to open (trip tests) and close (close tests).
Failure reason	The cause(s) of the recloser failure
Failure time	The time and date of the recloser failure

III. RECLOSER LIFETIME PREDICTION WITH INCOMPLETE DATA

There are several facets to the problem of managing low value unmonitored power assets. This section identifies a means of addressing each of these in order to obtain a predictive model of individual asset lifetime that is economic and accurate.

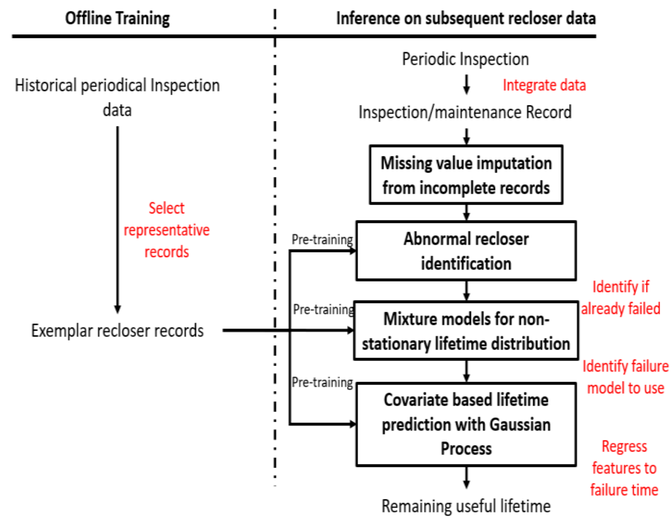

Figure 4 The data flow of maintenance records through the proposed model framework.

Figure 4 shows how the proposed modeling approach works on maintenance record data: a training phase takes an earlier portion of the data and identifies the representative exemplars for fitting the predictive model, omitting failed assets. This model is then used on the remaining, later portion of the maintenance records to predict failure times of subsequent records. During this phase, the inspection data needs to be preprocessed first, including imputing the missing values in records. Then the proposed data will be input into the abnormal recloser identification model to identify reclosers that are at high risk of failure and therefore are not representative of normally operating assets. The high risk reclosers can be classified into an appropriate life mode using a pre-trained clustering model. Finally, with a pre-trained lifetime prediction model, the lifetime of a given recloser can be estimated. The following sections now explain in detail how each of these parts is modeled.

A. Missing Value Imputation from Incomplete Records

Some inspections are conducted as part of a wider investigation and may only result in a subset of the regular tests being carried out, which results in a partial record. This poses a problem for most classifiers and regression models, as these require a complete input vector. Therefore, to ensure all records can be used irrespective of missing features, a missing data imputation model is used based on the joint distribution of the maintenance record values. The missing data can be imputed from the conditional form of this joint distribution using the observed features as conditioning variables. The data features can be rewritten as observed features X_o and missing features X_m.

$$X = \begin{bmatrix} X_m \\ X_o \end{bmatrix} \quad (1)$$

which have the following mean and covariance:

$$\mu = \begin{bmatrix} \mu_m \\ \mu_o \end{bmatrix} \quad (2)$$

$$\Sigma = \begin{bmatrix} \Sigma_{mm} & \Sigma_{mo} \\ \Sigma_{om} & \Sigma_{oo} \end{bmatrix} \quad (3)$$

The resulting mean and covariance of the conditional distribution $p(X_m|X_O = a)$ are [14]:

$$\bar{\mu} = \mu_m + \Sigma_{mo}\Sigma_{oo}{}^{-1}(X_o - \mu_o) \quad (4)$$

$$\bar{\Sigma} = \Sigma_{mm} - \Sigma_{mo}\Sigma_{oo}{}^{-1}\Sigma_{om} \quad (5)$$

The prior mean μ and covariance Σ are from training data, conditional mean $\bar{\mu}$, covariance $\bar{\Sigma}$ and observed data a are for test data. To avoid outliers skewing the mean of this distribution, the missing values are imputed from the median of samples taken from the conditional Multivariate Gaussian distribution.

