Risk-based Resource Optimization for Transmission System Maintenance

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Abstract: This paper describes a 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. This approach accounts for equipment failure probability, equipment damage, as well as outage consequence in term of dispatch cost. A method of computing the change of equipment failure probabilities and expected time to failure when equipment condition data is available is described. The method is illustrated on a 566-bus model of a US utility system.

Keywords: Power system, transmission equipment, maintenance, reliability, risk, security, optimization.

1. INTRODUCTION

The objective of the work reported in this paper is to develop a method of allocating economic resources and scheduling maintenance tasks among bulk transmission system equipment so as to optimize maintenance effects with respect to mitigation of component failure consequences. The central concept is that allocation of available economic resources for performing maintenance on a large number of facilities can be done strategically, as a function of cumulative-over-time risk associated with impact of the network dispatch cost and component damage to minimize risk of wide-area bulk transmission system failures.

The work makes use of two previously developed tools: redispatch cost assessment based on OPF and long term sequential simulation. Redispatch cost provides quantitative valuation of impact of contingency to the system operation cost, since an outage always requests removal of equipment out of service and redispatch is always needed to keep system in security. Here we take the redispatch cost as contingency severity and define the risk as the product of the severity and probability of equipment failure. We developed a simulator [1,2,3] that performs sequential long-term simulation of a power system on an hour-by-hour basis. It creates an hourly trajectory of operating conditions over a budget interval such as 1 year. The trajectory is formed by developing an hour by hour load forecast with corresponding unit commitment schedule and dispatch.

The long-term simulator, when integrated with hourly risk-based security assessment capability, provides hourly risk variation for each contingency of interest over the budget interval. This information, when combined with a set of proposed maintenance tasks, yields cumulative (over the budget interval) risk reduction (CRR) associated with each maintenance task and related possible start times. This overall process, (1) long term simulation with risk-based security assessment, (2) risk reduction calculation, and (3) optimal selection and scheduling, is illustrated in Fig 1. It is intended that this process be executed on a rolling basis throughout a budget interval as new information on unit schedules, equipment condition, loading projections, etc., become available. In addition, although a significant level of security assessment is built into the process, standard operational security studies for near-term maintenance outages may still be needed. The developed process provides optimal maintenance decisions for a transmission system on which constraints not included in the model (e.g., environmental, field constraints) may be superimposed.

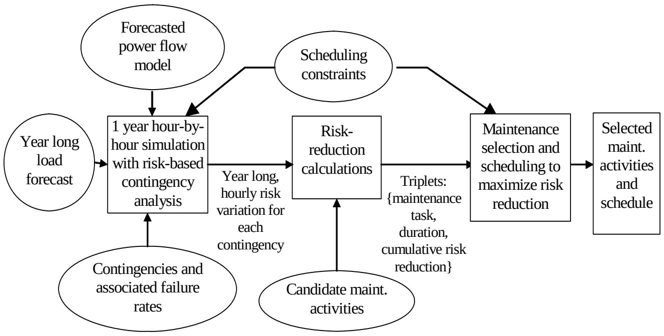

Fig.1: Overview of developed process for maintenance selection/scheduling

2. RELATIONSHIP TO CURRENT APPROACHES

Recently there has been a great deal of investment in developing asset management tools which may be classified by function. There are several which provide work-flow functions, work-order tracking, and data storage. Typical data stored includes nameplate, maintenance histories, and condition data. Some companies have several additional data repositories that house information such as outage schedules, operating histories (e.g., process-information or PI-historian), and equipment-specific condition data (e.g., tap changer temperatures). Because of the number and diversity of the asset management data repositories, there have also been efforts to build database integrators.

These efforts have mainly targeted the need to obtain and manage data. There has been less effort targeting tools that utilize data to facilitate decision-making. Towards this end, some companies select maintenance tasks by assigning weights to different attributes, scoring each maintenance task, and then prioritizing them based on score ranking. This approach lends itself towards decision-making but depends on a high degree of subjectivity.

Redispatch cost is linked to maintenance in two ways. First, they often restrict maintenance schedules when maintenance outages result in conditions that the cost might be too high. There are procedures at most control centers to identify such situations and then re-schedule the maintenance. However, these procedures are generally implemented as a human response to a maintenance request, in contrast to being an integral feature of a decision tool that initiates the maintenance request.

Second, the frequency of redispatch is affected by maintenance because a maintenance task may reduce the failure frequency of a piece of equipment's failure, and equipment failures can result in redispatch. The relation is complex because different pieces of equipment have different failure rates and consequently, the benefit of a maintenance task varies from one piece of equipment to another. In addition, the amount of redispatch cost resulting from failure of a piece of equipment at a given time (i.e., a given operating condition) varies from one piece of equipment to another. And these relative costs between equipment failures vary over time as conditions change. An important contribution of this paper is that the links between maintenance and redispatch cost are systematically embedded in the maintenance selection/scheduling software.

3. MAXIMIZING RISK REDUCTION

The objective of this paper is to describe an approach developed to maximize reliability benefit from maintenance selection and scheduling given constraints on financial and labor resources and network security, and to help direct resource management. As indicated in Fig. 1, 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.

The benefit of a maintenance task is captured via its risk reduction. In the work reported here, maintenance-induced risk reduction reflects (a) the reduction in frequency of operational constraints imposed following component failures (contingencies); (b) the savings incurred through extending the life of the component. Calculation of these risk reductions are described in Sections 4-6. Since the optimizer accepts any particular quantification of risk reduction deemed appropriate by the user, we describe it first.

Let N be the total number of maintainable transmission components; $k=1,...,N$ be the index over the set of maintainable transmission components; L_k be the number of maintenance tasks for component k; $m=1,...L_k$ be the index over the set of maintenance tasks for transmission component k; and $t=1,...T$ be the index over the time periods, typically denominated in either days or weeks.

