

Risk-based Maintenance Optimization for Transmission Equipment

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Abstract: This paper describes a new maintenance selection and scheduling approach for bulk transmission equipment that is based on the cumulative long-term risk caused by failure of each piece of equipment. This approach not only accounts for equipment failure probability and equipment damage, as do reliability centered maintenance (RCM) approaches, but it also accounts for the outage consequence in term of overload and voltage security in a rigorous and systematic way. In addition, the paper describes a rigorous method of computing equipment instantaneous failure probabilities based on time varying condition data. The method is illustrated on a 566-bus model of a US utility system.

Keywords: Power system, transmission equipment, maintenance, reliability, risk, security, Markov, 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 the effect of maintenance with respect to the 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 network security problems such as overloads, low voltages, cascading overloads, and voltage instability, and component damage so as to minimize risk of wide-area bulk transmission system failures.

The work makes use of two previously developed technologies: risk-based security assessment and long-term sequential simulation. Risk-based security assessment [1,2] provides quantitative valuation of network security level, risk, using probabilistic modeling of uncertainties in loading conditions and contingency states. We developed a simulator [3,4,5] that performs sequential long-term simulation of a power system on an hour-by-hour basis. It creates an 8760-hour trajectory of operating conditions. The trajectory is formed by developing an hour by hour load forecast and a yearly unit commitment schedule and dispatch.

The long-term simulator, when integrated with hourly risk-based security assessment capability, provides year-long hourly risk variation for each contingency of interest. This information, when combined with a set of proposed maintenance tasks and corresponding contingency

probability reductions, yields cumulative (year-long) risk reduction (CRR) associated with each maintenance task and 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, comprise what we call the integrated maintenance selection and scheduler (IMSS), illustrated in Fig 1. In Section 2, we relate our work to the state of art, and we describe the IMSS, including the long-term simulator in Section 3, the risk reduction calculation in Section 4, maintenance-induced contingency probability reduction in Section 5, and the optimization problem associated with the maximization of risk reduction in Section 6. We provide an illustration in Section 7; the work is discussed in the context of existing industry business climate in Section 8.

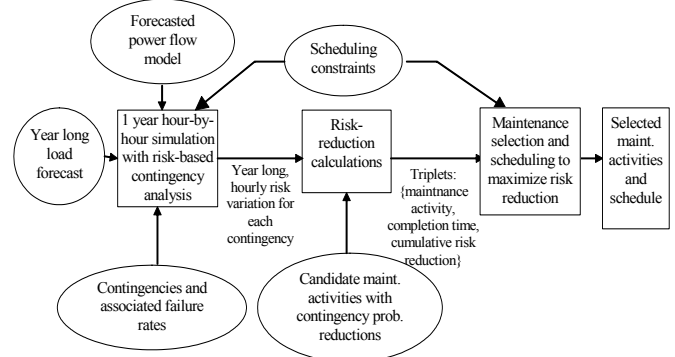


Fig. 1: Integrated Maintenance Selector and Scheduler (IMSS)

2. RELATIONSHIP TO CURRENT INDUSTRY

Recently there has been a great deal of investment in developing asset management tools. These tools may be classified by function. There are several which provide workflow functions, work-order tracking, and data storage. Examples of these tools are Maximo, Cascade, and Asset-Sentry. 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, EPRI developed the maintenance management workstation that acts as a database integrator.

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, the present state of the art is a maintenance-ranking assessor that assigns weights to different attributes, scores each maintenance task, and then prioritizes them based on score ranking. Tasks are then scheduled based on this prioritization. This approach lends itself towards decision-making, but the solution is heuristic and depends on a high degree of subjectivity in the scoring process.

The literature reflects little progress towards a systematic method tying maintenance selection and scheduling with operational constraints seen in transmission. This important effect is manifested in two different ways, only one of which is normally recognized. First, a maintenance-related outage may result in an operationally unacceptable condition that, if allowed, would require constrained operation (e.g., off-economic dispatch). 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.

The second manifestation of the operations-maintenance tie is less recognized, and as far as we know, not systematically addressed by any tool. This manifestation is that maintenance reduces the frequency of operational security constraints (due to overload, low voltage, voltage instability or cascading overloads) seen by the operator. The reason for this is that, if a maintenance task reduces the failure rate of a piece of equipment, and if failure of that equipment results in operational constraints, then the maintenance will also reduce the frequency of that operational constraint. The relation is complex because different pieces of equipment have different failure rates and consequently, the failure rate reduction of a maintenance task varies from one piece of equipment to another. In addition, the severity of the operational constraint 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 severities between equipment failures vary over time as conditions change. An important contribution of this paper is the relation between maintenance and operational constraints is systematically embedded in the maintenance selection/scheduling software.