B. Abnormal Recloser Identification

Failure data is required for learning an RUL model, and not all maintenance data will reflect exemplars of degradation based aging. This necessitates a means of identifying and removing normal maintenance data and catastrophic event based failures. To achieve this, an Ensemble Random Undersampling (RUS) Boosted Tree [15] is used to identify abnormal reclosers. RUSBoost is an ensemble classification model designed to alleviate adverse effects of data imbalance, a problem inherent in many operational data sets. In this application, at-risk reclosers will only make up a small proportion of the overall records, which will make a classifier inherently more competent at recognizing healthy reclosers.

C. Mixture Models for Non-Stationary Lifetime Distribution

Power system assets on distribution networks can be exposed to a variety of conditions that may influence their operational health. Consequently, lifetimes may be non-stationary. To accurately identify the lifetime of each asset, a Gaussian Mixture Model (GMM) [16] is used to approximate complex distributions from a linear combination of Gaussian distributions:

$$f(x) = \sum_{i=1}^{K} \varphi_i \frac{1}{\sqrt{(2\pi)^K|\sigma_i|}} \exp\left(-\frac{1}{2}(x-\mu_i)^T \sigma_i{}^{-1}(x-\mu_i)\right) \quad (6)$$

$$\sum_{i=1}^{K} \varphi_i = 1 \quad (7)$$

where in (6) and (7) φ_i denotes the proportion of the components, σ_i represents the variance, μ_i represents the mean, x represents the input lifetime (in this case, transformed into log space) and $f(x)$ denotes the probability density; K represents the number of mixture components used. Model selection criteria such as Bayesian Information Criteria (BIC) [16] can be used to determine K i.e. how many distributions are required.

$$\mathrm{BIC} = -2(\log \mathrm{L}) + N_{para} * \log(N_{obs}) \quad (8)$$

where $logL$ represents optimized log likelihood values, N_{para} and N_{obs} denote the number of parameters and the number of observations respectively.

D. Covariate Based Lifetime Prediction with Gaussian Processes

The test measurements can be considered as covariates in a regression model with the regression line being a count down to the time of failure. The form of this relation is unknown so a flexible regressor must be found to relate the routine measurement covariates to the life expectancy. A very flexible regression model is the Gaussian Process (GP). Given N data points of training data, $X = x_1, x_2, x_3 \dots x_N$, where each training data x_i is an m-dimensional vector of input features, and $Y = y_1, y_2, y_3 \dots y_N$ is a target variable. GP assumes any finite number of the input features have a joint Gaussian distribution:

$$p(f(x_i)|x_i) \sim N(0, K) \quad (9)$$

where X represents the input features, f denotes a latent variable function, and K is a covariance matrix containing elements from a kernel function which is normally parameterized by hyperparameters A and s. The hyperparameters of the kernel function are unknown and can be obtained from training data.The dimensionality of K is dictated by the lengthscale s and amplitude A. To select the most relevant input feature set, the Automatic Relevance Determination (ARD) Squared Exponential kernel [17] can be used:

$$K(x, x') = A\exp\left(-\frac{1}{2}M\|x - x_m\|^2\right) \quad (10)$$

where $M = diag(s)$ is a diagonal matrix constituted by the lengthscale of input features. A short lengthscale corresponds to high relevance. This partitions up as follows:

$$\begin{bmatrix} y \\ y_p \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X,X) & K(X,X_p) \\ K(X_p,X) & K(X_p,X_p) \end{bmatrix}\right) \quad (11)$$

Leading to the following expression for the predictor:

$$P(y_p|X, y, X_p) \sim N(\bar{y}_p, cov(y_p)) \quad (12)$$

To ensure the inputs are Gaussian distributed, a Box-Cox transformation is used [18]. Box-Cox is a transformation which can convert non-Gaussian distributed variables into ones approximating a Gaussian distribution. Box-Cox has a hyperparameter λ which is optimized according to goodness of fit to a Gaussian distribution, of transformed data [19]. Box-Cox covers two scenarios, when the parameter λ is non-zero:

$$X_{new} = \frac{X^\lambda - 1}{\lambda} \quad (13)$$

Otherwise:

$$X_{new} = \log(X) \qquad (14)$$

These candidate components will now be evaluated as a whole on a set of representative data to demonstrate how repurposed maintenance data can be used to evaluate recloser fleet lifetimes.

