Risk-Based Maintenance Allocation and Scheduling for Bulk Transmission System Equipment

Final Project Report

Power Systems Engineering Research Center

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Final Project Report

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Power Systems Engineering Research Center

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Executive Summary

In today's electricity business, it is more important than ever to cost effectively maintain reliability. In this project, we developed a method for efficiently allocating economic resources among maintenance activities for bulk transmission system equipment. Thus, the project addresses needs associated with asset management of transmission equipment. With this method, maintenance scheduling explicitly considers risks associated with such network security problems as overloads, low voltages, cascading overloads, and voltage instability. The method's objective is to allocate economic resources to minimize risk of wide-area bulk transmission system failures through the optimal choice of a maintenance schedule.

Selection and scheduling of maintenance tasks, subject to budget and labor constraints, is performed today with various levels of rigor. In some cases, maintenance schedules are fixed schedules, augmented when needed to address significant equipment maintenance concerns. In other case, maintenance is scheduled by using ranking mechanisms that score equipment based on weighted sums of different attributes characterizing either the failure likelihood or the failure consequence of each piece of equipment.

The maintenance management approach developed in this project improves upon existing practices by making two significant and unique contributions by explicitly modeling operational security risk reduction and by computing an optimal maintenance schedule.

<u>Operational security risk</u>

Given that available economic and labor resources for maintenance are constrained relative to the maintenance needs, the decision to expend resources on maintaining one piece of equipment over another is based on their relative failure likelihoods as well as their relative failure consequences. We formalized this procedure using cumulative-over-time risk, where the consequence evaluation includes operational security consequences (in particular, overload, low voltage, voltage instability, and cascading overloads).

<u>Optimization</u>

Optimization methods for maintenance scheduling have not been used widely in the industry because of the difficulty in properly quantifying risk and the challenges associated with nonlinear integer programming. We solved both of these problems using a novel combination of relaxed linear programming and dynamic programming that maximizes maintenance-induced cumulative risk reduction under budget, labor, and outage-risk constraints. This approach's advantages relative to a ranking approach are that it (1) obtains optimal solutions, (2) models attributes and constraints more rigorously, and (3) increases confidence in the choice of the preferred maintenance schedule because decision-makers can assess alternative options before making the final scheduling decision. In addition, the optimization software can be used to optimize resource allocation among budget categories such as type of equipment and/or regions.

Research-grade Matlab and C-source code implement the risk assessment and optimization methods. This software is available from the project team.

Table of Contents

Table of Contents
(continued)

Index of Tables

Index of Figures

1. Introduction

The phrase “asset management” has come to describe one of the electric power industry’s most challenging problems today. Asset management concerns the investment, operation, maintenance, replacement, and ultimate disposal of the equipment used to deliver electric power, including generation, transmission, and distribution facilities. Its increasing importance in recent years has occurred largely because the decreased availability of capital has inhibited investment in new facilities forcing companies to maintain and operate increasingly aged equipment. As a result, companies find that maintenance needs always exceed available economic and human (labor) resources so that the problem to be solved is not what are the minimum resources needed to achieve a particular reliability level, but rather, what is the maximum reliability level that can be achieved with a limited amount of resources.

For vertically integrated utilities, maintenance practices receive a significantly larger percentage of resources for generation than for transmission and distribution (T&D) because the generation equipment represents a much larger percentage of the total capital investment in facilities. In contrast, for today’s so-called “wires” companies, e.g., companies that own and/or operate transmission and/or distribution circuits but little or no generation, the T&D assets represent almost all of their capital investment. As a result, maintenance of the aging T&D facilities is a high priority, and the percentage of resources allocated to maintaining T&D facilities is high relative to the vertically integrated company. It is largely this fact that has motivated high industry-wide interest in T&D asset management as well as the work reported herein. This work focuses entirely on transmission maintenance, although the concepts are applicable to distribution maintenance as well.

1.1 Taxonomy of maintenance methods

Maintenance approaches may be divided into two basic classes [1]. In corrective maintenance (CM), also known as run-to-failure, a piece of equipment is not maintained until it fails. This approach is appropriate when the cost of failure is not significant. In preventive maintenance (PM), on the other hand, maintenance is performed in order to avoid a failure. Preventive maintenance strategies may be further divided into several different types: time-based maintenance, condition-based maintenance, and reliability-centered maintenance. Time-based maintenance is usually a conservative (and costly) approach, whereby inspections and maintenance are performed at fixed time intervals, often, but not necessarily, based on manufacturer’s specifications. Condition-based maintenance triggers a maintenance action from information characterizing the equipment condition. Relative to time-based maintenance, condition-based maintenance typically extends the interval between successive maintenances and, therefore, typically incurs less cost. However, condition-based maintenance requires a significant amount of infrastructure investment (e.g., sensors, diagnostic technology, communication channels, data repositories, processing software) to measure, communicate, store, and utilize the necessary information characterizing the state of the equipment. Reliability-centered maintenance (RCM), on the other hand, utilizes condition monitoring information together with an analysis of needs and priorities. RCM generally results in a prioritization of maintenance tasks based on some index or indices that reflect equipment condition and the equipment importance.

1.2 Risk-based maintenance and project objective

We call the maintenance approach developed in this project "risk-based maintenance" (RBM). It can be considered as a form of RCM, with the following specific attributes.

- The condition information is used to estimate equipment failure probability.
- Failure consequences are estimated and utilized in the prioritization of the maintenance tasks.
- Equipment failure probability and consequence at any particularly time are combined into a single metric called "risk".
- Equipment risk may be accumulated over a time interval (e.g., a year or several years) on an hour-by-hour basis to provide a cumulative risk associated with each piece of equipment.
- The prioritization (and thus selection) of maintenance tasks is based on the amount of reduction in cumulative risk that is achieved by each task.
- Scheduling and selection of maintenance tasks is performed at the same time (using optimization algorithms) since the amount of reduction in cumulative risk depends on the time a maintenance task is implemented.

It is useful at this point to clarify terms. Frequently, industry engineers use the word "maintenance" to refer to equipment testing, sampling, inspecting, monitoring, improving, replacing, etc. In this report, however, use of the term "maintenance" refers only to an activity that reduces the failure rate of a piece of equipment. Use of the term "monitoring" refers only to an activity that increases knowledge about the equipment's condition and, therefore, allows better estimation of equipment failure probability. For example, tree-trimming and transformer oil reconditioning are maintenance tasks; tree growth inspections and dissolved-gas-in-oil transformer tests are monitoring activities. Finally, it is useful to distinguish among failure modes for equipment in terms of whether it is maintainable or not. A line outage caused by an earthquake or a tornado cannot be prevented by maintenance, but a line outage caused by a failed dirty arrestor or contact to a tree could be prevented by maintenance. In this report, the latter are called "maintainable failure modes." The effect of maintenance on the failure rates associated with these failure modes is what drives the maintenance scheduling objective.

The objective of this project is to develop a method of allocating resources (economic and labor) and scheduling maintenance activities among transmission equipment as a function of system risk associated with network security, specifically overloads, low voltages, cascading overloads, and voltage instability. Accomplishing this objective will enable identification of economic maintenance schedules that minimize risks of equipment failure. The central concept is that allocation of available resources for performing maintenance on a large number of facilities can be done strategically and systematically so as to minimize risk of transmission system failures. This approach is unique in its use of risk in that it takes a system focus rather than component focus. In other words, its objective is to minimize system risk, not component failure probability. Although we have focused on the selection and scheduling of power transformers and transmission lines, the approach is applicable to other equipment as well.

1.3 Overview of risk-based maintenance approach

The risk-based maintenance approach developed in this project has three steps: (1) long term (e.g., a year or several years) simulation with risk-based security assessment performed at each hour, (2) risk reduction calculation, and (3) optimal selection and scheduling. These steps are illustrated in Fig. 1-1, and, taken as a whole, are referred to as the Integrated Maintenance Scheduler (IMS). Here, the long-term sequential simulator, when integrated with its hourly risk-based security assessment capability, provides year-long hourly risk variation for each contingency of interest. Sequential simulation of this nature was strongly recommended in a CIGRE publication [2]. The risk-based security assessment performs a contingency analysis for each hour using power-flow analysis for overload, cascading overload, and low voltage. A continuation power flow is used for voltage instability analysis.

The year-long, hourly risk variation, when combined with a set of proposed maintenance activities and corresponding contingency probability reductions, yields the cumulative-over-time risk reduction associated with each maintenance activity and associated possible start times. This cumulative risk-reduction captures, cumulatively over the next year (or more), the extent that failure of the component will adversely affect the system or other components in the system.

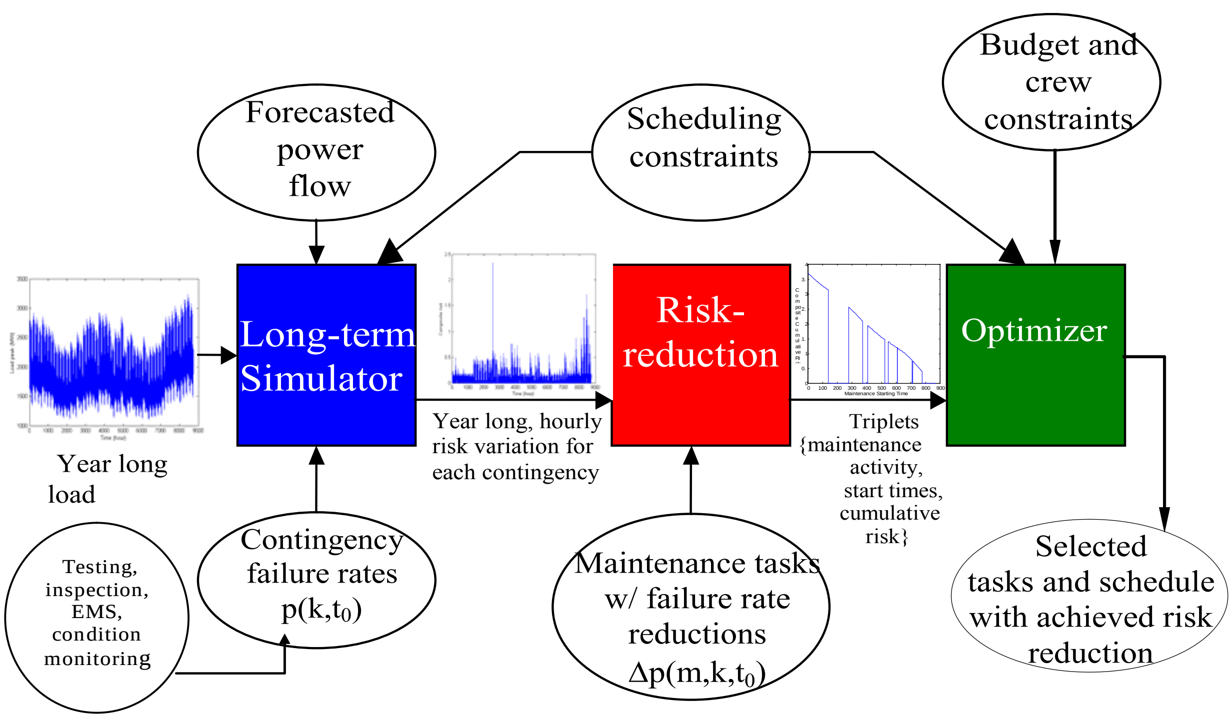


Figure 1-1: Integrated Maintenance Scheduler (IMS)

This process results in a very large number of possible task-time options. For example, if there are 1,000 possible maintenance tasks, and each task may be started in any of the next 52 weeks, then there are 52,000 task-time options for which we must decide whether to do it (1) or not (0), and no task may be selected more than once in the time interval. In addition, each of the maintenance tasks has associated with it an economic cost as well as a labor requirement, and, as mentioned, each task-time has associated with it a value of cumulative risk reduction. Finally, there may be times when a certain task cannot be performed. The primary reason for such constraints is the effect on the system that equipment outage would have. Thus, step (3) is a discrete (or integer-valued) optimization problem whereby we select a number of task-time options subject to the constraints on feasible times, total cost, and labor. In addition, the tasks are specified by cost and labor categories to conform to standard budgeting and labor management practices in industry. **We have encoded the selection and scheduling of maintenance tasks into a powerful and efficient optimization engine that identifies the optimal solution under the resource constraints such that the cumulative risk reduction achieved from allocation of those resources is maximized.** In addition to the selection and scheduling of the maintenance tasks, the optimization engine provides highly useful information pertaining to the significance of the constraints, their interaction, and resource tradeoffs between categories.

1.4 Industry significance of new maintenance orientation

The optimization problem that we have solved reflects in a significant way an important conceptual 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 a constraint on cost (or resources). Thus, the maintenance manager is provided with a certain budget and personnel to do the work. Yet, it is inevitably the case that in the coming year, the maintenance tasks that the manager would like to perform require resources that exceed what is available. Thus, the task is to "get the biggest bang from the buck;" in other words, to find the one way among the very large number of possible ways to utilize those resources so that the "good" that comes from those resources is maximized. Although one may think of that "good" in general terms as the system reliability; it is computationally convenient in our work to think of it as cumulative risk reduction.

It should not be misconstrued that this "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. Depending on the business decision that results in the resource allocation, the resulting reliability level may be higher, or lower, than some defined standard of reliability. The incentive to solve this "new" problem is simply the recognition of the practical reality that all 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, it is the economic decisions that result in lower resources that are the cause. The orientation of the problem we are solving in this project will neither encourage or discourage allocation of additional resources; rather it will just maximize the positive effect of using whatever resources are available.

1.5 Relation to industry state-of-the-art

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 work-flow functions, work-order tracking, and data storage. Examples of these tools are Maximo, Cascade, and Asset-Sentry. Typical data stored includes equipment data (nameplate, maintenance histories, and condition data). Some companies have several additional data repositories that house such information as outage schedules, operating histories (e.g., a process-informtion or PI-historian), and equipment-specific condition data (e.g., DGA, or tap changer temperatures). Because of the number and diversity of the asset management data repositories, EPRI has developed the maintenance management workstation (MMW) that acts as a database integrator providing a number of functionalities among which is the ability to bring data from multiple sources to a consolidated data set.

These efforts have mainly targeted the need to obtain and manage the data. There has been significantly less effort targeting tools that utilize the 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 a ranking of these scores. The task selection is then made by scheduling tasks in descending order until the budget is exceeded. This approach lends itself towards decision-making, but the solution depends on a high degree of subjectivity in the scoring process. In addition, it contains no systematic way to account for task scheduling.

Finally, there is no indication yet of progress towards providing a systematic method that ties maintenance selection and scheduling with operational constraints seen in the control center. This is a very important effect that is manifested in two different ways, only one of which is normally recognized. First, and most obviously, a maintenance-related outage may result in an operationally unacceptable condition that, if allowed, would require constrained operation (e.g., off-economic dispatch). Typically there are procedures at most transmission control centers (and/or independent system operators) to identify such situations and re-schedule the maintenance as a result. 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 most important, but least recognized, and as far as we know, not systematically utilized by any tool for maintenance selection and scheduling. This manifestation is that maintenance reduces the frequency of operational constraints seen by the operator (where operational constraints may be due to overload, low voltage, voltage instability or cascading overloads). The reason for this is simple. If a maintenance task reduces the failure rate of a piece of equipment, then frequency of failure of that equipment will reduce. If failure of that equipment results in operational constraints, then the maintenance will also reduce the failure 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 (i.e., this morning, failure of line 1 may be most severe, and this afternoon, failure of line 2 may be most severe).

It is the complexity of this issue that has inhibited the development of an associated new maintenance scheduling approach to date. The most important accomplishment of this project is that this issue has been effectively addressed so that the relation between maintenance and operational constraints is systematically embedded in the software developed to perform maintenance selection and scheduling.

1.6 Contents of report

In this report, we describe and illustrate the maintenance selection and scheduling procedure developed in this project. Chapter 2 describes the long-term simulator used to obtain the cumulative risk evaluation for each component. Chapter 3 develops the necessary relations for performing the risk reduction calculation associated with each maintenance task and each start-time. Chapter 4 describes the optimizer. Results on a medium size utility system having 36 generators, 566 buses, 561 transmission lines and 115 transformers are described in Section 5. Chapter 6 concludes the report and identifies essential follow-on work to this project.

2. Long Term Simulation

This project makes use of two previously developed technologies: risk-based security assessment (RBSA) and long-term sequential simulation. Risk-based security assessment [3][4] provides quantitative valuation of network security level (or risk) using probabilistic modeling of uncertainties in loading conditions and contingency states. We developed a simulator [5][6][7] that performs sequential long-term simulation of a power system on an hour-by-hour basis. It creates an 8,760-hour trajectory of operating conditions formed by developing an hour-by-hour load forecast together with a yearly unit commitment schedule and dispatch. Risk-based security assessment is made for each of the 8,760 operating conditions. This means that, in principle, a full contingency assessment and corresponding risk calculation is made for each hour. In practice, speed enhancements relieve this computational burden.

Sequential simulation was originally proposed to be done using Monte-Carlo simulations to select loading trajectories through time according to an assumed distribution of those trajectories [2]. Yet, to achieve statistical convergence of the Monte Carlo simulations, a large number of trajectories are required, making the computational burden unwieldy. In contrast, we develop only a single, *expected* trajectory with appropriate variance. The trajectory is formed by (1) developing an hour by hour load forecast, (2) identifying and modeling the load forecast error, (3) identifying a maintenance schedule (insofar as maintenance for any equipment, e.g., generation, is known a-priori), and (4) developing a unit commitment schedule and corresponding dispatch. Descriptions of the various features of our approach can be found in [8][9][10][11][12], but the simulator is quite modularized so that specific implementations of each feature can be replaced if a different implementation is desired. We call the approach a mean-variance sequential simulation (MVSS). The simulator has been described in previous works on annual overload risk assessment [10], and on annual voltage instability and generation adequacy risk assessment [11].

An alternative to sequential simulation is to:

- select M different conditions,
- assign a probability to each one, with the sum of all condition probabilities equal to 1,
- perform the contingency-based risk assessment on each condition, and
- aggregate the results weighted by the condition probability.

This is effectively what we are doing in sequential simulation where each operating condition has a probability of 1/8760. However, sequential simulation provides a systematic and rigorous way of obtaining the conditions and corresponding condition probabilities.

In Section 2.1 we summarize the procedures for computing risk for a given operation condition. Section 2.2 summarizes the procedures for using risk-based security assessment within sequential simulation for a long-term assessment.

2.1 Computation of risk

The risk index is an expectation of severity, computed by summing the product of the outcome probability and its severity (or consequence) over all possible outcomes. In Fig 2-2, if we assign probabilities to each branch, then the probability of each terminal state is the product of the probabilities assigned to the branches that connect the initial state to that terminal state.

By assigning severity values to each terminal state, the risk can be computed as the sum over all terminal states of their product of probability and severity, given by eq. 2.1:

$$\mathrm{Risk}(\mathrm{Sev} \mid X_{t,f}) = \sum_i \Pr(E_i)\Big(\sum_j \Pr(X_{t,j} \mid X_{t,f}) \times \mathrm{Sev}(E_i, X_{t,j})\Big) \tag{2.1}$$

The variables are defined below.

- $X_{t,f}$ is the forecasted operating condition at time *t*, generally specified in terms of loading. It is the expected value of the loading condition at time *t*.
- $X_{t,j}$ is the j^{th} possible loading condition at time *t*. It provides that load forecast uncertainty be included in the assessment. $\Pr(X_{t,j}|X_{t,f})$ is the probability of this condition and is obtained from a probability distribution for the possible loading conditions.
- E_i is the i^{th} contingency. $\Pr(E_i)$ is the probability for the i^{th} contingency. Here, we assume the existence of a contingency list.
- $\mathrm{Sev}(E_i,X_{t,j})$ quantifies the severity, or consequence, of the i^{th} contingency E_i occurring under the j^{th} possible operating condition. It represents the severity associated with problems such as overload, low voltage, voltage instability, and cascading overloads. Our approach for evaluating this function is based on post-contingency power flow analysis for overload, cascading overloads, and low voltage. Post-contingency continuation power flow analysis is used for voltage instability. We further describe the severity functions in the next section.

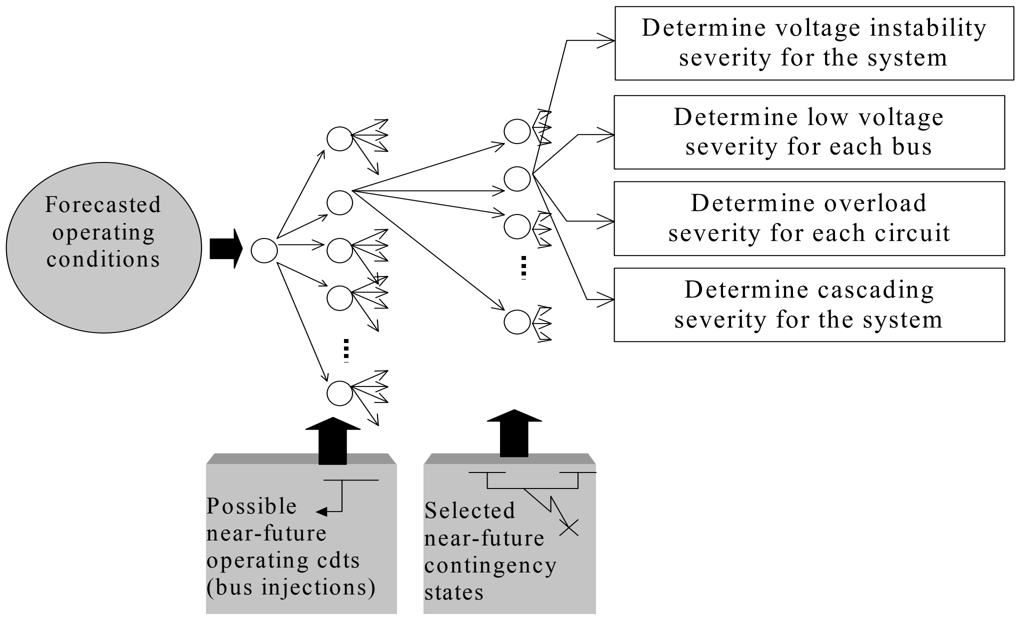


Figure 2-1: Illustration of RBSA calculation for a given operating condition

2.2 Modeling of severity

Severity provides a quantitative evaluation of what would happen to the power system in the specified condition in terms of severity, impact, consequence, or cost. CIGRE Task Force 38.02.21 [13] identified it as a challenging problem in probabilistic security assessment. One measure that is widely thought appropriate is loss of load. We have consistently resisted using such a measure because it is only an indicator and not indicative of what would really happen, yet it requires significant additional modeling and computation. To make the point, consider a line loaded to 105% of its emergency thermal rating. It is unlikely that an operator will interrupt load to off-load this line. Most likely, the operator will try to re-dispatch one or more generators to reduce the loading on the line. In many cases, an operator may even do nothing if the overload duration is relatively short. But a load-interruption based consequence measure would apply some criteria/algorithm to identify the load interruption necessary to reduce the line loading to 100% in spite of the fact that load interruption would not occur. Although evaluation of the consequence in this way may be useful, it is not worth the additional computation if other approximations can be found that are easier and faster to compute.

