Transmission System Equipment Maintenance: On-line Use of Circuit Breaker Condition Data

Satish Natti, *Student Member, IEEE*, and Mladen Kezunovic, *Fellow, IEEE*

***Abstract*--This paper defines a frame work of system level maintenance strategy based on probabilistic maintenance models. A concept of 'top-down' approach, listing various steps in operation and planning affected by maintenance strategy, is introduced. Illustration of these steps in detail is explained in 'bottom-up' approach with application to circuit breaker. A failure rate estimation model for circuit breaker is proposed using the on-line condition data. A brief discussion of probabilistic maintenance model is presented, followed by problem formulation for system level maintenance strategy.**

***Index Terms*--Circuit breaker, condition data, maintenance, optimization, probabilistic model, reliability**

I. Introduction

MAINTENANCE of power apparatus plays major role in asset management and reliability of power system. Failure of this equipment can greatly affect the power delivery and results in high cost associated with loss of load and component replacement. The "remaining life" of power apparatus and maintenance cost are two most important aspects, which affects the maintenance strategy. Undetected abnormal conditions may have a long term accumulated effect, which may cause major failures if no related maintenance action is taken. The power apparatus service availability and replacement cost should be balanced in order to get an optimal maintenance strategy.

An overview of existing maintenance approaches is reported in [1]. These strategies range from scheduled to predictive maintenance such as Reliability Centered Maintenance (RCM). In RCM approach, several alternative maintenance approaches are compared and most cost effective one with sustained reliability is selected [2]. RCM approaches are more attractive but they do not relate the effect of maintenance to the reliability quantitatively. Reference [1] also addresses how probabilistic models can help in optimizing the maintenance intervals and hence quantifying the effect of maintenance on reliability. Probabilistic models can give more insight about interplay between condition monitoring, inspection and maintenance actions. An effort was made to link the maintenance to reliability quantitatively in [3]. A strategy called Asset Management Planner (AMP) has been developed based on probabilistic maintenance model [4]. It models the component ageing process by representing the device in terms of condition stages. The AMP models takes state transition rates, mean state durations, maintenance and repair costs, and various decision probabilities as inputs and provide sensitivity to costs and unavailability or remaining life of the device.

A risk-based resource optimization based on transmission system maintenance has been described in [5]-[7]. This approach is based on the cumulative long-term risk caused by failure of individual equipment. First, an hourly risk is calculated associated with various contingencies with the help of a sequential simulator. Second, cumulative risk reduction due to each predefined maintenance task is estimated. Finally, an optimal selection and scheduling of maintenance tasks with objective being total cumulative risk reduction is achieved. An attempt was made to compare the effect of different preventive maintenance strategies on system reliability and cost in [8]. This approach, called Reliability-Centered Asset Management (RCAM), has been applied to study the impact of maintenance of distribution cables on system reliability. The method is developed based on RCM principles trying to relate more closely the effect of maintenance on system reliability and cost.

One way of quantifying the effect of maintenance at component level is by looking at the failure rates of the device before and after the maintenance. The estimates range from standard approach by taking number of failure per year [9]-[10] to probabilistic approaches such as Hazard rate models and Markov models [11]. These models can be used to capture the change in failure probability or change in life time or both. In [12], a multi-stage Markov model adapted from [4] is used to compute failure rates of power transformers using condition measurements. Our paper shows how to develop such failure rate estimation models for circuit breaker using on-line condition data.

Markov models can be further extended to modeling the aging process by representing the device life time using several condition stages [13]. These are also called probabilistic maintenance models. A probabilistic maintenance model for power transformer is developed and analyzed in [14]. The analysis covers the mean time to first

This work was supported by Pserc project "Automated Integration of Condition Monitoring with an Optimized Maintenance Scheduler for Circuit Breakers and Power Transformers", and in part by Texas A&M University.

Satish Natti, Mladen Kezunovic are with the Department of Electrical and Computer Engineering, Texas A&M University, College Station, TX 77843-3128 USA (e-mails: satish@ece.tamu.edu, kezunov@ece.tamu.edu)

failure (MTTFF) and probability of failure with respect to model parameters such as inspection rate in each stage. In addition, the probabilistic maintenance model facilitates the cost analyses with respect to model parameters, which makes them more suitable for long term planning for a given maintenance budget. Cost analyses include inspection, maintenance and failure cost of the equipment under consideration.

The paper is organized as follows. Section II describes the concept of 'top-down' approach followed by 'bottom-up' approach with application to circuit breaker in section III. A problem formulation of system level maintenance is proposed in section IV followed by conclusions.