IV. Operational Case Study

In order to demonstrate the use of a comprehensive model for assessing asset lifetime on unmonitored assets, a set of 1916 maintenance records for a distribution recloser fleet are considered. This data has been collected over a 30 year period from 1990 covering 3 different manufacturers and 6 different recloser models. Owing to progressively improving data quality control, recent years feature more complete records, leading to the selection of an identically distributed subset of records. The equivalence of the subset and complete data distribution was ascertained with a Wald-Wolfowitz test. The data used has 427 examples of failed assets - 105 cases have complete maintenance records, 322 have at least one test result missing from the record. The data forming each record includes a timing test, counter and three-phase contact resistances and three-phase insulation resistance measurements. For the timing tests, a recloser normally trips three times before lockout. However, the first shot (the opening operation) of the operational data is deemed invalid in this case; therefore, only the three-phase shot 2 and shot 3 timing tests are retained as input. In terms of counter, reclosers normally would record the count of operations before and after opening. To account for any wear effects resulting from an operation, the counter after the operation for each phase and total counter will be used as the input here. As a pre-processing stage, the abnormal plant classification process described in IIIB is tested using 5-fold cross validation. As Figure 5 shows, 95.45% of failed assets (21/22) are correctly predicted as failed when using complete maintenance records as input data. It also shows that only 6.25% of healthy assets (4/64) are incorrectly identified as failed.

A. Root Cause of Lifetime Modes

As online condition monitoring is not economically feasible for detecting degradation in recloser assets, using periodic inspection data would be a practical choice to predict recloser lifetime. However, the combination of build heterogeneity, operating environment and duty cycle of reclosers results in non-stationary behavior. As Section IIIC discussed, the population distribution of the lifetime of some assets can be represented using a mixture model. Figure 6 shows the distribution of the recloser installation times which are clearly multi-modal. Different policies may have prompted recloser installation programmes and these may have in turn resulted in different suppliers being used depending on the scale of upgrade investment. Figure 7 shows the installation times and associated failure times for the fleet of recloser assets considered, highlighting the range of installation times and how duration does not necessarily reflect the failure time.

Figure 8 shows the empirical distribution of lifetimes of a selection of recloser assets installed over 3 different periods, which as with Figure 6, indicates that the population of the

	Actual	Predicted
Healthy	64	60
Failed	22	21

Figure 5: Maintenance record classification performance for identifying anomalous records automatically. Training an RUL model on examples of equipment that have already failed will result in a poor predictor.

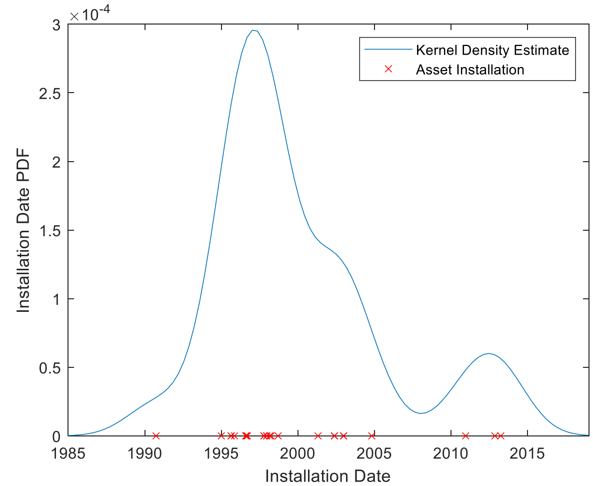

Figure 6: Distribution of installation times – network upgrade programmes have resulted in this exhibiting pronounced multimodality.