In addition, measuring consequence in terms of load interruption is only a measure of *system consequences* following an outage. There are consequences specific to the component (i.e., equipment damage) that are especially important in modeling the severity of a transformer failure. As a result, we decompose the evaluation of consequence following failure of a component as:

$$\mathrm{Sev}(E_i, X_{t,j}) = \mathrm{Sev}_{\mathrm{system}}(E_i, X_{t,j}) + \mathrm{Sev}_{\mathrm{component}}(E_i, X_{t,j}) \tag{2.2}$$

In Section 2.3, the modeling of the system severity function is described. In Section 2.4, the modeling of the component severity function is described.

2.3 System severity function

An appropriate and effective measure of system consequence is the cost of redispatch associated with avoiding the post-contingency violations of reliability criteria that may occur. Such cost can be modeled in computer simulation using optimization techniques where the objective is to minimize the redispatch cost subject to constraints on line loading. The simplest approach is to utilize DC power flow equations with linear programming, an approach that only accounts for overload-related violations. In order to account for low voltage or voltage collapse violations, one must utilize AC power flow equations with a nonlinear mathematical programming method, basically an optimal power flow. Such a method is quite computationally intensive, an issue which is significant given our simulator will perform full contingency assessments on 8,760 operating conditions. (Note that either DC or AC-based optimization models will also yield locational marginal prices – LMPs, to provide an indication of redispatch costs). Clearly, it is desirable to identify a solution that compromises between the efficiency of a DC-based optimizer and the rigor of an AC-based optimizer, and this is a worthy research goal that we are currently pursuing.

We have avoided this computational issue by utilizing a "proxy" for redispatch cost. The idea is that system severity is measured based on the extent of a violation rather than the corrective action cost necessary to avoid the violation under the assumption that the extent of a violation is a reasonable reflection of the corrective action cost (usually redispatch) necessary to avoid the violation. Although clearly an approximation, our system severity functions are (1) simple and easy to compute, (2) physically understandable, (3) tied to deterministic criteria, and (4) composable across the four different types of violations (overload, cascading overload, low voltage, and voltage collapse). These system severity functions are described in the following four subsections.

Two additional clarifying comments are in order. First, it is emphasized that these system severity functions represent the operational corrective actions required by an operator to mitigate the reliability violations in the system following the failure of a circuit. Thus, they are computed based on the post-contingency operating conditions.

Second, corrective actions associated with redispatch increase directly with outage duration. In computing the system severity functions to be described in what follows, it is implicit that the outage duration is the same for any outage. Therefore, it is convenient to think of the outage duration as "one unit of time" for any contingency. The assumption that all outage durations are the same is reasonable for transmission lines, for which it is generally possible to re-energize after a relatively short duration of a few hours. However, the assumption breaks down for transformer outages which can have significantly different outage times depending on the nature of the failure and the availability of spares. This issue for transformers is further addressed in Section 2.4.

2.3.1 System severity function for low voltage

The system severity function for low voltage is defined specific to the consequence of an outage on each bus in the power system. The voltage magnitude of each bus determines the low voltage severity of that bus. The system severity function for low voltage is illustrated in Fig. 2-2. For each bus, the severity is 1.0 at the deterministic limit and increases linearly as voltage magnitude falls below the limit. We have selected 0.95 p.u. as the deterministic minimum allowable steady-state bus voltage. Use of this severity function, like the other three to be described, results in non-zero risk for performance close to, but within a performance limit, reflecting the realistic sense that such a situation is in fact risky.

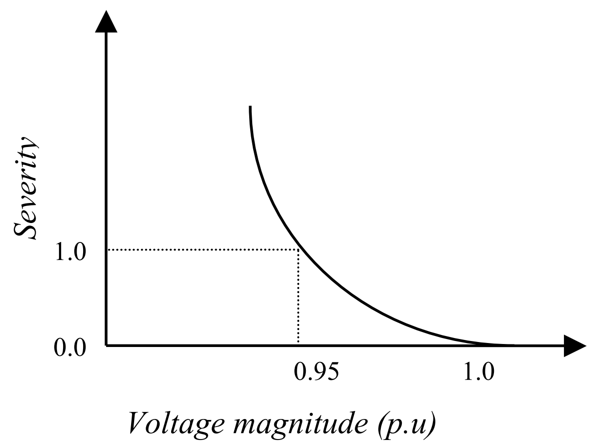


Figure 2-2: System severity function for low voltage

2.3.2 System severity function for voltage collapse

The system severity function for voltage collapse utilizes the loadability corresponding to the system bifurcation point to determine the voltage instability system severity. Here we define '%margin' as the percentage difference between the forecasted load and the loadability, as expressed in eq. (2.3) and shown in Fig. 2-3.

$$\%\text{margin} = \frac{\text{Loadability} - (\text{Forecasted\_Load})}{(\text{Forecasted\_Load})} * 100\% \tag{2.3}$$

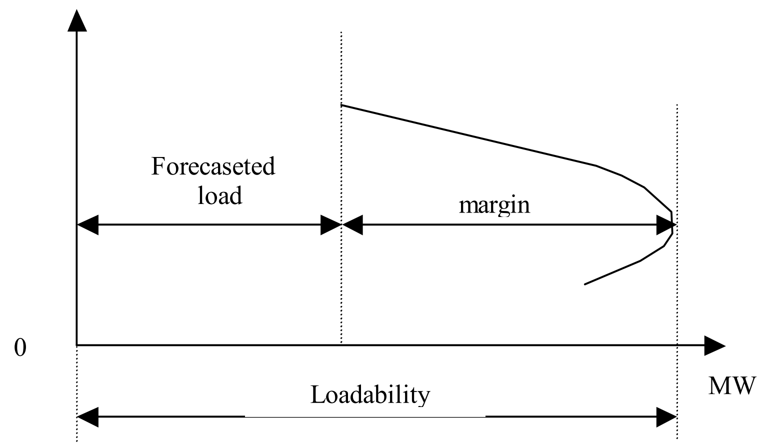


Figure 2-3: Relation between loadability and margin

For the voltage collapse problem, we use '%margin' to define the severity functions that are shown in Fig. 2-4. If %margin=0, a voltage collapse will occur for the given contingency state at the particular operating condition. The actual effects of such an outcome are quite difficult to identify, as the system dynamics play a heavy role. Nonetheless, it is safe to say the consequence is very severe and generally unacceptable under any condition. Therefore, we assign severity *B* to it, where *B* depends on the decision-maker's valuation of a voltage collapse relative to a violation of the deterministic criteria. We have used a value of *B*=100.

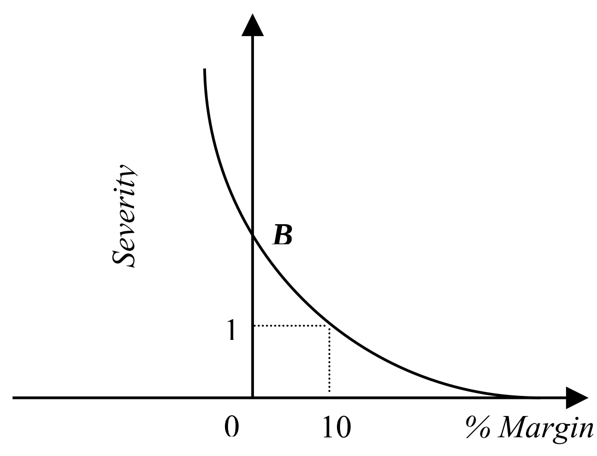


Figure 2-4: Severity function for voltage collapse

2.3.3 System severity function of overload

The system severity function for overload of any circuit is defined specific to that circuit, for both transmission lines and transformers. The power flow as % of rating (*PR)* of each circuit determines the overload severity of that circuit. The system severity function for overload is shown in Fig. 2-5.

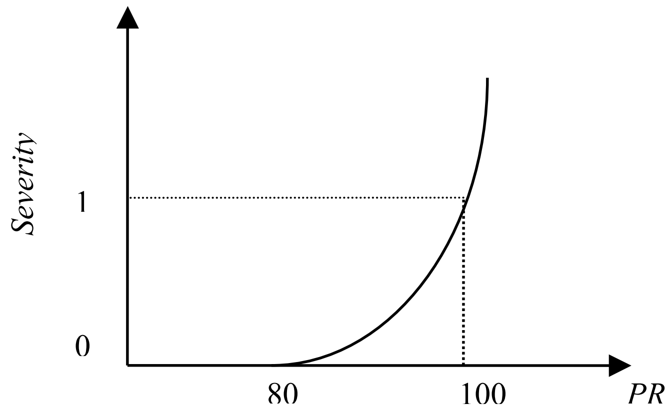


Figure 2-5: System severity function for overload

2.3.4 System severity function for cascading

"Cascading" is a sequential succession of dependent events. The types of events that may contribute to cascading phenomena vary widely. In this project, we only consider the cascading caused by high flows. We refer to the corresponding index as "cascading overload risk". This index reflects an important kind of security risk that is not captured by our other indices. We make the following assumption for the purpose of assessing the cascading overload security:

A circuit is outaged if its MVA flow exceeds K times its emergency overload rating.

A conservative choice of K is 1.0, indicating that a circuit outages when its flow exceeds its emergency overload rating.

The cascading overload analysis algorithm is as follows. Given a contingency state (the post-contingency power flow solution for a certain contingency in the contingency list):

1) Identify all circuits having flow exceeding K times its emergency overload rating;

2) Remove these circuits, and resolve the power flow; and

3) Repeat Step 1 and 2 until one of the following conditions are met:

a) No circuits are identified in step 1;

b) The power flow solution procedure diverges in step 2; and

c) The procedure exceeds a pre-specified number of iterations of step 1 and 2.

The *cascading level* is the number of iterations of step 1 and 2. The system severity function depends on the stopping criteria in step 3:

- If the algorithm terminates as a result of criterion 3-a, then the severity function is given as a function of the total number of outaged circuits found in Level 2 or higher. Therefore, the severity function used for cascading overload risk is a linearly increasing function with the number of outaged circuits. We do not include outaged circuits in Level 1 because this impact is reflected in the overload risk index.

- If the algorithm terminates as a result of criterion 3-b or 3-c, then we assume the system collapses. Thus, we assign the same severity as for voltage instability, *B*.

Whereas the system severity function for overload reflects the number of and the extent to which Level 1 circuits are overloaded following an initial contingency, the cascading risk index reflects the number of circuits that will cascade if the Level 1 overloaded circuits are opened. The severity function of cascading risk is shown in Fig. 2-6.

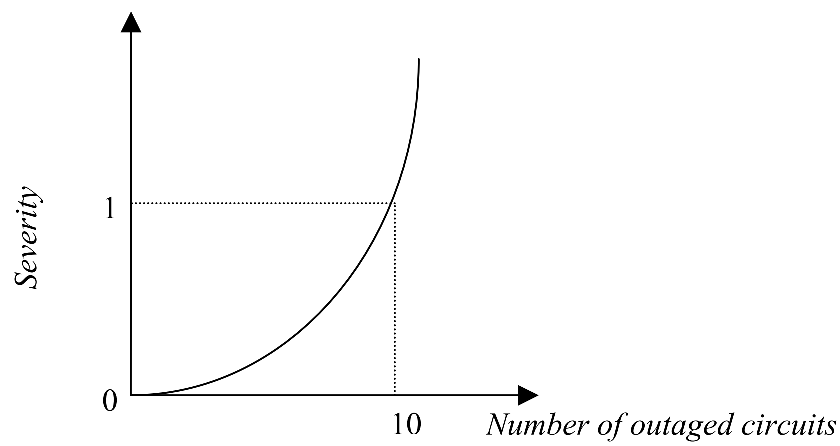


Figure 2-6: Severity function of cascading risk

2.4 Component severity functions

The severity functions described above, although approximate, represent the system consequence in terms of operational corrective actions such as redispatch cost necessary to relieve the reliability violations following an outage of a circuit. The representation is reasonable under two assumptions.

1. The failed equipment incurs no physical damage.
2. There is little variance in outage time for the failed equipment.

These two assumptions are not unreasonable for failed transmission lines. On the other hand, they are inappropriate when the failed equipment is a transformer, since:

(a) transformer failure can involve significant physical damage, and
(b) transformer outage time may vary significantly as a function of
    i. the extent of the damage, and

ii. the availability of a spare and whether the spare is on-site or not.

We make two modifications to the severity function to account for these issues. First, to account for transformer damage, we provide a non-zero value of component severity function $Sev_{component}$ in eq. (2.2). Assuming, conservatively, that any transformer failure requires its replacement, the component severity function, which represents the cost of purchasing a new transformer of the same MVA rating, is given by eq. (2.4):

$$Sev_{component}(E_i, X_{t,j}) = C * MVA_{rated} \tag{2.4}$$

where MVA_{rated} is the MVA rating of the transformer and C is a constant of proportionality that can be obtained based on eq. (2.5):

$$C = \frac{1}{100} \frac{\text{replacement cost of a 100 MVA xfmr}}{\text{1 hr corrective action cost for one line loaded just beyond its emergency rating}} \tag{2.5}$$

where obviously the numerator and denominator in eq. (2.5) must be estimated. We have used the following estimates:

- replacement cost of a 100 MVA xfmr = $1,000,000
- 1hr corrective action cost for 1 line loaded just beyond its emergency rating = $1,000.

These estimates yield C=10. Thus, with C=10, eq. (2.4) indicates that the severity of a transformer failure requiring replacement, relative to the severity of a single violation of reliability criteria, is given by 10 times the transformer's MVA rating.

Second, to account for variation in transformer outage duration based on the availability of spares, we require input data for each transformer indicating whether there is no spare available, an available off-site spare, or an available on-site spare. Because outage duration affects the system consequences, the information on spares is utilized to scale the system severity functions according to Table 2-1.

Table 2-1: System severity scaling factors

Availability of spares	System severity scaling factor
No spare	1000
Off-site spare	100
On-site spare	10

Given identical evaluations of the "one-time-unit" system severity function, the implications of the scaling factors in Table 2-1 are that the redispatch costs for transformer outages will be as follows:

- no spare case – scaling factor of 1,000 times that of a line outage

- off-site spare – scaling factor of 100 times that of a line outage
- on-site spare – scaling factor of 10 times that of a line outage.

2.5 Speed enhancement

The sequential simulator performs contingency-based risk assessment for each hour in the year. If there are N contingencies, 8,760 x N different risk assessments must be performed. This is computationally intensive so decreasing the computation time is an important concern. Several speed enhancements were implemented to achieve this goal. We describe the two most important of which in the following two subsections.

2.5.1 Avoiding redundant assessments for similar operating conditions

The number of hours that actually have a full contingency analysis performed for them can be reduced significantly without diminishing the integrity of the resulting information content. The idea is to compare the conditions of the next hour and all previously encountered conditions. If this comparison indicates that two conditions are *sufficiently similar*, then the computations for the next hour can be avoided and the computed risks for each contingency are assumed to be the same. To identify the similar hours the following method is used:

1. Determine the previous hours that have the same network topology as that of next hour. Then compare the load profile and generation profile of next hour, denoted as hour j, with that of the hours having similar network topology. If for previous hour i, for all buses k, the following criteria are satisfied, hour i is said to be similar to the next hour. In this case, the result of hour i is used as the result of the next hour.

$$abs\left(\frac{P_{gki} - P_{gkj}}{P_{gki}}\right) < \varepsilon \text{ and } abs\left(\frac{P_{gki} - P_{gkj}}{P_{gkj}}\right) < \varepsilon$$

$$abs\left(\frac{P_{lki} - P_{lkj}}{P_{lki}}\right) < \varepsilon \text{ and } abs\left(\frac{P_{lki} - P_{lkj}}{P_{lkj}}\right) < \varepsilon$$

   Here P_{gki} is the generation at bus k at hour i and P_{lki} is the load at bus k at hour i. We have used ε=0.01 in the studies reported in Chapter 5.

2. If there is no previous hour that has the same topology as that of next hour, or if none of the hours with the same topology satisfy the criteria presented above, then proceed as follows:

   a. Calculate the load flow of the next hour;
   b. Identify the branch with the lowest load flow;
   c. If this lowest load flow is smaller than a threshold β, then go to step d); otherwise stop searching for the similar hour and perform the risk assessment for this condition; and

d. Assume that the topology of the next hour does not have the branch found in b), then use the method described in point 1 above to identify the similar hour.

The idea behind these steps is that the presence or absence of very lightly loaded circuits has little effect on the risk assessment. We have used β=0.1 in the studies reported in Chapter 5.

Implementing this speed enhancement, the number of hours assessed can decrease dramatically. Increasing ε and β can reduce the number of hours assessed to any desired value. In doing so, the similarity of the hours becomes more and more of a very crude approximation. However, for a given computational time constraint, accepting the crude approximation may be desirable. Even under highly approximate similarity conditions, should doing so be necessary, the method still provides a systematic and rigorous way to identify condition probabilities.

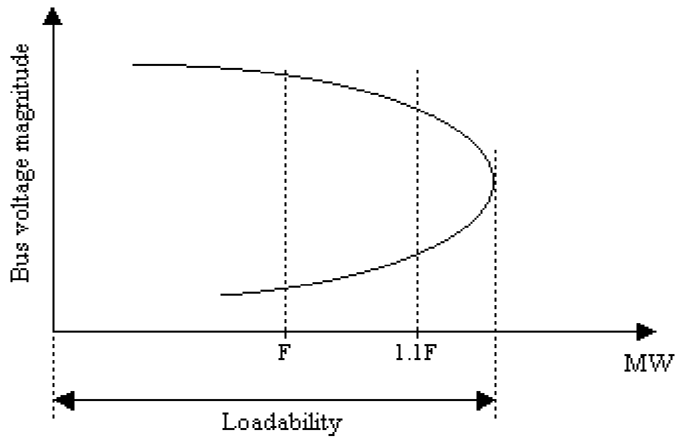
2.5.2 Contingency screening

In the previous subsection, we described a method for reducing the number of operating conditions for which we would perform contingency assessment. In this subsection we describe a method for reducing the time spent performing the assessment on each operating condition assessed.

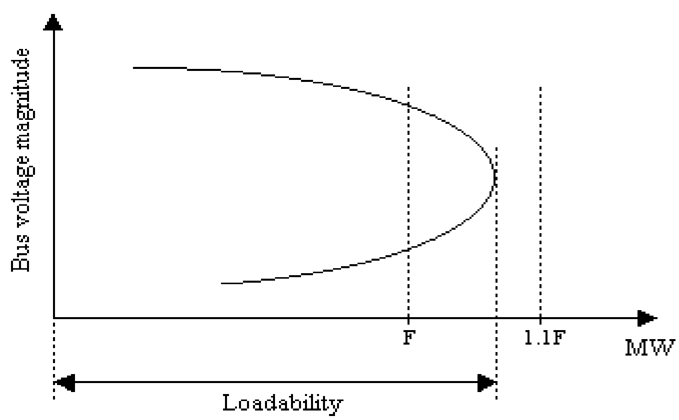
The most time-consuming part of the risk-based contingency assessment is the voltage instability assessment using the continuation power flow. As a result, we focused on reducing the time required in the voltage instability risk assessment. There are two basic approaches that we have implemented to do this.

1) *Contingency ranking*: The contingencies are ranked according to their loadability, which is used to quantify the voltage instability risk. The assessment proceeds down the ranking, from the most severe to less severe case, until a contingency results in zero voltage instability risk. For the contingencies less severe than this zero voltage instability risk contingency, the value zero is assigned to their voltage collapse risk without doing any further calculation.
2) *Improved continuation power flow*: The index of loadability is used to quantify the voltage instability risk. In order to get the exact value of loadability, it uses the CPF, a very computation-intensive algorithm. But, if the system load level is much less than the loadability value, the system has no voltage instability risk at all. From the severity function presented in Fig. 2-5, it can be seen that when the "%margin" is 10% or more, the voltage instability severity is zero. Under this condition, there in no need to get the exact loadability value. So, in the CPF, first it is judged whether the system has 10% or more; if yes, the value zero is assigned to the voltage instability risk of the system; if not, the CPF is used to get the exact loadability and thus the risk. Fig. 2-7 illustrates this approach where F represents the forecasted load in MW. Part a) shows a zero risk situation. The algorithm converges when evaluating for 10% margin, which means that there is no need to determine the loadability value. The case illustrated in part b) has non-zero voltage instability risk. The algorithm does not

converge when evaluating for 10 % margin, which means that it is required to find the exact loadability value.



a) Voltage instability risk is zero



b) Voltage instability risk is non-zero

Figure 2-7: Implementation of the improved continuation power flow

2.6 Summary

We have described fundamental methods for performing risk-based security assessment within the long-term simulator. Central to this discussion is the approach to assess the consequence of contingencies where we have used system severity and component severity functions. Key to the method is the ability to perform the computations efficiently. We have described several speed enhancements that have been implemented in the simulator.