3. LONG-TERM SIMULATION & RISK ASSESSMENT

Cumulative risk assessment performs sequential, hourly simulation over a long term, e.g., 1 year, and it evaluates the security levels in terms of quantitative indices, reflecting risk of overload, cascading overload, low voltage, and voltage instability. The risk index for a single contingency is an expectation of severity, computed as the product of contingency c probability $p(c)$ with contingency severity $sev(c|m,t)$, where m indicates the m^{th} maintenance task and thus the network configuration in terms of network topology and unit commitment, and t indicates the hour and thus the operating conditions in terms of loading and dispatch. The

risk is given by $R(c,m,t) = p(c)sev(c|m,t)$. A reference “basecase” network configuration (with no maintenance task) is denoted with $m=0$. The severity function $sev(c|m,t)$ comprises two parts: system related severity function $sev_{sys}(c|m,t)$ and component damage severity function $sev_{comp}(c|m,t)$. $sev_{sys}(c|m,t)$ captures the contingency severity in terms of overload, cascading overload, low voltage, voltage instability, while $sev_{comp}(c|m,t)$ describes severity related to component damage and redispatch cost.

The risk associated with any given network configuration and operating condition is computed by summing over the no-contingency condition ($c=0$) and all N contingencies:

$$R(m,t) = \sum_{c=0}^N p(c) [sev_{sys}(c|m,t) + sev_{comp}(c|m,t)] \quad (1)$$

If there are no maintenance tasks, contingency probabilities are constant, but risk still varies with time because operating conditions, and therefore contingency severities, vary with time.

The long-term cumulative risk simulator performs a full N-contingency security assessment for each hour in the year, and associated risk indices are computed as eq. (1). Therefore, given a contingency set, the simulator develops the power flow case and then, for each contingency, performs an assessment for overload, cascading overloads, low voltage, and voltage collapse. Overload and low voltage analysis are performed by simply modeling the contingency (e.g., removing one or more circuits and/or units) and resolving the power flow. Cascading analysis is performed by successively outaging overloaded circuits. Voltage collapse analysis is performed using a continuation method [6]. Risk indices are computed using severity functions specific to each problem type that reflects post-contingency performance. For example, the severity function for circuit

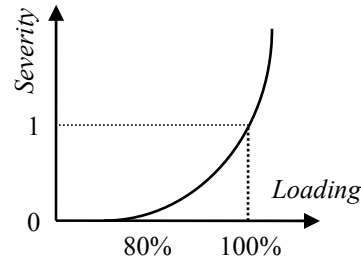


Fig. 2: Overload severity function

overload, low voltage, voltage instability and cascading overload are described in [1,2]. Key to each security function is that it evaluates to 1.0 at the performance threshold specified by reliability criteria. This means that the resulting risk may be interpreted as the expected number of reliability criteria violations. The severity function for transformers damage is given by $C \cdot MVA$ where MVA is the rating of the transformer and C is a constant which is determined by the component’s replacement cost, corrective action cost and availability of spare transformers. Three basic modules are required to use with the long-term cumulative risk assessment simulator, including load forecasting, unit commitment, and contingency set 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 one-year risk computation, some components may see their 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 time, or 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 [2]. We mention here the two most effective of these. At each hour, the simulator first compares the conditions of that hour to those of all previously encountered (and assessed) hours. If the conditions (topology, loading, unit commitment, and dispatch) are similar, the risk indices computed for the previous hour are used for the current hour, thereby avoiding a repeated assessment. “Similarity” between conditions of different hours is quantified in the form of network configuration (topology, unit commitment), loading and dispatch, with a user-specified tolerance so that it is easy to control the run-time at the expense of less-refined results, while maintaining the two key features of the simulator design as described above. The second speed enhancement pertains to the voltage collapse assessment. This is done using the continuation power flow (CPF) [6], which is quite computational in its simplest form. For each contingency, we take an initial “step” in the direction of loading increase that is long enough so that convergence can be interpreted as zero-risk for voltage collapse, and no further voltage collapse analysis need be done for that contingency.

4. RISK REDUCTION CALCULATIONS

We defined a maintenance task with respect to a particular component (line, transformer, circuit breaker) as a task that changes the component state. A monitoring activity such as inspection, testing, or sampling is a task that provides information useful in assessing the component state. The probability of failure decreases after a maintenance task; otherwise the maintenance task should not be performed. We have developed a table [7] matching maintenance tasks to the failure modes that they affect, based on [8-25] together with private resources obtained from industry contacts.