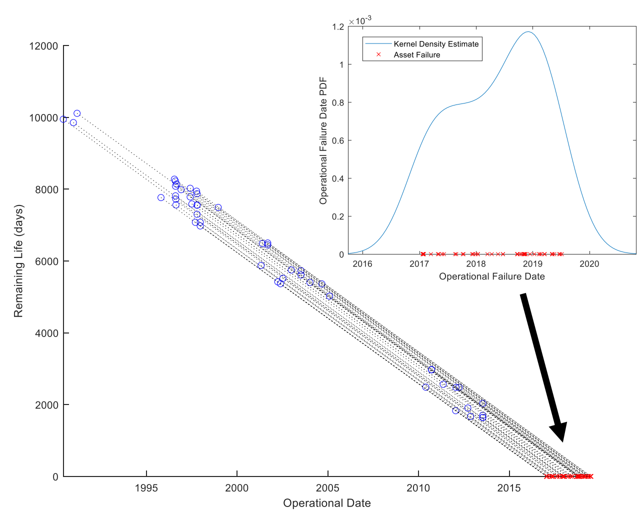

Figure 7: Trajectory and distribution of operating lives of the population of reclosers in the distribution network case study considered - blue circles are installation dates, red crosses are failure times.

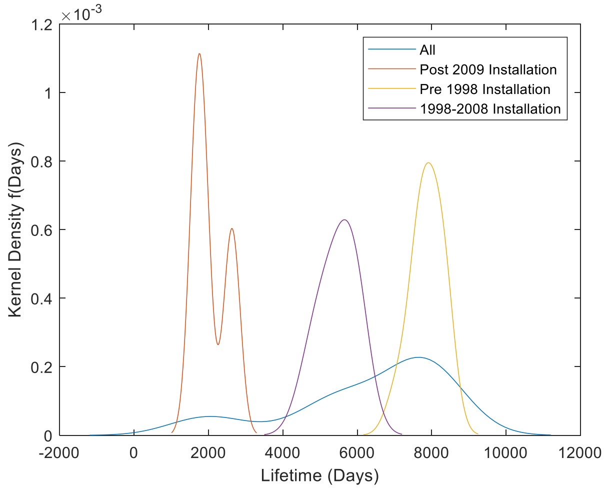

Figure 8: Lifetime distributions for all recloser assets and three subpopulations of recloser assets – different years of installation have resulted in completely different expected lifetimes.

lifetime of failed reclosers is composed of multiple probability distributions rather than a single Gaussian, Log Normal or Weibull distributions. Noteworthy from Figure 8 is that the installation times have a strong influence on the lifetime distribution mode – older reclosers have a longer lifetime, ones installed post 2009 have shorter lifetime. This may be due to changes in operating regime, less effective maintenance strategies or change in specification of the parts or materials used in the recloser asset in a given period. Either way, the installation time provides a useful indicator of the expected lifetime of the asset used in this analysis.

B. Features for Optimal Predictive Power

With the lifetime deterioration rate of reclosers divided into a range of modes, an appropriate regression model can be used to learn the trajectory of each lifetime mode and predict the lifetime of other reclosers. To do this, the optimum input features for the model need to be selected. Using the ARD Kernel given in (10), the relevance of each input feature is obtained [17] and given in Figure 9. From Figure 9, all three phase contact resistances are identified as relevant lifetime predictors by their non-zero kernel weights. The second timing test of phase A and Phase B, and ground resistance of phase A are also weighted so that they are informative predictors.