Define $Is(k,m,t)=1$ if the m^{th} maintenance task for component k begins at time t, and 0 otherwise, $Ia(k,m,t)=1$ if the m^{th} task for component k is ongoing at time t, and 0 otherwise. Define $d(k,m)$ to be the duration of task m for component k, so that

$$Ia(k,m,t)=\sum_{j=t-d(k,m)+1}^{t} Is(k,m,j), \forall (k,m,t) \tag{1}$$

Equation (1) indicates that determination of whether the m^{th} task for component k is active at time t is accomplished by searching the selection function over the duration of the task until t. Also, $cost(k,m)$ is the cost of the m^{th} task for component k, and $CRR(k,m,t)$ is its cumulative risk reduction if the task begins at time t. Let $Inf(k,m)$ be the set of periods for which task m for component k cannot be performed and are thus infeasible. Each {component, task} combination (k,m) is tagged with a budget category $B(k,m)=b$. For example, $b \in 1, 2, 3, 4,$ where 1=transformer maintenance, 2=tree-trimming, 3=insulator cleaning, and 4=circuit breaker maintenance. $Labor(k,m)$ is the labor-hour requirement for the m^{th} task for component k. $TotLabor(b,t)$ is the labor availabilities for maintenance category b at time t.

Two forms for the resulting optimization problem have been developed. Problem 1 is constrained by a cost budget; this problem conforms to the situation where the scheduler is paying for the maintenance. Problem 2 is constrained by only feasible schedules submitted by equipment owners. This problem conforms to the case where the ISO schedules for multiple equipment owners who pay for their own maintenance. Problem 1 is described below; comments about Problem 2 are given at the end of this section.

$$Max\,\Big(\sum_{k=1}^{N}\sum_{m=1}^{L_k}\sum_{t=1}^{T} CRR\,(k,m,t) \times Is(k,m,t)\Big) \tag{2}$$

subject to:

$$\sum_{m=1}^{L_m}\sum_{t=1}^{T} Is(k,m,t) \le 1,\ \ k=1,\cdots,N \tag{3}$$

$$Ia(k,m,t)=0, \forall\, t \in Inf\,(k,m), \forall\,(k,m) \tag{4}$$

$$\sum_{k=1}^{N}\ \sum_{\substack{m=1\\(k,m):B(k,m)=b}}^{L_k} Ia(k,m,t) * Labor(k,m) < TotLabor\,(b,t), \forall t, b=1,...4 \tag{5}$$

$$\sum_{\substack{k=1\\(k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_k}\ \sum_{t=1}^{T} cost(k,m) * Is(k,m,t) < TotCost(b), b=1,...,4 \tag{6}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_k} Ia(k,m,t) * \Delta R(k,m,t) \le \Delta Rmax(t), \forall t \tag{7}$$

$$Is(k,m,t) \in \{0,1\}, \forall (k,m,t) \tag{8}$$

The objective (2) is to maximize total cumulative risk reduction. Constraint (3) restricts each component to be maintained at most once. Constraint (4) specifies infeasible periods for task (k, m). Constraint (5) requires that the number of maintenance tasks ongoing during any period is limited by available labor hour constraints. Constraint (6) represents budget constraints for each budget category. Constraint (7) limits the amount of additional risk introduced by all maintenance related outages ongoing at any time t and therefore inhibits simultaneous maintenance outages. Input data for constraint (4), which are infeasible times for task *(k,m)* contained in *Inf(k,m),* and for constraint (5), which are risk increases contained in *ΔR(k,m,t)*, are obtained from the simulator described in Section 4.

To solve this optimization problem is to determine *Is(k,m,t)*, which then determines *Ia(k,m,t)*. The optimization problem is integer, with multiple constraints and high dimension and therefore is challenging to solve. We have tested three different solution methods: heuristic, branch and bound, and relaxed linear programming with dynamic programming/heuristic (RLP-DPH). The first two of these are described in [4]. In comparing these methods, we found that RLP-DPH provides the best compromise between optimality and computational efficiency, resulting in near-optimal solutions with computation time reduced by an order of magnitude. This approach first solves a relaxed linear program (RLP) to obtain Lagrange multipliers on budget (6) and risk (7) constraints, and then a new objective function is developed, comprised of the original objective together with weighted cost and weighted risk, where the weights are Lagrange multipliers obtained from the RLP. It then solves knapsack problems [5] over the labor constraints (5) one period at a time, where a period is taken to be one day or one week. The procedure follows.

A. Relaxed LP to get dual variables: Solve an RLP that includes constraints (3)-(7) in order to get approximations on budget and risk constraint Lagrange multipliers μ_1-μ_4 and λ_t, $t=1,\ldots T$, respectively. This LP is "relaxed" in that variables are allowed to be non-integer, and so constraint (8) is excluded and all decision variables can be non-integer between [0,1]. The solution to the linear program is not a solution to the original integer programming problem since the decision variables are not integer. However, the solution does provide reasonable estimates of the Lagrange multipliers. These estimates are used to form a Lagrangian function comprised of the original objective less the weighted constraint functions, where the weights are the Lagrange multiplier estimates. The advantage of doing this is that the resulting problem is in the form of a "knapsack" problem, a class of problems for which solution procedures are readily available. The knapsack problem is solved over the labor constraints (5) for the first period to identify the maintenance tasks to be performed in that period. Then we re-solve the RLP with the period-1 variables known, to get updated Lagrange multipliers on the budget and risk constraints, and then a knapsack problem for the second period is solved. The process is repeated for all periods.

B. Solving knapsack problems: Moving risk and budget constraints to the objective function, the new objective function is a weighted sum of cumulative risk reduction, cost, and period risk, with the various Lagrange multipliers quantifying trade-offs between them. The problem of maximizing this objective subject to labor constraints (5) is a classical knapsack problem, stated as follows:

$$\max F(Is(k,m,t)) = \sum_{k=1}^{N}\sum_{m=1}^{L_k} CRR(k,m,t)\times Is(k,m,t)$$

$$-\sum_{b=1}^{4}\mu_b\left\{\sum_{\substack{k=1\\(k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_k}\sum_{t=1}^{T} cost(k,m) * Is(k,m,t) - TotCos(b)\right\}$$

$$-\sum_{t}^{t+T_{\max}}\lambda_t\left\{\sum_{k=1}^{N}\sum_{m=1}^{L_m}\Delta R(k,m,t) * Is(k,m,t) - \Delta R\max(t)\right\} \qquad (9)$$

subject to

$$\sum_{\substack{m=1\\(m,n):B(m,n)=b}}^{M}\sum_{n=1}^{M_m} Ia(m,n,t) * Labor(m,n) \le TotLabor(b,t), \forall t, b = 1,\ldots,4$$