Given the hourly system risk variation over an extended period such as a year, we want to determine how different maintenance tasks reduce the risk as a function of time when they are scheduled during the period. We assume that each maintenance task decreases the probability of a particular contingency, and therefore probability reductions are in force from the maintenance task completion time until the end of the year. Thus, each maintenance task creates a risk reduction that is a function of its completion time. In addition, risk may increase during the maintenance task due to the system weakening from possible maintenance outage. These ideas are captured analytically by defining m to denote a particular maintenance task known to decrease the probability of contingency k by $\Delta p(m,k)$. It is convenient to also use m to denote the network configuration associated

with the maintenance task m . The network configuration may differ from the basecase configuration because maintenance task m may require outage of component k .

The cumulative-over-time risk reduction due to maintenance task m is $CRR(m,t_f)$, computed as a function of the completion time t_f according to:

$$CRR(m,t_f) = CRR_{during}(m,t_f) + CRR_{after}(m,t_f) \quad (2)$$

$$= \int_{t_f - T_d}^{t_f} (R(0,t) - R_{during}(m,t))dt + \int_{t_f}^{8760} (R(0,t) - R_{after}(m,t))dt$$

where T_d is the duration of the maintenance task, $R(0,t)$ is the risk variation over time with no maintenance outage, and $R(m,t)$ is the risk variation over time with the maintenance outage. The first integral in (2) is the risk reduction during the maintenance period, always non-positive indicating that risk may increase during the maintenance period. The second integral in (2) is the risk reduction after completion of the maintenance task, always positive due to the decrease in failure probability. In each integral, $R(0,t)$ is obtained from the long-term simulator. If, during the maintenance period, no component is outaged, then $CRR_{during}=0$. However, if the maintenance task requires removal of component k (a generator, line, transformer, circuit breaker), then $CRR_{during}<0$ because of changes in operating conditions, e.g., voltages, flows, etc., which change the severity of all contingencies except contingency k (contingency k cannot occur due to the fact that the corresponding component is on maintenance outage). Reference [26] derives from eq. (2) that the total risk reduction associated with maintenance task m completed at time t_f as:

$$CRR(m,t_f) = \int_{t_f - T_d}^{t_f} [R(0,k,t) + \sum_{c=0,c \neq k}^N p(c)(sev(c|0,t) - sev(c|m,t))]dt + \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t)dt \quad (3)$$

There are three main terms in the risk reduction expression of eq. (3). The first term inside the first integral represents the reduction in risk, relative to the basecase, due to the fact that contingency k can not occur when the corresponding component is on maintenance outage. The second term inside the first integral, the summation, represents the change in risk (usually a risk increase) from all remaining contingencies due to the change in operating conditions caused by the maintenance outage of component k . The third term, the second integral, represents the risk reduction after the maintenance period from the maintenance-induced probability reduction of contingency k .

In order to obtain the change in cumulative risk due to a maintenance task, we need to evaluate the two integrals. The first integral requires $p(c)$ for all contingencies $c=0,N$ (which we assume to be available), the severity of all contingencies associated with the basecase configuration $(0,t)$, and the severity of all contingencies occurring under the weakened configuration (m,t) . The contingency severities associated with the basecase configuration comes from one run of the simulator, but the contingency severities associated with configuration (m,t) would require rerunning the simulator for every maintenance task m requiring a maintenance outage. This would be excessively computational. Thus we evaluate the first integral using approximate methods. For example,

one may evaluate severities associated with configuration (m,t) under the assumption that severity is linear, superposition holds, and the severity of removing two lines is the sum of the severity of removing each line alone. Alternatively, one might assume that maintenance task m , which requires removal of component k , causes no change in severity so that $sev(c|0,t)=sev(c|m,t)$, and the summation in the first integral of (3) is 0. This is the case if we either require operator initiated system adjustments during the maintenance period or disallow any maintenance outage during a time period that results in significant risk. We accept this assumption for the remainder of the paper. Under this assumption, the total risk reduction associated with maintenance task m completed at time t_f is:

$$CRR(m,t_f) = \int_{t_f-T_d}^{t_f} R(0,k,t)dt + \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t)dt \quad (4)$$

We need $R(0,k,t)$, the risk variation for each contingency under the basecase configuration, information obtained from a simulator run (these contingencies include only those having probability affected by a maintenance task). In (4), the first term indicates the risk reduction accrued during the maintenance period because contingency k cannot occur and in general will be quite small. If one assumes, as we have above, that maintenance outages cause no severity increase, it is reasonable to assume 0 risk for all contingencies occurring under basecase condition, allowing us to neglect the first term in (4). This leaves only the second term in (4). We have remaining only the problem of how to obtain the contingency probability reduction $\Delta p(m,k)$ due to the maintenance task m . This problem is addressed in Section 5.