II. Top-Down Approach

A concept of "top-down" approach is introduced to summarize various steps in power system planning and operation affected by maintenance strategy. The flow of the process, shown in Fig.1 is "Operations and decisions – Maintenance strategies – Quantification of maintenance – Data". Ultimately, operator has to ensure availability of proper power flow according to network security and economic constraints. Operator has to take decisions according to asset management and reliability constraints to meet this need. Asset management policies and reliability of power system can be greatly affected by proper system level maintenance strategies. Existing maintenance strategies such as RCM approach, Risk-Based approach etc. make use of the results of individual component analyses. These maintenance strategies often neglect system level problems which require considering the effect of maintenance quantitatively through models such as probabilistic maintenance models and/or failure rate estimation models. These models depend on condition monitoring data and history of operation of power system equipment such as transmission lines, transformers and circuit breakers.

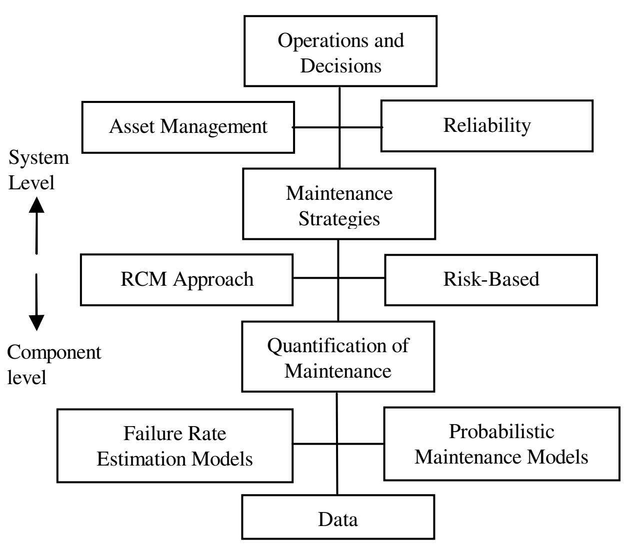

Fig. 1. Top-down approach

III. Bottom-Up Approach: Application to Circuit Breaker

This section describes the proposed bottom-up approach, specific to circuit breaker maintenance. This approach, as the name itself says, is reverse process of top-down approach briefed in earlier section. Though the process described is for circuit breaker, the same reasoning in general may be applicable to other power system equipment.

A. Data

Two types of data can be used for maintenance purposes. One is historical data which helps in understand the behavior of the equipment over a span of their life time. The other type of data is condition monitoring data which enables the condition based maintenance [15]-[17]. Majority of the circuit breaker failures are related to the operating mechanism. Control circuit signals, shown in Fig. 2 [18] contain information that can be used to evaluate the condition of different sub-assemblies of the operating mechanism. For example, delayed transition of phase current indicates a slow operation; the excessive noise during the contact transition indicates a dirty auxiliary contact; the excessive voltage drop of DC voltage indicates a battery problem, etc [19]. Control circuit data is basically a record of wave forms taken from the circuit breaker control circuit by using a portable [19] or on-line recorder [20] and respectively manually or automatically forcing a breaker operation.

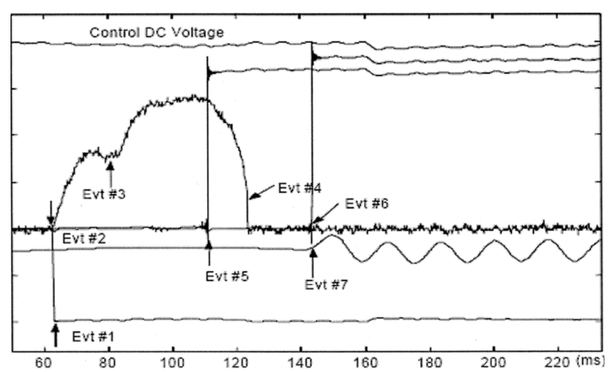

Fig. 2 Control circuit signal during close operation of circuit breaker [18]

TABLE I
Waveform Abnormalities and Signal Parameters [21]

Event	Event Description	Signal
1	Trip or close operation is initiated (Trip or close initiate signal changes from LOW to HIGH)	T1
2	Coil current picks up	T2
3	Coil current dips after saturation	T3
4	Coil current drops off	T4
5	B contact breaks or makes (a change of status from LOW to HIGH or vice versa)	T5
6	A contact breaks or makes	T6
7	Phase currents breaks or makes	T7
8	X coil current picks up	T8
9	X coil current drops off	T9
10	Y coil current picks up	T10

Signal processing and expert system modules developed in [21] can be used to extract the various features of the waveforms. A maximum of ten such features, also called events, and corresponding signal parameters are defined in Table I [21].

