

Risk-Based Maintenance Approach: A Case of Circuit Breaker Condition Based Monitoring

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Abstract--This paper presents an overview of resource optimization approach for transmission system maintenance selection and scheduling. The approach is based on failure rate estimation and risk reduction calculation followed by resource optimization. It also presents probabilistic models developed for circuit breakers and power transformers. An effort is made to quantify the effect of maintenance using the circuit breaker monitor's data.

Index Terms--Condition data, maintenance, optimization, power system, reliability, risk, security, transmission equipment

I. BACKGROUND

FREQUENTLY used maintenance strategies are reviewed and reported in [1]. They range from scheduled maintenance to reliability-centered maintenance (RCM) and condition based maintenance (CBM). Industry is slowly moving from scheduled maintenance to 'maintenance as needed'. This leads to the development of probabilistic maintenance models which help in optimizing the maintenance intervals and hence it is possible to quantify the effect of maintenance on reliability [2]. They allow modeling the component deterioration process and linking them to the condition of the device [3]. These models are further developed for circuit breakers and transformers with objective being Mean Time to First Failure (MTTFF), failure probability and cost analysis [4]-[7]. Reliability analysis and risk analyses often demand the effect of maintenance especially for devices like circuit breakers and power transformers. Quantifying maintenance is necessary to see the effect on reliability and it demands estimation of failure rates. A clear understanding of failure modes of components is necessary to develop failure rate estimation models [8]-[10].

The paper starts with discussion of proposed probabilistic maintenance models for both circuit breakers and transformers. Sensitivity analysis of model parameters at each stage is carried and the results are corroborated with that of an equivalent mathematical model. Various approaches for failure rate estimation are discussed. Circuit breaker failure rate estimation model is proposed which utilizes the control

circuit data. The paper ends with a discussion of resource optimization approach for transmission system maintenance selection and scheduling [11].

II. COMPONENT ANALYSIS FOR LONG TERM MAINTENANCE SCHEDULING

Long term maintenance scheduling is based on individual component performance and the objective is to maximize the residual life of equipments. The output is just recommended maintenance/inspection interval (usually in the unit of year) for components and it does not consider the network constraints and load trajectory. This is because for the long-term time frame, it is difficult to get accurate forecast on network model and loading conditions. There are multiple constraints which will affect the result of maintenance scheduling such as budget, labor, feasible time and many other factors. Also, the utility companies must consider the load variation during the maintenance time period, in the reason of maintaining system reliability. This information will be used in transmission maintenance scheduling.

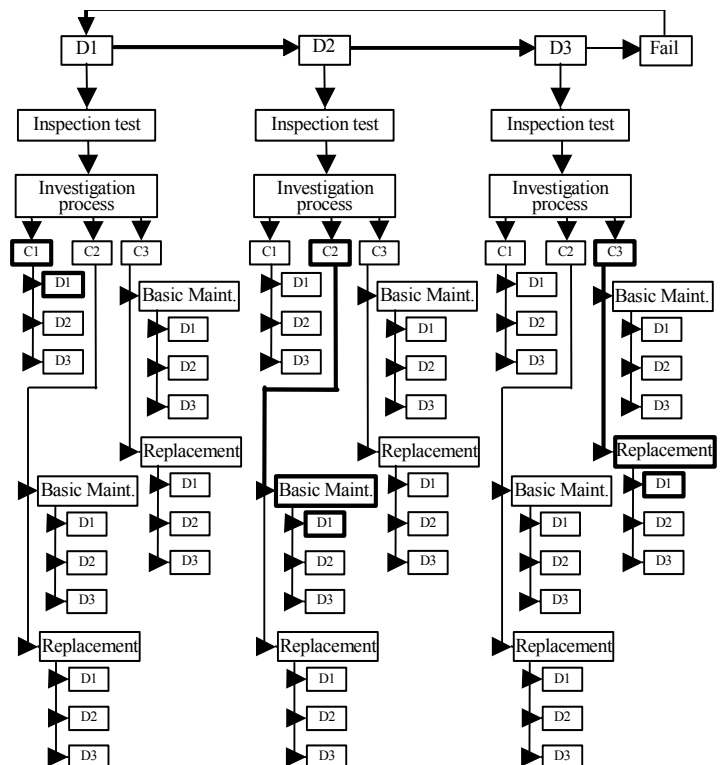


Fig. 1 Probabilistic maintenance model of circuit breaker

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.