5. CONTINGENCY PROBABILITY REDUCTION

The goal of this part of our work is to develop a systematic and consistent approach for associating to any maintenance task a quantitative evaluation of the reduction in probability of occurrence of the failure mode(s) the task is intended to affect. We assume a one-to-one mapping between a failure mode and a contingency k , so that there is no notational problem with denoting the desired probability reduction from maintenance m by $\Delta p(m,k)$. This assumption is easily lifted for a contingency that may be caused by multiple failure modes, as long as the failure modes are independent.

We approach this information-modeling problem probabilistically¹ given that we have at our disposal a set of condition measurements $\underline{x}(t)=[x_1(t),x_2(t),\dots,x_n(t)]$ for a number of similar components taken over an extended period of time $t=0,1,\dots,T$. Given such data, we choose an appropriate probability model such as Weibull or Markov which adequately characterizes the equipment deterioration. In most types of reliability analyses, one then uses the probability model to compute long-run (or steady-state) failure probabilities, which characterize the tendency, on average, of any one unit within a population to fail over an extended period of time. In contrast, the unique feature of our problem is that we desire failure probabilities characterizing

the tendency of a specific piece of equipment to fail “now.” These we call *instantaneous* failure probabilities.

In our approach, we assume the ability to characterize boundary conditions that separate D states of deterioration, in terms of the condition measurements $\underline{x}(t)$, via the deterioration function $g(\underline{x})$, such that deterioration level j is identified by $d_{j-1} < g(\underline{x}) < d_j$, where the last state $j=D$ represents the *failed* state. It is important to note that state D need not represent the rare “blue smoke” condition where the component has catastrophically failed (and for which very little data is typically available). Rather, state D represents a set of measurement values for which engineering judgment results in the action of removing the component from service.

The approach is illustrated in Fig. 3, based on a multi-state Markov probability model, where each of the D states is represented as a deterioration level. The particular representation of Fig. 3 shows $D=4$ 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 may occur between non-consecutive states (e.g., state 1 to state 3), the model can accommodate it. The transition from level 4 to level 1 stochastically represents the effects of maintenance, and since in our work, maintenance is a deterministic decision that results from the analysis, we would normally set $\mu_{41}=0$.

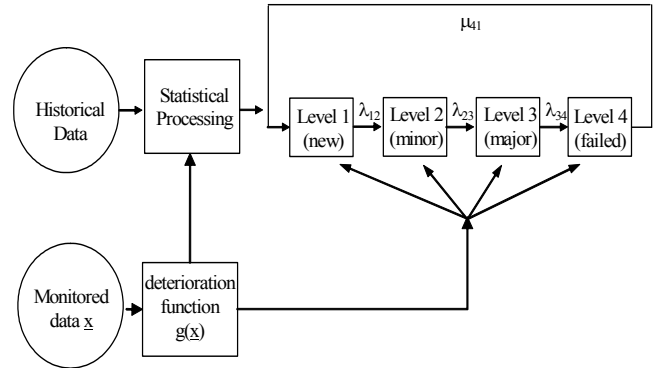


Fig. 3: Computing Contingency Probability Reductions

There steps to implementing the approach are: (a) Obtain the deterioration function $g(\underline{x})$. (b) Perform the statistical processing necessary to estimate the transition intensities λ_{jk} . (c) Use the model to obtain the failure probability.

(a) Deterioration function: The deterioration function, denoted by $g(\underline{x})$, may be an analytical expression if one is available or it may be a set of rules encoded as a program, likely 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, practical, and straightforward way of connecting our approach to the wealth of existing knowledge and experience contained in the industry in regards to interpreting condition monitoring measurements. For example, EPRI has made significant effort in summarizing such rules, and most companies have expertise embedded in engineering personnel from which such rules

¹ An alternative class of approaches for modeling information utilizes so-called fuzzy representation and warrants investigation for this problem.

may be developed. Often, such rules depend not only on the condition measurements \underline{x} but also the rates of change in such measurements. Alternatively, one may develop deterioration functions that return values of physical attributes characterizing the failure mode, but doing so requires fundamental understanding of physical processes involved in the component deterioration.