B. Failure Rate Estimation Model

A failure rate estimation model is proposed utilizing the breaker control circuit data [22]. The model quantifies the effect of maintenance in terms of reduction in failure probability and/or extended life time which can be utilized instantly in reliability and risk analyses. It differs from the probabilistic maintenance model, explained in later section, that it does not provide the cost analysis. The proposed model is shown in Fig. 3.

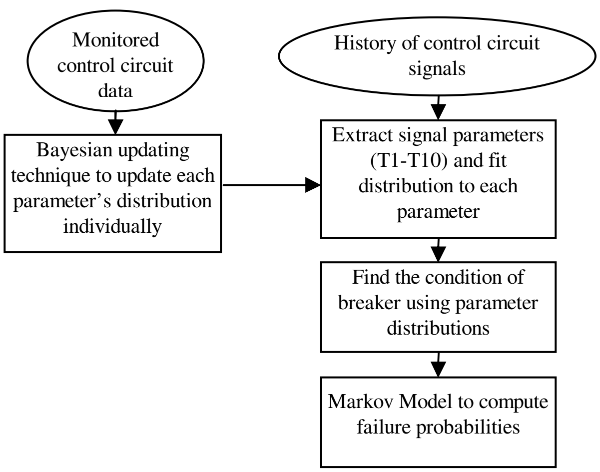

Fig. 3 Failure rate estimation model of circuit breaker

Following steps are involved in failure rate estimation process,

Step 1: Develop a history of control circuit signals

Step 2: Extract signal parameters and fit distribution to each parameter

Step 3: Update these distributions as the new condition data is coming using Bayesian updating approach.

Step 4: Relate the control circuit data to the health of the breaker in terms of different condition levels.

Step 5: Develop a Markov model to estimate the failure rate of the breaker having the condition levels and a history of data as inputs.

A Bayesian approach to update signal parameter distributions is discussed below. This effort can be related to left block of the failure rate estimation model in Fig. 3.

1) Initial Data Analysis

A history of each signal parameter, as is listed in the appendix is developed using the waveforms taken from the control circuit over a period of time. The records are taken on a group of circuit breakers from same manufacturer. Of the ten parameters (T1-T10), only a few are considered (T2-T6) because of their relative importance and for the ease of analysis. The idea is to see how the estimates of these parameters change as the new data are recorded. Before proceeding to the model, it is necessary to see the dependency among the variables. Assume that Y_1-Y_5 represents the signal parameters T2-T6 under consideration. It is observed from the scatter plot analysis that parameters Y_1, Y_2, Y_3 and Y_4 are independent, and a linearly increasing relationship between parameters Y_4 and Y_5 as shown in Fig. 4. A normal model is proposed based on the data and scatter plot analysis.

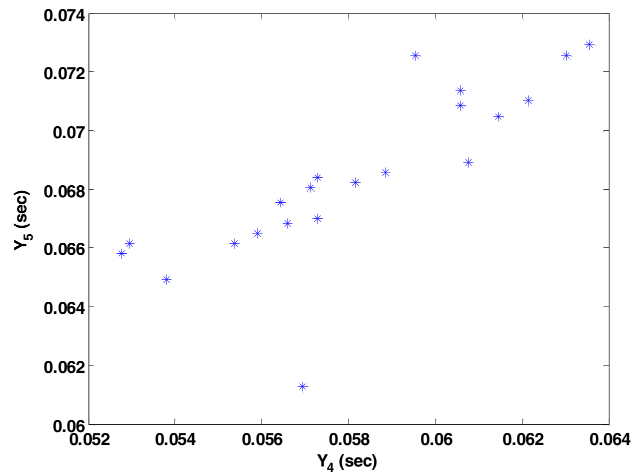

Fig. 4 Scatter plot of Y_4 and Y_5

2) Model selection

Let y_{ij} is the j_{th} observation of i_{th} variable and 'n' is the sample size,

$$y_{ij} \sim N(\mu_i, \sigma_i^2),\ \forall j,\ i = 1,2,3,4 \tag{1}$$

where μ_i and σ_i^2 are sample mean and variance of variables Y_1, Y_2, Y_3 and Y_4 respectively. Since there is a linear relationship between Y_4 and Y_5, Y_5 is expressed as,

$$y_{5j} = \beta_0 + \beta_1 y_{4j} + \varepsilon_{5j},\ \forall j \tag{2}$$

$$y_{5j} \sim N(\beta_0 + \beta_1 y_{4j}, \sigma_5^2), \tag{3}$$

where σ_5^2 is the error variance and, β_0 and β_1 are constants. The parameter set of the problem is,

$$\Theta = [\mu_1, \mu_2, \mu_3, \mu_4, \sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2, \sigma_5^2, \beta_0, \beta_1] \tag{4}$$