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A. Probabilistic Maintenance Model

Probabilistic maintenance models are proposed utilizing the concept of device-of-stages for both circuit breakers and transformers [4]-[5]. Fig. 1 shows the maintenance model for circuit breaker. The deterioration process is represented by three stages. At each stage, inspection test is implemented to determine the component condition during investigation process. Depending upon the maintenance action taken, the subsequent condition of the components will be determined.

B. Sensitivity Analysis of Model parameters

Table I shows the list and definition of parameters that are used in the circuit breaker maintenance model [7]. The probabilities in model parameter 3 can be treated as equivalent transition rates from one stage to others. The equivalent model is introduced to clarify this point later. Parameters 1 and 3 can be approximated from the historical data of a physical circuit breaker condition [3]. Whereas, parameter 2, which is the inspection rate of each stage can be varied to achieve high reliability with minimum cost. Therefore, this parameter is of the most concern in the analysis. The analysis covers two aspects: probability of failure and all associated costs (failure cost, maintenance cost and total cost). Model parameters used in simulation and the results from MATLAB are listed in [7]. Fig. 2 and 3 show probability of failure and total cost analysis with respect to the inspection rate of stage 3. Results suggest that small inspection rate of stage 1 and high inspection rate of stage 2 and stage 3 will lead to cost effective maintenance. Readers are advised to go through the mentioned references for full discussion of results.

C. Equivalent Mathematical Model

In order to check the validity of the maintenance model presented in Fig. 1, it is necessary to introduce an equivalent mathematical model. Fig. 4 shows the equivalent model with 3 discrete stages representing the deterioration process of the breaker. Assume that maintenance is implemented at every inspection, maintenance and inspection rate of each stage is considered to be an equivalent repair rate.

TABLE I
LIST OF MODEL PARAMETERS AND DEFINITIONS [7]

Model parameters	Definition
1. Mean time in each stage	It is defined as mean time the device spends in each stage. The inverse of the mean time is the transition rate of the corresponding stage in the deterioration process.
2. Inspection rate of each stage	It is defined as the rate at which the inspection is done. The inspection may be followed by the maintenance.
3. Probabilities of transition from one state to others	These parameters are the probabilities of transition from one state to others. These probabilities include: <ul style="list-style-type: none"> • The breaker conditions after the inspection process • Transfer from any breaker condition to a given stage • Basic maintenance or replacement • Transferring to each stage after the maintenance

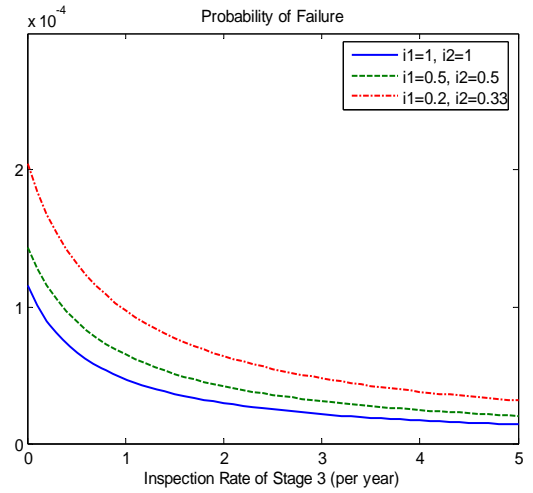


Fig. 2: Failure probability vs. Inspection rate of stage 3

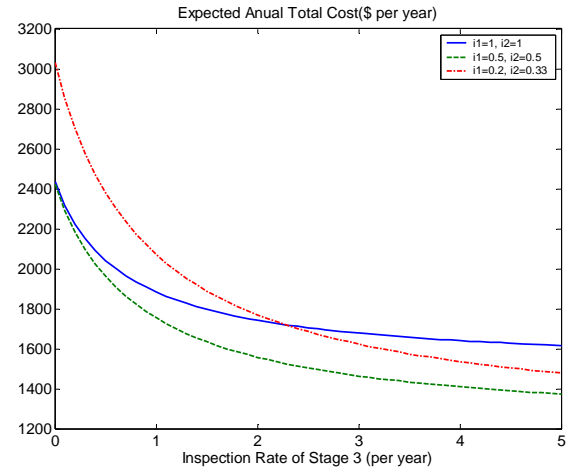


Fig. 3: Total annual cost vs. Inspection rate of stage 3

Let D1: stage 1

D2: stage 2, minor deterioration

D3: stage 3, major deterioration

F: failure stage

y_1 = mean time in stage 1 (year)

y_2 = mean time in stage 2 (year)

y_3 = mean time in stage 3 (year)