3. Risk Reduction Calculation

The central idea to our maintenance scheduling method is that each maintenance task decreases the probability of a particular contingency. We assume that probability reductions are in force from the time of the maintenance task to the end of the year. Therefore, each maintenance task creates a risk reduction that is a function of when that maintenance task is scheduled.

3.1 Maintenance-induced contingency probability reductions

We assume that component maintenance results in a reduction in the component failure probability. In order to perform the risk reduction calculation, we need to identify relationships between maintenance tasks and failure probability reductions. There are three basic steps: (1) identify the failure modes affected by each maintenance task, (2) identify the reduction in failure mode probability by each maintenance activity, and (3) determine the relationship between the failure mode probability and the contingency probability.

3.1.1 Failure modes affected by maintenance activities

We have developed a table of maintenance tasks, affected failure modes, and typical failure mode effects and maintenance frequencies based on a thorough literature review [14-31], interaction with industry engineers, and information from various PSERC companies about maintenance experiences. This table is provided in the appendix.

3.1.2 Reduction in failure mode probability by maintenance activities

To obtain contingency probability reduction caused by maintenance, we need the failure mode probabilities before and after each maintenance task. Then, the failure mode probability reduction is obtained by simply taking the difference between failure mode probabilities before and after the maintenance task. This section provides background on our approach to accomplishing this. We have utilized in this project what we feel is only a temporary solution to this problem; the problem is being addressed with more rigor in a follow-on project.

Physical assets are subjected to a variety of stresses. These stresses cause the asset to deteriorate by lowering its resistance to stress. Eventually this resistance drops to the point at which the asset can no longer deliver the desired performance – and so it fails. Exposure to stress is measured in a variety of ways including output, operating cycles, times of operation, calendar time and running time. In [15], six types of patterns are given representative of most kinds of aging and deterioration, as shown in Fig. 3-1. Pattern A is the well-known bathtub curve. It begins with a high incidence of failure (known as infant mortality) followed by a constant or gradually increasing failure probability, then by a wear-out zone. Pattern B shows constant or slowly increasing failure probability, ending in a wear-out zone. Pattern C shows slowly increasing failure probability, but there is no identifiable wear-out age. Pattern D shows low failure probability when the item is new, then a rapid increase to a constant level, while pattern E shows a constant failure probability at all ages. Pattern F starts with high infant mortality, which drops eventually to a constant or very slowly increasing failure probability. For a random failure, the failure probability in any short time interval, assuming that the device has been working up to that time, is constant. The time until failure is exponentially distributed and the hazard rate has the same shape of Pattern E in Fig. 3-1 [25, 26]. Because random failure modes have constant failure probabilities, maintenance has no influence. Thus, these types of failure modes are not maintainable. Failure modes associated with natural disasters (e.g., earthquakes, tornadoes, etc.) are of this sort.

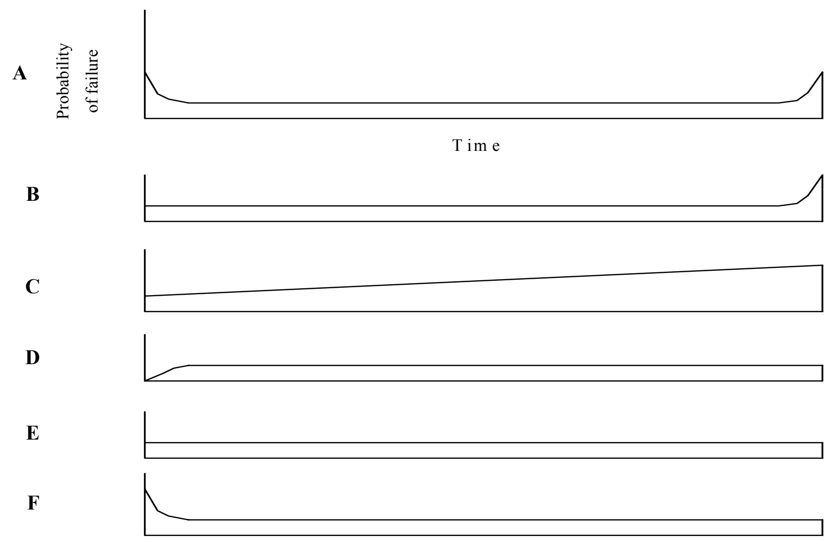


Figure 3-1: Probability of failure caused by aging and deterioration

Curve A is commonly used to model component deterioration. We adopt it for modeling failure modes associated with power transmission equipment. We assume the existence of such a hazard model for each failure mode contributing to the failure of a piece of equipment. Such hazard models may be estimated based on typical component lifetimes, or they may be obtained from statistics characterizing the performance of a large number of similar components. We have estimated hazard models for four types of failure modes: (1) transformer insulation failure due to oil deterioration; (2) transformer insulation failure due to a core problem, mechanical failure and general ageing; (3) conductor contact to trees; and (4) line insulator failure.

A rigorous method for estimating these hazard functions is being developed in a follow-on project, and preliminary work will appear in [32]. In this project, we elected to focus on the integration of the various IMS steps, with emphasis on the optimization procedure presented in Chapter 4, rather than rigorous and complete solution to the important but challenging problem of estimating failure rate reduction from maintenance tasks.

Given the hazard model estimate as illustrated in Fig. 3-2, we can obtain the failure probability reduction associated with a maintenance task using two alternative approaches.

1. Estimate the deterioration level: This amounts to estimating the discrete level of deterioration in which the component resides, and given the deterioration level, we are able to locate t_f in Fig. 3-2. Figure 3-2 shows five discrete deterioration levels, but there could be more or less depending on the fidelity of the measurement used to estimate the deterioration level. For example, a first order measurement for any component would be simply the time since the last maintenance. A very good measurement for transformer insulation failure would be the results of a recent dissolved-gas-analysis. The method given in [32] will provide the ability to utilize all any number of measurements to estimate the deterioration level.
2. Estimate the effects of a maintenance task: There are three possible ways to do this, depending on whether we want to estimate Δp, Δt, or t_0 for a given maintenance task, as indicated in Fig. 3-2. In our software we provide the option of using any of these three ways. However, we believe that the most promising approaches are to either estimate Δt or to estimate t_0 because by doing so, the probability reduction also depends on the existing deterioration level t_f, as it should. This provides two essential features that would not be available if we estimated Δp. First, probability reduction increases as the maintenance is delayed. Second, there are times for which a maintenance activity provides no probability reduction.

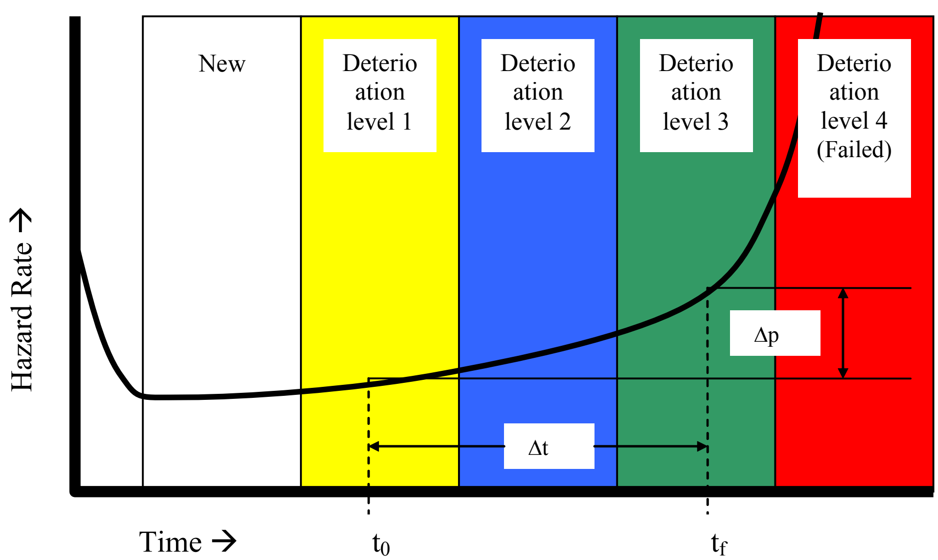


Figure 3-2: Maintenance induced contingency probability Δ*p*

Each maintenance renews the equipment to an identified discrete level, defined as t_0, on the hazard function. Therefore, $\Delta p=P(t_f)-P(t_0)$ is the maintenance-induced contingency probability reduction. In Chapter 5, we provide an example of actual hazard function, together with specific maintenance activity and the associated numerical calculation.

We emphasize that the hazard model characterizes a single failure mode. The contingency (e.g., a transformer outage) can be caused by any failure of several components; that is, the probability of a given contingency can be comprised by the probability of several failure modes. To account for this, we need to map the low-level effects of maintenance on each failure mode probability to the higher-level contingency probability. We have been investigating fault tree analysis as the means to do this and feel it is quite promising. For purposes of this report, however, we assume that for a given contingency, all maintainable failure modes are independent and that the contingency probability may be obtained as the summation of the failure mode probabilities.

3.2 Risk reduction calculation

The idea that maintenance results in risk reduction may be captured analytically by specifying that a particular maintenance task *m*, completed at time *t*, is known to decrease the probability of a contingency *c* by $\Delta p(m,c,t)$. Here, Δp is the maintenance induced contingency probability reduction. The cumulative-over-time risk reduction due to maintenance task *m* is $\Delta CR(m,t_f)$, computed as a function of the completion time t_f according to:

$$\begin{aligned}\Delta CR(m,t_f) &= \Delta CR_{during}(m,t_f) + \Delta CR_{after}(m,t_f) \\ &= \int_{t_f-T_d}^{t_f} (R(0,t) - R_{during}(m,t))dt + \int_{t_f}^{8760} (R(0,t) - R_{after}(m,t))dt\end{aligned} \tag{3.1}$$

where T_d is the duration of the maintenance activity, $R(0,t)$ is the risk variation over time with no maintenance, and $R(m,t)$ is the risk variation over time with maintenance. The first integral in (3.1) is the risk reduction during the maintenance period, always non-positive indicating that risk may increase during the maintenance period. The second integral in (3.1) is the risk reduction after completion of the maintenance activity, 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 $\Delta CR_{during}=0$. However, if the maintenance task requires removal of component *k* (such as a generator, line, transformer, or circuit breaker), then $\Delta CR_{during}<0$ because of resulting 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. Therefore, the risk "reduction" during maintenance task *m* is:

$$\Delta CR_{during}(m,t_f) = \int_{t_f-T_d}^{t_f} [R(0,t) - R(m,t)]dt = \int_{t_f-T_d}^{t_f} [\sum_{c=0}^{N} p(c)sev(c\,|\,0,t) - \sum_{c=0,c\neq k}^{N} p(c)sev(c\,|\,m,t)]dt$$

$$= \int_{t_f-T_d}^{t_f} [p(k)sev(k\,|\,0,t) + \sum_{c=0,c\neq k}^{N} p(c)\big(sev(c\,|\,0,t) - sev(c\,|\,m,t)\big)]dt \tag{3.2}$$

Now consider the second integral in (3.1), the risk reduction after the maintenance activity. Here, the maintenance activity *m* reduces contingency *k* probability by *Δp(m,k)* but does not affect the contingency *k* severity. We assume that maintenance activity *m* affects only contingency *k* probability and no others. The risk reduction after maintenance activity *m* is:

$$\Delta CR_{after}(m,t_f) = \int_{t_f}^{8760} \left\{ R(0,t) - R_{after}(m,t) \right\} dt$$

$$\begin{aligned} &= \int_{t_f}^{8760} \{ [p(k)sev(k \mid 0,t) + \sum_{\substack{c=0 \\ c \neq k}}^{N} p(c)sev(c \mid 0,t)] \\ &- [(p(k) - \Delta p(m,k))sev(k \mid 0,t) + \sum_{\substack{c=0 \\ c \neq k}}^{N} p(c)sev(c \mid m,t)] \} dt \end{aligned} \tag{3.3}$$

where we have pulled from each summation the risk associated with contingency *k*, since contingency *k* is the only one having a probability affected by the maintenance activity. After t_f, component *k* is back in service, and the operating conditions are unchanged relative to the case of no maintenance; therefore, $sev(c|0,t)=sev(c|m,t) \ \ \forall\, c=1,\ldots,N$, and the two summations within the integral of (3.3) are equal so that:

$$\begin{aligned} \Delta CR_{after}(m,t_f) &= \int_{t_f}^{8760} \left\{ p(k)sev(k \mid 0,t) - (p(k) - \Delta p(m,k))sev(k \mid 0,t) \right\} dt \\ &= \int_{t_f}^{8760} \left\{ \Delta p(m,k))sev(k \mid 0,t) \right\} dt \end{aligned} \tag{3.4}$$

Denoting the contingency *k* risk, without maintenance, as *R(0,k,t)*, we have *sev(k|0,t)=R(0,k,t)/p(k)*, so that:

$$\Delta CR_{after}(m,t_f) = \int_{t_f}^{8760} \Delta p(m,k) \left\{ \frac{R(0,k,t)}{p(k)} \right\} dt = \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t) dt \tag{3.5}$$

Substituting (3.3) and (3.5) into (3.1), and replacing *p(k)sev(k|0,t)* in (3.2) by *R(0,k,t)*, results in the following expression for the total risk reduction associated with maintenance activity *m* completed at time t_f:

$$\begin{aligned} &\Delta CR(m,t_f) \\ &= \int_{t_f - T_d}^{t_f} [R(0,k,t) + \sum_{c=0, c \neq k}^{N} p(c) \left(sev(c \mid 0,t) - sev(c \mid m,t) \right)] dt + \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t) dt \end{aligned} \tag{3.6}$$

There are three main terms in the risk reduction expression of equation (3.6). The first term inside the first integral represents the reduction in risk, relative to the base case, because of maintenance outage of component *k* means that contingency *k* can no longer occur. 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.

To obtain the change in cumulative risk due to a maintenance activity, 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 base case configuration $(0,t)$, and the severity of all contingencies occurring under the weakened configuration (m,t). The contingency severities associated with the base case configuration come from one run of the simulator, but the contingency severities associated with configuration (m,t) would require rerunning the simulator for every weakened condition (i.e., for every maintenance activity m). This would be excessively computational. Thus, we evaluate the first integral using approximate methods. For example, one might evaluate the 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 (3.6) is 0. This might be true as a result of, for example, operator initiated system adjustments during the maintenance period. We accept this assumption for this project. Under this assumption, the total risk reduction associated with maintenance task m completed at time t_f is:

$$\Delta CR(m,t_f) = \int_{t_f - T_d}^{t_f} R(0,k,t)dt + \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t)dt \qquad (3.7)$$

Thus, we need $R(0,k,t)$, the risk variation for each contingency affected by a maintenance task under the base case network configuration, which is information obtained from a simulator run. In (3.7), 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 that maintenance outages cause no severity increase, then it is reasonable to also neglect the first term in (3.7).

3.3 Risk reduction with simultaneous-maintenance activities

There may also be situations where it is desirable to schedule simultaneous maintenance activities. Although contingency probability reductions are independent in such cases, the severity increases due to the planned maintenance outage are not. Consider the simultaneous maintenance activities illustrated in Fig. 3-3.

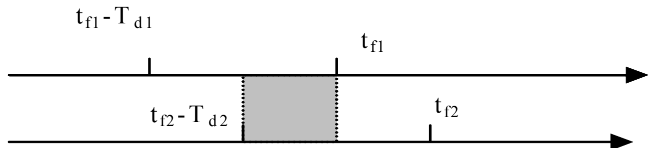


Figure 3-3: Simultaneous maintenance activities

The total cumulative risk reduction is:

$$\Delta CR(m_1, m_2, t_{f1}, t_{f2}) = \Delta CR_{during\ m_1} + \Delta CR_{\substack{during\ m_1 \\ during\ m_2}} + \Delta CR_{\substack{after\ m_1 \\ during\ m_2}} + \Delta CR_{\substack{after\ m_1 \\ after\ m_2}}$$

$$= \int_{t_{f1}-T_{d1}}^{t_{f2}-T_{d2}} R(0,k_1,t) + \sum_{\substack{c=0 \\ c\neq k_1}}^{N} p(c)(sev(c\,|\,0,t) - sev(c\,|\,m_1,t)dt$$

$$+ \int_{t_{f2}-T_{d2}}^{t_{f1}} R(0,k_1,t) + R(0,k_2,t) + \sum_{\substack{c=0 \\ c\neq k_1,k_2}}^{N} p(c)(sev(c\,|\,0,t) - sev(c\,|\,m_1,m_2,t))dt$$

$$+ \int_{t_{f1}}^{t_{f2}} R(0,k_1,t) + R(0,k_2,t) + \sum_{\substack{c=0 \\ c\neq k_1,k_2}}^{N} p(c)(sev(c\,|\,0,t) - sev(c\,|\,m_2,t)) - R(m_2,k_1,t) + \frac{\Delta p(k_1,m_1)}{p(k_1)} R(m_2,k_1,t)dt$$

$$+ \int_{t_{f2}}^{8760} \frac{\Delta p(k_1,m_1)}{p(k_1)} R(0,k_1,t) + \frac{\Delta p(k_2,m_2)}{p(k_2)} R(0,k_2,t)dt \qquad (3.8)$$

Under the assumption that maintenance activities do not affect severity, severity function differences in (3.8) are zero, leaving:

$$\Delta CR(m_1, m_2, t_{f1}, t_{f2})$$

$$= \int_{t_{f1}-T_{d1}}^{t_{f2}-T_{d2}} R(0,k_1,t)dt + \int_{t_{f2}-T_{d2}}^{t_{f1}} R(0,k_1,t) + R(0,k_2,t)dt + \int_{t_{f1}}^{t_{f2}} R(0,k_2,t) + \frac{\Delta p(k_1,m_1)}{p(k_1)} R(m_2,k_1,t)dt$$

$$+ \int_{t_{f2}}^{8760} \frac{\Delta p(k_1,m_1)}{p(k_1)} R(0,k_1,t) + \frac{\Delta p(k_2,m_2)}{p(k_2)} R(0,k_2,t)dt \qquad (3.9)$$

Neglecting risk reduction as a result of the maintenance outage, (3.9) becomes:

$$\begin{aligned} \Delta CR(m_1, m_2, t_{f1}, t_{f2}) = &\int_{t_{f1}}^{t_{f2}} \frac{\Delta p(k_1,m_1)}{p(k_1)} R(m_2,k_1,t)dt \\ &+ \int_{t_{f2}}^{8760} \frac{\Delta p(k_1,m_1)}{p(k_1)} R(0,k_1,t) + \frac{\Delta p(k_2,m_2)}{p(k_2)} R(0,k_2,t)dt \end{aligned} \qquad (3.10)$$

If risk reduction is calculated for more than two simultaneous maintenance activities, the equation will be more complex, and the calculation will be very difficult. In this case, we assume the risk caused by all simultaneous maintenance outages is a linear summation of the risk caused by each maintenance activity alone.

3.4 Summary

This chapter has addressed two issues: 1) computing the failure probability reduction of a contingency caused by a maintenance task in relation to its maintainable failure mode, and 2) computing the cumulative risk reduction given the failure probability reduction of a contingency. The end result is, for each maintenance task m and completion time t_f, we obtain a value of cumulative risk reduction $\Delta CR(m,t_f)$. These values are inputs to the optimizer, to be described in Chapter 4.

4. Maintenance Selection and Scheduling

This chapter describes the optimization problem and corresponding solution for selecting and scheduling maintenance tasks to maximize the associated risk reduction.

Summarizing the Integrated Maintenance Scheduling (IMS) process (see Fig. 2-1), the simulator is run first to compute risk as a function of time for each hour over a long-term period (such as a year), and then eq. (3.6) is used to compute the risk reduction associated with each proposed maintenance activity. This step results in triplets comprised of: {maintenance activity m, completion time t_f, risk reduction $\Delta CR(m,t_f)$}. These triplets serve as the input to the optimizer. The optimization problem is presented in Section 4.1. Possible solution methods are summarized in Section 4.2. Finally, Section 4.3 describes the solution method selected and implemented in this project.

4.1 Problem statement

We define the following terms: (1) N is the total number of maintainable transmission components; (2) $k=1,...,N$ is the index over the set of transmission components; (3) L_k is the number of maintenance tasks for component k; (4) $m=1,...L_k$ is the index over the set of maintenance activities for transmission component k; and (5) $t=1,...T$ is the index over the time periods.

For transmission maintenance, define: (1) $Iselect(k,m,t)$=1 if the m^{th} maintenance task for component k begins at time t, and 0 otherwise; and (2) $Iactive(k,m,t)$=1 if the m^{th} task for component k is ongoing at time t, and 0 otherwise. Define $d(k,m)$ as the duration of task m for component k, so that:

$$Iactive(m,n,t) = \sum_{k=t-d(m,n)+1}^{t} Iselect(m,n,k), \forall (m,n,t) \tag{4.1}$$

Also, $cost(k,m)$ is the cost of the m^{th} task for component k, and $\Delta CR(k,m,t)$ is its cumulative risk reduction if it begins at time t. In Chapter 3, we used notation $\Delta CR(m,t)$; here, the additional argument is necessary because we have allowed various levels of each maintenance activity. Let $Infeas(k,m)$ be the set of time periods when task m for component k cannot be performed. Each {component, task} combination (k,m) is tagged with a budget category $B(k,m)=b\in 1, 2, 3, 4,$ where 1 = tree trimming, 2 = transformer major maintenance, 3 = transformer minor maintenance, and 4 = transmission line maintenance. Additional categories or other categories could be used if desired. $Crew(k,m)$ is the required number of crews for the m^{th} maintenance of component k. $TotCrew(b,t)$ is the total number of crews available for transmission maintenance category b at time t.

