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Assessing circuit breaker performance using condition-based data and Bayesian approach

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ABSTRACT

This paper proposes a methodology to assess the performance of circuit breaker utilizing its control circuit data. Various performance indices are defined to assess the condition of breaker using probability distributions. Bayesian updating approach is implemented to update these indices as the new data becomes available. An approximation in implementing the Bayesian approach to deal with large amounts of data on-line is considered. The methodology is applied to data recorded at different times during both open and close operations on a group of similar circuit breakers. The methodology can be used to quantify the effect of maintenance making use of the defined performance indices, which further helps in developing system level risk-based decision approaches for maintenance optimization.

1. Introduction

Trying to cut down the budget spent on maintenance every year, utilities need to come up with optimized maintenance schedules with limited budget. This task involves quantifying maintenance impact, which is a bit challenging task. Existing system level maintenance strategies such as RCM approach, Risk-Based approach etc. reported in Refs. [1–6] require considering the effect of component maintenance quantitatively through models such as probabilistic maintenance models [7–10] and/or failure rate estimation models. These models depend on condition-based data and history of operation of power system equipment such as transmission lines, transformers or circuit breakers (CBs).

This paper proposes a probabilistic methodology to quantify the effect of device maintenance for circuit breakers. The proposed methodology utilizes the control circuit data of CB to define several performance indices. Fig. 1 shows the electrical representation of CB control circuit and the data consists of several voltage and current wave forms measured across trip coil, close coil and auxiliary contacts captured when the CB operates (either open or close operation). A sample representation of these signal waveforms measured during close operation of CB is shown in Fig. 2. The figure also shows several events (marked as Evt #1, Evt #2, etc.) which needs to occur in that order for correct operation of the breaker. The event definitions and the time instants (t_1, t_2, etc.) at which these events occur are shown in Table 1. These timing instants should occur within in manufacture specified tolerance bands to ensure that the CB is functioning properly. The proposed methodology defines performance indices using these time instants to reflect the health/condition of various assemblies such as trip coil, close coil,

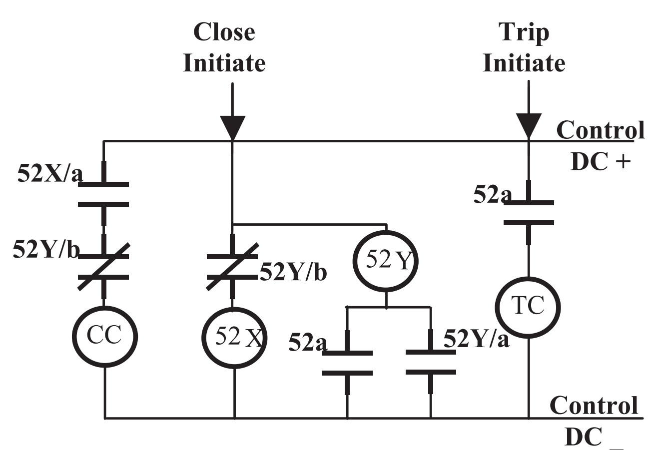

Fig. 1. Electrical representation of CB control circuit.

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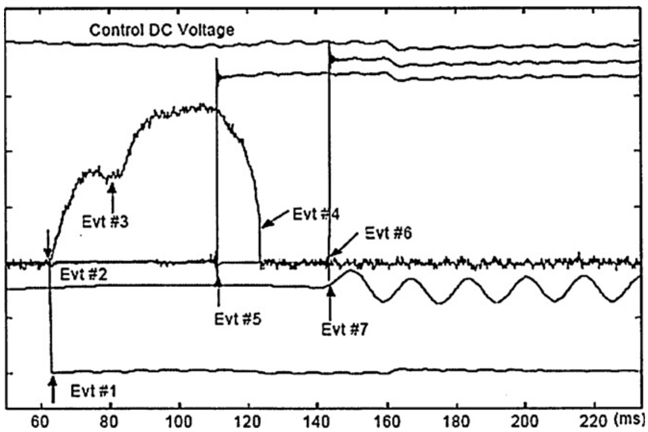

Fig. 2. CB control circuit signal waveforms during close operation.

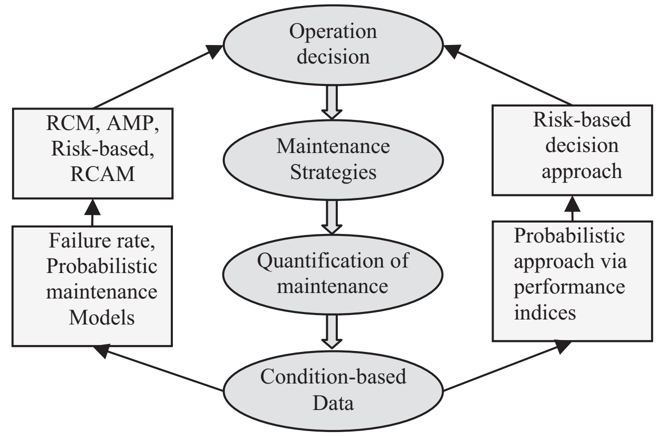

Fig. 3. Top–down approach.

auxiliary contacts etc. Whenever the CB operates, the control circuit data is captured and the proposed methodology updates the defined performance indices using Bayesian updating approach. An initial methodology to achieve this task was proposed earlier [11] but it lacks the ability of updating the computed performance indices on-line. To overcome this inability, we introduced Sequential Bayesian approach to make the proposed methodology suitable for practical applications so that it can be applied in real time using field condition-based data. The proposed methodology finds its use in development of optimized, system level, risk-based maintenance strategies. Though CB is considered in this work, the proposed concepts can be easily extended with few modifications to other devices such as power transformers.

This paper is organized as follows. Section 2 presents a brief background of the problem. The proposed methodology is presented in Section 3. Illustration of the methodology is presented in Section 4. An approximate procedure in implementing the Bayesian updating approach is presented in Section 4.3. Section 5 provides conclusions about the whole approach.