There is a knapsack problem for each period, and they are solved in chronological sequence. Some qualifying remarks follow. (a) The risk reduction is only for the given period *t*, so the first term of the objective function does not sum over the time intervals. (b) The Lagrange multipliers on the budget constraints are found for the budget, so the second term of the objective function does sum over the time intervals. (c) There is a Lagrange multiplier on maximum risk for each period, but in solving for a single period, if we require that no task has duration exceeding a single period, we need only include the constraint corresponding to period *t*. However, some tasks may have durations exceeding one period. In this case, we must include the risk constraints for the current period *t* up to $t+T_{max}$, where T_{max} is the longest duration for any task. Therefore, the third term in the objective function must sum over period *t* to $t+T_{max}$. (d) Available hours for any period must be reduced by ongoing tasks that begin in earlier periods. (e) Infeasible periods from constraint (4) are enforced using negative objective function coefficients.

These knapsack problems may be solved to optimality using dynamic programming (DP). For high-dimensional problems, DP is computationally expensive, so our solution algorithm allows for some percentage of the solution to be obtained heuristically using ratio scores, i.e., the ratio of each task's objective function contribution to its required number of labor hours, to fill some percentage of the knapsack. The remaining space is then filled with dynamic programming. The solution procedure for this problem is as follows:

1. Choose a speed control percentage, SCP (0 is fast but suboptimal, 100 is slow but optimal). Set j=1.
2. For period j,
   a. Rank all unselected and feasible tasks in order of their ratio score. Identify the first N-ranked of these tasks, where N is chosen as a function of SCP (the larger is SCP, the larger is N).
   b. Identify the remaining (100-SCP)% of the tasks using dynamic programming.
   c. Flag all identified tasks as "selected."
   d. If j=52, stop, else, j=j+1 and go to (a).

Application of the above procedures to solving Problem 2, useful to ISOs, involves elimination of the resource constraints (5) and (6). This problem can be solved using the above procedure with the second term in (9) eliminated and the right-hand-side of the labor constraint very large.

The algorithm described above may only provide sub-optimal result because it utilizes linear relaxation, where the integer constraint is not enforced. Lagrange relaxation is known to provide accurate Lagrange multipliers for the integer programming, and the solution is optimal [5]. The Lagrange multipliers in our method are only approximates of the real Lagrange multipliers of the integer solutions. However, they are obtained with much less computation. We have tested the method by comparing its solution with that from the commercial integer programming software CPLEX and find that the method is much faster with very little loss in accuracy (error<5%).

4. LONG-TERM SIMULATION & RISK ASSESSMENT

Cumulative risk assessment performs sequential, hourly simulation over a long term, e.g., 1 year, and it evaluates the severity of contingency in terms of redispatch cost. This simulation capability is used to obtain the cumulative-over-time risk to which the system is exposed due through failure of equipment *k*, i.e., contingency *k*. The contingencies assessed by the simulator are those for which the corresponding equipment is a candidate for maintenance.

The risk index for a single contingency is an expectation of severity, computed as the product of contingency *k* probability $p(k)$ with contingency consequence $con(k,t)$, where *t* indicates the hour and thus the operating conditions in terms of loading and dispatch. The risk is given by $R(k,m,t)= p(k)con(k,t)$. The consequence $con(k,t)$ captures the contingency consequence in terms of the cost of redispatch necessary to relieve violations resulting from the contingency.

The cumulative risk from t_0 to T of a contingency *k*, given a defined network configuration and operating condition at each time *t* is computed by summing over time $t=t_0,\dots,T$:

$$\boldsymbol{R(k,t_0) = \sum_{t=t0}^{T} p(k)\times con(k,t)} \qquad (10)$$

The long-term cumulative risk simulator performs a full N-contingency security assessment for each hour in the budget period, and associated risk indices for each contingency are computed by eq. (10). Given a contingency set, the simulator steps through a sequence of power flow cases spanning the budget interval, and for each power flow case and each contingency, it calculates the cost of redispatch necessary to relieve any security violations. In its most efficient mode, the simulator assesses overload only, and on detecting an overload, it performs a linear-programming-based optimal power flow (LP-OPF) to alleviate the overload(s) at minimum cost re-dispatch. The re-dispatch cost is taken as the outage consequence. Outage consequence associated with voltage and voltage stability violations requires redispatch and other controls best identified using a nonlinear OPF. Alternatively, one may use severity functions [6,7].

Three basic modules are required to use with the long-term cumulative risk assessment simulator, including load forecasting, unit commitment, and contingency selection. The specific implementation used for each of these modules is interchangeable. The sequential approach used in our simulator evaluates a trajectory of operating conditions over time. The key features that drive the design are: (1) *Hourly assessment*: In making a long-term risk computation, some components may see highest risk during off-peak or partial-peak conditions, when weak network topologies, weak unit commitment patterns, or unforeseen flow patterns are more likely to occur. (2) *Sequential simulation*: Load-cycles, weather conditions, unit shut-down and start-up times, and maintenance strategies are examples of chronologically dependent constraints that affect system reliability. Several speed enhancements are used to offset the computational intensity of the simulator, as described in [7].

The main task of the simulator is to obtain cumulative risk for each contingency per eq. (10). However, since contingencies correspond to failure modes under consideration for maintenance, and if that maintenance requires outaging the component, it is convenient to also employ the simulator to assess security of each outaged state for identifying infeasible times associated with constraint (4) of Section 3. A fast DC power-flow is used to do this.

5. QUANTIFICATION OF MAINTENANCE BENEFITS

We have developed a table [8] matching maintenance tasks to the failure modes that they affect, based on literature review [9-26] together with resources obtained from industry contacts, where a maintenance task is, with respect to a particular component (line, transformer, circuit breaker), a task that changes the state of the component. A monitoring activity such as inspection, testing or sampling is a task that provides information useful in assessing the component state. The change in component state resulting from a maintenance task should result in either failure probability reduction or extended life or both.