We have developed two forms for the optimization problem. In problem 1, we are constrained by a cost budget. This problem conforms to the situation where the scheduler is also paying for the maintenance activities as in the traditional vertically integrated industry. In problem 2, we are constrained by only feasible schedules submitted by equipment owners. This problem conforms to the competitive industry where, for example, the ISO schedules for a large number of equipment owners who pay for their own maintenance. We present only problem 1 since problem 2 can be solved as a special case of problem 1.

$$Max(\sum_{k=1}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T}\Delta CR(k,m,t)\times Iselect(k,m,t)) \tag{4.2}$$

Subject to:

$$\sum_{n=1}^{L_m}\sum_{t=1}^{T} Iselect(k,m,t)\le 1,\ k=1,\Lambda\ ,N \tag{4.3}$$

$$Iactive(k,m,t)=0,\forall\, t\in Infeas(k,m),\forall\,(k,m) \tag{4.4}$$

$$\sum_{\substack{k=1\\(k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m} Iactive\ \ (k,m,t)*Crew(k,m)<TotCrew\ \ (b,t),\forall t,b=1,...4 \tag{4.5}$$

$$\sum_{\substack{k=1\\(k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T}cost(k,m)*Iselect(k,m,t)<TotCost(b),b=1,...,4 \tag{4.6}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m} Iactive(k,m,t)*\Delta Sev(k,m,t)\le \Delta Sevmax(t),\forall t \tag{4.7}$$

$$Iselect(k,m,t)\in\{0,1\},\forall\,(k,m,t) \tag{4.8}$$

In this optimization problem, the objective (4.2) is to maximize the total cumulative risk reduction. The constraint (4.3) indicates that each component is maintained at most once during the time frame. Constraint (4.4) requires that each maintenance task be performed only within its feasible time period. Constraint (4.5) stipulates that the number of maintenance tasks ongoing during any period is limited by crew constraints. Constraint (4.6) represents the budget constraints. Constraint (4.7) ensures that maintenance task *(k,m)* resulting in a severity increase of *ΔSev(k,m,t)* due to outage of component *k* at time *t* does not exceed the maximum allowable severity increase for time *t*, *ΔSevmax(t)*. The maximum allowable risk increase for time *t* is set so that no maintenance outage may cause a violation of reliability criteria. After simulation, we check the system condition under each outage. If any reliability criteria is violated (e.g., voltage of one bus is lower than 0.95 or load flow in one branch is exceeds its normal rating), then *ΔSev(k,m,t)* is set to a very large value to ensure that this maintenance task will not be scheduled at time *t*. To solve this optimization problem is to determine *Iselect(k,m,t)*, which then determines *Iactive(k,m,t)*.

$$\Delta Sev = \begin{cases} 1000 & \text{if any criterion is violated} \\ \Delta Sev \text{ from simulation} & \text{otherwise} \end{cases} \tag{4.9}$$

4.2 Possible solution methods

From the description above, we observe that the problem to solve is an integer programming problem, a type known for its difficulty. We have tried three different solution methods: heuristic, branch and bound, and relaxed linear programming (LP) with dynamic programming (DP). We have focused on the LP with DP method since we believe it to be more promising in finding good solutions without significant increase in computation.

4.2.1 Heuristic method

A heuristic approach was initially used to solve the integer programming optimization problem. The approach is based on the fact that each $\Delta CR(k,m,t)$ can be regarded as a function of t. The curve for $\Delta CR(k,m,t)$ with respect to t varying in the entire maintenance time frame gives all possible cumulative risk reductions that could be incurred by maintenance. In the heuristic method, we use some index to determine the priority of maintenance activities. The index can be some heuristic ratio (i.e., the ratio of each project's objective function to its required cost). The algorithm for problem 1 is as follows:

1. For each hour t in the maintenance time frame, calculate $\Delta cumuRisk(i,j,t)$. If $t \in Infeas_{i,j}$, then $\Delta cumuRisk(i,j,t) = 0$.
2. Scale the $\Delta cumuRisk(i,j,t)$ curve by the their maintenance cost $cost_{ij}$. Put all CRR/Cost curves in the waiting list.
3. Find the maximum CRR/Cost from the waiting list. Set $IsSelect(i,j,t) = 1$ for the curve (a unit maintenance task), which maximizes this ratio.
4. Remove this curve from the waiting list and deduct $cost_{total}$ by cost of this maintenance.
5. If the remaining budget is non-negative, put this maintenance task in the schedule, update the feasible time periods for all remaining tasks, and go to step 4; else stop.

Problem 2's solution algorithm is similar to that for problem 1 except that we take the CRR as a ranking index, instead of *CRR/*cost. The algorithm terminates when all projects are scheduled. The benefits of using these heuristic algorithms are that they are fast and that they always provide a feasible solution. However, the solutions, although usually good, are sub-optimal.

4.2.2 Branch and Bound

The branch and bound (B&B) algorithm is a robust algorithm capable of solving integer programming problems to optimality. In the general case, the algorithm begins with a linear program identical to the original integer program except that all variables are relaxed to be real. The problem is solved and then one variable is selected. Two additional problems are formed, one with the selected variable constrained to be zero and the other with the selected variable constrained to be one. The two problems are solved, and the one with the best objective value is selected as the next branching point. From this point, a new variable is selected, and two new problems are again formed, one with the selected variable constrained to be zero and the other with the selected variable constrained to be one. At this stage, then, the two new problems have two variables that are constrained to be integer. The process continues in this fashion until a branching point is reached where there are no more real-valued variables. The algorithm terminates at this point.

The B&B algorithm was applied to solve the maintenance scheduling integer programming problem identified in eqs. (4.2)-(4.7) above. In this implementation, the algorithm ranks each maintenance task in order of their CRR/cost ratio. Once the maintenance tasks have been ranked, the algorithm enumerates possible sequences until the optimal one is found. The rank is used to determine the order in which the various sequences are considered. In each iteration, a bound is computed for a partial sequence as follows: each maintenance task that is included in the sequence is scheduled at its earliest possible time given its place in the sequence. We assume that no two maintenance tasks can be simultaneously ongoing. Further, we assume that any pair of unit/transmission projects can be performed simultaneously. All remaining projects are given the CRR value that they would attain if they were scheduled as soon as possible following the final maintenance task in the sequence.

We found that the B&B algorithm is very effective for small problems, but it is computationally expensive for larger problems. As a result, it may not be the best algorithm to solve the maintenance scheduling problem.

4.2.3 Relaxed linear programming with dynamic programming

Dynamic programming has been widely used in solving complex problems of planning and optimal decision-making. However, the size of problem must be quite limited because of its computational requirements. Our approach uses a novel combined method to achieve good computational performance without sacrificing optimality. This approach first solves a relaxed linear program (LP) to obtain Lagrange multipliers on the budget constraint (4.6) and the risk constraint (4.7), 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 over the labor constraints (4.5) one period at a time, where a period is taken to be one week. The procedure is described in the next subsection.

4.3 Description of solution method used

The relaxed linear programming with dynamic programming approach (RLP-DP) is used to solve the problem of (4.2)-(4.8) in our project. The procedure is described below.

4.3.1 LP Relaxation to get dual variables

We solve a relaxed LP that includes all of the constraints (4.3)-(4.8) in order to get approximations on Lagrange multipliers μ_1-μ_4 on budget constraints 1-4 and λ_t, $t=1,\ldots T$ on the risk constraints. This LP is "relaxed" in that variables are allowed to be non-integer. In solving the linear program, a vector of variables x is defined as

$$x(n,t) = \{x(1,1),\ldots,x(1,T),\ldots\ldots,x(N,1),\ldots,x(N,T)\} \qquad n = 1,\ldots,N; t = 1,\ldots,T \tag{4.10}$$

where n is the number of maintenance tasks and t is the number of periods. $x(n,t) = 1$ means that the n^{th} task is scheduled in period t; otherwise, it means the task is not scheduled at time t. A constraint matrix is set up so that each cell represents the weight value for the variables. Fig 4-1 shows the constraint matrix used in the linear programming.

*#Tasks * #Periods*

	Task 1					. . .	*Task (N-1)*			*Task N*			
Budget	$a_{1,1}$	$a_{1,2}$	…	$a_{1,T-1}$	$a_{1,T}$	…	$a_{1,(N-2)*T+1}$	…	$a_{1,(N-1)*T}$	$a_{1,(N-1)*T+1}$	…	$a_{1,N*T-1}$	$a_{1,N*T}$
	$a_{2,1}$	$a_{2,2}$	…	$a_{2,T-1}$	$a_{2,T}$	…	$a_{2,(N-2)*T+1}$	…	$a_{2,(N-1)*T}$	$a_{2,(N-1)*T+1}$	…	$a_{2,N*T-1}$	$a_{2,N*T}$
	…												…
	…												…
labor	…												…
	…												…
	…												…
	…												…
Sev	…												…
	…												…
One	…												…
time	…												…
	…												…
	$a_{M,1}$	$a_{M,2}$	…	$a_{M,T-1}$	$a_{M,T}$	…	$a_{M,(N-2)*T+1}$	…	$a_{M,(N-1)*T}$	$a_{M,(N-1)*T+1}$	…	$a_{M,N*T-1}$	$a_{M,N*T}$

Figure 4-1: Constraint matrix of linear programming

The columns of matrix have the same structure as x in (4.10). The matrix contains rows of constraints, described as follows:

1) Budget: The number of rows is equal to the number of maintenance categories, corresponding to constraint (4.6). In each cell, the value is the ratio of cost of that task to the total budget for the category in which that task resides.
2) Labor: The number of rows is equal to the number of categories times the number of periods, corresponding to constraint (4.5). In each cell, the value is the ratio of labor of that project to the total available labor in the category in which this task resides, in each specific hour.
3) Severity: The number of rows is equal to that of the number of periods, corresponding to constraint (4.7). In each cell, the value is the ratio of increased severity to the total acceptable severity increase for the whole system.
4) One time: This guarantees that each project is scheduled at most once, corresponding to eq. (4.8). The number of rows is equal to Projects. For each row, the value in the columns corresponding to the same project as the row number will be set to be one, otherwise zero.

The linear program incorporating the transformed constraints (4.5-4.8) becomes:

$$Max(\sum_{k=1}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T}\Delta CR(k,m,t)\times Iselect(k,m,t))$$

subject to:

$$\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m} Iactive\quad(k,m,t)*\frac{Crew\,(k,m)}{TotCrew\quad(b,t)}<1,\forall t,b=1,\ldots 4 \tag{4.11}$$

$$\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} cost(k,m)*\frac{Iselect(k,m,t)}{TotCost(b)}<1,b=1,\ldots,4 \tag{4.12}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m} Iactive(k,m,t)*\frac{\Delta Sev(k,m,t)}{\Delta Sevmax(t)}\leq 1,\forall t \tag{4.13}$$

$$\sum_{t=1}^{T} Iselect(k,m,t)\leq 1,\forall k,m \tag{4.14}$$

The solution to the above linear program is not a solution to the original integer programming problem since the decision variables are not integers. However, the solution does provide reasonable estimates of the LaGrange multipliers on the constraints, which are μ_1-μ_4 on the budget constraints and λ_t, $t=1,\ldots T$ on the risk constraints. These LaGrange multiplier estimates can be 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 standard solution procedures are readily available. The knapsack problem will be solved over the labor constraints (4.11) for the first period (e.g., first week) to identify the maintenance tasks to be performed in that week. Then we re-solve the LP with the week-1 variables known to get updated LaGrange multipliers on the budget and risk constraints, and a knapsack problem for the second period (e.g., second week) is solved. The process is repeated until all periods are solved.

4.3.2 Solving the knapsack problems

The name “knapsack” arises from the situation where we need to fill a knapsack with items, each of which has weight and a specified value, and we desire to maximize the total value of items subject to a constraint on the total weight. The key features of the problem are as follows.

- The decision variables are whether to include an item or not; therefore, the problem is integer.
- There is only one constraint, the constraint on the total weight on the items chosen.

Although our original problem has multiple constraints, the estimation of the LaGrange multipliers allows us to represent their effects in the objective function, with the exception of the labor constraints, which become the one constraint allowable by the form of the knapsack problem. Thus, the labor consumed is equivalent to the weight of the items and the evaluation of our objective function (with the weighted constraints using the LaGrange multiplier estimates from the LP) is equivalent to the value of the items.

The new objective function to be optimized is a weighted sum of cumulative risk reduction, cost and period risk, with the various Lagrange multipliers quantifying the trade-offs between them. The problem of maximizing this objective subject to the labor constraints (4.5) is a classical knapsack problem, stated as follows:

$$\begin{aligned}\max F(Iselect(k,m,t)) = &\sum_{k=1}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T}\Delta CR(k,m,t)\times Iselect(k,m,t)\\ &-\sum_{b=1}^{4}\mu_b\left\{\sum_{\substack{k=1\\(k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} cost\ (k,m) * Iselect\ (k,m,t) - TotCost\ (b)\right\}\\ &-\sum_{t=1}^{T}\lambda_t\left\{\sum_{k=1}^{N}\sum_{m=1}^{L_m}\Delta R(k,m,t) * Iselect(k,m,t) - \Delta R\max(t)\right\}\end{aligned} \quad (4.15)$$

subject to

$$\sum_{\substack{m=1\\(m,n):B(m,n)=b}}^{M}\sum_{n=1}^{M_m} IsActive(m,n,t) * Crew(m,n) \le Crew(b,t), \forall\, t, b = 1,\ldots,4 \quad (4.16)$$

There is a knapsack problem for each period. They are solved in chronological sequence, where available hours for any period need to be reduced by ongoing projects that began in earlier periods. Constraint (4.3) is accounted for heuristically in the solution procedure, and the infeasible time periods from constraint (4.4) are enforced using negative objective function coefficients. We solve these knapsack problems using dynamic programming.

Fig 4-2 illustrates the dynamic programming computational process. The horizontal axis represents the task; the vertical axis represents the labor used or the labor available. On the figure, the value of point (x,y), f(x,y), denotes the value of maximum objective function in (4.15) for tasks (from 1 to x) with the labor hour y. We see from the figure that f(x,y) is a non-decreasing function with both x and y. That means, for fixed available hour, more candidate maintenance tasks will increase the objective function or at least keep it the same. Likewise, more labor hours may increase the objective function or at least keep it the same. We set up the figure by adding new tasks. In the parentheses in the denominator is the labor cost of the maintenance while the numerator is the objective function in (4.5) with specific project at specific time. Therefore, we set up the matrix in the forward direction, and then choose the projects in the backward direction.

The algorithm is as follows:

1. From the up-right corner of the figure, we begin to check the value at each point. The value of that point means the maximum objective function value, f(x,y), with all the candidates' projects and all the available hours.
2. Moving horizontally to the left side, check the f(x,y) of the points with the same y (available labor hour). If two points have the same value, keep on going. If two points have different value, or, in other words, f(x-1,y)<f(x,y), then adding task x will increase the objective function. Then go to step 3.
3. Move vertically with the length of labor hour of project x. Task x is scheduled and the labor it needs are subtracted from the total available labor.
4. Go to step 2 and repeat until y = 0.

4.4 Summary

The optimization method problem and its solution is a key part of finding the optimum maintenance schedule. It provides a systematic way to optimally select and schedule maintenance tasks to maximize the risk reduction achieved from a given allocation of economic and human resources. The optimization problem is integer, with multiple constraints, and has high dimension. Therefore, the problem is quite challenging to properly solve. Different solution methods have been utilized and investigated. We have concluded that relaxed linear programming with DP knapsack solutions is a very effective solution method. It provides extremely good solutions in a computationally feasible way. We will provide and analyze the results in the next chapter.

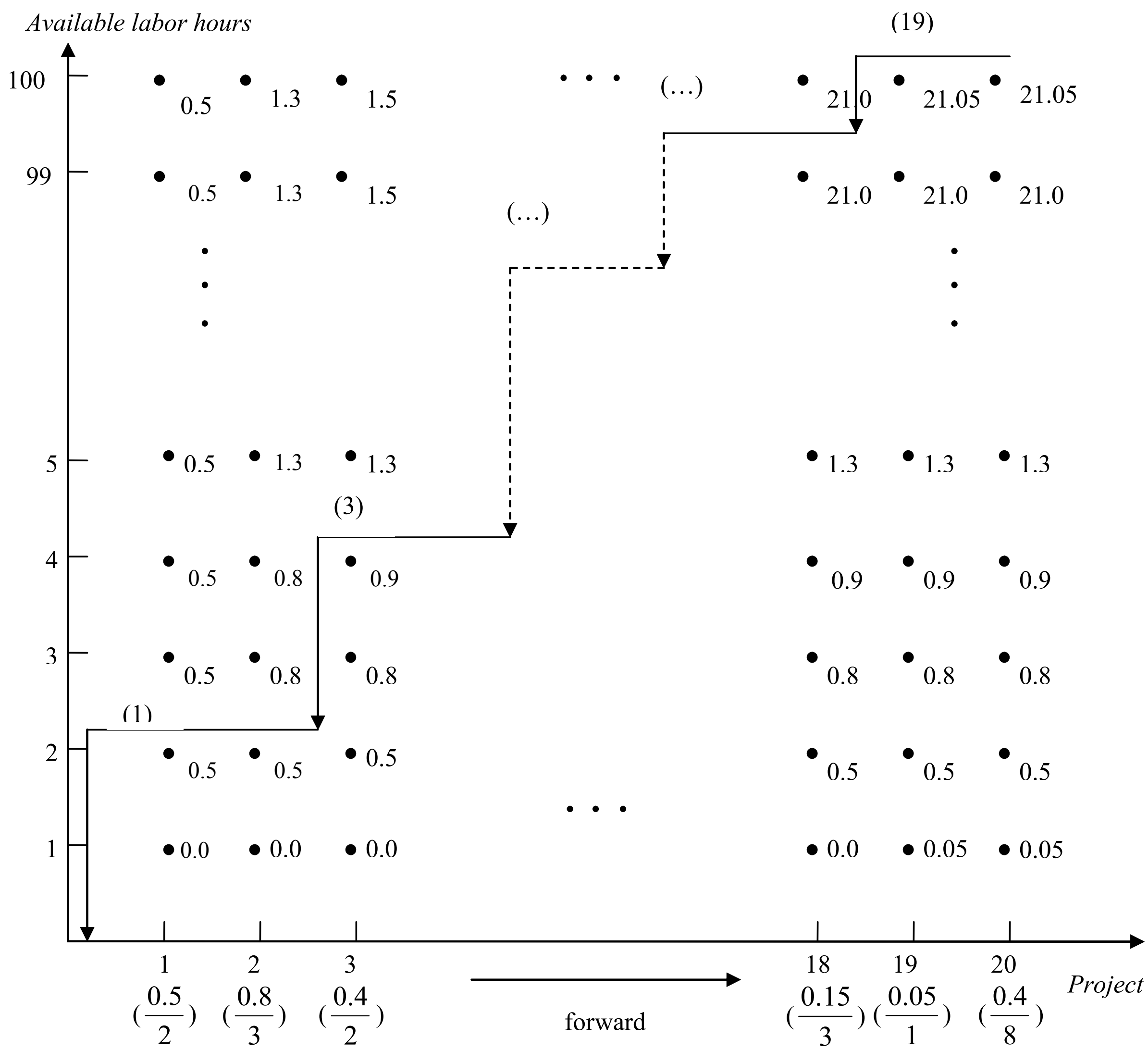


Figure 4-2: Example illustrating the dynamic programming approach

5. Results

To illustrate our optimal maintenance scheduling method, we use a model of an actual utility system but with hypothetical maintenance activities. The system has 36 generators, 566 buses, 561 transmission lines and 115 transformers. The power flow model also includes switchable shunt capacitors and reactors to ensure an appropriate voltage profile as loading changes. In addition, the data characterizing one-year projected hour-by-hour operating conditions was obtained. This data included:

- Total system load projection
- Expected tie-line flows
- Generation unit maintenance schedules which, together with the total load and tie-line projections, enable computation of unit commitment.

The total system load projection and expected tie-line flows were obtained by scaling the corresponding data from the previous year. This data was extracted from history files stored by the Energy Management System (EMS).

The hour-by-hour one-year loading trajectory, obtained from the EMS-history file and shown in Fig.5-1, was used as the next year's expected loading trajectory.

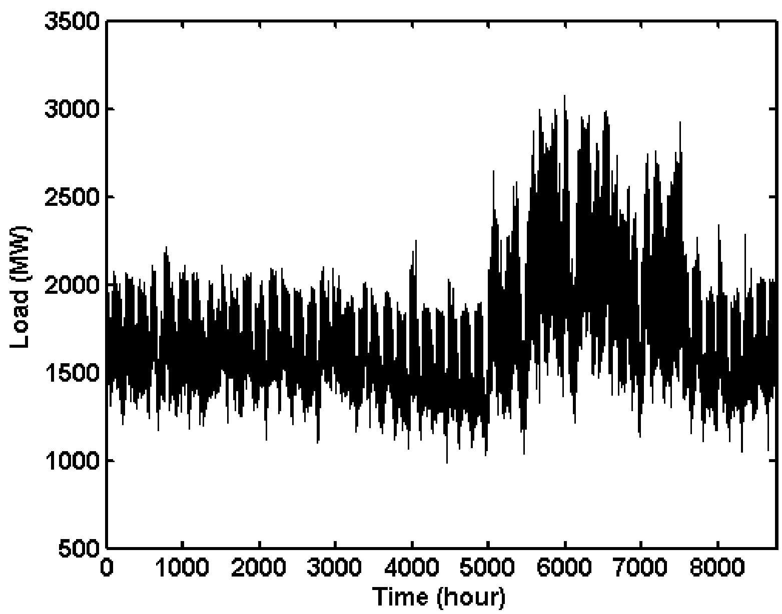


Figure 5-1: One-year loading trajectory of testing system

The time t = 0 corresponds to October 1. The yearly peak load is 3,077 MW occurring at the end of July. The minimum load is 955 MW occurring at the end of September.

5.1 Description of contingencies and maintenance activities

Contingency analysis must be done for any component that we are considering to maintain. As a result, we do not consider contingencies involving generator outages, assuming that scheduling generator unit maintenance is done a-priori and serves as an input to our procedure, as indicated in the previous section. Therefore, the contingency list includes only branch outages (that is, outages involving lines and transformers). In addition, we have limited the contingency list to lines and transformers that could result in system security violations during the year. For purposes of this project, we have assumed that the relevant lines or transformers are connected at 115 kV or above.