2. Background

A concept of "top–down" approach is introduced to summarize various steps in power system planning and operation affected by maintenance strategies. The flow of the process is shown in Fig. 3 and it links the operation decisions to condition-based data. Ultimately, the operator has to ensure required power flow while taking into account decisions regarding asset management and reliability constraints. Asset management policies and reliability of power system can be greatly affected by selected system level maintenance strategies [1–6]. This approach is summarized in the left side of the Fig. 3 and the quantification of maintenance is achieved through failure rate estimation models and probabilistic maintenance models [7–10]. A different approach may be taken by developing probabilistic models as shown in the right side of the Fig. 3. The quantification of maintenance is achieved through a probabilistic methodology which converts the condition-based data into performance indices. These indices can further be used in developing risk-based decision approaches. The contribution of this paper is to establish a link between the 'condition-based data' and 'risk-based decision approach' through the proposed probabilistic methodology.

Table 1
List of events and signal parameters [16].

Event	Event description	Signal parameter
1	Trip or close operation is initiated (trip or close initiate signal changes from low to high)	t_1
2	Trip coil current picks up	t_2
3	Trip coil current dips after saturation	t_3
4	Trip coil current drops off	t_4
5	B contact breaks or makes (a change of status from low to high or vice versa)	t_5
6	A contact breaks or makes	t_6
7	Phase current breaks or makes	t_7

3. Proposed methodology

The proposed methodology is shown in Fig. 4, and has the following steps: (i) develop a history of CB control signals and extract timings of each signal parameter using signal processing module (ii) analyze the relationship between the parameters using scatter plots and fit probability distribution to each parameter (iii) define performance indices using these distributions to assess the condition (health) of the breaker (iv) as the new data arrives, update the distributions and performance indices using Bayesian updating approach. The methodology is further discussed in the following subsections.

3.1. Condition-based Data

According to a failure survey conducted by CIGRE working group A3.12, majority of CB failures are due to malfunction of operating mechanism and control circuit in that order compared to other CB assemblies [12]. The condition-based data from the control circuit is used in this work, as it allows assessment of the performance of control circuit and the operating mechanism as well. A representation of control circuit is shown in Fig. 1. The condition monitoring techniques are relatively easy to develop since the secondary cir-

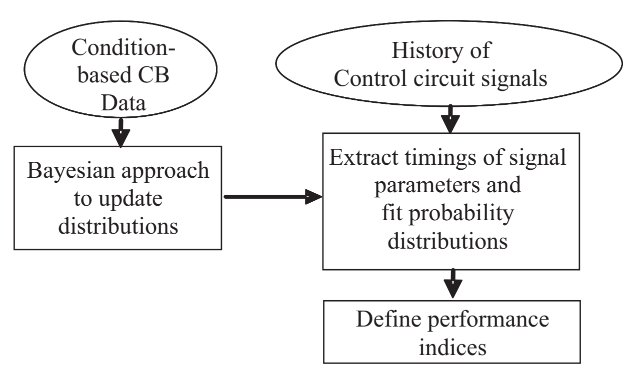

Fig. 4. Model to assess the condition of breaker.

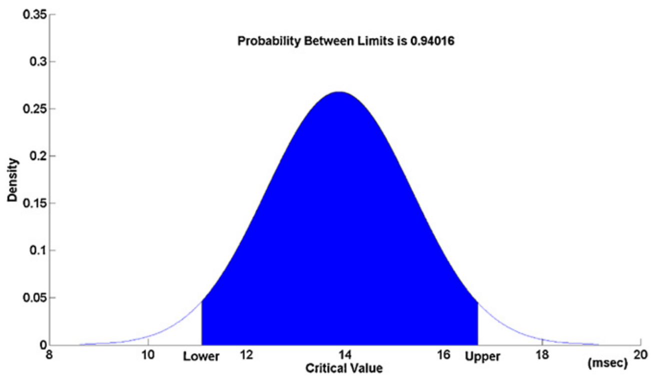

Fig. 5. Probability distribution of parameter 't_2'.

cuit is readily accessible for on-line monitoring. There are portable test devices available on the market to collect and display the control circuit signals which are analog and/or digital waveforms [13]. The collected waveforms represent a "signature" of the circuit breaker and a sample representation is shown in Fig. 2. The list of events, corresponding definitions and timing parameters are presented in Table 1. The timing parameters t_2–t_6 are considered in this work. A low cost circuit breaker monitor (CBM) development for acquisition and automated analysis of condition-based data both offline and online is reported in Refs. [14,15]. Signal processing and expert system modules are developed for extracting the exact timings of the signal parameters for both open and close operations [16,17].

3.2. Probability distribution

Before fitting a distribution to each parameter, understanding the dependency between the parameters is needed. This can be done through scatter plot analysis [18]. One of the most common patterns is a linear relationship between the two variables. A simple linear regression model is appropriate to represent the response variable Y in terms of X, such as $Y=\beta_0+\beta_1 X+\varepsilon$. Some times the response variable Y linearly depends on more than one variable, say X_1 and X_2. In this case, Y can be represented as, $Y=\beta_0+\beta_1 X_1+\beta_2 X_2+\varepsilon$. This situation can get complex if a co-linearity exists between the predictive variables X_1 and X_2. Such cases can be dealt by a technique called 'Principle Component Analysis' (PCA) [18]. In simple terms, PCA orthogonally transforms X_1, X_2 into Z_1, Z_2, respectively such that there is no correlation among Z_1 and Z_2. Now Y can be expressed as $Y=\beta'_0+\beta'_1 Z_1+\beta'_2 Z_2+\varepsilon$.

A normal distribution is assumed for all signal parameters for the purpose of illustration. The probability distribution of signal parameter t_2 is shown in Fig. 5. To proceed with the methodology, define upper and lower limits for each timing parameter such that if new value of 't_i' falls in this range, then those parts of the breaker which cause the occurrence of time instant 't_i', operate properly. For example, if t_2 falls out of the limits, it means that there is some problem associated with close coil. The shaded area between the lower and upper limits is the probability that the breaker will operate properly. These limits are specific to each circuit breaker and can be determined from manuals supplied by the manufacturer. It is likely that circuit breakers of same voltage level, type and manufacturer will have same limits associated with each timing parameter.