The hazard function is a useful conceptual model for illustrating these benefits. A hazard function for a typical transmission equipment failure mode is shown in Fig. 2. Two intervals of this curve are considered: 1) constant failure rate period and 2) deterioration period with increasing failure rate. The level of each benefit from maintenance, with respect to a particular failure mode for a specific component, is associated with where on the hazard curve the component lies when the maintenance is performed. If the maintenance is performed during the deterioration period, e.g., at time t_f in Fig. 2, the benefit comes mainly from the decrease of failure rate, which results in a decrease in failure probability Δp, but for maintenance performed during the constant failure rate period, e.g., at time t_d, the benefit comes mainly from the life extension Δt because of delay of the deterioration period (t_d in Fig. 2).

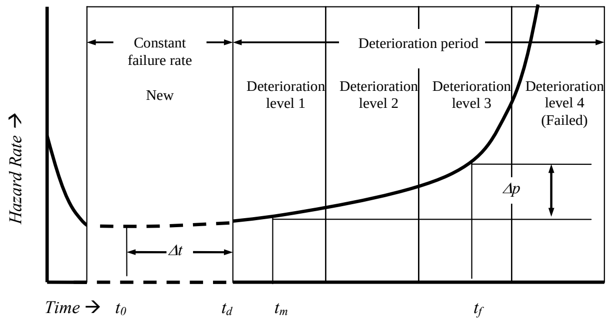

Fig 2: Hazard function and maintenance induced contingency probability Δp

Good estimates of Δp and Δt resulting from a maintenance task may be obtained by statistically characterizing the failure mode deterioration level before and after the maintenance using condition assessment tools [27]. Such deterioration levels are illustrated in Fig. 2. However, the hazard function is not well-suited to discretization of condition. Therefore we turn to a method better suited to discrete-state models.

We employ a multi-state Markov model [28] adapted from [29] to compute failure rates from condition measurements. Our model, together with its development procedure, is illustrated in Fig. 3.

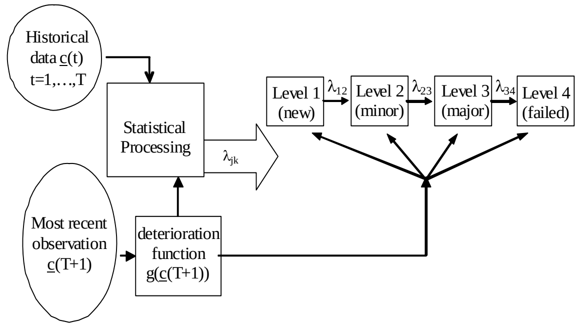

Fig. 3: Computing Contingency Probability Reductions

We assume that we have at our disposal a set of condition vectors $\underline{c}(t)=[\underline{c}_1(t),\underline{c}_2(t),\ldots,\underline{c}_K(t)]$ for K similar components taken over an extended period of time $t=0,1,\ldots,T$, where each vector $\underline{c}_k(t)$ provides M different measurements $c_{k1}(t), c_{k2}(t),\ldots c_{kM}(t)$, on component k characterizing its condition at time t. Each of the J states of the Markov model represents a deterioration level. The particular representation of Fig. 3 shows $J=4$ deterioration levels, and deterioration level j can be reached only from deterioration level j-1. However, the model is flexible so that any number of deterioration levels can be represented, and, if data indicates that transitions occur between non-consecutive states (e.g., state 1 to state 3), the model can accommodate. The main features of this approach are described in what follows.

<u>(a) Deterioration function</u>: The deterioration function, denoted by $g(\underline{c}_k)$, 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. For the model of Fig. 3, the assessment value would be a deterioration level 1, 2, 3, or 4. This represents a flexible and practical way of connecting our approach to the wealth of existing knowledge and experience contained in the industry in regards to interpreting condition monitoring measurements. Often, such rules depend not only on the measurements $\underline{c}_k(t)$ but also on the rates of change in such measurements. For example, reference [30] provides a comprehensive compilation of such rules for transformers that identifies different measurements for characterizing various transformer failure modes. Examples of the most common measurements (and some of the failure modes they detect) include dissolved gas analyses results on main tank oil (insulation deterioration, deterioration of cooling system, oil pump failure) and load tap changer oil (oil dielectric weakening), thermography testing (magnetic circuit overheating, bushing overheating), ultrasonic testing (oil pump failure), partial discharge testing (magnetic circuit overheating), winding and oil temperature (deterioration of cooling system).

<u>(b) Transition intensities</u>: 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. 3, λ_{12}, λ_{23}, and λ_{34} are computed. Suppose we have a set of condition measurements $\underline{c}(t)=[\underline{c}_1(t),\underline{c}_2(t),\ldots,\underline{c}_K(t)]$ for K similar components taken over an extended period of time $t=0,1,\ldots,T$, where $\underline{c}_k(t)$ for component k represents all measurements taken that characterize the component's condition with respect to a particular failure mode. Each measurement vector $\underline{c}_k(t)$ is processed by the deterioration function to associate a deterioration level with component k at time t. Processing the data for $t=1,\ldots,T$ enables identification of the time each component spends in deterioration level j. The estimated time spent in state j is the mean of these durations. Reasonable estimates of the desired transition intensities are obtained by inverting these mean duration times. This same processing of historical data enables identification of change in state caused by maintenance.

<u>(c) Desired failure probability</u>: For a particular set of transition intensities, the transition probability matrix for the model shown in Fig. 3 is given by eq. (11).

$$\underline{\boldsymbol{P}}=\begin{bmatrix} \mathbf{1-\lambda_{12}} & \boldsymbol{\lambda_{12}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{1-\lambda_{23}} & \boldsymbol{\lambda_{23}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1-\lambda_{34}} & \boldsymbol{\lambda_{34}} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{1} \end{bmatrix} \quad (11)$$

The state probability vector gives the probability that a component is in any particular deterioration level at a given time, and is denoted by $p(hT)=[p_1(hT)\quad p_2(hT)\quad p_3(hT)\quad p_4(hT)]$, where $h=1,2,3,\ldots$, and T is the time step. If at time $t=0$, the component resides in deterioration level 1, then the initial state probability vector is $\underline{p}(0)=[1\quad 0\quad 0\quad 0]$. The probability of finding the component in any deterioration level at time hT is then given by $\underline{p}(hT)=\underline{p}(0)\underline{P}^h$. Given that at time t_0, we know the component's deterioration level, this last equation provides the probability of residing in the failed state in any future time interval. We denote this failure probability for the k^{th} component as $p(k)$. This probability is a function of the time-dependent physical condition of the equipment $\underline{c}(t)$.