Assuming non informative prior for all σ_i^2 and uniform prior for all other parameters, the prior distribution is,

$$p(\theta) \propto \prod_{i=1}^{5} \frac{1}{\sigma_i^2} \tag{5}$$

The likelihood function is,

$$L(Y|\Theta) = \prod_{j=1}^{n} \left[\prod_{i=1}^{4} \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(y_{ij}-\mu_i)^2}{2\sigma_i^2}} \left(\frac{1}{\sqrt{2\pi\sigma_5^2}} e^{-\frac{(y_{5j}-(\beta_0+\beta_1 y_{4j}))^2}{2\sigma_5^2}} \right) \right] \tag{6}$$

The joint posterior distribution is given as,

$$p(\theta|_{Y}) \propto \left(\prod_{i=1}^{5}\frac{1}{\sigma_i^2}\right)\prod_{j=1}^{n}\left[\prod_{i=1}^{4}\frac{1}{\sqrt{2\pi\sigma_i^2}}e^{-\frac{(y_{ij}-\mu_i)^2}{2\sigma_i^2}}\left(\frac{1}{\sqrt{2\pi\sigma_5^2}}e^{-\frac{(y_{5j}-(\beta_0+\beta_1 y_{4j}))^2}{2\sigma_5^2}}\right)\right] \quad (7)$$

It is difficult to compute the normalizing constant that makes the above posterior distribution a density. Hence, Markov Chain Monte Carlo (MCMC) technique is used to estimate the posterior distribution of the parameters. MCMC using Gibbs sampler is implemented as it is easy to obtain conditional and marginal distributions for this particular normal distribution [23].

3) Conditional distributions

$$\mu_i\Big|_{\theta,y} \sim N(\bar{y}_i, \sigma_i^2/n),\ i = 1,2,3,4 \quad (8)$$

Retaining those terms that involve β_0 in the likelihood function (6) and after rearranging, conditional distribution for β_0 is given by,

$$\beta_0\Big|_{\beta_1,\sigma_5^2,y} \sim N(\bar{a}, \sigma_5^2/n), \qquad where,\quad \bar{a} = \frac{1}{n}\sum_{j=1}^{n}(y_{5j} - \beta_1 y_{4j}) \quad (9)$$

Retaining those terms that involve β_1 in the likelihood function (6) and after rearranging, conditional distribution for β_1 is given by,

$$\beta_1\Big|_{\beta_0,\sigma_5^2,y} \sim N(D/C, \sigma_5^2/C), \qquad where,\quad C = \sum_{j=1}^{n} y_{4j}^2,\quad D = \sum_{j=1}^{n}(y_{5j} - \beta_0)y_{4j} \quad (10)$$

4) Marginal distributions

$$\sigma_i^2\,|_y \sim Inv-\chi^2(n-1, s_i^2), \qquad i = 1,2,3,4 \quad (11)$$

Retaining those terms that involve σ_5^2 in the likelihood function (6) and after rearranging, marginal distribution for σ_5^2 is given by,

$$\sigma_5^2\,|_y \sim Inv-\chi^2(n, K/n), \quad where \quad K = \sum_{j=1}^{n}(y_{5j} - \beta_0 - \beta_1 y_{4j})^2 \quad (12)$$

5) Implementation

- start with initial vector of parameters, θ_0
- draw σ_i^2 , i = 1,2,3,4 from marginal distributions (11)
- draw σ_5^2 , from marginal distribution (12)
- draw β_0 from conditional distribution (9)
- draw β_1 from conditional distribution (10)
- draw μ_i, i = 1,2,3,4 from conditional distributions (8)
- new set of parameters, θ_1 is available
- repeat the above steps up to a predefined length

The above procedure is implemented in MATLAB. Table II shows posterior mode and 95% Highest Posterior Density (HPD) region for all the parameters under consideration. 95% HPD region means that the sample values of the parameters fall under this interval with a probability of 0.95. As the new data comes, it is possible to update the parameter distributions using the Bayesian approach described above. The posterior distribution of parameter Y_1 (T2, instant at which the coil current rises) is shown in Fig. 5.