In general, probability that breaker operates correctly with respect to 't_i' is defined as, $p(t_i)=\Pr(l_i \le t_i \le u_i)$, where, l_i is the lower limit and u_i is the upper limit. These probabilities are used to define performance indices for various assemblies of circuit breaker.

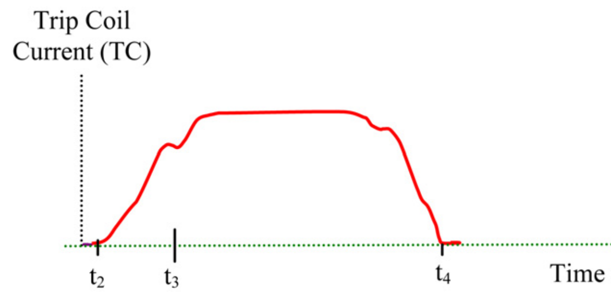

Fig. 6. Trip coil current.

3.3. Condition assessment

3.3.1. Performance of trip and close coils

A sample representation of trip coil current and close coil current is shown in Figs. 6 and 7, respectively. After the trip or close initiate is active, the coil current makes a gradual transition to a nonzero value at time 't_2'. The time instant 't_3' corresponds the time at which the operating mechanism starts moving with the help of trip or close coil energy. The coil current starts dropping down to zero at time 't_4'. The trip and close coil current signals should be fairly smooth except for the dips at the beginning and end of the waveform.

Possible abnormalities associated with trip and close coil include: pick up delayed, dip delayed, drop-off delayed, etc. In worst case, these abnormalities may result in not opening/closing the breaker when it is supposed to. These abnormalities can be addressed by probabilities $p(t_2)$, $p(t_3)$ and $p(t_4)$ corresponding to the timing parameters, t_2, t_3 and t_4. These time instants should occur with in the tolerance limits to assure proper operation of trip and close coils. The performance index related to trip coil is defined as the probability that trip coil fails to operate properly,

$$p_f(\mathrm{TC}) = 1 - p(t_2)p(t_3)p(t_4) \quad (1)$$

Similarly, the probability that the close coil fails to operate correctly can be computed as,

$$p_f(\mathrm{CC}) = 1 - p(t_2)p(t_3)p(t_4) \quad (2)$$

3.3.2. Performance of auxiliary contacts

As the breaker opens or closes its main contacts, it also changes the status of the auxiliary 'a' and 'b' contacts as shown in Figs. 8 and 9. Some possible abnormalities associated with operation of "a" and "b" contacts are: delay in transition, premature transition, unstable contacts, noise and contacts bounce. If the timings t_5 and t_6 fall with in their tolerance limits, we can say the auxiliary contacts operate normally. The performance index related to auxiliary contacts can be defined as, the probability that auxiliary contacts fails to operate properly,

$$p_f(\mathrm{AB}) = 1 - p(t_5)p(t_6) \quad (3)$$

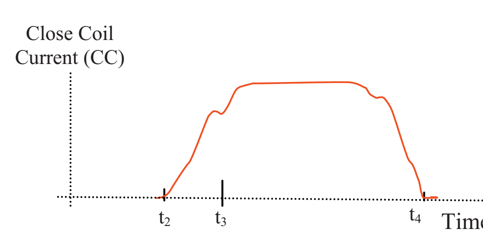

Fig. 7. Close coil current.

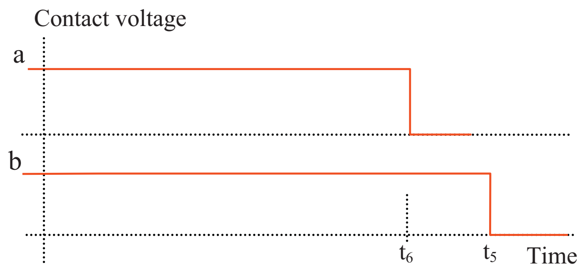

Fig. 8. "*a*" and "*b*" contacts transition during open operation.

3.3.3. Performance of operating mechanism

The time period between the instant at which the TC (CC) rises (t_2) and the instant at which the dip occurs (t_3) is the 'free travel time' that equals to $|t_3 - t_2|$. This free travel time reflects the performance of the trip (close) latch mechanism. The timings t_2 and t_3 need to fall in the tolerance limits for the breaker to have normal free travel time. Any violation reflects an improper operation of trip (close) latch mechanism. The corresponding performance index is defined as the probability that free travel time is abnormal,

$$p_f(\mathrm{FT}) = 1 - p(t_2)p(t_3) \tag{4}$$

Note that this index reflects the performance of trip (close) latch mechanism alone, where as indices p_f (TC) and p_f (CC) defined earlier reflect performance of trip (close) coil operation and latch mechanism together.

The coil current also needs to correlate with the event of "*a*" or "*b*" contact. The time period between the dip and the operation of "*a*" for open operation ("*b*" for close operation) is the mechanism travel time which is equal to $|t_6 - t_3|$ for open ($|t_5 - t_3|$ for close) operation [17]. For normal 'mechanism travel time', the timings t_5 and t_6 need to fall in corresponding tolerance limits. Any violation of these timings can be reported as abnormal operation of breaker. The corresponding performance index is defined as the probability that the mechanism travel time is abnormal,

$$p_f(\mathrm{MT}) = 1 - p(t_3)p(t_6) \quad \text{(Open)} \tag{5}$$

$$p_f(\mathrm{MT}) = 1 - p(t_3)p(t_5) \quad \text{(Close)} \tag{6}$$

3.3.4. Performance of breaker

In addition to the performance of individual components of breaker, an over all performance of the breaker may be assessed. If none of the timings ($t_2 - t_6$) is violated, we can say that breaker operates properly. In other words, if any of these timings fall out side the corresponding tolerance limits, we can say that the breaker fails to operate properly. This quantity can be defined as probability that the breaker does not operate properly and is estimated as,

$$p_f(\mathrm{Br}) = 1 - \prod_{i=2}^{6} p(t_i) \tag{7}$$

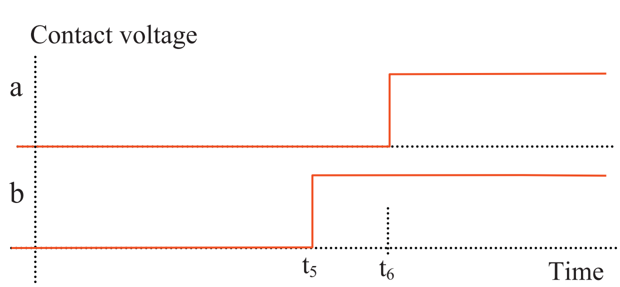

Fig. 9. "*a*" and "*b*" contacts transition during close operation.