The maintenance scheduling method could, in principle, be applied to generator units as well, or, to both generator units and transmission components simultaneously. However, generator maintenance (or power plant maintenance) is a much more complicated subject because of the large number of failure modes and corresponding maintenance activities.

The 115 kV assumption does not imply that equipment at lower voltage levels (e.g., sub-transmission and distribution equipment) should not be maintained. It means rather that the failure consequence for equipment at lower voltages is different than the failure consequence for equipment at higher voltages. We measure failure consequence of high voltage equipment in terms of removal and replacement (R&R) cost and security violations/redispatch cost. On the other hand, we measure failure consequence of lower voltage equipment in terms R&R cost and load interruption. Given this difference, we think the approach proposed in this project would also apply to the selection and scheduling of distribution equipment maintenance tasks, a possibility that we would like to pursue in a follow-on project.

We have also not included circuit breaker maintenance in this project. However, circuit breaker maintenance is amenable to the same procedures (with some adjustments). We are pursuing this enhancement in another project that is already funded.

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 four failure modes. This means that there are 108 contingencies to assess: 70 line outages and 38 transformer outages. The failure modes and corresponding maintenance activities are listed in Table 5-1.

Table 5-1: Failure modes and corresponding maintenance activities

Contingency	Failure modes	Maintenance activity	Frequency
Transmission line outage	Tree contact	Tree trimming	1 per year
	Line or equipment failure	Insulator cleaning, replacement and hardware tightening/replacement near the tower position.	1 per year
Transformer outage	Core problem, mechanical failure and general ageing	Transformer major maintenance (complete analysis including parts replacement, complete off-line testing and corresponding maintenance and oil change.)	1 per 6 years
	Oil deterioration	Transformer minor maintenance: (annually test and oil filtering makeup including some minor maintenance and oil analysis and filtering).	1 per year

5.2 Failure rate determination and effect of maintenance

We have used typical failure-rate data based on certain assumptions for the equipment in our test system. These data and assumptions are given for transformers and lines in the following two subsections. Individual companies may be able to provide equipment-specific failure rates that, if available, could be used in place of the typical data described below.

5.2.1 Transformers

Reference [33] provides a typical MTTF for power transformers of 25 years. We make a number of assumptions consistent with Section 3.1.2.

1. No transformer is allowed to have two maintenances in the same assessment interval.
2. Wear out for a transformer begins at 10 years.
3. All transformers have one of two ages: 11 or 16.
4. Maintenance effects are:
   - Minor maintenance of a transformer reduces the failure rate to the value of the previous year.
   - Major maintenance of a transformer reduces the failure rate to the value of the 10^{th} year.
5. The Weibull distribution is used to model this wear-out process where the Weibull parameters are α=7E-7 and β=5.097. The resulting hazard function is shown in Fig. 5-2. Failure rate (cumulative hazard function) is 1.66% in year 10 and 5% in year 16.

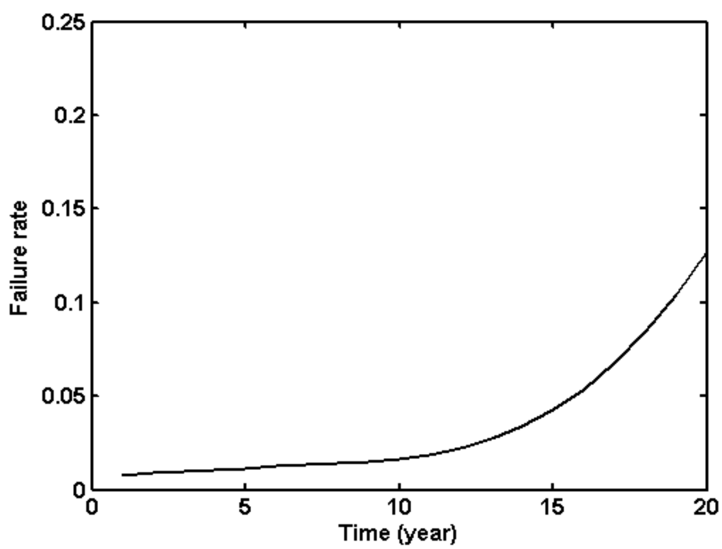


Figure 5-2: Failure rate (cumulative hazard function) assumed for transformers

Based on the above assumptions, then, we see, for example, that if a 16 year-old transformer is not maintained in the current year, the failure rate increases from 5.4% to 6.8%, but if major maintenance is performed, the failure rate returns to that of the 10 year age of 1.66%. Since both major and minor maintenance return an 11-year-old transformer to the 10 year level, it only makes sense to perform minor maintenance to the 11-year old transformer, reducing the failure rate from the 11-year-old level of 2.5% to the 10-year-old level of 1.66%.

The core issues are the ability to estimate failure rates specific to each piece of equipment at any particular time, and the ability to identify the effect of maintenance on failure rate. Both of these issues relate to the use of condition date (testing, sampling, inspecting, and monitoring). These issues are being pursued in depth in another PSERC-funded project.

5.2.2 Transmission lines

Typical transmission line failure rate data is one outage/100km/year for 345kV and 161 kV lines [34].

From [35], the typical failure rate of tree contact is p=0.05 outages/100miles/year or 0.03125 outages/100km/year. We assume that after tree trimming, the failure rate drops to zero so that the maintenance induced probability reduction is $\Delta p=p$. The failure rate of tree contact also changes during the year and can be expected to increase linearly, since according to the high voltage test (U50), the disruptive voltage with 50% of discharge probability increases linearly with decreasing distance if the distance is less than two meters. Otherwise, it is nearly constant. We make the assumption that all tree-contact-related failure rates are one outage/100km/year at the beginning of year, and if the tree trimming is not scheduled, the failure rate increases linearly to 1.03125 occ/100km/year. In the middle of the year, the failure rate will be determined by the linear function.

Transmission line device failure is also related to the line length and voltage level. For 161KV, the typical failure rate is set to be p=0.26 occurrences/100miles/year. For 345KV, the typical failure rate is set to be p=0.20 occurrences/100miles/year.

5.3 Maintenance activities

Four categories of maintenance are considered. We desire to identify the maintenance tasks and their schedule that result in the largest risk decrease for the specified contingencies. We consider performing tree-trimming for every line, insulator cleaning for every line, and minor and major maintenance for every transformer, where each task may be done at any time of the year. Table 5-2 summarizes the possible tasks and their attributes along with the corresponding contingencies.

In Table 5-2, *type* indicates the category of maintenance tasks (1-Tree trimming; 2-Transformer major maintenance; 3-Transformer minor maintenance; 4-Transmission line insulator maintenance). *Hour* is the total labor hours required for the maintenance task. *Cost* and *Duration* are the budget and time interval required to perform the maintenance task. For each maintenance*, Hour=Crew* Duration*, where "*Crew*" is the number of persons in the crew required to perform the task. The column of contingency gives the bus numbers terminating the line or transformer identified for the contingency.

Table 5-2: Proposed transmission component maintenance tasks

ID	Name	Type	Hour	Cost	Duration	Contingency		ID	Name	Type	Hour	Cost	Duration	Contingency	
1	Trim1	1	120	1000	40	11	12	90	Xrmj20	2	480	6000	120	203	206
2	Trim2	1	48	400	16	11	13	91	Xrmi1	3	240	2625	120	21	71
3	Trim3	1	192	1600	64	13	19	92	Xrmi2	3	240	2625	120	21	72
4	Trim4	1	192	1600	64	14	16	93	Xrmi3	3	240	2100	120	73	24
5	Trim5	1	192	1600	64	14	52	94	Xrmi4	3	240	2247	120	79	29
6	Trim6	1	264	2200	88	16	17	95	Xrmi5	3	240	2352	120	88	94
7	Trim7	1	240	2000	80	17	18	96	Xrmi6	3	240	1764	120	112	113
8	Trim8	1	240	2000	80	17	19	97	Xrmi7	3	240	1764	120	119	118
9	Trim9	1	168	1400	56	18	85	98	Xrmi8	3	240	1764	120	129	167
10	Trim10	1	144	1200	48	19	85	99	Xrmi9	3	240	1743	120	408	136
11	Trim11	1	96	800	32	21	30	100	Xrmi10	3	240	3150	120	138	137
12	Trim12	1	264	2200	88	21	31	101	Xrmi11	3	240	3150	120	139	140
13	Trim13	1	96	800	32	22	33	102	Xrmi12	3	240	3150	120	141	142
14	Trim14	1	48	400	16	23	39	103	Xrmi13	3	240	2100	120	534	173
15	Trim15	1	48	400	16	24	26	104	Xrmi14	3	240	1890	120	497	207
16	Trim16	1	120	1000	40	25	41	105	Xrmi15	3	240	1890	120	211	212
17	Trim17	1	120	1000	40	27	28	106	Xrmi16	3	240	1890	120	233	232
18	Trim18	1	72	600	24	27	41	107	Xrmi17	3	240	2625	120	232	562
19	Trim19	1	96	800	32	28	29	108	Xrmi18	3	240	1890	120	235	234
20	Trim20	1	168	1400	56	29	44	109	Trans1	4	120	2200	60	11	12
21	Trim21	1	132	3600	44	29	253	110	Trans2	4	48	1480	24	11	13
22	Trim22	1	132	2800	44	31	88	111	Trans3	4	192	2920	96	13	19
23	Trim23	1	72	600	24	88	99	112	Trans4	4	192	2920	96	14	16
24	Trim24	1	120	1000	40	103	59	113	Trans5	4	192	2920	96	14	52
25	Trim25	1	168	1400	56	103	161	114	Trans6	4	264	3640	132	16	17
26	Trim26	1	180	3000	60	112	115	115	Trans7	4	240	3400	120	17	18
27	Trim27	1	144	1200	48	118	161	116	Trans8	4	240	3400	120	17	19
28	Trim28	1	144	1200	48	135	143	117	Trans9	4	168	2680	84	18	85
29	Trim29	1	96	800	32	135	374	118	Trans10	4	144	2440	72	19	85
30	Trim30	1	48	400	16	139	374	119	Trans11	4	96	1960	48	21	30
31	Trim31	1	120	1000	40	141	143	120	Trans12	4	264	3640	132	21	31
32	Trim32	1	180	4000	60	141	148	121	Trans13	4	96	1960	48	22	33
33	Trim33	1	72	600	24	141	391	122	Trans14	4	48	1480	24	23	39
34	Trim34	1	120	1000	40	153	154	123	Trans15	4	48	1480	24	24	26
35	Trim35	1	228	3400	76	154	156	124	Trans16	4	120	2200	60	25	41
36	Trim36	1	264	2200	88	156	159	125	Trans17	4	120	2200	60	27	28
37	Trim37	1	96	800	32	159	161	126	Trans18	4	72	1720	36	27	41
38	Trim38	1	144	1200	48	161	163	127	Trans19	4	96	1960	48	28	29
39	Trim39	1	96	800	32	166	167	128	Trans20	4	168	2680	84	29	44
40	Trim40	1	216	2600	72	166	323	129	Trans21	4	132	5320	66	29	253
41	Trim41	1	228	4400	76	168	175	130	Trans22	4	132	4360	66	31	88
42	Trim42	1	96	800	32	172	175	131	Trans23	4	72	1720	36	88	99
43	Trim43	1	192	1600	64	172	323	132	Trans24	4	120	2200	60	103	159
44	Trim44	1	72	600	24	174	175	133	Trans25	4	168	2680	84	103	161
45	Trim45	1	48	400	16	177	351	134	Trans26	4	180	4600	90	112	115
46	Trim46	1	96	800	32	179	181	135	Trans27	4	144	2440	72	118	161
47	Trim47	1	96	800	32	181	351	136	Trans28	4	144	2440	72	135	143

ID	Name	Type	Hour	Cost	Duration		Contingency	ID	Name	Type	Hour	Cost	Duration		Contingency
48	Trim48	1	72	600	24	183	196	137	Trans29	4	96	1960	48	135	374
49	Trim49	1	192	1600	64	184	187	138	Trans30	4	48	1480	24	139	374
50	Trim50	1	96	800	32	184	193	139	Trans31	4	120	2200	60	141	143
51	Trim51	1	120	1000	40	185	200	140	Trans32	4	180	5800	90	141	148
52	Trim52	1	96	800	32	186	189	141	Trans33	4	72	1720	36	141	391
53	Trim53	1	48	400	16	186	205	142	Trans34	4	120	2200	60	153	154
54	Trim54	1	72	600	24	186	212	143	Trans35	4	228	5080	114	154	156
55	Trim55	1	120	1000	40	187	188	144	Trans36	4	264	3640	132	156	159
56	Trim56	1	216	1800	72	188	204	145	Trans37	4	96	1960	48	159	161
57	Trim57	1	168	1400	56	189	207	146	Trans38	4	144	2440	72	161	163
58	Trim58	1	72	600	24	190	197	147	Trans39	4	96	1960	48	166	167
59	Trim59	1	186	3200	62	191	229	148	Trans40	4	216	4120	108	166	323
60	Trim60	1	240	2000	80	191	539	149	Trans41	4	228	6280	114	168	175
61	Trim61	1	96	800	32	193	204	150	Trans42	4	96	1960	48	172	175
62	Trim62	1	96	800	32	195	203	151	Trans43	4	192	2920	96	172	323
63	Trim63	1	72	600	24	196	205	152	Trans44	4	72	1720	36	174	175
64	Trim64	1	72	600	24	199	203	153	Trans45	4	48	1480	24	177	351
65	Trim65	1	48	400	16	200	203	154	Trans46	4	96	1960	48	179	181
66	Trim66	1	327	4400	109	207	210	155	Trans47	4	96	1960	48	181	351
67	Trim67	1	264	2200	88	210	225	156	Trans48	4	72	1720	36	183	196
68	Trim68	1	186	3200	62	225	232	157	Trans49	4	192	2920	96	184	187
69	Trim69	1	72	600	24	232	555	158	Trans50	4	96	1960	48	184	193
70	Trim70	1	48	400	16	350	455	159	Trans51	4	120	2200	60	185	200
71	Xrmj1	2	480	2000 0	120	21	11	160	Trans52	4	96	1960	48	186	189
72	Xrmj2	2	480	2000 0	120	22	12	161	Trans53	4	48	1480	24	186	205
73	Xrmj3	2	480	2000 0	120	27	14	162	Trans54	4	72	1720	36	186	212
74	Xrmj4	2	480	5000	120	27	76	163	Trans55	4	120	2200	60	187	188
75	Xrmj5	2	480	5000	120	79	29	164	Trans56	4	216	3160	108	188	204
76	Xrmj6	2	480	1200 0	120	89	86	165	Trans57	4	168	2680	84	189	207
77	Xrmj7	2	480	4480	120	88	94	166	Trans58	4	72	1720	36	190	197
78	Xrmj8	2	480	1200 0	120	135	134	167	Trans59	4	186	4840	93	191	229
79	Xrmj9	2	480	1200 0	120	135	134	168	Trans60	4	240	3400	120	191	539
80	Xrmj10	2	480	3720	120	149	148	169	Trans61	4	96	1960	48	193	204
81	Xrmj11	2	480	3320	120	155	154	170	Trans62	4	96	1960	48	195	203
82	Xrmj12	2	480	3360	120	161	162	171	Trans63	4	72	1720	36	196	205
83	Xrmj13	2	480	3320	120	163	164	172	Trans64	4	72	1720	36	199	203
84	Xrmj14	2	480	3320	120	168	169	173	Trans65	4	48	1480	24	200	203
85	Xrmj15	2	480	4000	120	179	180	174	Trans66	4	327	6280	164	207	210
86	Xrmj16	2	480	3600	120	464	186	175	Trans67	4	264	3640	132	210	225
87	Xrmj17	2	480	3600	120	192	190	176	Trans68	4	186	4840	93	225	232
88	Xrmj18	2	480	3600	120	224	191	177	Trans69	4	72	1720	36	232	555
89	Xrmj19	2	480	6000	120	203	206	178	Trans70	4	48	1480	24	350	455

5.4 Description of results

We simulate the process of risk-based transmission component maintenance scheduling using the given system data. For the contingencies identified in Table 5-2, we perform risk assessment over one year. The composite risk variation through the year (the sum of risk over all contingencies and all problem types) is shown in Fig. 5-3. This figure provides a global sense of how the system risk varies through the year. However, optimization of the maintenance is based entirely on contingency-specific risk variation. We will discuss and illustrate contingency-specific risk variation in terms of each of the four problem types in the following four subsections. In each subsection, we identify the highest risk contingencies for the specified problem type at three different load levels (i.e., peak, minimum, and average) and then, for a selected contingency, illustrate the contingency-specific hourly risk variation over the year.

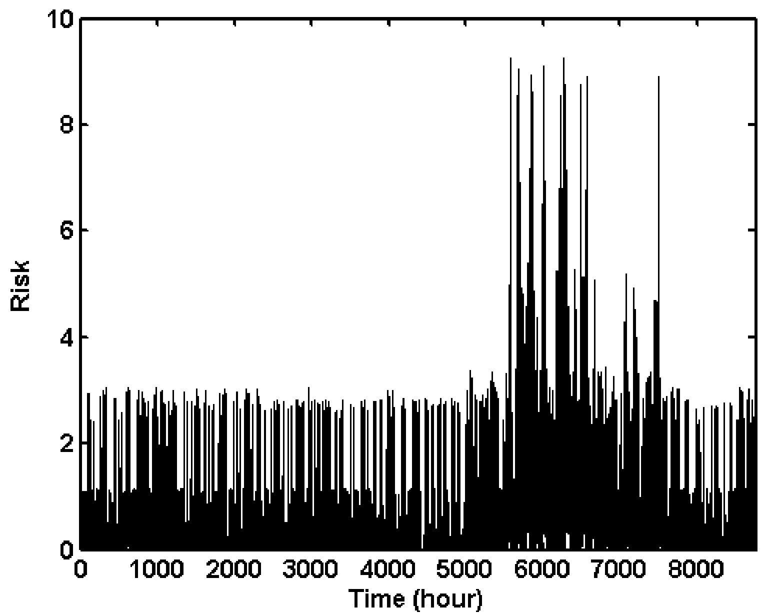


Figure 5-3: Composite system risk

5.4.1 Risk assessment result for low voltage

Table 5-3 lists the highest-risk contingencies for low voltage risk at the three different load levels. Figures 5-4 and 5-5 are the yearly low voltage risk curves for the two contingencies, 177 and 168, which have the highest risk at peak load and minimum load, respectively.

Table 5-3: Highest risk contingencies for low voltage risk at different load levels

System peak load, P=3073MW, hour=5993			
Order	Contingency ID	Risk	Category
1	177	0.003220	161KV Transmission line failure
2	144	0.000960	161KV Transmission line failure
3	175	0.000635	161KV Transmission line failure
4	69	0.000610	161KV Transmission tree contact
5	150	0.000609	161KV Transmission line failure
6	143	0.000519	161KV Transmission line failure
7	130	0.000450	161KV Transmission line failure
8	141	0.000431	161KV Transmission line failure
9	149	0.000418	161KV Transmission line failure
10	131	0.000391	161KV Transmission line failure
System minimum load, P=987MW, hour=4445			
Order	Contingency	Risk	Category
1	168	0.2239E-7	161KV Transmission line failure
2	19	0.0651E-7	161KV Transmission tree contact
3	60	0.0421E-7	161KV Transmission tree contact
4	93	0.0043E-7	161-69KV Transformer failure
5	None		
System average load, P=1693MW, hour=33			
Order	Contingency	Risk	Category
1	127	0.5145E-4	161KV Transmission line failure
2	175	0.2828E-4	161KV Transmission line failure
3	141	0.2629E-4	161KV Transmission line failure
4	177	0.2147E-4	161KV Transmission line failure
5	169	0.2095E-4	161KV Transmission line failure
6	144	0.1433E-4	161KV Transmission line failure
7	150	0.1420E-4	161KV Transmission line failure
8	135	0.1311E-4	161KV Transmission line failure
9	149	0.1117E-4	161KV Transmission line failure
10	145	0.0999E-4	161KV Transmission line failure

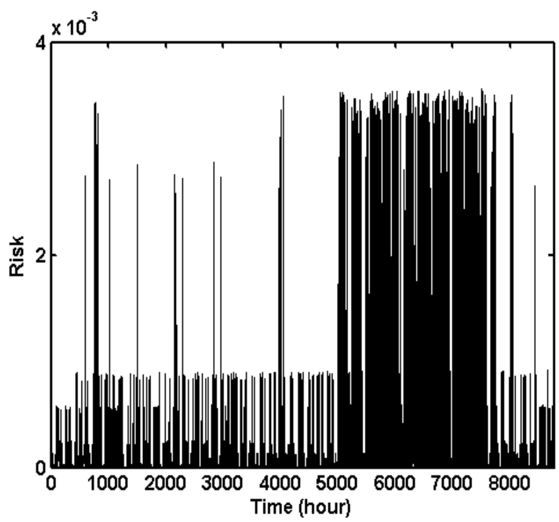


Figure 5-4: Low voltage risk evaluation over one year for contingency 177

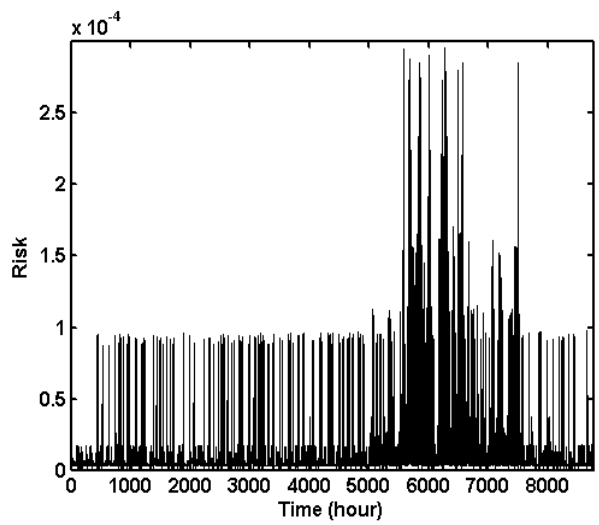


Figure 5-5: Low voltage risk evaluation over one year for contingency 168

5.4.2 Risk assessment result for overload

Table 5-4 lists the highest-risk contingencies for overload risk at the three different load levels. Figures 5-6 and 5-7 are the yearly overload risk curves for the two contingencies, 135 and 61, which have the highest overload risk at peak load and minimum load, respectively.