In addition to failure probability, this modeling provides the ability to predict maintenance-induced probability reduction $\Delta p(m,k)$ and expected time to failure $\Delta p(m,k)$. For a 4-level model, if a particular maintenance task results in renewing a component to deterioration level 1 (as indicated by the deterioration function) for example, then, if the component is in deterioration level 3, the probability reduction for maintenance task m, $\Delta p(m,k)$, is given by the last element of the 1×4 row vector resulting from the calculation:

$$[1\ \ 0\ \ 0\ \ 0]\underline{P}-[0\ \ 0\ \ 1\ \ 0]\underline{P}=[1\ \ 0\ \ -1\ \ 0]\underline{P} \qquad (12)$$

The expected time to failure is captured by computing first passage times. First passage time is the expected value of the amount of time the process will take to transition from a given state j to another state i, under the assumption that the process begins in state j. From this computation, then, we may estimate the remaining life of the component. We utilize the method introduced in [31] and [32] to calculate the first passage time to failure as:

$$T_f = p(0) \times T \times (I - P_r(T))^{-1} \tag{13}$$

where T_f is the vector of time to failure from different states, I is identity matrix, and $P_r(T)$ is a partition of the transition matrix $\underline{P}$ corresponding to non-failure states [32]. The life extension Δt_k is obtained by calculating difference of time to failure of the states before and after maintenance. One should recognize, however, the existence of significant variance in the estimate of Δt_k.

Although the discussion of this section has focused on equipment maintenance, the approach is also applicable to failures caused by tree-contact and associated tree-trimming maintenance. Here the condition vectors (measurements) $c_k(t)$ for this failure mode consist of clearance between vegetation and power lines. Decreasing clearance intervals are assigned as discrete condition levels to conform to the model of Fig. 3. Transition rates between intervals are computed from the condition data. The failed state is defined based on FERC requirements on distance between conductors and vegetation [33].

6. MAINTENANCE-INDUCED RISK REDUCTION

The effect of maintenance m on component k completed at time t is expressed through its risk reductions due to failure rate reduction and life extension, as:

$$CRR(m,k,t) = CRR_1(m,k,t) + CRR_2(m,k,t) - C(m,k,t) \tag{14}$$

CRR_1 is the risk reduction from failure probability reduction, CRR_2 is the risk reduction from life extension, and C is the dispatch cost needed to schedule the maintenance outage.

We show in [4] that the cumulative-over-time risk reduction associated with failure probability reduction resulting from maintenance task m, component k, is $CRR_1(k,m,t)$, computed as a function of the task completion time t_0 according to:

$$CRR_1(k,m,t_0) = \frac{\Delta p(m,k)}{p(k)} R(k,t_0) \tag{15}$$

where $R(k,t_0)$ is the cumulative risk for contingency k under the system basecase configuration, an expected cost, obtained from a simulator run, $\Delta p(m,k)$ is the failure probability reduction due to the maintenance task m and $p(k)$ is the failure probability of contingency. Calculation of $\Delta p(m,k)$, and $p(k)$ is described in the discussion of Section 5.

The risk reduction from life extension due to maintenance-induced deterioration delay is the difference in present value of investments made at $t=MTTF$ and $t=MTTF+\Delta t_k$, given by:

$$\boldsymbol{CRR_2(m,k,t) = RC(k) \times (1+r)^{-(MTTF-t)}\left[1-(1+r)^{-\Delta t_k}\right]} \tag{16}$$

Here, $RC(k)$ is the restoration (repair or replacement) cost of the component after the failure, Δt_k is component k's life extension, described in the Section 5 and obtained via. (13), $MTTF$ is the component mean time to failure, and r is the expected rate of return on investment.

When a maintenance task requires the component to be temporarily removed from service, there may be need for redispatch to avoid security violations. By including this redispatch cost C in (14), we provide the means of assessing tradeoffs between maintenance schedules at critical times requiring high redispatch costs and the risk-reduction obtained from them via CRR_1 and CRR_2.

7. ILLUSTRATION

The methods described in the previous sections are illustrated in the following three subsections.

A. Failure rate estimation: Transformer dissolved gas analysis (DGA) test data obtained from a utility company was used to illustrate the failure rate estimation method. A small sample of this data is provided in Table 1. Criteria given in IEEE Standard C57 [34] was used as the deterioration function in interpreting the data. Transition intensities computed for the Markov model are given in Table 2. Fig. 4 shows the failure rate of this transformer corresponding to the failure mode of oil degradation.

TABLE 1
DGA TEST DATA FOR TRANSFORMER

Equip Num	Sample date	H_2	CO	CO_2	CH_4	C_2H_2	C_2H_4	C_2H_6	TDCG
001	2001-5-21	2	19	1479	0	0	0	0	183474
001	2001-6-25	87	48	1464	3	31	6	0	84410
001	2001-9-24	343	75	2704	35	251	34	0	105296
001	2001-12-26	710	105	3686	83	569	75	5	105617
001	2002-6-12	1093	122	3459	99	939	125	7	119459
001	2003-5-12	1726	355	5480	285	2182	327	15	100115

TABLE 2
ESTIMATED TRANSITION INTENSITIES FOR MARKOV MODEL

Transition rate	1(new)	2	3	4 (failure)
$\lambda_{i,i}$	0.91468	0.93933	0.99693	1
$\lambda_{i,i+1}$	0.08532	0.06067	0.00307	N/A

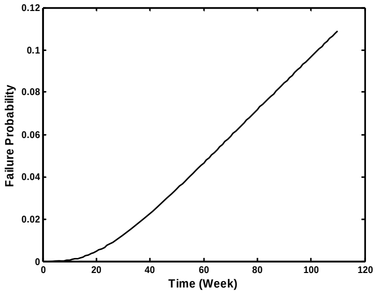

Fig 4: Failure probability of transformer

B. Risk reduction calculation: Testing of the risk reduction calculation was done using a 566-bus model of a US utility's system. The expected hour-by-hour 1-year loading trajectory used in the analysis is shown in Fig 5. For transmission lines, tree contact and insulator failure are the two most common failure modes. For transformers, mechanical failure and insulation oil deterioration are the two most common failure modes. For circuit breaker, the failure which is caused by mechanical excessive wear and maladjustments is a major failure mode and could cause the failure of protection action. We limit the maintenance tasks scheduled in our illustration to those affecting these failure modes. This means there are 259 contingencies to assess; 178 line outages, 46 transformer outages and 35 circuit breaker failures. The failure modes and corresponding maintenance tasks are listed in Table 3.