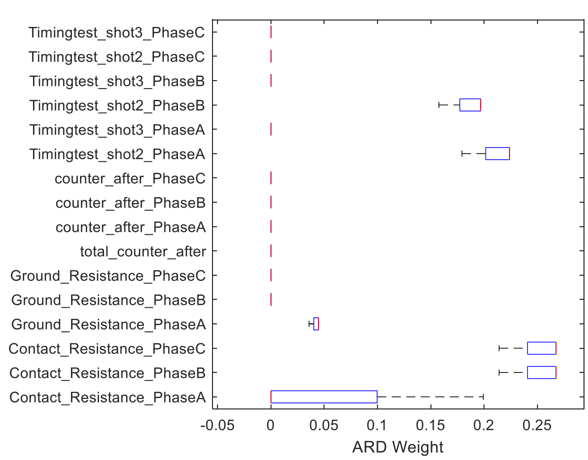

Figure 9 Gaussian Process Regression ARD kernel weights for all input features considered.

C. Lifetime Prediction

Once the lifetime mode is identified for each recloser, the next step is to build the degradation trend model for each lifetime mode. This is undertaken using Gaussian Process Regression as described in Section III to predict the RUL trajectory. This model is validated using Time Series Cross Validation (TSCV). TSCV is normally used to validate time ordered events which use historical data to predict the next value. Therefore, the size of the training set increases continually as the test size decreases. Here, the training set starts with 30 historical events with the model used to predict the 31st event, and ends with using the past 104 events to predict the latest event. The implied distribution from the errors that result from this are shown in Figure 10.

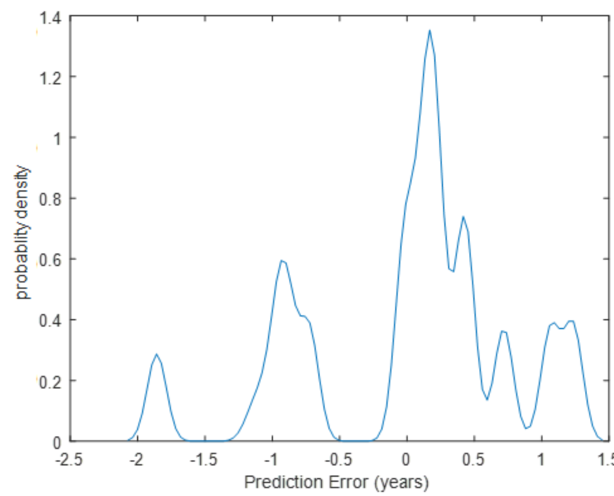

Figure 10 Prediction errors for models where parameters are censored in maintenance records.

The prediction error range give in Figure 10 is from -2 to 1.5 years. The average Root Mean Square Error (RMSE) of the lifetime prediction is around 1.05 years, however, pronounced modality of the error distribution indicates that this is driven by underlying factors such as the model or location where unmeasured hazards may have had an influence.

D. Lifetime mode comparison

Previous works [20][21] assumed asset lifetime population belongs to a single distribution – an assumption which, if incorrect, would result in predictions being an unrepresentative aggregate of different lifetime modes. To address this, Mixtures of Weibull distributions [22][23] have been used to approximate the lifetime population. A Gaussian Mixture Model (GMM) is a flexible means of approximating lifetime distributions of an arbitrary form. To evaluate the performance of this GMM distribution, the RUL prediction accuracies are contrasted against existing lifetime distribution models in Table II with the resulting predictive accuracies associated with using each model. It can be seen from Table II that the GMM with the number of modes implied by BIC model selection, provides the lowest prediction error, with the optimal number of modes having been automatically implied by the data.

TABLE II
LIFETIME POPULATION DENSITY MODEL

MODEL	AVERAGE RMSE (YEAR)
GAUSSIAN MIXTURE WITH ORDER SELECTED BY BIC	**0.707**
GAUSSIAN MIXTURE WITH 3 COMPONENTS	0.813
WEIBULL MIXTURE WITH 2 COMPONENTS	1.15
WEIBULL MIXTURE WITH 3 COMPONENTS	0.92
EXPONENTIAL MIXTURE WITH 2 COMPONENTS	2.57
MIXTURE OF WEIBULL AND EXPONENTIAL	2.49

E. *Predictive Performance Evaluation*

To evaluate the predictive performance of the Gaussian Process in the proposed method, the performance of different benchmark regression models with complete data are given in Table III.