Table 5-4: Highest-risk contingencies for overload risk at different load levels

System peak load, P=3073MW, hour=5993			
Order	Contingency ID	Risk	Category
1	135	0.003760	161KV Transmission line failure
2	177	0.003238	161KV Transmission line failure
3	176	0.003149	161KV Transmission line failure
4	121	0.003073	161KV Transmission line failure
5	129	0.003049	161KV Transmission line failure
6	148	0.002697	161KV Transmission line failure
7	141	0.002691	161KV Transmission line failure
8	149	0.002550	161KV Transmission line failure
9	131	0.002363	161KV Transmission line failure
10	147	0.002320	161KV Transmission line failure
System minimum load, P=987MW, hour=4445			
Order	Contingency	Risk	Category
1	61	0.4047E-5	161KV Transmission tree contact
2	127	0.0365E-5	161KV Transmission line failure
3	168	0.0236E-5	161KV Transmission line failure
4	None		
System average load, P=1693MW, hour=33			
Order	Contingency	Risk	Category
1	33	0.1138E-3	161KV Transmission tree contact
2	60	0.0736E-3	161KV Transmission tree contact
3	127	0.0529E-3	161KV Transmission line failure
4	61	0.0468E-3	161KV Transmission tree contact
5	175	0.0291E-3	161KV Transmission line failure
6	141	0.0270E-3	161KV Transmission line failure
7	177	0.0221E-3	161KV Transmission line failure
8	169	0.0215E-3	161KV Transmission line failure
9	67	0.0152E-3	161KV Transmission tree contact
10	42	0.0152E-3	161KV Transmission tree contact

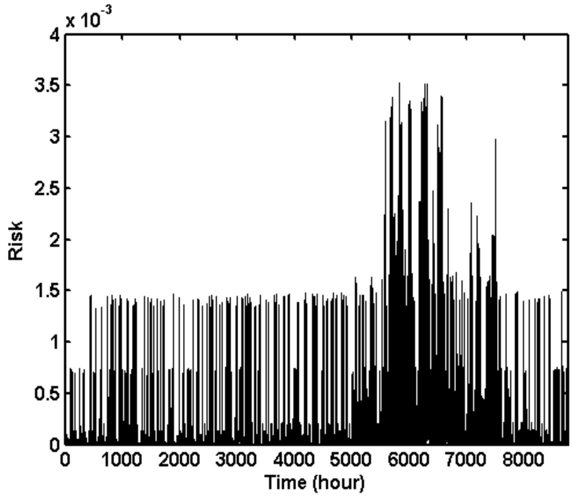


Figure 5-6: Overload risk evaluation over one year for contingency135

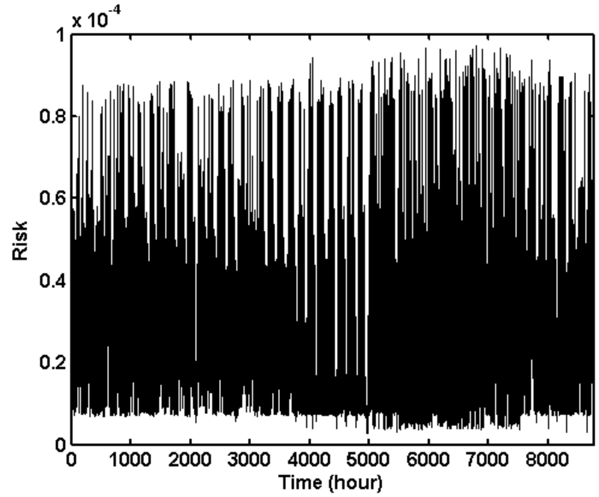


Figure 5-7: Overload risk evaluation over one year for contingency 61

5.4.3 Risk assessment result for voltage collapse

Table 5-5 lists highest-risk contingencies for voltage collapse risk at different load levels. Figures 5-8 and 5-9 are yearly voltage collapse risk curves for the two contingencies, 177 and 127, having the highest voltage collapse risk at peak and minimum load, respectively.

Table 5-5: Highest-risk contingencies for voltage collapse risk at different load levels

System peak load, P=3073MW, hour=5993			
Order	Contingency ID	Risk	Category
1	177	0.003151	161KV Transmission line failure
2	150	0.001015	161KV Transmission line failure
3	125	0.000957	161KV Transmission line failure
4	176	0.000413	161KV Transmission line failure
5	121	0.000381	161KV Transmission line failure
6	67	0.000376	161KV Transmission tree contact
7	72	0.000323	161-345KV Transformer failure
8	130	0.000314	161KV Transmission line failure
9	22	0.000307	161KV Transmission tree contact
10	89	0.000301	161-69KV Transformer failure
System minimum load, P=987MW, hour=4445			
Order	Contingency	Risk	Category
1	127	0.0512E-8	161KV Transmission line failure
2	168	0.0236E-8	161KV Transmission line failure
3	None		
System average load, P=1693MW, hour=33			
Order	Contingency	Risk	Category
1	127	0.5294E-4	161KV Transmission line failure
2	61	0.3922E-4	161KV Transmission tree contact
3	175	0.2911E-4	161KV Transmission line failure
4	141	0.2706E-4	161KV Transmission line failure
5	177	0.2210E-4	161KV Transmission line failure
6	169	0.2155E-4	161KV Transmission line failure
7	144	0.1476E-4	161KV Transmission line failure
8	150	0.1461E-4	161KV Transmission line failure
9	135	0.1350E-4	161KV Transmission line failure
10	116	0.1149E-4	345KV Transmission line failure

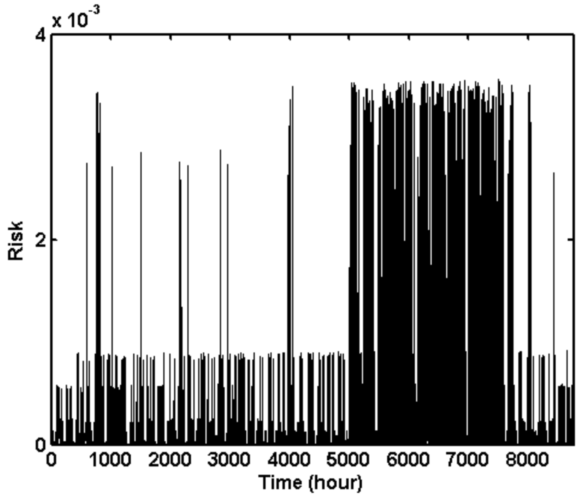


Figure 5-8: Voltage collapse risk evaluation over one year for contingency 177

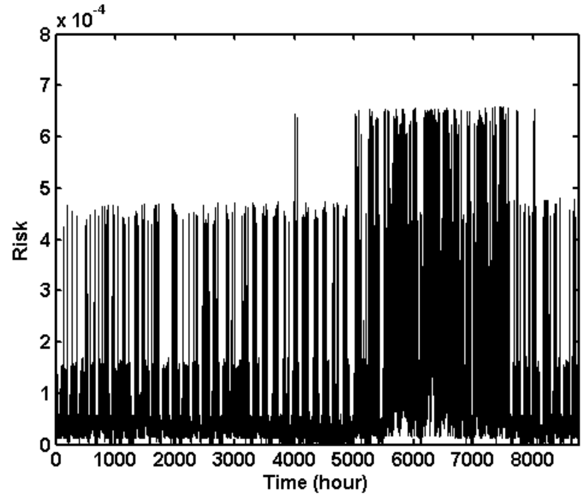


Figure 5-9: Voltage collapse risk evaluation over one year for contingency 127

5.4.4 Risk assessment result for cascading

Table 5-6 lists highest-risk contingencies for cascading risk at different load levels. Figures 5-10 and 5-11 are yearly cascading risk curves for the two contingencies, 177 and 127, having the highest cascading risk at peak and minimum load, respectively.

Table 5-6: Highest-risk contingencies for cascading risk at different load levels

System peak load, P=3073MW, hour=5993			
Order	Contingency ID	Risk	Category
1	177	0.003091	161KV Transmission line failure
2	144	0.001978	161KV Transmission line failure
3	33	0.000803	161KV Transmission tree contact
4	175	0.000672	161KV Transmission line failure
5	60	0.000647	161KV Transmission tree contact
6	150	0.000645	161KV Transmission line failure
7	143	0.000548	161KV Transmission line failure
8	4	0.000475	345KV Transmission tree contact
9	141	0.000458	161KV Transmission line failure
10	149	0.000442	161KV Transmission line failure
System minimum load, P=987MW, hour=4445			
Order	Contingency	Risk	Category
1	127	0.0424E-8	161KV Transmission line failure
2	168	0.0052E-8	161KV Transmission line failure
3	None		
System average load, P=1693MW, hour=33			
Order	Contingency	Risk	Category
1	60	0.3083E-4	161KV Transmission tree contact
2	21	0.2528E-4	161KV Transmission tree contact
3	61	0.1961E-4	161KV Transmission tree contact
4	108	0.0634E-4	161-138KV Transformer failure
5	127	0.0529E-4	161KV Transmission line failure
6	175	0.0291E-4	161KV Transmission line failure
7	141	0.0270E-4	161KV Transmission line failure
8	177	0.0221E-4	161KV Transmission line failure
9	169	0.0216E-4	161KV Transmission line failure
10	144	0.0148E-4	345KV Transmission line failure

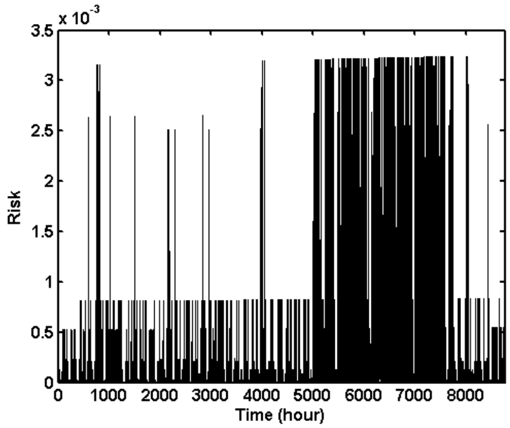


Figure 5-10: Cascading risk evaluation over one year for contingency 177

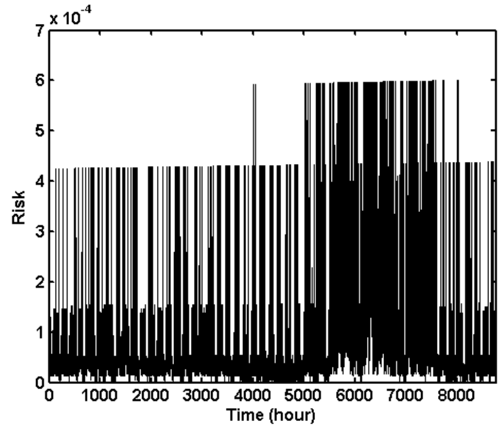


Figure 5-11: Cascading risk evaluation over one year for contingency 127

5.4.5 Risk reduction with maintenance

Based on cumulative risk assessment, risk reduction curves *ΔcumRisk(k,m,t)* (for component *k*, task *m*, completed at time *t*) are computed for each maintenance task using eq. (3.7). Figures 5-12 and 5-13 show the risk reduction curves for maintenance Trans69 and Trans19. One such curve exists for each component *k*, task *m* combination. We see it is non-increasing, indicating that the earlier the maintenance is scheduled, the larger will be the risk reduction. However, not all the maintenance start times indicated in Figures 5-12 and 5-13 are feasible because some of them incur very high risk due to maintenance-outage. This constraint is represented in the optimization model.

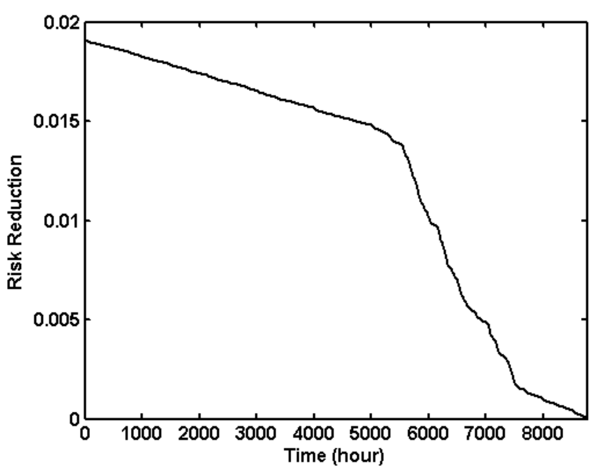


Figure 5-12: Risk reduction of contingency 177 (Maintenance-Trans69)

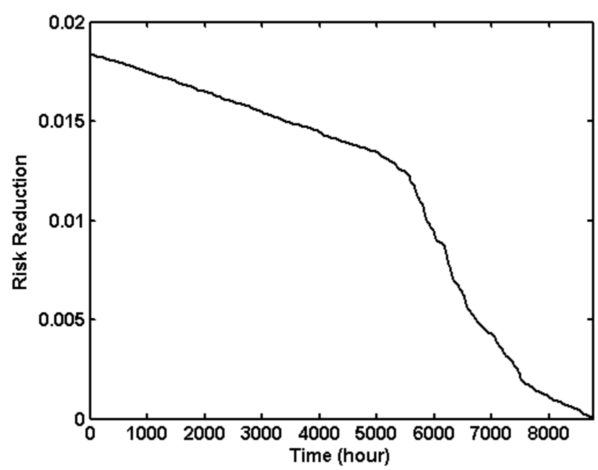


Figure 5-13: Risk reduction of contingency 127 (Maintenance-Trans19)

5.5 Maximum risk reduction with budget and labor constraints

The labor and budget constraints are summarized in Table 5-7. These constraints, combined with the risk-reduction curves for each contingency and corresponding maintenance task, constitute the input to our optimization problem. The column titled "Total Cost" indicates the cost of all desired maintenance tasks under each of the four categories if they were performed. Comparison of "total cost" to the budget constraint for each category indicates there are more tasks than the budget will allow.

As described in Chapter 4, this problem is solved using a novel relaxed linear programming/dynamic programming algorithm. Although we use only four maintenance types in this illustration, it is easy to use our algorithm for any number of maintenance types. We may also easily accept different types of categorization; for example, it may be of interest to provide budget and labor constraints by geographical regions.

Table 5-7: Constraints for maintenance scheduling

Maint. type	Maintenance description	Labor constraint (# of employees)	Budget constraint ($)	Total Cost ($)
1	Tree_Trimming	10	80,000	97,200
2	Transformer_major_maintenance	12	125,000	154,320
3	Transformer_minor_maintenance	8	32,000	40,719
4	Transmission_line_maintenance	12	150,000	186,640

This scenario characterized by Table 5-7 is referred to as the *base case scenario* in order to distinguish it from two other scenarios that will be described in Sections 5.6 and 5.7. The maintenance task selection and schedule computed by the optimization program is shown in Table 5-8, where the schedule is given by weekly periods. Because the total budget is less than the cost needed to perform all of the desired maintenance tasks, there are some maintenance tasks left unscheduled based on their lower level or risk reduction.

The total cumulative risk reduction over the year for the base case scenario is 41.5. This means that the above maintenance schedule can be expected (on average if the base case scenario were experienced many times) to result in a decrease of 41.5 units of risk over the next year. One unit of risk associated with post-disturbance system performance may be roughly thought of as a violation of reliability criteria in one hour of the year following one contingency. This interpretation of the risk would be precise if we used severity functions (Fig. 2-2, 2-4, and 2-5) that were 0 or 1 depending on whether a violation occurred or not. We chose the severity functions shown in Chapter 2 in order to (a) reflect some risk at performance close to but within the reliability criteria and (b) reflect increasing risk as performance degrades beyond reliability criteria.

Table 5-8: Transmission maintenance schedule

Periods	Tree trimming	XFMR major maintenance	XFMR minor maintenance	Transmission line maintenance
1	Trim18, Trim66	Xrmj3	Xrmi17	Trans22, Trans66
2	Trim69, Trim66	Xrmj3	Xrmi17	Trans22, Trans66
3	Trim64, Trim66	Xrmj3	Xrmi17	Trans34, Trans66
4	Trim32, Trim59	Xrmj15	Xrmi3	Trans34, Trans66
5	Trim32, Trim59	Xrmj15	Xrmi3	Trans21, Trans66
6	Trim20, Trim35	Xrmj15	Xrmi3	Trans20, Trans32, Trans21
7	Trim20, Trim35	Xrmj9	Xrmi5	Trans16, Trans32, Trans32
8	Trim41, Trim57	Xrmj9	Xrmi5	Trans16, Trans32, Trans32
9	Trim41, Trim57	Xrmj9	Xrmi5	Trans35, Trans60
10	Trim22, Trim60	Xrmj8	Xrmi2	Trans35, Trans60
11	Trim22, Trim60	Xrmj8	Xrmi2	Trans35, Trans60
12	Trim3, Trim68	Xrmj8	Xrmi2	Trans36, Trans40
13	Trim3, Trim68	Xrmj19	Xrmi12	Trans36, Trans40
14	Trim26, Trim40	Xrmj19	Xrmi12	Trans36, Trans40
15	Trim26, Trim40	Xrmj19	Xrmi12	Trans59, Trans36
16	Trim43, Trim49	Xrmj4	Xrmi4	Trans39, Trans68, Trans59
17	Trim43, Trim49	Xrmj4	Xrmi4	Trans39, Trans68,Trans59
18	Trim34, Trim36	Xrmj4	Xrmi4	Trans3, Trans62, Trans68
19	Trim16, Trim36	Xrmj1	Xrmi13	Trans26, Trans3, Trans62
20	Trim2, Trim48, Trim36	Xrmj1	Xrmi13	Trans52, Trans3, Trans26
21	Trim25, Trim56	Xrmj1	Xrmi13	Trans43, Trans26, Trans52
22	Trim25, Trim56	Xrmj5	Xrmi7	Trans41, Trans65, Trans43
23	Trim58, Trim65, Trim67	Xrmj5	Xrmi7	Trans70, Trans41, Trans43
24	Trim23, Trim70, Trim67	Xrmj5	Xrmi7	Trans18, Trans57, Trans41
25	Trim51, Trim67	Xrmj7	Xrmi6	Trans15, Trans67, Trans57
26	Trim7, Trim27	Xrmj7	Xrmi6	Trans53, Trans57, Trans67
27	Trim7, Trim27	Xrmj7	Xrmi6	Trans56, Trans67
28	Trim4, Trim14, Trim38	Xrmj20	Xrmi18	Trans56, Trans67
29	Trim53, Trim4, Trim38	Xrmj20	Xrmi18	Trans6, Trans56
30	Trim10, Trim28, Trim39	Xrmj20	Xrmi18	Trans29, Trans51, Trans6
31	Trim50, Trim10, Trim28	Xrmj10	Xrmi14	Trans6, Trans29, Trans51
32	Trim6, Trim55	Xrmj10	Xrmi14	Trans6, Trans38, Trans69
33	Trim30, Trim63, Trim6	Xrmj10	Xrmi14	Trans19, Trans27, Trans37, Trans38
34	Trim24, Trim6	Xrmj13	Xrmi9	Trans28, Trans19, Trans27, Trans37
35	Trim15, Trim29, Trim45, Trim52, Trim 62	Xrmj13	Xrmi9	Trans2, Trans24, Trans25, Trans28
36	Trim19, Trim46, Trim61	Xrmj13	Xrmi9	Trans49, Trans24, Trans25
37	Trim5	Xrmj18	Xrmi8	Trans31, Trans25, Trans49
38	Trim5	Xrmj18	Xrmi8	Trans14, Trans17, Trans31, Trans49
39		Xrmj18	Xrmi8	Trans12, Trans46, Trans17
40		Xrmj11	Xrmi16	Trans55, Trans12, Trans46
41		Xrmj11	Xrmi16	Trans50, Trans12, Trans55
42		Xrmj11	Xrmi16	Trans13, Trans12, Trans50
43		Xrmj12	Xrmi15	Trans4, Trans5, Trans13
44		Xrmj12	Xrmi15	Trans4, Trans5
45		Xrmj12	Xrmi15	Trans4, Trans5
46		Xrmj14		
47		Xrmj14		
48		Xrmj14		
49		Xrmj16		
50		Xrmj16		
51		Xrmj16		
52				
# scheduled	55	17	15	51
Total cost	79200	118720	31794	147960

Table 5-8 indicates that maintenance tasks are scheduled early in the year, insofar as crew and risk constraints allow, to reduce the risk of the most risky components as soon as possible. Reducing those risks for the remainder of the year tends to maximize the risk reduction achieved, consistent with the objective of the maintenance scheduling procedure. No maintenance is scheduled in the last week since a task scheduled in that period would incur a cost without a risk-reduction in the budget year. Scheduling for 53 weeks, instead of 52, eliminates this modeling problem.

5.6 Effect of constraints on optimization results

Using our optimization software we obtain the selection and scheduling of tasks to maximize cumulative risk reduction under the given constraints. This software also provides useful indices reflecting different attributes of the solution.