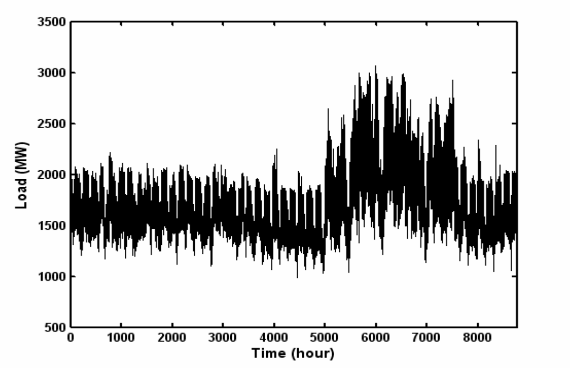

Fig 5: 1-year loading trajectory

TABLE 3
FAILURE MODES AND CORRESPONDING MAINTENANCE TASKS

Contingency	Failure modes	Maintenance category
Transmission line outage	Tree contact	Tree trimming
	Line or equipment failure	Insulator cleaning, replacement and hardware tightening/replacement near the tower position.
Transformer outage	Oil deterioration	Transformer minor maintenance: (oil filtering)
	Core problem, mechanical failure and ageing	Transformer major maintenance (including parts replacement, off-line testing and corresponding maintenance and oil change.)
Circuit Breaker Failure	Mechanical failure, excessive wear and maladjustments	Circuit breaker inspection and maintenance (visual inspection and operation test, repair and replacement of the cracked mechanical parts and polish the contact surface, lubrication)

The composite risk curve for the system is shown in Fig 6. The high-risk hours occur because the system is heavily stressed during these hours. The risk-reduction curve for transformer major maintenance associated with contingency 215 is shown in Fig 7. We observe that at the end of scheduling period the risk reduction falls below zero. This is because at end of the scheduling period, the cumulative risk reduction in (14) will be smaller than the risk caused by maintenance itself.

Due to the limitation of labors and feasible times, it is impossible to schedule all maintenance during the scheduling period. So the optimization method provides the optimal tradeoff between the scheduling times for various tasks.

C. Resource optimization: The RLP-DPH method was applied to obtain the maintenance selection and scheduling of this system. The labor and budget constraints are summarized in Table 4 (case A). Tasks scheduled were 62 tree trimmings, 51 transmission line tasks, 14 transformer minor maintenance and 16 major maintenance, and 23 circuit breaker maintenance. Total cumulative risk reduction is 569.38k$.

We have plotted the results in Fig 8, in which the consumed resource (labor hour, cost) and benefit (CRR) are shown with quarterly data and for the entire year. From Fig. 8 we can compare the performance of each category of maintenance across different seasons. This figure enables comparison of each maintenance activity in terms of risk reduction and resources allocated during the different times of the year.

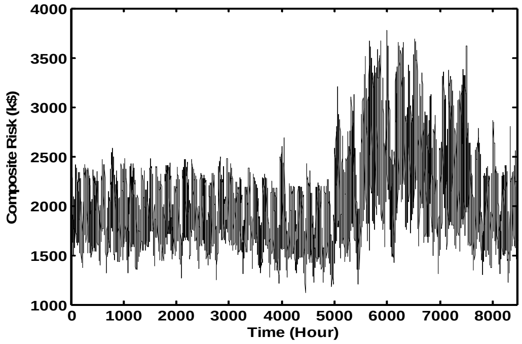

Fig 6: Composite risk of the whole system in one year

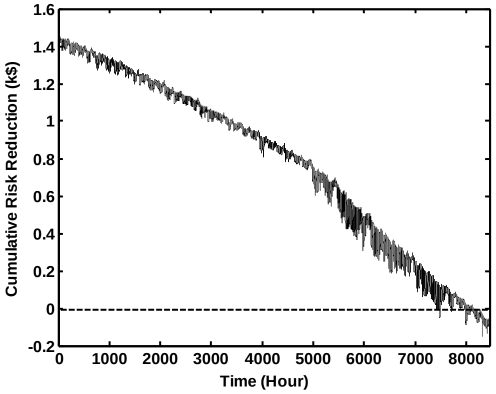

Fig 7: Risk reduction of contingency 215 (Transformer major maint. 11)

TABLE 4
CONSTRAINTS FOR MAINTENANCE SCHEDULING FOR CASE A

Maint. type	Maintenance description	Crew constraint (labor hour)	Budget constraint ($)
1	Tree_Trimming	480	80000
2	Transmission_line_maintenance	560	125000
3	Transformer_minor_maintenance	560	32000
4	Transformer_major_maintenance	600	120000
5	Circuit_breaker_maintenance	480	90000

The Lagrange multipliers indicate the decrease in objective function for a per-unit increase in the right hand side of the corresponding constraint and are good indicators for resource allocations. So we have developed an iterative algorithm to reallocate resource according by tracking the change of Lagrange multipliers of each category. In each iteration, the category with the maximum Lagrange multiplier will be identified and all other categories should reallocate part of their resource to the category with highest multiplier. The amount of reallocated resource will be determined by the difference between the Lagrange multipliers in each category with the maximum multiplier. This iteration stops when Lagrange multipliers for each category are within some tolerance of each other, or further allocation according to the

Lagrange multipliers cannot produce further risk reduction. Table 5 gives the resource reallocation process, starting from case A. Table 6 gives the Lagrange multipliers for each category in every case. From case A, we reallocate budget and labor resources according to their respective Lagrange multipliers, with each successive solution B-E improving. Solution F solution worsens and so Solution E is accepted and the corresponding cumulative risk reduction is 631.53k$.