TABLE III
LIFETIME PREDICTOR PERFORMANCE COMPARISON

PREDICTOR	RMSE
THE PROPOSED METHOD WITH COMPLETE DATA	0.7 YEARS
THE PROPOSED METHOD WITH INCOMPLETE DATA	1.38 YEARS
LINEAR REGRESSION WITH COMPLETE DATA	6.3781 YEARS
TREE WITH COMPLETE DATA	4.3781 YEARS
SVM WITH COMPLETE DATA	3.0575 YEARS
ENSEMBLE WITH COMPLETE DATA	3.4712 YEARS
NEURAL NETWORK WITH COMPLETE DATA	6.7836 YEARS

The Gaussian Process, via its use of the ARD kernel function, was chosen because it automatically selected input variables by their predictive power. As the predictive power of variables is not known in advance or through domain expertise, this a key practical feature. As Table III shows though, even with incomplete data, the proposed Gaussian Process regression model is also the best performer.

V. OPERATIONAL CONSIDERATIONS

The previous sections worked on the assumption of a complete set of recloser tests within each record. However, each recloser normally only recorded a part of the full complement of tests which would mean the input to a lifetime prediction model usually is incomplete and therefore unusable. In the recloser data considered, more than half of the records have over 50% of test measurements missing. Therefore, this section tests the GP RUL predictor with incomplete data backfilled with imputed values using the technique described in Section IIIA.

A. *Imputation Error*

An imputation model based on a conditional Gaussian distribution (itself a limiting form of Gaussian Process) is used to populate the missing values. This analysis randomly deletes a part of the features for all the reclosers, then the proposed model is used to predict the values, which can be compared with

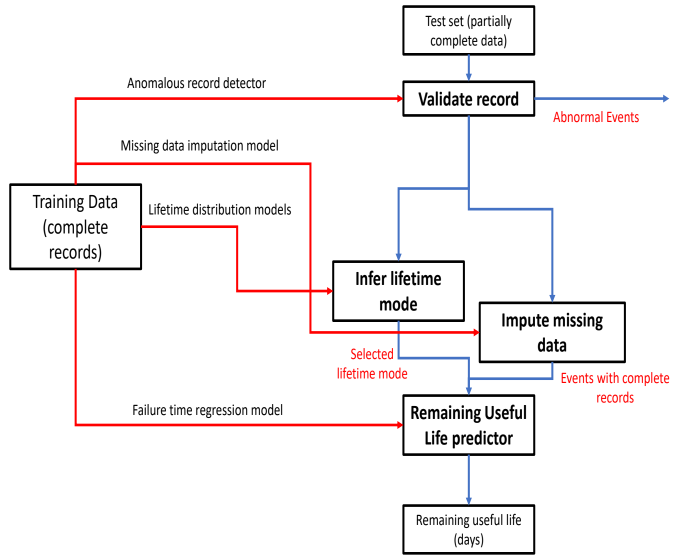

Figure 12 Model RUL inference process using an incomplete data set. In the practical context, not all maintenance records will include all tests.

the censored value. Since the missing features were randomly selected, the same process was repeated 50 times to ensure that as many scenarios as possible were covered. The performance of this imputation model is shown in Figure 11.

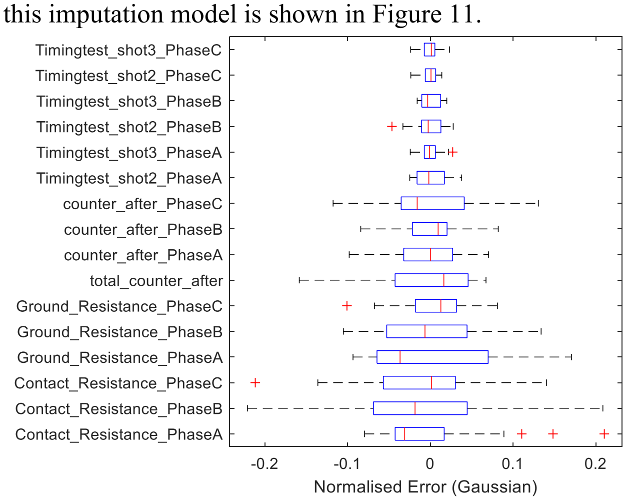

Figure 11 Imputation errors for parameters censored in maintenance records.