Table 2
Performance indices.

Operation	Performance index	Performance
Open	p_f(TC)	Trip coil
	p_f(AB)	Auxiliary '*a*' and '*b*' contacts
	p_f(FT)	Trip latch mechanism
	p_f(MT)	Operating mechanism
	p_f(Br)	Breaker as a whole
Close	p_f(CC)	Close coil
	p_f(AB)	Auxiliary '*a*' and '*b*' contacts
	p_f(FT)	Close latch mechanism
	p_f(MT)	Operating mechanism
	p_f(Br)	Breaker as a whole

This failure probability index is sensitive to the measured data such that if this index is computed using the breaker operational (both maintenance and failure) data measured over its lifetime, then it converges to failure rate of the breaker which is measured as number of failures per year. The advantage of the proposed failure probability index is that it gives insight into which component of the breaker is causing the problem instead of just reporting the failure rate (number of failures per year). A summary of all performance indices for both open and close operation is given in Table 2.

3.3.5. Bayesian updating approach

This section provides a brief discussion of the Bayesian approach to update the performance indices as the new data arrives. Let θ denote parameter of interest and y denote observed data, the posterior distribution due to Bayes' theorem is expressed as [19]:

$$p(\theta \big| y) = \frac{\pi(\theta)L(y|\theta)}{\int_{\Theta} \pi(\theta)L(y|\theta)d\theta} \tag{8}$$

where $\pi(\theta)$ is the prior distribution and $L(y|\theta)$ is likelihood function. The denominator of the above equation is a constant for a given 'y', and hence the equation can be written as:

$$p(\theta \big| y) \propto \pi(\theta)L(y|\theta) \tag{9}$$

Efficient Markov Chain Monte Carlo (MCMC) algorithms such as Gibbs Sampler can be used to draw samples from the posterior distribution and any posterior inference can be based on the samples-thus obtained. The likelihood in (9) is the joint likelihood of entire data ($y_1 \ldots y_n$), as shown in Fig. 10. In our problem, y_i is a vector of observed timing parameters (t_2, t_3, t_4 and t_5) and a total of n such observations are available.

3.4. Sequential Bayesian approach

The Bayesian approach discussed in previous section is often suited for offline analysis, i.e. entire observed data set ($y_1 \ldots y_n$) is used in defining the likelihood to estimate posterior distribution. Now, if a new observation y_{n+1} is made, it will be appended to the already existing data set and the whole data set ($y_1 \ldots y_{n+1}$) is used in constructing the joint likelihood $L(Y)$ to estimate the posterior distribution $P(\theta|Y)$. This means that each time a new observation is

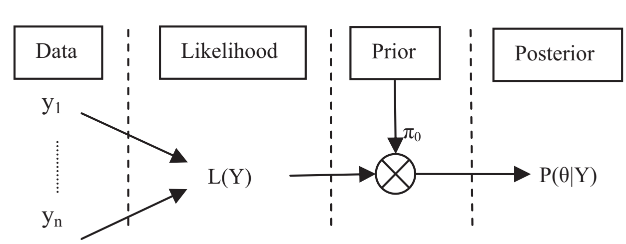

Fig. 10. Flow chart of Bayesian approach.

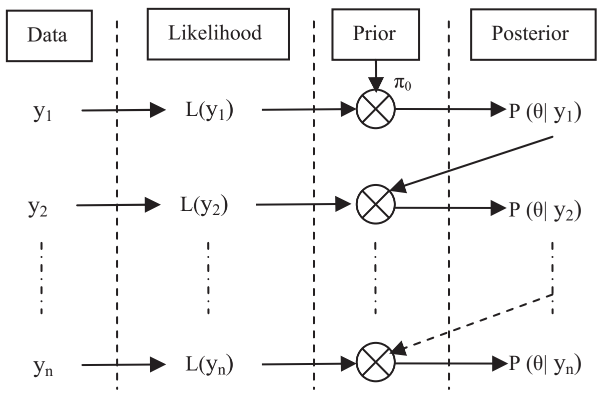

Fig. 11. Sequential Bayesian approach.

available, it will be appended to the existing observations and the data set will be processed in carrying out MCMC simulations. If the data set gets accumulated enough, it might demand extra processing time in MCMC simulations and storage capacity on computer. This difficulty can be overcome by Sequential Bayesian approach shown in Fig. 11. In this approach, when an observation is made, the likelihood will be formed with that observation alone, and posterior of previous data set will become the current prior. For example, when the observation y_{n+1} is made, the likelihood $L(y_{n+1})$ is constructed with data point y_{n+1} alone to estimate the posterior distribution $P(\theta|y_{n+1})$. Hence for each MCMC simulation, we will be dealing with previous posterior distribution (which captures the information of already measured observations) and current observation. This way one does not have to deal with huge data sets and computation time can be greatly improved. This approach is best suited for analyzing the condition-based data by updating the performance indices online.

Table 3
Tolerance limits for normal operation [17].

Event	Lower (ms)	Upper (ms)
t_2	0	2
t_3	13.6	18.6
t_4	26.4	35.4
t_5	28.7	38.7
t_6	22.4	32.4

4. Case studies

To illustrate the proposed methodology, a history of each signal parameter is developed using the waveforms taken from control circuit of similar circuit breakers over a period of time. The type of breaker and manufacturer with corresponding signal timings are listed in Appendix A. Two case studies are considered to demonstrate the proposed methodology.