μ_{21} = repair rate from stage 2 to 1 (/year)

μ_{32} = repair rate from stage 3 to 2 (/year)

μ_{31} = repair rate from stage 3 to 1 (/year)

μ_F = repair rate (/year).

Transition rate from stage 1 to 3 (λ_{13}) is introduced to describe an imperfect inspection of stage 1. This accounts for the probability that inspection of stage 1 might cause the system to transit to stage 3. The mathematical analysis is

based on steady state probability calculations and the equations will be used to verify the simulation results presented in previous section. The analyses cover both the probability of failure and cost analysis. Detailed mathematical equations and analysis can be found in [5] and [7].

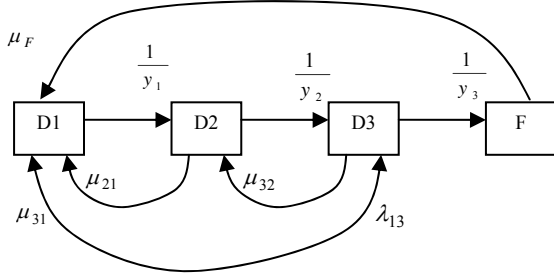


Fig. 4: Equivalent mathematical model

III. QUANTIFICATION OF MAINTENANCE

Both circuit breakers and power transformers and are critical and capital intensive asset within a power system. Due to the limited capital investment for new facilities, many breakers and transformers are close to or beyond their designed life. As these components age beyond their expected life, there is a risk of an increasing number of catastrophic failures. There is a great deal of focus on maintenance and life extension of aged circuit breakers and transformers to maximize the return on investments. This naturally leads to the use of reliability centered maintenance (RCM) approach where equipments with higher failure probabilities are given higher priority in maintenance. Thus failure probability estimation of equipment is required in maintenance asset management. Hazard function model and Markov model are widely used in quantifying the effect of maintenance by estimating failure rates of transmission equipment. These methods demand a clear understanding of relation between various failure modes and corresponding maintenance tasks [4]-[6] and [13].

A conceptual description of the deterioration process is effectively communicated using the hazard function. Consider the hazard function for a typical transmission equipment failure mode as shown in Fig. 5. In Fig 5 we observe that there are 4 deterioration levels corresponding to four different failure rate areas. Consider that the effect of a maintenance task could be to move the deterioration level from 3 to 1. The benefits from doing so are quantified in two ways: the failure probability is lowered by Δp , and the life is extended by Δt . The relative magnitudes of these two benefits depend on where the component is on the curve when the maintenance is performed. If the component is far to the right, then $\Delta p/\Delta t$ is large. If the component is far to the left, $\Delta p/\Delta t$ is small.

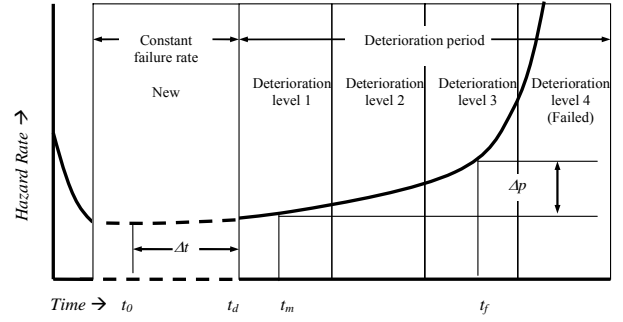


Fig. 5: Hazard function and maintenance induced contingency probability Δp [11]

The Markov model adapted from [3] is further developed to compute failure rates from condition measurements [11]. The model, together with its development procedure, is illustrated in Fig. 6. Three steps in implementing the approach are: (1) obtain the deterioration function $g(x)$, (2) perform the statistical processing necessary to estimate the transition intensities, and (3) use the model to calculate failure probability.