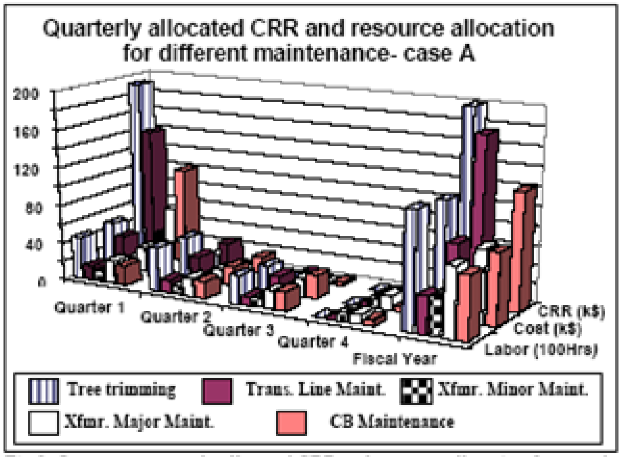

Fig 8: One year - quarterly allocated CRR and resource allocation for case A

TABLE 5

RESOURCE ALLOCATION AMONG MAINTENANCE CATEGORIES

Case	Maintenance category									
	1		2		3		4		5	
	Budget	Crew	Budget	Crew	Budget	Crew	Budget	Crew	Budget	Crew
A	80000	480	125000	560	32000	560	120000	600	90000	480
B	80000	456	165000	760	32000	469	80000	531	90000	464
C	78192	450	185000	743	27090	343	72450	480	84268	664
D	76980	500	205000	793	20565	276	63140	480	81315	631
E	91980	516	201584	813	18767	240	56154	480	78515	631
F	94980	511	201266	833	18635	240	53770	480	78347	615

TABLE 6

LAGRANGE MULTIPLIERS OF RESOURCES REALLOCATION

Case		A	B	C	D	E	F
Lagrange multipliers on budget constraint	1	-16.50	-16.44	-16.29	-19.47	-13.45	-12.99
	2	-27.18	-21.16	-18.52	-11.60	-12.20	-12.19
	3	-8.75	-8.33	-6.52	-15.33	-12.93	-12.84
	4	0	-1.43	-1.40	-3.38	-4.06	-6.913
	5	-7.46	-6.18	-13.09	-13.02	-12.79	-12.76
Lagrange multipliers on labor constraint	1	-44.91	-47.23	-47.63	-41.04	-41.49	-42.31
	2	-57.34	-43.93	-47.88	-45.96	-44.36	-43.87
	3	-10.32	-11.58	-14.99	-14.74	-18.67	-18.69
	4	-21.85	-20.61	-31.27	-29.39	-28.32	-26.57
	5	-48.85	-48.80	-31.87	-33.89	-33.72	-33.04
CRR (k$)		569.38	614.82	624.77	626.29	631.53	627.38

In this procedure, one must recognize that the multipliers describe the relationship between constraints and objective function for the relaxed linear program when decision variables are continuously valued. But the CRR is computed from the knapsack solutions where decision variables are integers. Therefore, improvements suggested by the multipliers, although generally useful, do not always translate into equivalent improvements in the CRR.

The process described above can be utilized to improve the effectiveness and efficiency of resource allocation, and to maximize the system risk reduction caused by maintenance. The optimizer may also be used to provide insight into the effects on solution quality of different resource allocations. Such insight is useful in managerial decision-making associated with company budgeting processes.

D. Variations on the optimization approach: The approach developed provides a "one-shot" solution over an entire year. In practice, however, as the year progresses, new information will become available, e.g., additional condition data will provide the ability to refine estimates of failure rates and time to failure, and budget changes may occur. As a result, one may like to "roll" the optimization to update the solution periodically, e.g., quarterly, where for each quarter, we optimize across a one-year study period beginning the first week of that quarter, but using only remaining candidate tasks and resources for the given budget cycle. An illustration of this approach is provided in [35].

8. DISCUSSION AND CONCLUSIONS

The optimization problem that we have solved reflects an important departure from the past. In a traditionally regulated industry environment, the emphasis of maintenance scheduling is on cost minimization subject to achieving a certain required level of reliability. In contrast, the problem today is driven more by the business decision to allocate a certain level of resources to maintaining equipment, with the objective to achieve the best level of reliability subject to constraints on resources. If the maintenance tasks that the manager would like to perform require more resources than what is available, the objective then is to find the optimal way among the very large number of possible ways to utilize those resources so that the benefit that comes from them is maximized. It is computationally convenient in our work to think of the reliability benefit as cumulative risk reduction.

The inclusion of cumulative-over-time risk is essential to account for system failure consequences and its variation over time. Use of sequential simulation to compute operational risk accounts for inter-temporal dependencies prevalent in power system operation. Condition data can be effectively used to estimate the effects of maintenance tasks on equipment failure indices. An efficient optimization algorithm to select and schedule maintenance tasks under constrained resources, incorporating effects of and on system security, was developed and tested. Lagrange multipliers are used to improve resource allocation effectiveness. We conclude there is significant potential for using the procedures and methods described in this paper to expend maintenance resources and therefore better manage aging assets.

ACKNOWLEDGMENT

The work described in this paper was sponsored by the Power Systems Engineering Research Center (PSERC) and by the National Science Foundation under grant NSF EEC-0002917 received under the Industry / University Cooperative Research Center program.

References:

[1] Y. Dai, J. McCalley, V. Vittal, "Annual Risk Assessment for Overload Security," IEEE Trans. on Power Systems, Vol. 16, No. 4, Nov., 2001, pp 616 –623

[2] Y. Dai, M. Bhuiyan, J. McCalley, V. Vittal, "Annual Risk Assessment for Voltage Security and Generation Adequacy," Proceeding of the 6th International Symposium on Probabilistic Methods Applied to Power Systems, Sept., 2000, Madeira Island, Portugal

[3]W. Qin, "Risk-based maintenance scheduling for power systems," Master Thesis --Iowa State University, 2000

[4] Y. Jiang, M. Ni, J. McCalley, T. Van Voorhis, "Risk-based Maintenance Allocation and Scheduling for Bulk Electric Power Transmission System Equipment," Proceeding of the 15th International Conference on Systems Engineering, Aug. 6-8, 2002, Las Vegas, USA

[5] G. Nemhauser, L. Wolsey, "Integer and combinatorial optimization," chapter 1, John Wiley & Sons, 1988

[6] M. Ni, J. McCalley, V. Vittal, T. Tayyib, "On-line risk-based security assessment," IEEE Trans. on Power Systems, Vol. 18, No. 1, Feb., 2003, pp 258-265

[7] M. Ni, J. McCalley, V. Vittal, S. Greene, et al "Software implementation of on-line risk-based security assessment," IEEE Trans. on Power Systems, Vol. 18, No. 3, Aug., 2003, pp 1165-1172.