4.1. Case study I

The data set consists of 19 records taken during opening of circuit breaker under consideration. The sequence of timing of parameter changes during opening is: $t_2-t_3-t_6-t_4-t_5$. The parameters are renamed as, y_1-y_5 in that order. The lower and upper tolerance limits for each timing parameter are shown in Table 3.

The scatter plot analysis of the parameters is shown in Fig. 12. The off diagonal plots show the dependency of each parameter with other parameters. It is observed from the figure that, parameters y_1, y_2 and y_3 show no particular relationship with any other parameters and hence can be treated as independent. A linear relationship is observed between y_3 and y_4, and can be expressed as, $y_4=\beta_0+\beta_1 y_3+\varepsilon_4$. The parameter y_5 is linearly dependent on both y_3 and y_4 and can be represented by a multiple regres-

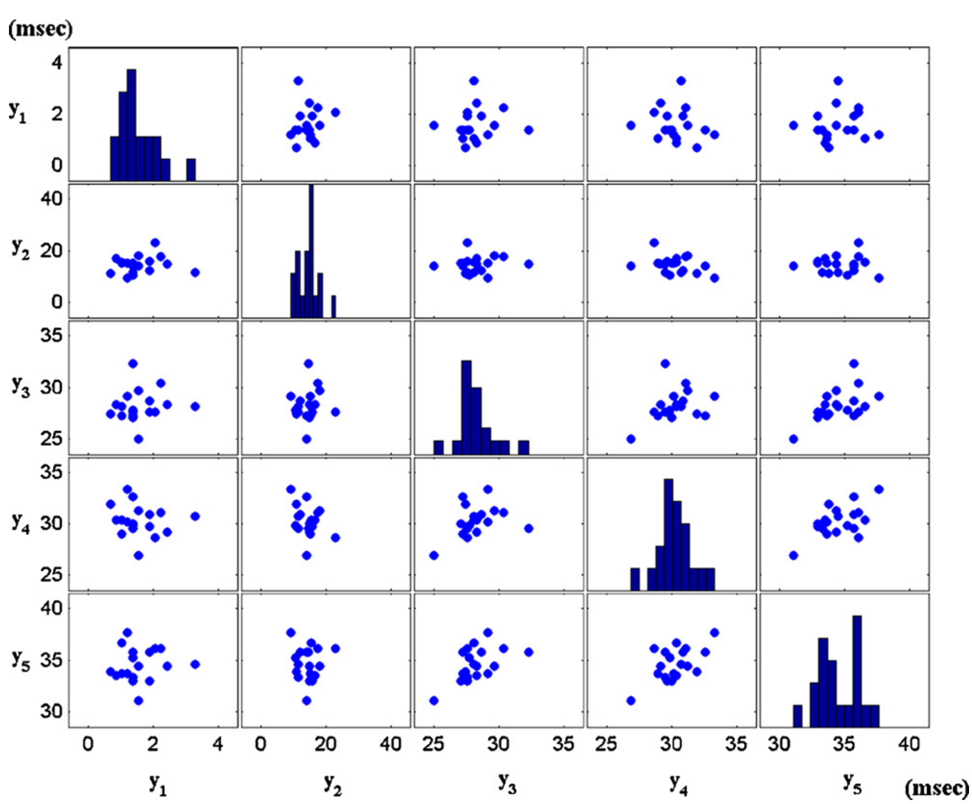

Fig. 12. Scatter plot analysis of timing parameters.

sion model. Since there is a linear dependency between y_3 and y_4, principle component analysis explained in Section 2 can be used to represent y_5 and the modified representation is given by $y_5 = \beta_0 + \beta_1 y_3 + \beta_2 y_4 + \varepsilon_5$.

Model formulation. Let $j = 1, 2, 3, 4, 5$, be the index over parameter; n be the total number of observations; Y: $(n \times j)$ be the data set; the likelihood function and covariates using multiple linear regression set-up are given below.

$$Y_j \sim N(X_j \beta_j, \sigma_j^2 I), \quad \text{for} \quad j = 1, 2, 3, 4, 5 \tag{10}$$

$$X_j = J, \quad \text{for } j = 1, 2, 3 \tag{11}$$

$$X_4 = [J \quad Y_3] \tag{12}$$

$$X_5 = [J \quad Y_3 \quad Y_4] \tag{13}$$

where $J = [1,\ldots,1]^{\mathrm{T}}$ of dimension $(n \times 1)$, β_j is the parameter vector of interest, σ_j^2 is the measurement variance. In a Bayesian frame work, all the unknown parameters are considered as random variables and the uncertainty in the parameters is expressed in terms of prior distribution. For the sake of analytical tractability and the computational efficiency, we elicit conjugate priors for all the unknown parameters in, given by:

$$\beta \sim N(\mu, \Sigma) \tag{14}$$

$$\frac{1}{\sigma^2} \sim \Gamma(a, b) \tag{15}$$

where μ, Σ, a and b are prior parameters that are assumed to be known or set in a way to express lack of knowledge about the parameters of interest. A non informative prior for β and σ^2 with parameters $\mu = 0$, $\Sigma = \sigma^2 I$, $a = b = 1$, was assumed in this simulation. The posterior conditional distributions required in the Gibbs sampling stage are given below.

$$\beta\Big|_{Y,\sigma^2,\mu,\Sigma} \sim N(\Lambda(X^T Y \sigma^{-2} + \sum\nolimits^{-1} \mu), \Lambda) \quad \text{where,}$$

$$\Lambda = ((X^T X)\sigma^{-2} + \sum\nolimits^{-1})^{-1} \tag{16}$$

$$\frac{1}{\sigma^2}\Big|_{Y,\beta,\mu,\Sigma} \sim \Gamma(a + (Y - X\beta)^T J, b + n) \tag{17}$$

MCMC simulation is carried out to estimate the posterior distribution of the parameters of interest. WinBUGS, an open source platform is used for performing MCMC simulations [20]. We used diagnostic tools available such as Gleman–Rubin statistic to monitor the convergence of the MCMC chains. We threw-away the first thousand samples as burn-in (during which MCMC chains are still in the process of converging), and thinned down the subsequent samples by a factor of ten to reduce the correlation in the samples. After burn-in and thinning, we obtained five thousand samples based on which all the posterior inferences were drawn.