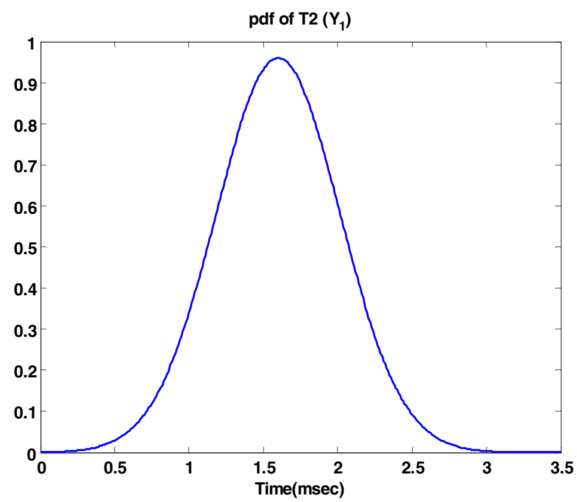

Fig. 5. Probability density function of Y_1

TABLE II
MODE AND 95% HIGHEST POSTERIOR DENSITY REGIONS

PARAMETER	MODE	95% HPD REGION
μ_1	0.0016	(0.0014, 0.0018)
μ_2	0.0130	(0.0125, 0.0134)
μ_3	0.0359	(0.0352, 0.0368)
μ_4	0.0582	(0.0578, 0.0585)
σ_1^2	0.0173E-05	(0.0093, 0.0325)E-05
σ_2^2	0.0094 E-05	(0.0502, 0.1818) E-05
σ_3^2	0.3517 E-05	(0.1886, 0.6552) E-05
σ_4^2	0.0520 E-05	(0.0278, 0.0949) E-05
σ_5^2	0.0148 E-05	(0.0079, 0.0277) E-05
β_0	0.0249	(0.0248, 0.0251)
β_1	0.7476	(0.7432, 0.7511)

6) Discussion

One way to see the effect of maintenance is to compare the hazard rates of each individual parameter before and after maintenance. Any difference at a particular instant is the direct result of maintenance. More research is needed towards relating these individual parameter distributions to the health of the breaker and anticipated condition levels. Currently we are exploring various possibilities in this regard. After this, we can easily apply the well known Markov process to get the failure rates of the breaker.

Further, it is possible to associate probabilities to the recorded time events of the control circuit signals. For example, it can be noted from Fig. 5 that if the next measurement for T2 is 1.5 msec, then the associated probability is 0.9313. During the inspection process of the breaker, instead of reporting only the times at which the predefined events happen, we can report the associated probabilities. This may give some insight into the condition of the breaker and may be useful in taking a better decision about the maintenance activities.

C. *Probabilistic Maintenance Model*

A probabilistic maintenance model developed earlier for transformer [13]-[14], is extended to circuit breaker [24]. Component aging process is modeled in terms of three deterioration stages i.e., the initial stage (D1), minor (D2) and, major (D3) deterioration stages, followed by a failure stage are considered and is shown in Fig. 6. The model parameter that can be varied is the inspection rate in each stage to get high reliability with minimum cost. Sensitivity analysis of inspection rate with respect to 'failure probability' and various costs is carried. The expected annual cost, which includes cost of inspection, cost of maintenance and cost of failure is shown in Fig. 7 with respect to change in inspection rate of stage D3. A detailed analysis can be found in [25]. This model finds its importance in long term maintenance and operation planning, and hence allows one to allocate the budget properly among maintenance and inspection activities. The system level maintenance strategy that will be explained in later section is based on this model.