(b) Transition intensities: Once we decide how many deterioration levels to model and consequently how many Markov states are needed, (for example, 4, as shown in Fig. 3), the transition intensities between these states can be obtained from life-histories of multiple units of the same manufacturer and model. In the case of Fig. 3, we would need to compute λ_{12} , λ_{23} , and λ_{34} . As indicated above, suppose we have a set of condition measurements $\underline{x}(t)=[x_1(t), x_2(t), \dots, x_n(t)]$ for N similar components taken over an extended period of time $t=0, 1, \dots, T$. For transformer i , we use the deterioration function to compute the deterioration level for each component. This enables identification of the time it spends in deterioration level j , e.g., y_{ij} . For the same type of transformer population, the estimated time spent in state j would be the mean of these durations, which is $\bar{y}_j = \frac{1}{N} * \sum_{i=1}^N y_{ij}$. The desired transition intensities are

obtained by inverting these mean duration times. In this procedure, one must not use data across maintenance periods to compute mean duration times since a maintenance task inhibits the deterioration process being modeled.

(c) Desired failure probability: For a particular set of transition intensities, the transition probability matrix for the case represented by Fig. 3 as:

$$\underline{P} = \begin{bmatrix} 1 - \lambda_{12} & \lambda_{12} & 0 & 0 \\ 0 & 1 - \lambda_{23} & \lambda_{23} & 0 \\ 0 & 0 & 1 - \lambda_{34} & \lambda_{34} \\ \mu_{41} & 0 & 0 & 1 - \mu_{41} \end{bmatrix} \quad (5)$$

The state probability vector gives the probability that a component is in any particular deterioration level at a given time, and is denoted by

$$\underline{p}(hT) = [p_1(hT) \ p_2(hT) \ p_3(hT) \ p_4(hT)] \quad (6)$$

where $h=1, 2, 3, \dots$, and T is the time step. If at time $t=0$, we know that the component resides in deterioration level j , then the initial state probability vector is comprised of all zeros except for element j , which is 1. For example, if we know that the component is in deterioration level 1 at $t=0$, then

$$\underline{p}(0) = [1 \ 0 \ 0 \ 0] \quad (7)$$

The probability of finding the component in any deterioration level at time hT is then given by:

$$\underline{p}(hT) = \underline{p}(0)\underline{P}^h \quad (8)$$

Given that at any time ($t=0$) we know the component's deterioration level, then (8) provides the probability of residing in the failed state in any future time interval.

Remark 1: This equation is used to obtain the contingency probability for our long-term simulation (described in Section 3), but we must also have a *deterioration assumption* that describes the levels of deterioration the component is

expected to be in throughout the simulation period. The simplest deterioration assumption is that each component remains in the deterioration level characterized by the most recent condition measurement. In this case, we use $h=1$ in (8) and the obtained probability of residing in the failed state is the contingency probability used in each simulation time step. We might also assume that the component does in fact deteriorate throughout the year so that at certain times it moves from one deterioration level to another.

Remark 2: The contingency probability reduction from a maintenance task requires an assumption on the deterioration level resulting from the maintenance task. If we assume that a particular maintenance task results in renewing the component to deterioration level 1, then, if the component is in deterioration level 3 (for example), the contingency k 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: $[1 \ 0 \ 0 \ 0]\underline{P}-[0 \ 0 \ 1 \ 0]\underline{P}=[1 \ 0 \ -1 \ 0]\underline{P}$.

Remark 3: The above modeling also provides us with the ability to compute first passage times. The 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 k , under the assumption that the process begins in state j . From this computation, then, we may estimate the remaining life of the component. The method of computing first passage times is provided in [27], and reference [28] discusses this issue from a power system reliability perspective.

Remark 4: Because condition measurements for a component continue over time, the Markov model is not static. One effective way to account for this time dependency in the model uses Bayesian updating [29,30].

6. MAXIMIZING RISK REDUCTION

As indicated in Fig. 1, we first run the simulator to compute risk as a function of time for each hour over a long-term such as a year and then, for the example of this paper, use (4) to compute risk reduction associated with each proposed maintenance task. This step results in triplets comprised of: {maintenance task, completion time, risk reduction}. These triplets serve as the input to the optimizer.

Let N be the total number of maintainable transmission components; $k=1, \dots, N$ be the index over the set of maintainable transmission components; L_k be the number of maintenance tasks for component k ; $m=1, \dots, L_k$ be the index over the set of maintenance tasks for transmission component k ; and $t=1, \dots, T$ be the index over the time periods.