The computed performance indices for each data point are shown in Fig. 13. It is observed that all indices follow decreasing pattern as the new data point comes in. The indices p_f (TC), p_f (FT) and p_f (MT) have probabilities lying above 0.6, suggesting abnormal behavior of respective assemblies. The mechanism travel time is the difference between t_6 and t_3, in which the time instant t_3 related to trip coil current and time instant t_6 related to auxiliary 'a' contact. So, it is necessary to check which timing parameter is responsible for high values of index p_f (MT).

We have already seen the auxiliary contacts are functioning well, which means that t_5 occurs with in the tolerance limits. Hence the problem is with t_3, because of improper operation of trip latch mechanism. The performance index p_f (Br), which depicts the performance of breaker has probabilities above 0.6 due to the abnormal

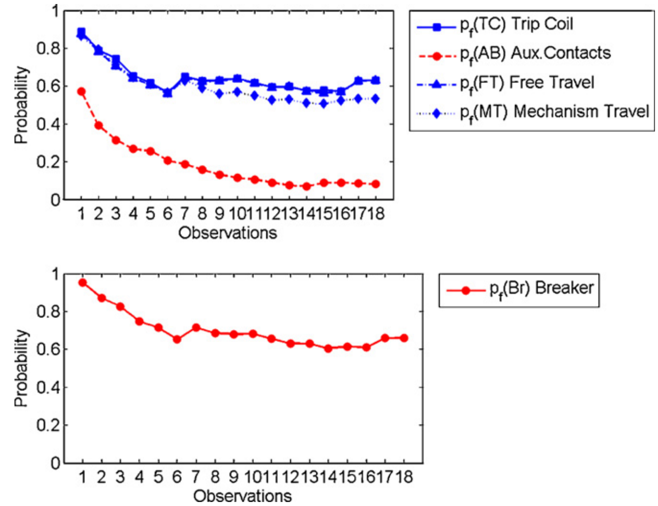

Fig. 13. Performance indices for CB opening.

Table 4
Summary of analysis.

Performance index	Observations	Maintenance action required?
p_f(TC)	Abnormal behavior of trip coil current.	Yes
p_f(AB)	Auxiliary contacts are operating properly	No
p_f(FT)	Abnormal free travel times. Improper operation of trip latch mechanism	Yes
p_f(MT)	Abnormal mechanism travel times. Improper operation of operating mechanism.	Yes
p_f(Br)	Improper operation of breaker as a whole	Yes

operation of trip coil, trip latch and operation mechanism. A summary of the analysis is shown in Table 4.

4.2. Case study II

The data set consists of 23 records taken during closing of circuit breaker under consideration. The sequence of timing parameters occurrence during closing is: $t_2 - t_3 - t_4 - t_5 - t_6$. Rename the parameters as, $y_1 - y_5$. The lower and upper tolerance limits for each timing parameter are shown in Table 5.

The scatter plot analysis of the parameters is shown in Fig. 14. It is observed that, parameters y_1, y_2 y_3 and y_4 show no particular relationship with any other parameters and hence can be treated as independent. A linear relationship between y_4 and y_5 and, y_5 can be used to expressed as $y_5 = \beta_0 + \beta_1 y_4 + \varepsilon_5$.

Model formulation. The model formulation presented in earlier section can be used for the data under consideration. The likelihood is expressed by (10). The covariate matrix X in (10) changes as:

$$X_j = J, \quad \text{for } j = 1, 2, 3, 4 \tag{18}$$

$$X_5 = [J \quad Y_4] \tag{19}$$

Table 5
Tolerance limits for normal operation [17].

Event	Lower (ms)	Upper (ms)
t_2	0	5.5
t_3	9.8	16.4
t_4	26	43.4
t_5	49.9	67.5
t_6	62	75.8

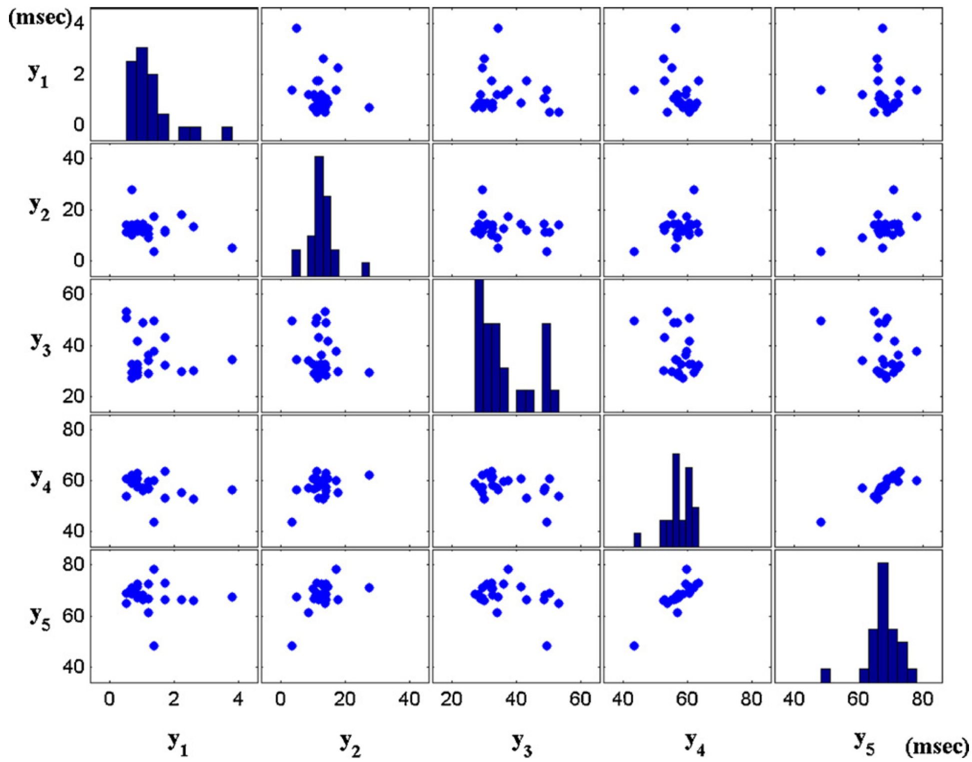

Fig. 14. Scatter plot analysis of timing parameters.