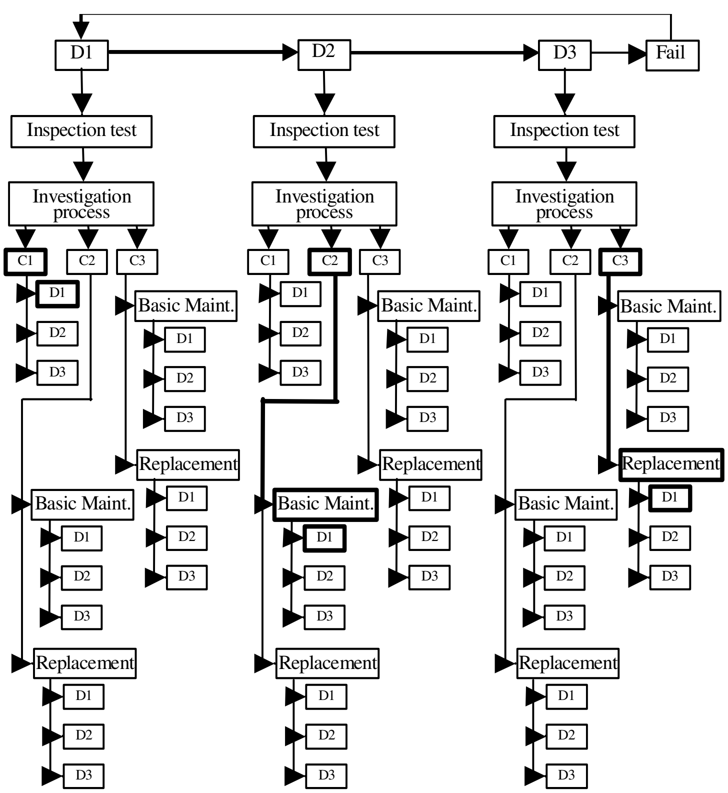

Fig. 6 Probabilistic maintenance model for circuit breaker

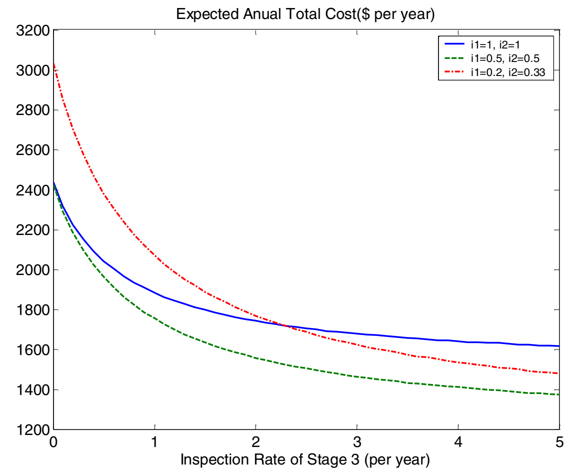

Fig. 7 Total annual cost vs. Inspection rate of stage 3

IV. System Level Maintenance Strategy

Problem formulation of system level maintenance strategy is presented in this section. The idea is summarized in several steps and given below.

Step 1: Component aging process is modeled using probabilistic maintenance model.
Step 2: Model parameters are identified and their sensitivity to probability of failure and various costs such as inspection, maintenance, and failure costs are carried.
Step 3: All components under consideration are analyzed similarly.
Step 4: An optimization problem is introduced with objective being to reduce the total operating cost. Operating cost include cost of inspection, maintenance and failure of those components which is scheduled for maintenance and the cost of customer damage.
Step 5: Budget and reliability constraints are incorporated.
Step 6: Output is an optimized system level maintenance strategy.

Let N be the total number of components under consideration and k = 1, 2, 3, … N, is the index over N,

r is the frequency of inspection/maintenance and varies from 0 (No maintenance) to a non-integer value, R.

Assume that, for each component k, we know its deterioration stage (D1, D2 or D3). Our objective is to find the optimal maintenance rate 'r', associated with each component 'k' such that the overall operating cost is minimized.

Define,

$C_F(k,r)$ = failure cost of component k with inspection rate of 'r' per year

$C_M(k,r)$ = maintenance cost of component k with inspection rate of 'r' per year

$C_I(k,r)$ = inspection cost of component k with inspection rate of 'r' per year

C_D is the customer damage function

The objective function can be defined as,

$$Min \left\{ \sum_{k=1}^{N} \sum_{r=0}^{R} \left(C_F(k,r) + C_M(k,r) + C_I(k,r) \right) + C_D \right\}$$

Subject to:

- Budget constraints
- Security constraints
- Labor hours

This problem formulation is under development. It is necessary to investigate how to define budget and security constraints to meet the required reliability of system operation.

V. Conclusions

A frame work for transmission system equipment maintenance assessment and planning is proposed. A concept of 'top-down' approach is introduced to give an idea about various steps involved in developing system level maintenance strategies. These steps are discussed in detail in 'bottom-up' approach with application to circuit breaker. Failure rate estimation model using circuit breaker control circuit data is proposed. Bayesian approach is implemented to update parameter distributions, which is part of failure rate estimation model. A system level approach to the optimized maintenance problem is proposed based on probabilistic maintenance models.

VI. Acknowledgment

The authors gratefully acknowledge the support from Dr C. Singh from Texas A&M University in related discussions.