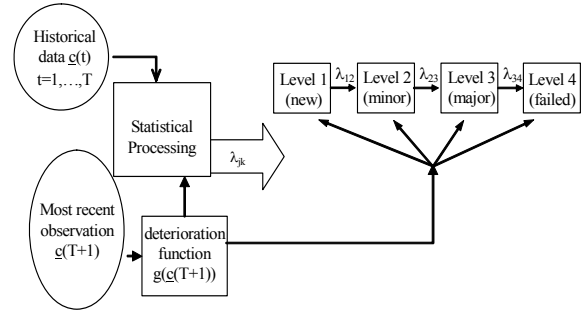


Fig. 6: Computing contingency probability reductions [11]

A detailed discussion of the model is reported in [11]. The main features of this approach are described in what follows [12].

(a) Deterioration function: The deterioration function, denoted by $g(c_k)$, may be an analytical expression if one is available or it may be a set of rules encoded as a program, consisting of a nested set of *if-then* statements that returns a scalar assessment value.

(b) Transition intensities: The transition intensities between the various states of the model can be obtained from life-histories of multiple units of the same manufacturer and model. In the case of Fig. 6, λ_{12} , λ_{23} , and λ_{34} are computed.

(c) Desired failure probability: For a particular set of transition intensities, the transition probability matrix for the model can be calculated using steady state probability calculations. The expected time to failure is captured by computing the first passage times [14]-[15]. An illustration of the whole process on a practical system is presented in [11].

IV. ESTIMATE OF CB MAINTENANCE INTERVALS USING DATA FROM CB MONITORS (CBMS)

Quantifying the effect of maintenance is a challenging task for reliability engineers. It is not easy to see the effect of maintenance, especially with equipment like circuit breaker which rarely operates. This section discuss the possibilities of utilizing circuit breaker control circuit data in evaluating the effect of maintenance and in estimating the failure rate as well. The idea is to first develop a procedure to relate the control circuit data to the health of the breaker in terms of different condition levels. Having these condition levels and a history of data as inputs, a Markov model will be developed to estimate the failure rate of the breaker. The proposed concept is at its early stages and needs further research. Fig. 7 shows the proposed failure rate estimation model which utilizes both Bayesian approach and Markov model concepts. In this paper, an attempt is made to apply the Bayesian technique to update the parameter distributions.

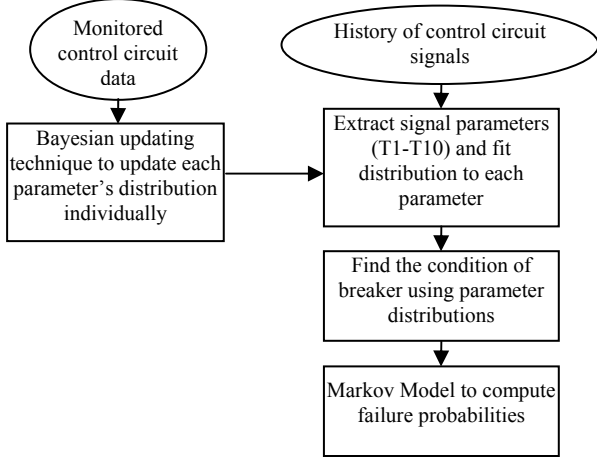


Fig. 7: Proposed failure rate estimation model of CB

Control circuit data is basically a record of wave forms taken from the circuit breaker control circuit by using a portable [16] or on-line recorder [17] and respectively manually or automatically forcing an operation. Signal processing and expert system modules developed in [18] can be used to extract the various features of waveforms. A maximum of ten such features, also called as events, and corresponding signal parameters are defined in Table II [19]. Fig. 8 shows typical record of waveforms taken during the closing operation of circuit breaker.

A history of each signal parameter is developed using the waveforms taken from control circuit over a period of time, and is listed in appendix. The records are taken on a group of circuit breakers of same manufacturer. Of these ten parameters (T1-T10), only a few are considered (T2-T6) for now 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 come. Following subsections present the problem formulation and implementation followed by a brief discussion on how to make use of the simulation results in evaluating the effect of maintenance.