Define $Iselect(k, m, t)=1$ if the m^{th} maintenance task for component k begins at time t , and 0 otherwise, $Iactive(k, m, t)=1$ 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

$$Iactive(k, m, t) = \sum_{j=-d(k, m)+1}^t Iselect(k, m, j), \forall (k, m, t) \quad (9)$$

Equation (9) 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 it begins at time t . (In Section 4, we used notation $CRR(k,t)$; here, the additional argument is necessary because we have allowed various levels of each task.) Let $Infeas(k,m)$ be the set of periods for which task m for component k cannot be performed. 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. $Crew(k,m)$ is the required number of crews for m^{th} task for component k . $TotCrew(b,t)$ is the number of crews available for maintenance category b at time t .

We have developed two forms for the resulting optimization problem. 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. We present only problem 1 here as problem 2 can be solved as a special case of problem 1.

$$\text{Max} \left(\sum_{k=1}^N \sum_{m=1}^{L_m} \sum_{t=1}^T CRR(k,m,t) \times Iselect(k,m,t) \right) \quad (10)$$

Subject to:

$$\sum_{n=1}^{L_m} \sum_{t=1}^T Iselect(k,m,t) \leq 1, \quad k = 1, \dots, N \quad (11)$$

$$Iactive(k,m,t) = 0, \quad \forall t \in Infeas(k,m), \quad \forall (k,m) \quad (12)$$

$$\sum_{k=1}^N \sum_{m=1}^{L_m} Iactive(k,m,t) * Crew(k,m) < TotCrew(b,t), \quad \forall t, b = 1, \dots, 4 \quad (13)$$

$$\sum_{k=1}^N \sum_{m=1}^{L_m} \sum_{t=1}^T cost(k,m) * Iselect(k,m,t) < TotCost(b), \quad b = 1, \dots, 4 \quad (14)$$

$$\sum_{k=1}^N \sum_{m=1}^{L_m} Iactive(k,m,t) * \Delta R(k,m,t) \leq \Delta Rmax(t), \quad \forall t \quad (15)$$

$$Iselect(k,m,t) \in \{0,1\}, \quad \forall (k,m,t) \quad (16)$$

In this optimization problem, the objective (10) is to maximize total cumulative risk reduction. Constraint (11) restricts each component to be maintained at most once. Constraint (12) requires each maintenance task be performed only within its feasible time period. Constraint (13) stipulates the number of maintenance tasks ongoing during any period is limited by crew constraints. Constraint (14) represents budget constraints. Constraint (15) ensures maintenance task (k,m) resulting in a risk increase of $\Delta R(k,m,t)$ due to outage of component k at time t does not exceed the maximum allowable risk increase for time t , $\Delta Rmax(t)$. The maximum allowable risk increase for time t is set so that no maintenance outage may cause a violation of reliability criteria. To solve this optimization problem is to determine $Iselect(k,m,t)$, which then determines $Iactive(k,m,t)$. The optimization problem is integer, with multiple constraints and high dimension and therefore is challenging to solve. We have tried 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 [26]. We found that RLP-DPH provides

superior solutions in a computationally efficient way. This approach first solves a relaxed linear program (RLP) to obtain Lagrange multipliers on the budget constraint (14) and the risk constraint (15), and then develops a new objective function comprised of the original objective together with weighted cost and weighted risk, where the weights are Lagrange multipliers. It then solves knapsack problems [31] over the labor constraints (13) one period at a time, where a period is taken to be one week. The procedure follows.

A. LP Relaxation to get dual variables: Solve a RLP that includes all of the constraints (11)-(16) in order to get approximations on budget and risk constraint Lagrange multipliers $\mu_1-\mu_4$ and λ_t , $t=1, \dots, T$, respectively. This LP is "relaxed" in that variables are allowed to be non-integer. 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 Lagrange 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 (13) for the first period (e.g., first week) to identify the maintenance tasks to be performed in that week. Then we re-solve the RLP with the week-1 variables known, to get updated Lagrange multipliers on the budget and risk constraints, and then a knapsack problem for the second period (e.g., second week) is solved. The process is repeated until all periods are solved.

B. Solving knapsack problems: Move 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 (13) is a classical knapsack problem, stated as follows:

$$\begin{aligned} \max F(Iselect(k,m,t)) = & \sum_{k=1}^N \sum_{m=1}^{L_m} \Delta CR(k,m,t) \times Iselect(k,m,t) \\ & - \sum_{b=1}^4 \mu_b \left\{ \sum_{k=1}^N \sum_{m=1}^{L_m} \sum_{t=1}^T cost(k,m) * Iselect(k,m,t) - TotCost(b) \right\} \\ & - \sum_t^{t+T_{max}} \lambda_t \left\{ \sum_{k=1}^N \sum_{m=1}^{L_m} \Delta R(k,m,t) * Iselect(k,m,t) - \Delta Rmax(t) \right\} \end{aligned} \quad (20)$$

subject to

$$\sum_{m=1}^{M_m} \sum_{n=1}^{M_n} Iactive(m,n,t) * Crew(m,n) \leq Crew(b,t), \quad \forall t, b = 1, \dots, 4$$

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 yearly 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 (i.e., greater than 1 week). In this case, we 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) Constraint (11) is enforced heuristically in the solution procedure, and infeasible periods from constraint (12) are enforced using negative objective function coefficients.