VII. References

[1] IEEE/PES Task Force on Impact of Maintenance Strategy on Reliability of the Reliability, Risk and Probability Applications Subcommittee, "The present status of maintenance strategies and the impact of maintenance on reliability", *IEEE Trans. Power Systems*, vol. 16, no. 4, pp. 638- 646, November 2001.

[2] John Moubray, *Reliability-Centered Maintenance*, 2nd ed., New York, Industrial Press Inc. 1997.

[3] J. Endrenyi, and S. H. Sim, "Availability optimization for continuously operating equipment with maintenance and repair", in *Proceedings of the Second PMAPS Symposium*, California, September 1988.

[4] J. Endrenyi, G. J. Anders, and A. M. Leite da Silva, "Probabilistic evaluation of the effect of maintenance on reliability- An application", *IEEE Trans. Power System*, vol. 13, no. 2, pp. 576-583, May 1998.

[5] Y. Jiang, M. Ni, J. McCalley, T. Van Voorhis, "Risk-based resource optimization for transmission system maintenance," *IEEE Trans. Power Systems*, vol 21, no. 3, pp 1191-2000, August 2006.

[6] Y. Dai, J. McCalley, and V. Vittal, "Annual risk assessment for overload security", *IEEE* Trans. *Power Systems*, vol. 16, no. 4, pp 616-623, November 2001.

[7] Y. Dai, M. Bhuiyan, J. McCalley, and V. Vittal, "Annual risk assessment for voltage security and generation adequacy", in *Proc. 6th Int. Symp. Probabilistic Methods Applied to Power Systems*, Maderia Island, Portugal, September 2000.

[8] Lina Bertling, Ron Allan, Roland Eriksson, "A reliability-centered asset maintenance method for assessing the impact of maintenance in power distribution systems", *IEEE Trans. Power Systems*, vol. 20, no. 1, pp 75-82, February 2005.

[9] George Anders, Henryk Maciejewski, Bruno Jesus, and Faruq Remtulla, "Analysis of failure rates of Air Blast Circuit Breakers as a function of age and usage", *IEEE Bologna Power Tech Conference*, June 23rd-26th, Bologna, Italy, 2003.

[10] Tommie Lindquist, Lina Bertling and Ronald Eriksson, "A feasibility study for probabilistic modeling of aging in circuit breakers for maintenance optimization," *8th International Conference on Probabilistic Methods Applied to Power Systems*, Iowa State University, Ames, Iowa, September 2004.

[11] Z. Zhang, Y. Jiang, J. McCalley, "Condition-based failure-rate estimation for transformers," in *Proc. 2003 North American Power Symposium Conf.*, Rolla, USA.

[12] Y. Jiang, Z. Zhong, J. McCalley, T. Van Voorhis, "Risk-based maintenance optimization for transmission equipment," in *Proc. 12th Substations Equipment Diagnostics Conf.,* New Orleans, LA, Feb. 15-18, 2004, sponsored by Electric Power Research Institute.

[13] Panida Jirutitijaroen, and Chanan Singh, "Oil-immersed transformer inspection and maintenance: Probabilistic models", in *Proc. 2003 North American Power Symposium Conf.*, pp. 204-208.

[14] Panida Jirutitijaroen, and Chanan Singh, "The effect of transformer maintenance parameters on reliability and cost: A probabilistic model" , *Electric Power Systems Research*, Volume 72, Issue 3, 15 December 2004, Pages 213-224

[15] R. D. Garzon, *High Voltage Circuit Breakers: Design and Applications*, 2nd ed. New York: Marcel Dekker, 2002.

[16] IEEE Guide for the Selection of Monitoring for Circuit Breakers, IEEE standard C37.10.1-2000, December 2000.

[17] IEEE Guide for Diagnostics and Failure Investigation of Power Circuit Breakers, IEEE standard C37.10-1995, December 1995.

[18] Zhifang Ren, "Wavelet Based Analysis of Circuit Breaker Operation," Masters Thesis, Dept. of ECE, Texas A&M University, College Station, 2003.

[19] L. T. Rumfield "Circuit Breaker Diagnostic Response Testing Using the RTR-84 Response Time Recorder," presented at the Sixty-First Annual International Conference of Doble Clients, June, 1994.

[20] M. Kezunovic, G. Latisko, N. Ved, "Real-time monitoring and assessment of circuit breaker operations for diagnostics and control applications", *EPRI Substation Equipment Diagnostics Conference XIII,* New Orleans, Louisiana, March 2005.

[21] M. Kezunovic, Z. Ren, G. Latisko, D. R. Sevcik, J. Lucey, W. Cook, E. Koch, "Automated monitoring and analysis of circuit breaker operations," *IEEE Trans. Power Delivery*, vol. 20, no. 3, pp. 1910-1918, July 2005.