1) *CRR*: Cumulative Risk Reduction. This is the value of the objective function and a high-level indicator of the solution quality. We identified it as 41.5 in the base case scenario.
2) *CRR/Cost*: Ratio of CRR to total cost. This index indicates the risk reduction per unit dollar spent. Higher values indicate more desirable solutions.
3) *Cost/Budget (%)*: This index indicates, for each maintenance category, the percentage of the budget actually spent. Solutions that have values of this index significantly less than 100% indicate that the corresponding category may be over-budgeted.
4) *CRR/labor*: Ratio of CRR to total labor in hours. This index indicates the risk reduction per labor hour. Higher values indicate more desirable solutions.
5) *Labor/available labor (%)*: This index indicates, for each maintenance category, the percentage of the available labor actually utilized. Solutions that have values of this index significantly less than 100% indicate that the corresponding category may have an over-allocated number of assigned personnel.
6) *CRR/*Total possible *CRR (%)*: This index indicates the percentage of possible risk reduction that is actually achieved. The possible risk reduction can be computed in two ways. It can be computed assuming that there are no labor constraints so that *all selected tasks* (given the budget constraint) could be scheduled in the *first* week. The index computed in this way provides a measure of additional benefit that could be achieved from additional labor under the given budget. Alternatively, it can be computed assuming that there are no labor or budget constraints so that *all proposed tasks* could be scheduled in the *first* week. The index computed in this way provides a measure of additional benefit that could be achieved from additional budget and labor resources. We have elected to compute the index in the first way. For both ways, solutions that have values of this index much less than one may significantly benefit from additional economic and/or labor resources.
7) *Unscheduled number of tasks/Total number of tasks (%)*: This index indicates the percentage of tasks that could be completed with additional financial or labor resources. Solutions that have values of this index close to one may significantly benefit from additional financial and/or labor resources.

It is also possible to utilize the LaGrange multipliers (μ_1-μ_4 on the budget constraints and λ_t, $t=1,...T$ on the risk constraints) to obtain useful information about the solution. Specifically,

- μ_1-μ_4 give the increase in cumulative risk reduction when the corresponding budget is increased by a dollar. Thus, the budget *b* with the highest μ_b provides the largest benefit in risk reduction if it were increased.
- λ_t, $t=1,...T$ give the increase in cumulative risk reduction when the corresponding week *t* risk is allowed to increase by one unit. The week *t* with the highest λ_t provides the largest benefit in risk reduction if we relieve security constraints to allow additional maintenance-related outages during that week.

We compute and plot these various indices for two scenarios differing from the base case scenario. In Section 5.6.1, we fix the labor constraints for each maintenance type and vary the budget constraint. In Section 5.6.2, we fix the budget constraints for each maintenance type and vary the labor constraints.

Additionally, in Section 5.6.3, we illustrate how to use the optimizer for performing comparative analysis of different resource allocations among the defined categories assuming that the total economic and labor resources are limited.

The objectives of the studies summarized in the next three sections are to (1) validate the reasonableness of the models and algorithm, and (2) illustrate the potential of using the tool to perform analysis of different maintenance resource allocations.

5.6.1 Effect of budget variation on maintenance scheduling

To illustrate the effect of total budget on maintenance scheduling, a fixed number of crew members are assigned to each type of maintenance, as shown in Table 5-9, and the budget is varied from $192k to $480k. The effects on the various indices are summarized in Table 5-10.

Table 5-9: Labor level for budget variation

Maintenance type	Maintenance description	Number of employees
1	Tree_Trimming	10
2	Transformer_major_maintenance	12
3	Transformer_minor_maintenance	8
4	Transmission_line_maintenance	12

Table 5-10: Indices calculated from different budget settings

Total Budget	CRR	CRR/ Cost	CRR/ labor	Cost/ Budget (%)	Labor/ Available labor (%)	CRR/ Possible CRR(%)	Unscheduled Maintenance (%)
192	32.3	0.1757	2.2250	96.00	48.56	92.57	65.73
240	36.0	0.1534	1.9795	98.02	60.58	90.15	56.74
288	39.5	0.1330	1.7865	103.38	73.07	87.85	45.50
336	40.5	0.1196	1.6451	101.15	80.77	85.42	34.27
384	41.0	0.1060	1.5229	100.99	86.06	82.76	23.03
432	41.7	0.0960	1.4500	100.78	90.87	80.89	12.92
480	41.8	0.0886	1.3073	98.50	96.63	77.74	1.12
528	41.8	0.0886	1.3073	89.54	96.63	77.74	0.0

Table 5-10 indicates that, in some cases, the cost/budget is a little above 100%. This is caused by a program feature that allows a maintenance task to be scheduled if the remaining budget is very close to the cost of the next maintenance task to be scheduled. Variations in indices with increasing budget are illustrated in Figs. 5-14 to 5-20. We make the following observations.

1. CRR: Fig. 5-14 shows that as the budget increases, the cumulative risk reduction increases until a budget of about $400k after which the budget covers the cost of all the maintenance. Budget increases beyond that value are of no value.
2. CRR/budget and CRR/total labor: Figs. 5-15 and 5-16 indicate that, as the budget increases, the CRR per dollar budgeted and CRR per hour of labor decreases, indicating that resource effectiveness in reducing risk tails off as resources increase. This is not surprising since our algorithm always selects the most effective maintenance tasks first, so as resources increase, the less effective maintenance tasks will be selected, resulting in the trend seen in Figs. 5-15 and 5-16. This does not necessarily imply that one should not utilize the greater resource levels. To this end, the decision to allocate a certain level of resources to maintenance depends on the effectiveness of those resources in reducing risk, quantifiable by our program (see especially Section 5.6.3 below) as compared to the effectiveness of using those resources elsewhere in the company.
3. Cost/budget: Fig. 5-17 indicates that as the budget increases, the maintenance cost approximately equals the budgeted dollars (so that the budget constraint is active) until the budget becomes very large (about $400k), and for larger budgets, the labor constraints become active and maintenance cost is almost constant. Fig. 5-17 also indicates that cost/budget ratio increases between $200k and $300k from about 97% to almost 100%, implying that lower budgets are not totally utilized whereas higher budgets are. This apparent anomaly is a result of the lumpiness of maintenance projects. In other words, the lower budgets became “stuck” at 97% because any additional project would result in a budget limit violation, whereas the higher budgets got “stuck” at values much closer to 100%.
4. *CRR/*Total possible *CRR*: Fig 5-18 shows that as the budget increases, this index decreases, indicating that the rate of increase of CRR with budget is significantly less than the rate of increase of possible CRR with budget. The reason for this result is that higher budgets allow more tasks to be selected, but because of labor constraints, most

of these tasks must be scheduled in the latter part of the year. Tasks scheduled at the later part of the year do not provide much CRR but do provide significant amount of possible CRR.

5. Labor hours/available labor hours: Fig. 5-19 shows that, as the budget increases, the labor hours used/available labor hours ratio increases. This is reasonable as long as labor constraints are not active, implying crews are more fully utilized as the budget increases.
6. Unscheduled maintenance: Fig. 5-20 shows that the percentage of unscheduled maintenance tasks decreases as the budget increases.

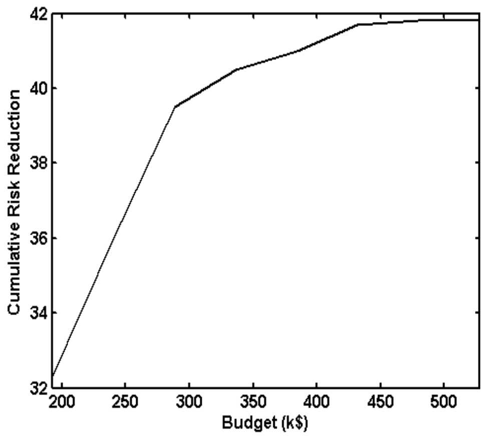


Figure 5-14: Cumulative Risk Reduction

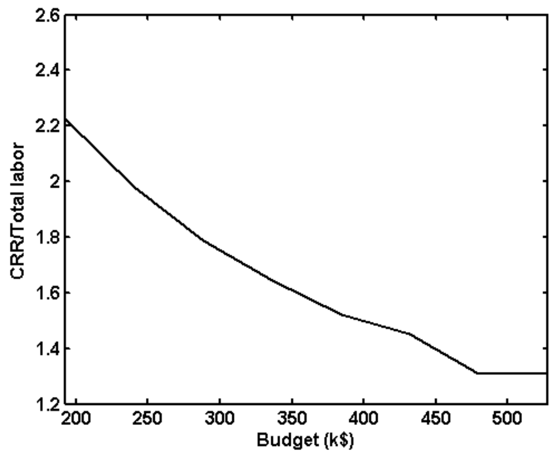


Figure 5-16: CRR/Total labor

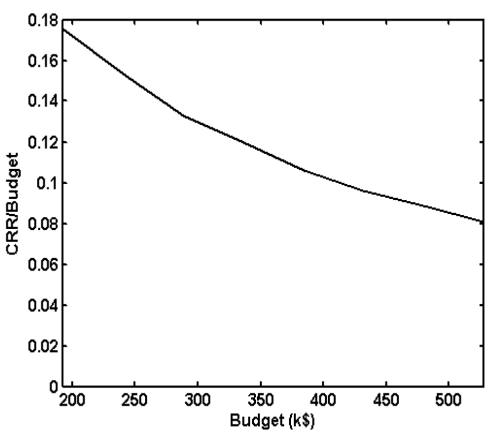


Figure 5-15: CRR/Budget

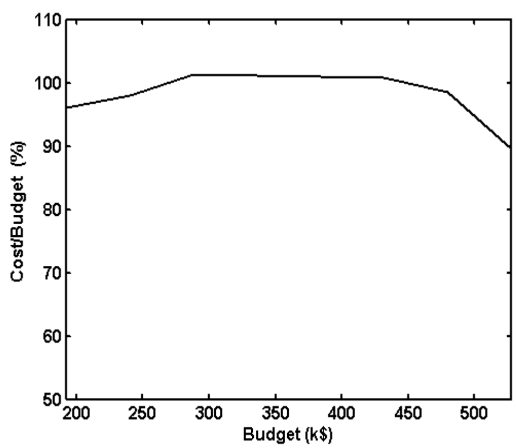


Figure 5-17: Cost/Budget

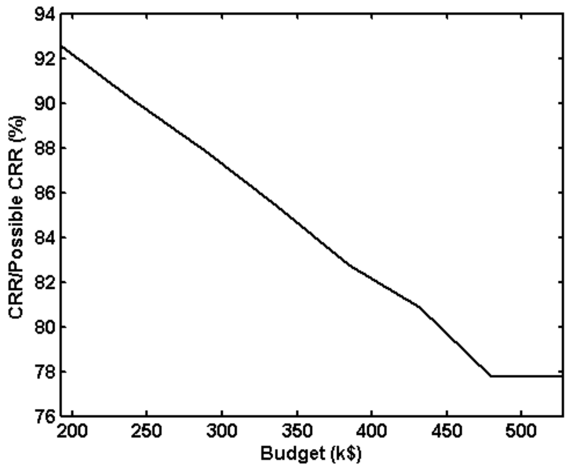


Figure 5-18: CRR/Possible CRR

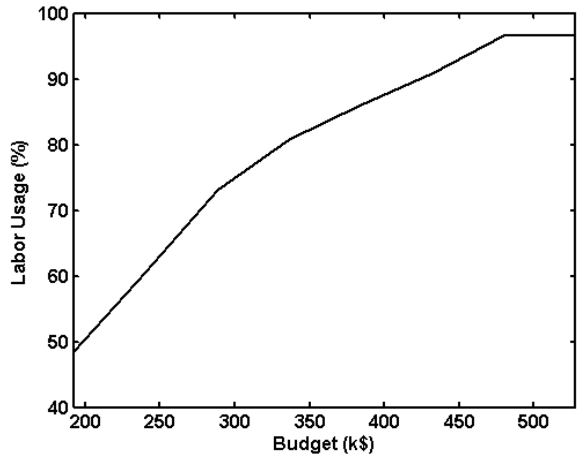


Figure 5-19: Labor usage

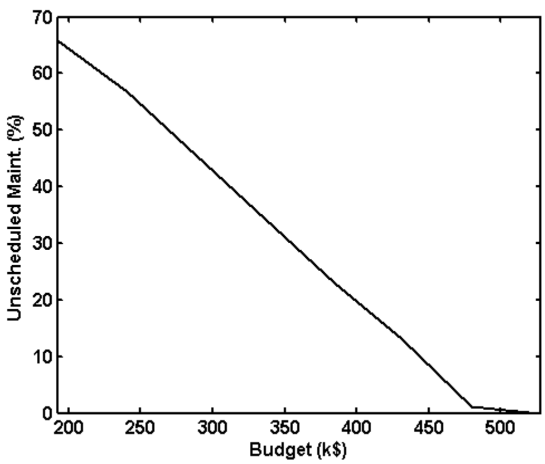


Figure 5-20: Unscheduled maintenance

5.6.2 Effect of labor variation on maintenance scheduling

To illustrate the effect of labor on maintenance scheduling, fixed budgets are assigned to each type of maintenance, as shown in Table 5-11. The labor is varied by number of crew members, as indicated in Table 5-12, where the increments are in units of four crew members, with one crew member allocated to each of the four different categories. The results for the various indices are summarized in Table 5-12.

Table 5-11: Budget level for labor variation

Maintenance type	Maintenance description	Budget ($)
1	Tree_Trimming	97,200
2	Transformer_major_maintenance	154,320
3	Transformer_minor_maintenance	40,719
4	Transmission_line_maintenance	186,640

Table 5-12: Indices calculated from different labor settings

Total Crew	CRR	CRR/ Cost	CRR/ labor	Cost/ Budget (%)	Labor/ Available labor (%)	CRR/ Possible CRR (%)	Unscheduled Maintenance (%)
23	12.5	0.046	0.7194	56.21	83.65	76.35	47.75
27	15.9	0.0528	0.7896	62.88	89.9	78.41	34.27
31	26.8	0.0814	1.2345	68.79	93.75	79.74	30.33
35	33.3	0.093	1.3778	74.81	100	79.53	26.4
39	33.9	0.0865	1.2864	81.82	100	75.13	18.54
43	37.6	0.0928	1.3828	84.64	100	80.06	17.98
47	38.5	0.0921	1.3383	87.25	87.98	78.61	14.61
51	39.8	0.0909	1.322	91.46	86.54	78.39	9.55
55	41.1	0.0898	1.318	95.59	84.61	78.24	4.5
59	43.3	0.0918	1.354	98.5	79.8	80.68	1.12
63	44.3	0.0939	1.385	98.5	76.4	82.41	1.12
67	47.3	0.0987	1.436	100	58.65	87.33	0

Variations in indices with changing labor are illustrated in Figs. 5-21 to 5-27. We make the following observations.

1. <u>CRR</u>: Fig. 5-21 shows that CRR increases with increasing labor. With increasing budget, we observe a leveling off of CRR (see Fig. 5-14) when the budget is sufficient to perform all projects. However, increasing labor resources make it possible to continuously shift projects earlier in time, so we do not observe the same leveling of CRR.
2. <u>CRR/budget and CRR/total labor</u>: Figs. 5-22 and 5-23 show that as the labor increases, the CRR per dollar budgeted and CRR per hour of labor generally increase, indicating that resource effectiveness in reducing risk increases as labor resources increase. This effect is due to the fact that additional labor enables more maintenance tasks to be completed earlier in the year, thereby increasing the cumulative yearly risk reduction. We make two qualifying comments.
    a. This effect is reasonable for CRR/total labor; however, increasing CRR/budget with labor may not be reasonable and only observed in this case because labor is allowed to increase without increasing budget (i.e., labor and budget are treated independently). In reality, the budget should increase as labor increases. Modeling this effect (we have not done so yet) may cause the CRR/budget ratio to flatten or even decrease as labor is increased, a trend that is observed in Section 5.6.1.
    b. Figs. 5-22 and 5-23 are not monotonically increasing with labor but rather exhibit noticeable "hiccups" between labor values of about 35 and 40 crew members. This

is because additional maintenance tasks do not vary continuously with increases in labor. For example, if a task requires a 5-person crew, then a labor increase of 1-4 persons will not enable an additional task. In this situation, a labor increase actually causes a decrease in the CRR/labor ratio.

3. Cost/budget: Fig. 5-24 indicates that, as the labor increases, the percent of budget actually utilized continues to increase. This effect is very reasonable since the additional labor provides the ability to perform more maintenance tasks.
4. Labor hours/available labor hours: Fig. 5-25 shows that, as the labor increases, the ratio of labor hours used/available labor hours increases to a peak of 100% between 35 and 45 crew members. Then it decreases, indicating that, for a fixed budget, there may be an optimal labor-resource allocation.
5. *CRR/*Total possible *CRR*: Fig 5-26 shows that, as the labor increases, this index stays relatively constant at about 75-85%, implying that CRR (and possibly CRR) increase at about the same rate with labor.
6. Unscheduled maintenance: Fig. 5-27 shows that the percentage of unscheduled maintenance tasks decreases as the labor increases.

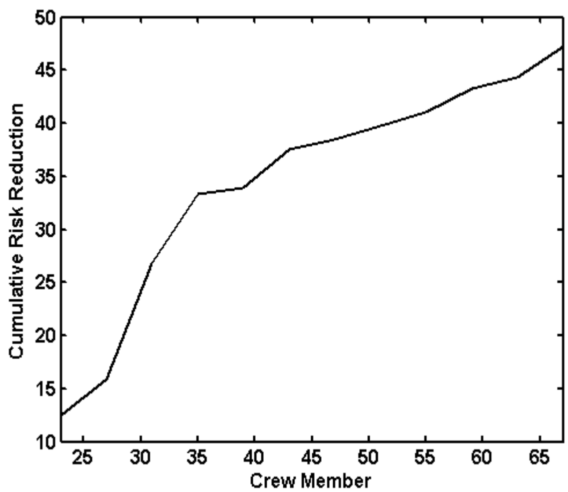


Figure 5-21: Cumulative risk reduction

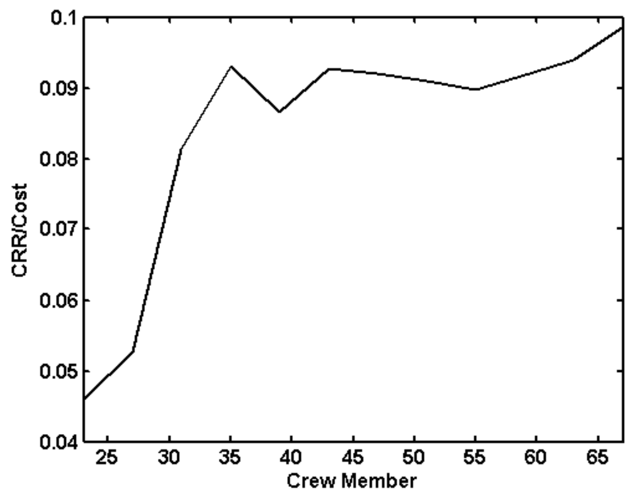


Figure 5-22: CRR/Cost

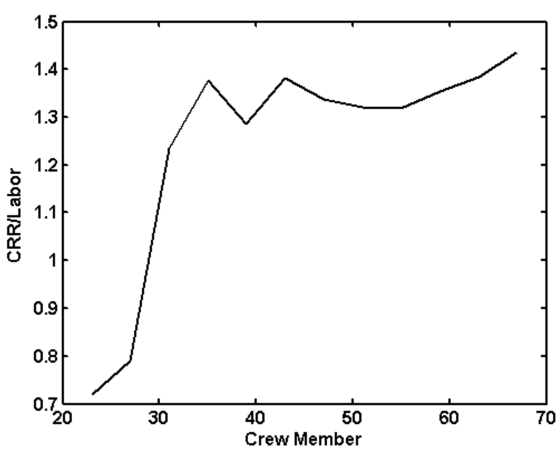


Figure 5-23: CRR/Labor

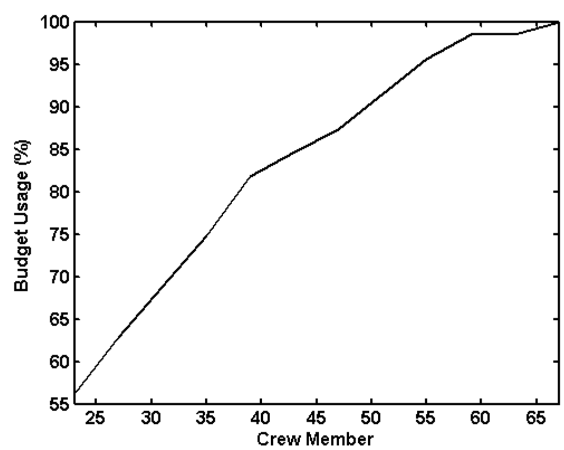


Figure 5-24: Cost/Budget ratio

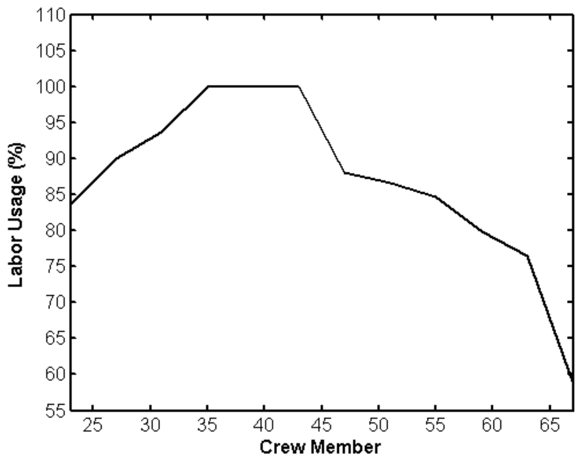


Figure 5-25: Labor usage

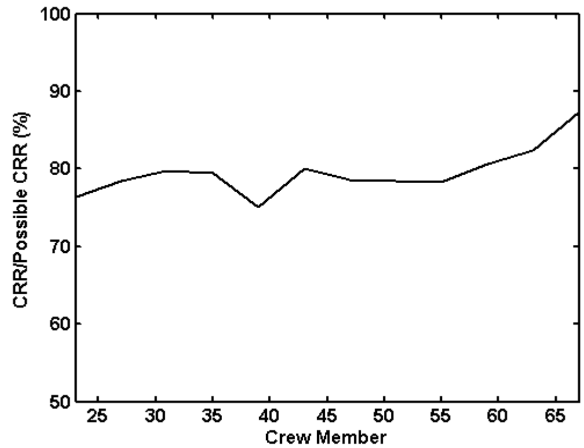


Figure 5-26: CRR/Possible CRR

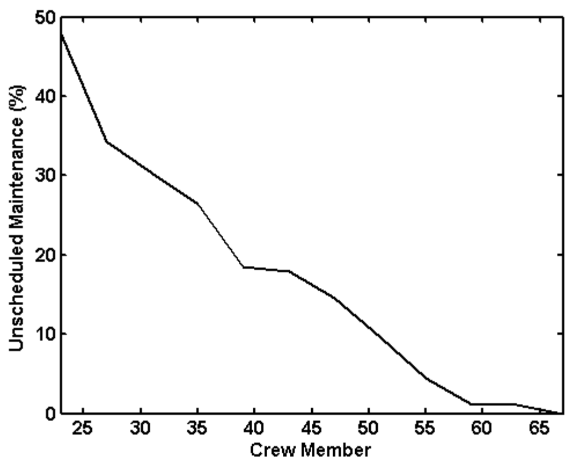


Figure 5-27: Unscheduled maintenance

5.6.3 Different budget allocation among maintenance categories

In this section, we study the cumulative risk reduction achievable from various allocations of economic resources among the maintenance categories assuming that the total economic resources are limited. This exercise illustrates how one might identify the most effective allocation of resources among the various defined maintenance categories.