These knapsack problems may be solved to optimality using dynamic programming (DP), and this is reasonable for low-dimensionality problems. For high-dimensionality 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 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 $j=8760$, stop, else, $j=j+1$ and go to (a).

7. ILLUSTRATION

We have performed preliminary testing of the procedure, using a 566-bus model. The expected hour-by-hour 1-year loading trajectory used in the analysis is shown in Fig. 4. 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. We limit the maintenance tasks scheduled in our illustration to those affecting these failure modes. This means there are 108 contingencies to assess; 70 line outages and 38 transformer outages. The failure modes and corresponding maintenance tasks are listed in Table 1. The composite risk curve for the system is shown in Fig 5. The high-risk hours occur because the system is heavily stressed during these hours. The risk-reduction curve for transformer minor maintenance associated with contingency 177 is shown in Fig. 6. We observe a rapid drop of risk reduction during the peak-load period leading to the expected conclusion that if we apply the maintenance before the stress period, the cumulative risk reduction is high. Due to the limitation of crews and feasible times, it is impossible to schedule all maintenance before the peak load period. So the optimization method provides the optimal tradeoff between

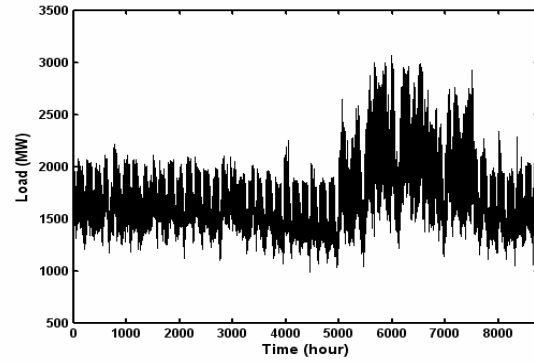


Fig. 4: 1-year loading trajectory

TABLE 1
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	Core problem, mechanical failure and ageing	Transformer major maintenance (including parts replacement, off-line testing and corresponding maintenance and oil change.)
	Oil deterioration	Transformer minor maintenance: (oil filtering)

the scheduling times for various tasks.

The RLP-DPH method was applied to the maintenance scheduling of this system. The labor and budget constraints are summarized in Table 2 (case A). Tasks scheduled were 57 tree trimmings, 18 transformer major maintenance, 15 transformer minor maintenance, and 60 transmission line tasks. Total cumulative risk reduction is 37.9.

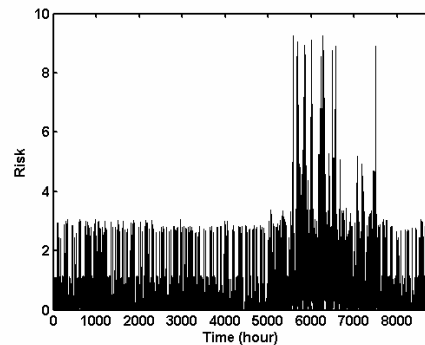


Fig. 5: Composite risk of the whole system in one year

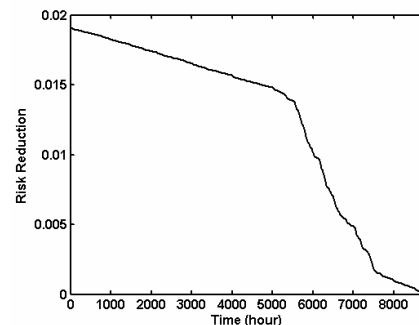


Fig. 6: Risk reduction of contingency 177 (Maintenance-Trans69)

TABLE 2
CONSTRAINTS FOR MAINTENANCE SCHEDULING FOR CASE A

Case	Maintenance category							
	1. Tree trimming		2. Transformer major maint.		3. Transformer minor maint.		4. Trans. Line maintenance	
	Budget	Crew	Budget	Crew	Budget	Crew	Budget	Crew
A	80000	10	125000	12	32000	8	150000	12

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. Table 3 shows different resource allocation among maintenance categories for cases B, C, D, E. In each case, the allocation is made so that one type of maintenance is favored over the others. In Table 4, the Lagrange multipliers for every category, and for each case, are listed.