The prior distribution is given by (14) and (15), and the posterior distribution is given by (16) and (17).

The computed performance indices for each data point are given in Fig. 15. It can be observed that the index p_f (AB) lies below 0.5 except for one record which has a probability of 1. This situation can be interpreted as follows. Due to the abnormal operation of auxiliary contracts at that instant, one of the quantities $p(t_5)$ and $p(t_6)$ are either zero or close to zero. Hence the index $p_f(\mathrm{AB}) = 1 - p(t_5)p(t_6)$, is either 1 or close to 1. Except that one observation, we can say that the auxiliary contacts are working properly. Also, the index p_f (AB) has very low probabilities compared to other indices which are also shown in Fig. 14.

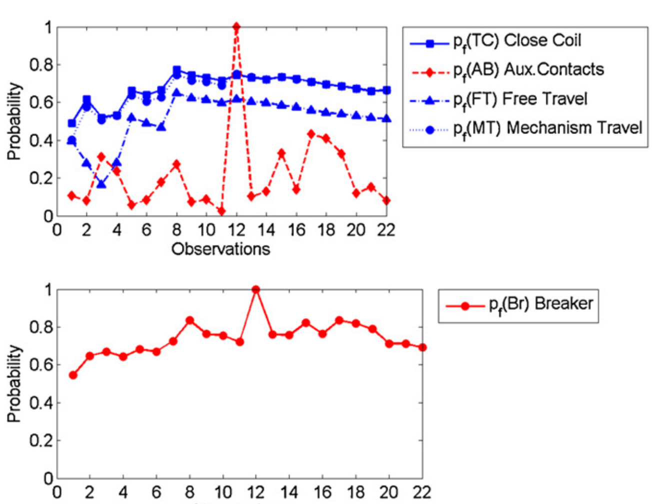

Fig. 15. Performance indices for CB closing.

The other indices follow almost the same pattern and a decreasing trend can be observed as more observations come in. The indices lie in the range of 0.6–0.8 for most of the records suggesting improper operation of close coil and close latch mechanism. The performance index, p_f (Br) also lies above 0.6 suggesting that the breaker is not operating properly.

A summary of the analysis is shown in Table 6. The table also suggests if any maintenance action is required.

4.3. Sequential Bayesian approach

The computed performance indices using Sequential Bayesian approach for both case studies are shown in Figs. 16 and 17. It can be observed that all indices have almost similar probability range as obtained using the Bayesian approach in Section 3, and hence the obtained conclusions about the performance of breaker can still hold. Such a sequential approach is very suitable for on-line posterior-inferences as it makes use of the posterior distribution already obtained instead of the previously obtained data.

In order for this approach to be computationally attractive and to be put in a recursive frame work (as shown in Fig. 11), we

Table 6
Summary of analysis.

Performance index	Observations	Maintenance action required?
p_f(CC)	Abnormal behavior of close coil current.	Yes
p_f(AB)	Auxiliary contacts are operating properly	No
p_f(FT)	Abnormal free travel times. Improper operation of close latch mechanism	Yes
p_f(MT)	Abnormal mechanism travel times. Improper operation of operating mechanism.	Yes
p_f(Br)	Improper operation of breaker as a whole	Yes

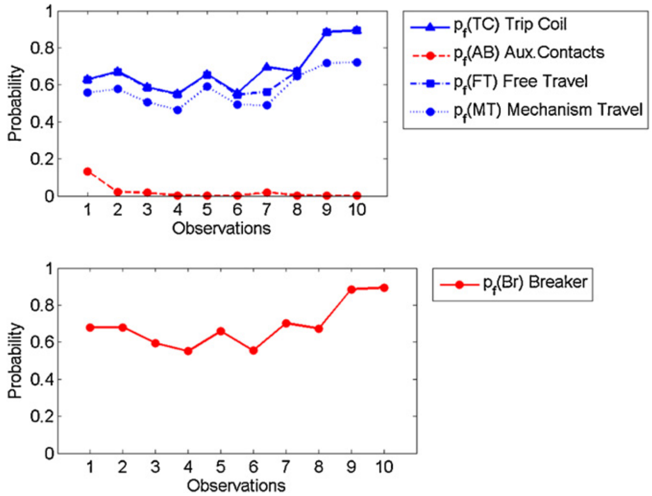

Fig. 16. Performance indices for CB opening.

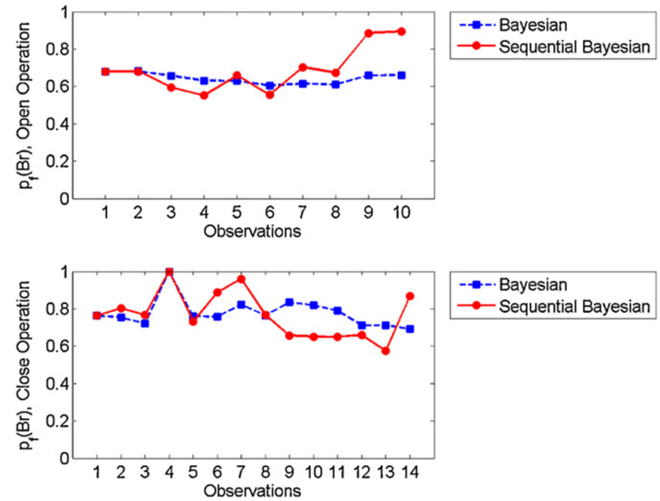

Fig. 18. Comparison of index p_f(Br) between Bayesian and Sequential Bayesian approach for both open and close operation.

require that prior and posterior distribution be from the same family of distributions such as normal distribution for mean parameters and inverse gamma distribution for variances. In our analysis we approximate the marginal posterior distribution with a normal distribution. The accuracy of this approximation is given in Fig. 18. The upper subplot shows the index, p_f(Br) for open operation. It can be seen that except for the last observation, both follows the same pattern and same values.