TABLE II
WAVEFORM ABNORMALITIES AND SIGNAL PARAMETERS [19]

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

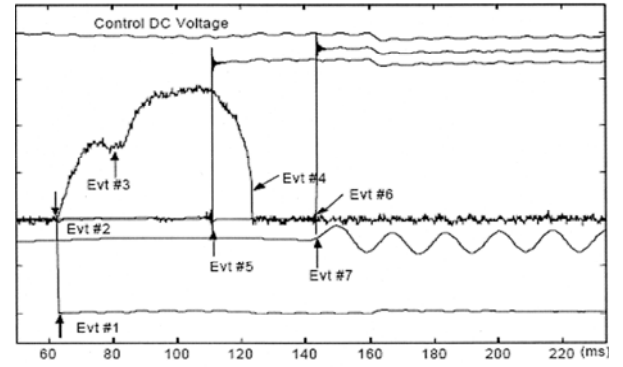


Fig. 8: Event features for a circuit breaker closing operation [19]

A. Bayesian Approach to Update the Parameter Distribution

Assume that Y_1 - Y_5 represents the signal parameters T2-T6 under consideration. Let y_{ij} is the j th observation of i th variable and 'n' is the sample size,

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

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,

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

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

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

$$\Theta = [\mu_1, \mu_2, \mu_3, \mu_4, \sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_4^2, \sigma_5^2, \beta_0, \beta_1] \quad (4)$$

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

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

The likelihood function is,

$$L(Y|\Theta) = \prod_{j=1}^n \left[\prod_{i=1}^4 \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(y_j - \mu_i)^2}{2\sigma_i^2}} \left(\frac{1}{\sqrt{2\pi\sigma_5^2}} e^{-\frac{(y_j - (\beta_0 + \beta_1 y_4))^2}{2\sigma_5^2}} \right) \right] \quad (6)$$

where 'n' is the sample size. The joint posterior distribution is given as,

$$p(\theta|y) \propto \left(\prod_{i=1}^5 \frac{1}{\sigma_i^2} \right) \prod_{j=1}^n \left[\prod_{i=1}^4 \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(y_j - \mu_i)^2}{2\sigma_i^2}} \left(\frac{1}{\sqrt{2\pi\sigma_5^2}} e^{-\frac{(y_j - (\beta_0 + \beta_1 y_4))^2}{2\sigma_5^2}} \right) \right] \quad (7)$$

B. Implementation and Results

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 [20]. The above mentioned procedure is implemented in MATLAB. Mixing of Markov chains and kernel density are plotted for each parameter. For the purpose of understanding, plots of selected parameters are shown in Figs. 10 and 11. It can be seen that the Markov chains mixed very well and the kernel density is almost normally distributed.

Table III shows the 95% Highest Posterior Density (HPD) region for all the parameters under consideration. It 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. 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. However more research is needed towards relating these individual parameter distributions (or hazard rates) to the health of the breaker interns of condition levels. Currently we are exploring various possibilities in this regard.

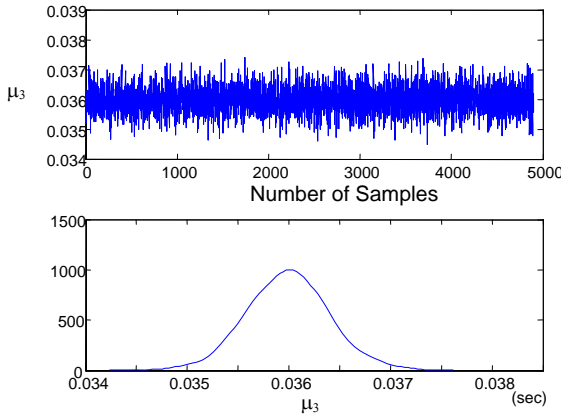


Fig. 9: Mixing and Kernel density plots of parameter μ_3

TABLE III

95% HIGHEST POSTERIOR DENSITY REGION OF EACH PARAMETER

μ_1	(0.0014, 0.0018)
μ_2	(0.0125, 0.0134)
μ_3	(0.0352, 0.0368)
μ_4	(0.0578, 0.0585)
σ_1^2	(0.0093, 0.0325)E-05
σ_2^2	(0.0502, 0.1818) E-05
σ_3^2	(0.1886, 0.6552) E-05
σ_4^2	(0.0278, 0.0949) E-05
σ_5^2	(0.0079, 0.0277) E-05
β_0	(0.0248, 0.0251)
β_1	(0.7432, 0.7511)