In Figure 11, for comparative purposes, the imputation error for each variable is normalized by its own standard deviation. The average imputation error is within the range [-0.2, 0.2] and the majority have an absolute expected value of less than 0.1.

B. *End-to-end RUL prediction*

In practice, only a subset of the tests is actually performed during each periodic inspection. To further investigate the operational impact of these missing input values on the RUL assessment, an end-to-end prediction is conducted on a test set with randomized missing values which is given in Figure 12. The whole process is again validated with 5-fold cross validation.

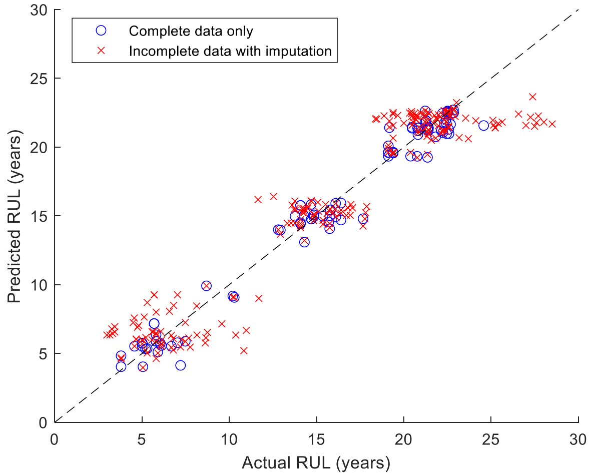

Figure 13 Complete and imputed data predictive capabilities: imputed data offers poorer predictive performance for late life asset failures underestimating them by around 5 years. Early life prediction accuracies almost matches those of complete data.

TABLE IV
PERFORMANCE OF THE PROPOSED REMAINING USEFUL LIFE PREDICTION

MODEL	SENSITIVITY	SPECIFICITY	PRECISION
ABNORMAL EVENT IDENTIFICATION WITH COMPLETE DATA	84%	98.36%	95.45%
ABNORMAL EVENT IDENTIFICATION WITH INCOMPLETE DATA	68.85%	89.78%	56%

Table IV shows that the abnormal event identification model performs well at identifying abnormal events with complete data (Specificity and precision >95%). With working on the incomplete data, it becomes more likely to misidentify the abnormal events. However, it still performs well at identifying normal events and the proposed data imputation model can reduce the burden of collecting high quality data. This is also reflected in Figure 13 where the complete and incomplete input data are compared in terms of performance. From Figure 13, the complete data provides the stronger predictor, but the imputed data still offers an estimate based on what would otherwise be unusable data. The overall performance is summarized using RMSE which is widely used to evaluate RUL prediction performance [24].

VI. CONCLUSION

With increasing use of low value automation and sensing devices on power distribution networks, new approaches to assessment of reliability are required in order to manage these new assets effectively. Fleet sizes are large and heterogeneous both in terms of OEM and operating environments, bearing this in mind, a non-stationary, adaptive RUL model based on Gaussian Process Regression has been developed here to base asset fleet lifetime estimates on routinely gathered performance data. To address the data quality issues that may be seen in the field, a missing data imputation strategy is also proposed to allow predictions to continue to be made in the event that predictor inputs are missing. While this work has focused entirely on the application of these analytical tools to recloser assets, many of the principles apply to other low value high volume assets such as switching capacitors and some types of distribution switchgear – indicating the subsequent developments of this research. An information system that can benchmark asset performance in the context of fleet wide behavior exhibited historically during routine maintenance [3], offers a route to harnessing additional assets insight without investing in condition monitoring. For utilities going forward, tools such as these will be essential as they are expected to provide high service quality without large investments in distribution monitoring down to the individual asset level.

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