From Table 4, we observe that budget category 4 (line maintenance) and labor category 2 (transformer major maintenance) generally have higher multipliers. This suggests reallocating resources in favor of budget category 4 and labor category 2. So the multipliers may be used to guide the resource reallocation, to achieve greater risk reduction. In Table 5, we start from case A which has the allocation in Table 2, with CRR=37.9. The multipliers show that risk reduction is sensitive to constraints on budget categories 1 and 4. So reallocation is done by moving \$10k from budget category 2 to 4 and \$5k from budget category 3 to 1, resulting in case A1. Consequently, the CRR improves from 37.9 to 38.1. Then we find that labor category 4 has high multipliers and so move 2 workers from labor category 3 to 4, resulting in case A2 with a CRR of 39.1.

TABLE 3
RESOURCE ALLOCATION AMONG MAINTENANCE CATEGORIES

Case	Maintenance category							
	1. Tree trimming		2. Transformer major maint.		3. Transformer minor maint.		4. Trans. Line maintenance	
	Budget	Crew	Budget	Crew	Budget	Crew	Budget	Crew
B	225000	16	75000	12	75000	6	75000	8
C	75000	8	225000	20	75000	6	75000	8
D	75000	8	75000	12	225000	14	75000	8
E	75000	8	75000	12	75000	6	225000	16

TABLE 4
LAGRANGE MULTIPLIER FOR DIFFERENT RESOURCE ALLOCATION

Case	CRR	Lagrange Multipliers for budget constraint				Lagrange Multipliers for labor constraint			
		Maintenance category				Maintenance category			
		1	2	3	4	1	2	3	4
B	34.1	0.0	-0.55	0.00	-7.16	-0.45	-2.02	-0.37	-0.94
C	32.9	-1.61	0.00	0.00	-7.16	-1.43	-1.32	-0.37	-0.94
D	33.0	-1.61	-0.55	0.00	-7.16	-1.43	-2.02	-0.07	-0.94
E	38.9	-1.61	-0.55	0.00	0.00	-1.43	-2.02	-0.37	-2.53

TABLE 5
REALLOCATION OF RESOURCES BASED ON LAGRANGE MULTIPLIERS

Case		Case A	Case A1	Case A2
Lagrange multipliers on budget constraint for each maintenance category	1	-2.38	-2.27	-2.27
	2	-0.00	-0.00	-0.00
	3	-0.28	-0.34	-0.22
	4	-6.16	-3.93	-5.47
Lagrange multipliers on labor constraint for each maintenance category	1	-0.65	-0.81	-0.80
	2	-2.89	-2.89	-2.89
	3	-0.11	-0.07	-0.16
	4	-3.60	-4.94	-2.53
CRR		37.9	38.1	39.1

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, to maximize the system risk reduction caused by maintenance. So 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.

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 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 the equipment, with the objective to achieve the best level of reliability subject to constraints on resources. Since the maintenance tasks that the manager would like to perform require more resources than what is available, our task is to find the one way among the very large number of possible ways to utilize those resources so that the benefit that comes from those resources is maximized. It is computationally convenient in our work to think of the reliability benefit as cumulative risk reduction.

It should not be misconstrued that the “new” problem of reliability maximization subject to resource constraints necessarily results in lower levels of reliability relative to the “old” problem of resource minimization subject to reliability constraints. The incentive to solve the “new” problem is the recognition that maintenance managers are asked to do their jobs with limited resources. If it is true that power systems have a lower level of reliability than in previous years, the cause is the financial decisions that result in diminished resources. The orientation of the problem we have addressed in this paper will neither encourage nor discourage allocation of additional resources; rather it will maximize the positive effect of using available resources.

We identified weaknesses in today’s maintenance scheduling and provided a solution to address them. The inclusion of cumulative-over-time risk is essential to account for system failure consequences and its variation over time. A systematic procedure is given for including in the decision process the influence of undesired operational performance created by equipment failure in terms of system security and component damage. Use of sequential simulation to compute operational risk accounts for inter-temporal dependencies prevalent in power system operation. Relationships between maintenance tasks and failure modes are developed to facilitate the modeling of risk-based maintenance scheduling, and component failure rates are estimated with a rigorous

method based on Markov modeling. A new optimization algorithm was developed and tested to obtain optimal selection and scheduling of transmission component maintenance tasks. Lagrange multipliers are used to improve the resource allocation effectiveness. We conclude there is significant potential for using the procedures and methods developed 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.

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