[22] M. Kezunovic, Satish Natti, "Risk-based maintenance approach: A case of circuit breaker condition based monitoring", *3rd International CIGRE workshop on Liberalization and Modernization of power systems*, Irkutsk, Russia, August 2006.

[23] Andrew Gelman, John B. Carlin, Hal S. Stern and Donald B. Rubin, "*Bayesian Data Analysis,*" 2nd ed. Chapman & HALL/CRC.

[24] Satish Natti, Panida Jirutitijaroen, Mladen Kezunovic, and Chanan Singh, "Circuit breaker and transformer inspection and maintenance: probabilistic models", *8th International Conference on Probabilistic Methods Applied to Power Systems*, Iowa State University, Ames, Iowa, September 2004.

[25] Satish Natti, Mladen Kezunovic, and Chanan Singh, "Sensitivity analysis on the probabilistic maintenance model of circuit breaker", *9th International Conference on Probabilistic Methods Applied to Power Systems*, Stockholm, Sweden, June. 2006.

VIII. Biographies

Satish Natti (S'06) received the B.E degree from Andhra University, India, in 2001, and the M.Tech. degree from Indian Institute of Technology, Kanpur, India, in 2003. He is pursuing the Ph.D. degree in Electrical and Computer Engineering at Texas A&M University, College Station. His research interests are power system reliability, maintenance and asset management.

Mladen Kezunovic (S'77-M'80–SM'85–F'99) received the Dipl. Ing. , M.S. and Ph.D. degrees in electrical engineering in 1974, 1977 and 1980, respectively. Currently, he is the Eugene E.Webb Professor and Site Director of Power Engineering Research Center (PSerc), an NSF I/UCRC at Texas A&M University. He worked for Westinghouse Electric Corporation, Pittsburgh, PA, 1979-1980 and the Energoinvest Company, in Europe 1980-1986. He was also a Visiting Associate Professor at Washington State University, Pullman, 1986-1987. He spent his sabbatical in 1999-2000 at EDF Research Center in Clamart. His main research interests are digital simulators and simulation methods for relay testing as well as application of intelligent methods to power system monitoring, control, and protection. Dr. Kezunovic is a Fellow of IEEE, a member of CIGRE and Registered Professional Engineer in Texas.

IX. APPENDIX

SUMMARY OF TEST RECORDS DURING CLOSING OPERATION OF CIRCUIT BREAKER

Manufacturer and Type: GE VIB-15.5-20000-2					
Date	T2 (sec)	T3(sec)	T4(sec)	T5(sec)	T6(sec)
2/12/2002	0.001215	0.010417	0.028993	0.056597	0.066840
2/12/2002	0.000868	0.012500	0.032639	0.058160	0.068229
2/13/2002	0.001042	0.014236	0.048785	0.055903	0.066493
2/13/2002	0.001736	0.011979	0.043229	0.052951	0.066146
2/19/2002	0.001389	0.017361	0.037500	0.059896	0.007813
2/21/2002	0.003819	0.004861	0.034375	0.056424	0.067535
2/21/2002	0.000694	0.011632	0.027257	0.058854	0.068576
2/21/2002	0.000521	0.011285	0.050521	0.060764	0.068924
2/21/2002	0.000694	0.027604	0.029514	0.062153	0.071007
3/05/2002	0.001215	0.012674	0.036285	0.059549	0.072569
3/05/2002	0.002257	0.017882	0.029687	0.055382	0.066146
3/05/2002	0.000868	0.011458	0.029514	0.057292	0.067014
3/05/2002	0.001389	0.003646	0.049653	0.043576	0.048437
6/10/2002	0.000868	0.014236	0.028299	0.057292	0.068403
6/10/2002	0.001215	0.008854	0.034028	0.056944	0.061285
6/10/2002	0.000521	0.013889	0.053299	0.053819	0.064931
6/10/2002	0.008680	0.014583	0.041493	0.060590	0.071354
6/11/2002	0.002604	0.013194	0.030208	0.052778	0.065799
6/11/2002	0.001736	0.011285	0.032292	0.063542	0.072917
6/11/2002	0.000868	0.014236	0.031076	0.063021	0.072569
6/11/2002	0.000694	0.010243	0.032465	0.060590	0.070833
6/11/2002	0.000694	0.013889	0.032639	0.061458	0.070486
6/11/2002	0.001042	0.011111	0.048958	0.057118	0.068056