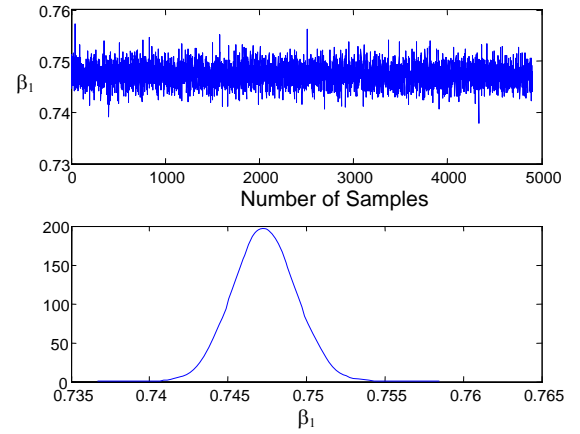


Fig. 10: Mixing and Kernel density plots of parameter β_1

V. RISK-BASED RESOURCE OPTIMIZATION

This section briefly discusses the developed resource optimization approach for transmission system maintenance selection and scheduling that is based on the cumulative long-term risk caused by failure of each piece of equipment [11], [12]. The approach has three steps: 1) long-term simulation with risk-based security assessment performed at each hour, 2) risk reduction calculation, and 3) optimal selection and scheduling, illustrated in Fig. 11. Here, the long-term sequential simulator, when integrated with hourly risk-based security assessment capability, provides year-long hourly risk variation for each contingency of interest. The risk-based security assessment performs a contingency analysis for each hour using power-flow analysis for overload, cascading overload, and low voltage, and continuation power flow for voltage instability analysis.

The year-long hourly risk variation, when combined with a set of proposed maintenance activities and corresponding contingency probability reductions, yields cumulative-over-time risk reduction associated with each maintenance activity

and associated possible start times. This cumulative risk-reduction captures, cumulatively over the next year (or more), the extent that failure of the component will adversely affect the system or other components in the system. Then, step 3) is an optimization whereby we select a number of task-time options subject to the constraints on feasible-times, total cost, and labor, with the objective to maximize the cumulative-over-time risk reduction.

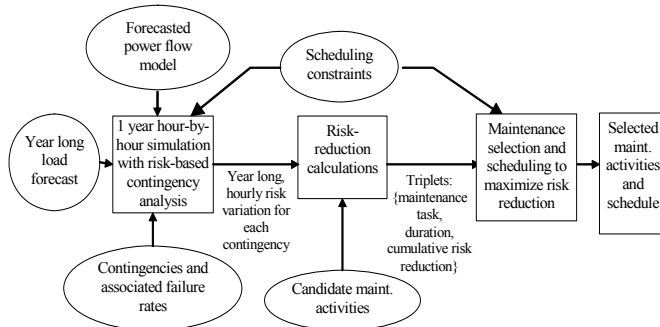


Fig. 11: Overview of developed process for maintenance selection/scheduling [11], [12]

As indicated in Fig. 11, the simulator is first run to compute risk as a function of time for each hour over a long-term such as a year and then the risk reduction associated with each proposed maintenance task is computed. This results in triplets comprised of: {maintenance task, task duration, risk reduction}. These triplets serve as input to the optimizer. An optimization problem constrained by a cost budget has been developed and its application to a practical system is discussed in [11], [12].

VI. CONCLUSION

Probabilistic maintenance models find their importance in long-term planning and allocation of resources over the life time of transmission equipment such as circuit breakers and power transformers. Reliability and risk analyses demand estimation of failure rates of components. Risk-based resource optimization for transmission system maintenance selection and scheduling is developed. It is illustrated with the case of circuit breaker condition based monitoring.

VII. ACKNOWLEDGEMENT

The contributions used in this paper come from the PSerc study that was led by Prof. Jim McCalley from Iowa State University with Professors Mladen Kezunovic and Chanan Singh from Texas A&M University as Co-PIs. The risk-based maintenance optimizer concept is developed by Prof. McCalley and his students. The maintenance modeling and analysis for circuit breakers is developed by Satish Natti under advice from Prof. Kezunovic and Prof. Singh. The power transformer modeling and analysis is developed by Panida Jirutitijaroen under advice from Prof. Singh. Prof. Kezunovic has developed the CB monitoring software with other group of student in an earlier project.

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