The lower subplot shows the same index for close operation. In this case also, the index computed in both Bayesian approaches follows the same pattern and the index values lie above 0.6 for both cases. However, a slight variation in computed indices can be observed especially for last few data points. This is due to the fact that we have less number of observed data points. It is anticipated that as the observed data increases, the accuracy of the proposed Sequential Bayesian approach also increases. Based on the results for the data sets considered in this work, Sequential Bayesian approach can be utilized as approximation to the Bayesian approach, such that it can be used for computing performance indices online. Note that the proposed Sequential Bayesian approach is data driven and hence the accuracy of the method.

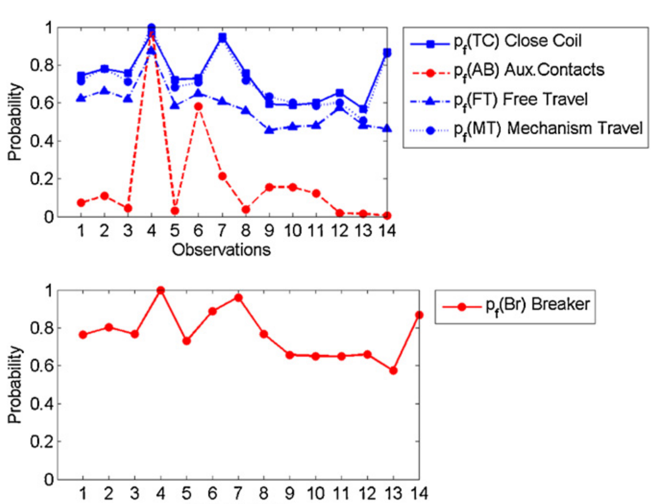

Fig. 17. Performance indices for CB closing.

The proposed methodology can be used to quantify the effect of maintenance. This quantification can be visualized in two aspects (i) an immediate maintenance action can be suggested depending on which performance index has high probability and (ii) the impact of such maintenance action by observing the reduction in performance index probability. The procedure is to measure the new data after a maintenance action. Then update the timing distributions and performance indices, and compare with that of previously calculated indices. Any difference can be reported as the direct result of that particular maintenance action. This way, it is possible to quantify the effect of maintenance and hence to develop system level optimized risk-based maintenance strategies.

5. Conclusion

A probabilistic methodology has been developed to achieve quantification of maintenance. The developed methodology relates the condition-based data to health of the breaker in terms of performance indices. These indices are defined based on probability distributions of timing parameters of control circuit signals. Bayesian approach is utilized to update the indices as the new data arrives. The methodology has the ability to compute and update the indices on-line, as the field data arrives. The indices may be used to develop risk-based decision approaches.

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Appendix A.

See Tables A and B.

Table A
Summary of test records taken during the open operation.

Manufacturer and type: GE VIB-15.5-20000-2					
Date	t_2 (ms)	t_3 (ms)	t_4 (ms)	t_5 (ms)	t_6 (ms)
2/12/2002	2.257	17.708	31.076	36.111	30.382
2/13/2002	1.215	9.375	33.333	37.674	29.167
2/13/2002	1.389	14.062	32.639	35.764	27.257
2/19/2002	1.389	14.757	29.514	35.764	32.292
2/21/2002	1.042	15.625	30.382	36.632	28.125
2/21/2002	1.563	18.056	31.250	34.375	29.687
2/21/2002	0.868	16.840	30.382	33.507	28.299
3/05/2002	2.083	23.090	28.646	36.111	27.604
3/05/2002	1.910	15.972	29.687	32.986	27.604
3/05/2002	2.431	14.931	29.167	34.375	28.299
6/10/2002	1.389	10.590	29.861	35.243	27.778
6/10/2002	1.215	15.278	30.208	33.681	29.167
6/10/2002	1.389	15.104	30.035	32.986	27.083
6/10/2002	1.389	11.458	29.514	33.333	27.604
6/11/2002	1.042	15.278	28.993	33.681	27.257
6/11/2002	1.563	14.062	26.910	31.076	25.000
6/11/2002	0.694	11.111	31.944	33.854	27.431
6/11/2002	3.299	11.458	30.729	34.549	28.125
6/11/2002	1.910	12.153	30.903	35.764	28.646

Table B
Summary of test records taken during the close operation.

Manufacturer and type: GE VIB-15.5-20000-2					
Date	t_2 (ms)	t_3 (ms)	t_4 (ms)	t_5 (ms)	t_6 (ms)
2/12/2002	1.2150	10.417	28.993	56.597	66.840
2/12/2002	0.8680	12.500	32.639	58.160	68.229
2/13/2002	1.0420	14.236	48.785	55.903	66.493
2/13/2002	1.7360	11.979	43.229	52.951	66.146
2/19/2002	1.3890	17.361	37.500	59.896	78.130
2/21/2002	3.8190	4.861	34.375	56.424	67.535
2/21/2002	0.6940	11.632	27.257	58.854	68.576
2/21/2002	0.5210	11.285	50.521	60.764	68.924
2/21/2002	0.6940	27.604	29.514	62.153	71.007
3/05/2002	2.2570	17.882	29.687	55.382	66.146
3/05/2002	0.8680	11.458	29.514	57.292	67.014
3/05/2002	0.8680	14.236	28.299	57.292	68.403
3/05/2002	1.2150	8.854	34.028	56.944	61.285
6/10/2002	0.5210	13.889	53.299	53.819	64.931
6/10/2002	8.6800	14.583	41.493	60.590	71.354
6/10/2002	2.6040	13.194	30.208	52.778	65.799
6/10/2002	1.7360	11.285	32.292	63.542	72.917
6/11/2002	0.8680	14.236	31.076	63.021	72.569
6/11/2002	0.6940	10.243	32.465	60.590	70.833
6/11/2002	0.6940	13.889	32.639	61.458	70.486
6/11/2002	1.0420	11.111	48.958	57.118	68.056

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