[8]Y. Jiang, Z, Zhang, T. Van Voorhis, J. McCalley, "Risk-based maintenance optimization for transmission equipment," Proceeding of 35th North American Power Symposium, Oct., 2003, Rolla, USA

[9] B. Ward, S. Lindgren, "A survey of development in insulation monitoring of power transformers," Conference Report of the 2000 IEEE International Symposium on Electrical Insulation, pp.141 –147, April, 2000, Anaheim, USA

[10] K. Harker, "Power System Commissioning and Maintenance Practice," INSPEC/IEE, UK, 1998.

[11] CIGRE Working Group 13.08, "Life management of Circuit Breakers," Proceeding of the International Conference on Large High Voltage Electrical System, Aug., 2000, Paris.

[12] W. Bergman, "Reliability centered maintenance applied to electrical switchgear," Proceeding of IEEE Power Engineering Society Meeting, pp. 1164–1167, Jul., 1999, Edmonton, Canada.

[13] J. Moubray, "Reliability-Centered Maintenance," Industrial Press Inc., New York, 1997.

[14] J. Endrenyi, S. Aboresheid, R.N.Allan et al., "The present status of maintenance strategies and the impact of maintenance on reliability." IEEE Transaction on Power Systems, Vol. 16, No. 4, Nov., 2001, pp 638 –646.

[15] Y. Liang, "Simulation of Top-Oil Temperature for Transformers", Master Thesis and Final Report, PSERC Publication 01-21, Feb., 2001

[16] M. Minhas, PJ. de. Klerk, JP Reynders, "A study of failure modes of large power system transformers," 10th International symposium on high voltage engineering. Aug. 25-29, 1997, Montreal, Quebec.

[17] GJ. Cliteur, JM. Wetzer, "Condition assessment of power transmission and distribution components," International Conference and Exhibition on Electricity Distribution (CIRED), Jun. 18-21, 2001, Amsterdam.

[18] G. Spence, AC. Hall, "On-load tap-changers current experience and future development: Users experience and perspective," IEE European Seminar on Current Experience and Future, Nov. 9 1995, Regensburg, Germany.

[19] A. Salinas, J. Pruente, "Enhancing circuit breaker reliability through effective mechanism maintenance and lubrication," Transmission and Distribution Conference and Exposition, 2001 IEEE/PES, Vol. 1, 2001, Atlanta, USA.

[20] R. Radwan, M. El-Marsafawy, "Failure analysis of circuit breakers in the Upper Egypt Zone of the Egyptian Unified Power System network," Third International Conference on Future Trends in Distribution Switchgear, pp. 23-25, Apr., 1990, London, UK

[21] J. Schlabbach, T. Berka, "Reliability-centered maintenance of MV circuit-breakers," Proceeding of IEEE Porto Power Tech, 2001, Vol. 4, Sept., 2001, Porto, Portugal.

[22] P. Werelius, P. Tharning, R. Eriksson et al. "Dielectric spectroscopy for diagnosis of water tree deterioration in XLPE cables," IEEE Trans. on Dielectrics and Electrical Insulation, Vol. 8, Issue 1, Feb., 2001.

[23] E. Pudney, R. Wales, "Optimized overhead line maintenance on 25 kV electrified railways using remotely monitored distance protection," Seventh International Conference on (IEE) Developments in Power System Protection, Apr., 2001, Amsterdam, Netherlands

[24] "IEEE guide for maintenance, operation, and safety of industrial and commercial power systems," IEEE Standard 902-1998.

[25] CAISO maintenance coordination committee documents, www.caiso.com/pubinfo/BOG/documents/grid/mcc/archives.html

[26] H. Willis, G. Welch. R. Schrieber, "Aging power delivery infrastructures," Marcel Dekker Inc., New York, 2001

[27] G. Cliteur, J. Wetzer, "Condition assessment of power transmission and distribution components" Electricity Distribution, 2001. Part 1: Contributions. CIRED. 16th International Conference and Exhibition on (IEE Conf. Publ No. 482) , Volume: 1 , 18-21 June 2001

[28] Y. Jiang, Z. Zhong, J. McCalley, T. Van Voorhis, "Risk-based Maintenance Optimization for Transmission Equipment," Proceedings on the 12th Annual Substations Equipment Diagnostics Conference, Feb 15-18, 2004, New Orleans, sponsored by the Electric Power Research Institute.

[29] J. Endrenyi, G. Anders, A. Leite da Silva, "Probabilistic Evaluation of the Effect of Maintenance on Reliability- An Application", IEEE Trans on Power System, Vol 13 Issue 2, May 1998, pp 576-583.

[30] Electric Power Research Institute (EPRI) Final Report, Integrated Monitoring and Diagnostics, EPRI, Palo Alto, CA,2000, TE-1000511.

[31] G. Anders, Probability Concepts in Electric Power Systems, John Wiley, New York, 1990.

[32] A. Leite da Silva and J. Endrenyi, "Application of First Passage Times in the Markov Representation of Electric Power Systems," Proceedings of the 4th International Conference on Probabilistic Methods Ap er Systems, Rio de Janeiro, Brazil, September 1994.

[33] FERC, "Utility Vegetation Management Final Report" 4 http://www.ferc.gov/cust-protect/moi/uvm-final-report.pdf

[34] IEEE Guide for the Interpretation of Gases Generated in Oil- Immersed Transformers, IEEE Std C57.104-1991.

[35] Y. Jiang, "Condition-based hazard rate estimation and optimal maintenance scheduling for electrical transmission systems," Ph.D. dissertation, Iowa State University, August, 2006.

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