Suppose we have four proposed budget and labor allocations, as listed in Table 5-13. The total budget is $450,000 and there are 42 crew members. In each case, we emphasize one type of maintenance and assign half the budget and more than 1/3 of the crew members to it. The results are shown in Table 5-14.

Table 5-13: Resource allocation among maintenance categories

Case	Maintenance category							
	1 Tree trimming		2 Xfmr major maint		3 Xfmr minor maint		4 Line maint	
	Budget(k$)	Crew	Budget(k$)	Crew	Budget(k$)	Crew	Budget(k$)	Crew
1	225	16	75	12	75	6	75	8
2	75	8	225	18	75	6	75	10
3	75	6	75	12	225	14	75	10
4	75	6	75	12	75	6	225	18

Table 5-14: Indices calculated for 4 different resource allocations

Case	*CRR*	Total Cost (k$)	*CRR/Cost* (1/k$)	Cost/Budget (%)				
				Maintenance category				Total
				1	2	3	4	
1	36.1	287.119	0.1257	43.2	104.4	54.29	94.51	63.8
2	35.8	326.279	0.1097	93.6	61.32	54.29	103.20	72.51
3	36.3	264.039	0.1374	90.13	104.43	18.10	103.20	58.68
4	45.8	383.479	0.1194	103.73	104.43	54.29	82.95	85.22

Table 5-15: Indices calculated for 4 different resource allocations

Case	Total labor (Khours)	*CRR/labor* (1/KHours)	Labor hour/ Available labor hour (%)				
			Maintenance category				Total
			1	2	3	4	
1	24.34	1.4832	53.84	28.85	34.62	19.9	76.44
2	22.25	1.6090	69.23	92.31	100.0	63.46	81.25
3	21.46	1.6915	88.46	86.54	51.92	63.46	72.60
4	28.41	1.6121	98.08	85.54	100.0	69.23	88.46

Table 5-16: Indices calculated for 4 different resource allocations

Case	*CRR/Total possible CRR* (%)	Unscheduled Maintenance (%)				
		Maintenance category				Total
		1	2	3	4	
1	90.17	0.0	25.0	0.0	70.0	30.33
2	88.47	28.5	0.0	22.2	68.5	40.45
3	89.09	30.0	25.0	0.0	68.6	41.57
4	88.23	14.3	25.0	0.0	0.0	8.43

We can see from the Table 5-14 that, when resource allocations favor maintenance category 4 (transmission line maintenance), as in case 4, the CRR is 45.8. This is significantly higher than the CRR of the other three cases where maintenance categories 1-3 are favored, respectively. This means that, for this illustration, resource allocation to transmission line maintenance is more effective in reducing risk than to other categories.

This result is also supported by other data in Tables 5-14, 5-15, and 5-16, as indicated by the following.

- Table 5-14 shows that the total cost/budget for each of the four cases is highest for case 4 (85.22%), indicating that case 4 utilizes a larger percentage of its budget than the other three cases.
- Table 5-15 shows that the total labor hours/available labor hours are highest for case 4 (88.46%), indicating that case 4 utilizes a larger percentage of its labor hours than the other three cases.
- Table 5-16 shows that case 4 has the smallest percentage of total unscheduled maintenance tasks (8.43%), indicating that case 4 accomplishes more of its proposed maintenance tasks than the other three cases.

There are three reasons for this result.

1. <u>Severity function</u>: In this example, the component severity function was set to zero. Recalling the severity function from eq. (2.2), repeated here for convenience,

$$\mathrm{Sev}(E_i, X_{t,j}) = \mathrm{Sev}_{\mathrm{system}}(E_i, X_{t,j}) + \mathrm{Sev}_{\mathrm{component}}(E_i, X_{t,j}) \qquad (2.2),$$

2. We see that with zero component severity function, we model only the system severity components. Therefore, the cost of transformer replacement is not accounted for in this illustration. Section 2.4 describes how to account for it. If the component severity function were represented in this example, it is likely that we would find significantly more risk reduction from favoring resource allocation to transformer maintenance.
3. <u>Number of maintenance tasks</u>: Category 4 (transmission line maintenance) has significantly more proposed maintenance tasks (70) than transformer major maintenance (20) and minor maintenance (18).
4. <u>Probability reduction</u>: Category 4 maintenance generally causes more probability reduction than category 1 (tree-trimming).

It may be that we can achieve an even better resource allocation than case 4. Manual iterative use of our optimizer could be implemented to accomplish this. We leave it for future research to determine an algorithmic and automated approach to optimize the resource allocation.

5.7 Summary

A 566 bus system was used to test the effectiveness of the Integrated Maintenance Scheduler. In this chapter, the results were provided and analyzed. Results are in terms of task selection, task scheduling, and indices characterizing the quality of the solution. We conclude that the tool performs very well, giving results that are consistent with our expectations. 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.

6. Summary, Conclusions, and Recommendations

6.1 Summary

This project has successfully developed the Integrated Maintenance Scheduler (IMS) to identify the most effective selection and scheduling of maintenance tasks associated with bulk transmission equipment. A key characteristic of the scheduling problem is that resources (labor and budget) are limited and insufficient to perform all proposed maintenance tasks within a defined time interval. We have chosen the time interval to be one year to be consistent with most company's budgeting processes. However, the time interval could be shorter or longer as the situation dictates.

Fundamental to the solution approach are the ideas that (1) maintenance reduces the "cumulative-over-time" risk caused by the equipment being maintained, where risk is the product of failure probability and failure consequence; (2) failure consequence is assessed in terms of system security and component damage; and (3) different maintenance tasks at different times cause different risk reduction. Thus, we select and schedule the maintenance tasks to maximize the cumulative-over-time risk reduction. An important contribution of this project is that the optimal scheduling approach provides a way to account for cumulative-over-time effects of maintenance on the costly operational constraints caused by equipment failure. The IMS accomplishes this in three basic stages: (1) long-term hourly simulation (Chapter 2), (2) risk reduction calculation (Chapter 3), and (3) maintenance selection and scheduling via an optimizer (Chapter 4). The testing of the procedure using a 566 bus system, reported in Chapter 5, demonstrates the use of IMS in selecting and scheduling a designated set of maintenance tasks.

6.2 Conclusions

During the two years of work in this project, the investigators have made significant effort to canvas industry to determine the state of art in managing transmission assets. Based on this effort, we conclude that there are several fundamental weaknesses in industry practice that might be overcome using the approach developed in this project. We summarize these weaknesses below and identify how they have been addressed in this project.

1. <u>Basis for decision</u>: Regarding maintenance selection and scheduling, the basis of maintenance decisions in most companies is the state or condition of the equipment, which is an indication of failure probability. Although this is clearly an improvement over performing maintenance at fixed intervals, it fails to account for two other essential elements that heavily influence the outcome of the decision. The first element is the failure consequence, and the second is the variation of that failure consequence over time. The inclusion of cumulative-over-time risk in the decision-making process is essential for effective allocation of resources.

2. Inability to account for operational risk: We have not encountered any company having a systematic procedure for including the influence of undesired operational performance created by equipment failure (in terms of overload, cascading overloads, low voltage, and voltage collapse) in the decision process. These constraints create real costs through the necessary corrective actions, such as unit redispatch, that must be taken to adjust system performance to meet reliability criteria. The procedures developed in this project provide a way to include these effects. Of particular interest is the use of sequential simulation to account for operational risk. Sequential simulation, unlike traditional reliability assessment programs, provides the ability to account for inter-temporal dependencies that are so prevalent in power system operation.
3. Limited use of condition data: Most companies today are in fact utilizing some kind of condition data to identify the state of their equipment. Such data includes testing, sampling, inspection, and monitoring data. However, we found no company that utilizes such data to estimate failure probability of the equipment. By doing so, one immediately lifts the asset management problem into a realm where it can be rigorously treated using computational procedures from reliability and optimization theory. Although estimation of failure probability from condition data is an extremely challenging problem, we have made significant progress towards its solution. The maintenance management procedure developed in this project illustrates the usefulness of a solution to this problem.
4. Use of ranking: The state of art decision-making mechanism is ranking. With ranking, each maintenance task is "scored" in all of a number of different attributes that are perceived to influence the decision, and then the attributes are aggregated in some fashion, typically as a weighted sum. The tasks are selected in descending value of aggregate score until resources are utilized. Optimization methods have not been utilized in the industry so far. Two reasons for this include the difficulty in quantifying risk and the challenges associated with nonlinear integer programming. We have solved both of these problems using a novel combination of relaxed linear programming and dynamic programming that maximizes maintenance-induced cumulative risk reduction under budget, labor, and outage-risk constraints. The advantages of this approach relative to ranking are that it obtains optimal solutions, attributes and constraints may be more rigorously modeled, and there is more flexibility to the nature of the information available from optimization that allows decision-makers to view the options in different ways before accepting a decision.

We conclude that there is significant potential for using the procedures and methods developed in this project for enhancing management of transmission asset maintenance. Although the program code for doing so is research grade, it is quite feasible that this code could be moved to demonstration grade within the near future and from there to commercial grade. We recommend enhancing this code in several ways, as detailed in the next section. These enhancements, together with commercialization of the code, should be of immediate usefulness to industry.

6.3 Recommendations

We have several recommendations for follow-on activities that would help make the tools developed in this project useful to industry. These recommendations are:

1. Obtain data for failure modes
2. Apply to other equipment
3. Enhance the software
4. Coordinate between transmission and generation maintenance.

We discuss these recommendations in the following subsections.

6.3.1 Obtain data

An important part of the IMS procedure relates to the estimation of failure rate (or failure probability) of the different failure modes causing equipment outage. This problem is unlike traditional development of failure rates for power system equipment where the failure rates are average values characterizing long-term failure behavior, typically for assessments used in facility planning decisions, and the required data is statistical histories for a large sample of each equipment type. In contrast, the problem here is to estimate “instantaneous” failure rates that characterize the current state of the equipment. To do this, for most types of equipment, we need different types of condition data *histories* characterizing each piece of equipment to be maintained. For example, for power transformers, it would be helpful to have maintenance histories together with all testing and sampling histories, including, for example, the dissolved gas analysis (DGA) histories, the oil dielectric test histories, and loading and/or temperature histories. For transmission lines, maintenance histories on tree-trimming and insulator cleaning would be essential; in addition, underlying foliage inspection histories including underlying foliage characterization would be important. For circuit breakers, operation count, oil test histories, and maintenance histories would be essential.

The level at which this kind of data is collected and maintained at different utilities varies greatly. Some utilities have very advanced database, internet, and communication systems to facilitate this effort. Other utilities collect and maintain only a relatively small amount of data, and systems to facilitate the corresponding efforts are rudimentary. Nonetheless, it is expected that within the next five years, most utilities will have moved to state of the art internet or intranet database communication systems. Gaining access to the raw data would be useful; even more useful would be gaining access to the advanced systems that facilitate the data collection and maintenance of this data. We have made significant effort to gain access to such systems, but we have only been able to obtain a relatively small amount of raw data. This data has been useful, but we will not be able to fully develop and test the failure rate estimation methods until we can obtain a comprehensive set of data and/or (preferably) access a database system.

6.3.2 Apply to other equipment

The project's maintenance management approach was applied only to transmission lines and transformers. However, we see no reason why this approach could not be applied to other types of equipment. Indeed, we are proceeding in a follow-on project to apply the approach to transmission-level circuit breakers. Of equal interest is the application of the approach to load tap changers and distribution equipment, particularly wood poles, reclosers, surface-mounted equipment, capacitors, vaults and manholes, and line regulators. Key to this extension of the current work will be the need to properly assess the risk. We assessed transmission risk in terms of security violations and/or redispatch cost. It may be more effective to assess distribution risk in terms of load interruption.

6.3.3 Enhance the software

There are a number of software enhancements that should be made. We limited the following list to those enhancements that are significant relative to improving the integrity of the program output. Commercialization of this software would require additional work (e.g., user interface, error handling, etc).

The software enhancements to the Integrated Maintenance Scheduler (IMS) are identified in three categories according to the three basic IMS functions.

1. <u>Long-term simulator</u>:
    a. *Redispatch costs*: Our approach to assessing the consequence of transmission failures has been based on severity functions built around equipment and system limits imposed by reliability criteria. We also intend to assess consequences in terms of the cost of redispatch to avoid the security violation. A straightforward approach would be to embed an optimal power flow within the long-term simulator; however, there may be more computationally efficient techniques.
    b. *Outage duration*: We have indirectly accounted for transformer outage duration via modifications in the severity function depending on the status of spares (see Section 2.4). However, we have assumed all other outages are uniform. Probabilistic treatment of outage duration is desirable.
    c. *Breaker failure*: Modeling breaker failure is necessary if we want to utilize our approach for selecting and scheduling breaker failure maintenance. The difficulty is that it requires assessment of high-order initiating contingencies (rather than just N-1 initiating contingencies) within the simulator. This could significantly increase computation for an already computationally intensive procedure. We may need to use highly efficient contingency analysis computational techniques.
    d. *Risk of dependent (sequential) failure modes*: So far we have associated all maintenance-induced risk reduction with failure modes that initiate contingencies. However, maintenance may also reduce the risk associated with failure modes that occur as a result of another failure mode. For example, the August 14, 2003 blackout in the northeast US resulted from an initiating

event that later resulted in at least one line coming in contact with a tree. Tree-trimming in this case would have diminished the risk associated with the original initiating event through the prevention of the subsequent events. Breaker failure modeling (described in part (c) above) is a special case of this situation where one failure causes a fault that needs to be cleared and then the breaker failure-to-open occurs. Such failure modes B caused by failure modes A can be addressed by computing the failure probability reduction as $\Delta p(B \cap A) = p(A) \times \{ p_{before}(B|A) - p_{after}(B|A) \}$ where p_{before} and p_{after} are the probabilities of the dependent event given the initiating event, before and after the maintenance, respectively.

2. <u>Risk reduction calculation (failure rate estimation)</u>:
    a. *Utilize Markov probability model*: A Markov model relating the probabilistic representation of the equipment deterioration process is described in [36]. Different stages of the deterioration process are modeled. The transition intensities between these states can be obtained from historical equipment life information or condition monitoring. Then, the long-run probabilities that the condition of the equipment will be in any particular state at a given time t, can be calculated. A rigorous treatment of this problem is developed in [32].
    b. *Integrate with long-term maintenance plan*: The objective of the Integrated Maintenance Scheduler (IMS) is to maximize risk reduction in the time interval specified. The time interval is intended to be short relative to the life of most equipment; one year is both computationally tractable and consistent with most company's budgeting cycle. Another objective that is not uncommon in considering maintenance policies is to maximize equipment life. Maintenance policies based on this latter objective typically focus on scheduling maintenance over the lifetime of the equipment. Such an objective and corresponding time frame are clearly different from the objective and time frame specified in our approach. We believe that the approaches may complement one another in that the long-term maintenance plan would serve as input to the IMS, so that the resulting solution would, in effect, be a modulation about the long-term plan. This idea needs to be investigated.
    c. *Bayesian method to update probability model*: One salient characteristic of the failure rate estimation problem is that the condition data on which the estimate is based is multi-valued with each value varied through time. Therefore, an estimate for any particular point in time must be made with respect to a variety of different condition indicators. In addition, the estimate must be updated every time a condition indicator is renewed. This constitutes a problem where a parameter characterizing a probability model (such as a failure rate or a Markov model transition rate) is initially known with a certain level of uncertainty, and as more (from other indicators) or newer (as time passes) data provides more information about the probability model, the uncertainty decreases. This problem can be effectively addressed using Bayesian statistical updating of the probability model.

d. *Multiple failure modes*: We have assumed that each individual equipment failure mode results in a network contingency. However, there may cases where a specific network contingency may be caused by any one of several failure modes. For example, a line outage may occur as a result of a fault followed by normal operation of all protection. Alternatively it may occur as a result of inadvertent operation of either breaker at the respective ends of the line. As a result a total of three failure modes exist for that line. We may account for this influence using fault tree modeling.

e. *Tree growth model*: The probability of a line contacting a tree grows with the time since the last tree-trimming maintenance task. The rate of growth depends on the type of underlying foliage. Modeling this time dependent probability requires a tree growth model. One such model is found in [37,38].

f. *Circuit breakers*: We have indicated in Section 6.3.2 that we should apply our methods to maintenance of circuit breakers. This is particularly the case for failure rate estimation. This work is ongoing in a follow-on project, where we are especially emphasizing the estimation of failure rate.

3. <u>Optimizer</u>:

    a. *Linkage between budget and labor*: Our optimization program accounts for the two constraints of budget and labor independently. However, they are clearly related as more labor requires more budget. This functional dependence should be represented in the program.

    b. *Utilize LaGrange multipliers*: We have developed a number of different indices, some of which are closely related to the LaGrange multipliers computed in the relaxed LP step of the optimizer. We should compare these LaGrange multipliers to the indices in terms of information content and ease of computation.

6.3.4 Coordinate between unit maintenance and transmission maintenance

In this project, we assumed that generation unit maintenance scheduling would be done in advance of the transmission maintenance scheduling. As a result, generation unit maintenance schedule was an input to the Integrated Maintenance Scheduler (IMS). However, it is clear that the ability to outage generation depends on available transmission, and the ability to outage transmission depends on available generation and its dispatch. This interdependency between the two problems suggests an integrated solution. We believe that the basic approach embedded in IMS is appropriate for such an integrated solution so that a combined generation and transmission maintenance schedule could be developed with one pass of the IMS. This approach is attractive because it can achieve a global maximization of the risk reduction for the maintenance activities.

Appendix: Summary of failure modes and maintenance tasks

Table A1: Circuit Breakers (Oil)

Failure mode (criticality)	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency
Loss of Sealing ability (medium)	Nitrile seals	Moisture ingress leading to dielectric failure For small section seals, the deterioration is pressure dependent	Loss of sealing ability leading to increased demand on, and the early failure of air system equipment. Insulation media loss. Environmental concern	Visual inspection	Replacement	1 month for inspection
	Nebar / Cork Gaskets /joints	Reduction in thickness due to "hammer action" moisture ingress		Visual inspection	Replacement	1-10 years
Fail to close or re-close (medium)	Lubrication	Loss of lubrication oil; lubrication degradation	Failure of one of the main purposes of breaker	Check oil level	Re-lubrication	1 year
	Mechanical part	Motor failure; compressor seizure; loose connection; contact wear; switch failure; wrong setting		Operational test	Repair mechanical parts; replacement	1 year
	Insulation oil	Oil degradation, contamination; moisture accumulation;		Insulation oil test	Oil filtering, oil replacement	300 hours
	Control circuit	Close coil fail		Operational test	Repair, replace	1 year
Fail to open (high)	Lubrication	Lubrication degradation	System instability. Major failure. High cost of repair	Inspection	Re-lubrication	5 years
	Mechanical	Mechanism out of adjustment; wrong setting		Check key measurements	Adjustment	1 year
		Weld or shaft crack; glass fiber rods shearing		Visual inspection	Repair, replacement	1 year
	Insulation	Oil contaminated		Insulation oil test	Oil filtering; oil replacement	Each interval inspection
	Control circuit	Trip coil failure		Functional test	Repair, replacement	1 month for test
Fail to insulate (high)	Insulation oil	Oil loss, contamination, degradation; moisture ingress	Severe damage	Visual inspection; Insulation oil test	Sealing; refilling	Each interval inspection
	Bushing	External bushing insulation failure		Power factor test	Cleaning, greasing; replacement	5 years
Pressure switch fail to operate (high)	Mechanical parts	Loose connection; subcomponent failure; out of adjustment; mechanical clog (or crack);contact fouling	Closing with insufficient pressure may result in damage	Operational checking of pressure switch	Tighten; repair; adjust; replacement	1 year

Table A1: Circuit Breakers (Oil)
(continued)

Failure mode (criticality)	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency
Auxiliary contacts fail to operate (medium)	Mechanical parts	Loose connection; mechanism out of adjustment; linkage binding; subcomponent worn; cracked shaft; contact fouling, contamination	This failure can prohibit proper automatic and manual operation	Physical check of wire termination points/check of auxiliary switch	Mechanical maintenance	Each local breaker excercise
Loss of mechanical strength (medium)	Porcelain to metal joints-cermets, oxide jacking	Frost or rust oxide jacking	Tracture and/or destruction of porcelain Chemical aging of cermets	Visual inspection; operational test	Cleaning and lubricating Replacement	Each breaker maint
Coating corrosion (medium)	Paint and other coatings	Corrosion, aggravating items: seals, joints, bushings and tanks	Sealing failure; loss of mechanical strength; insulation failure	Visual inspection	Recoat	1 year for visual inspection
	Housing	Corrosion			Replacement	
	Oil storage tank	Corrosion			Inspection, replacement	
Governor fail to operate (medium)	Governor	Loose connection/ sub-component failure/ out of adjustment / contact fouling	Can lead to excessive run time and compressor failure	Physical check of wire termination points/check of governor	Mechanical maintenance	1 year
Heater failure (medium)	Heater	Heater element failure /thermostat failure	Air valves and poor response.	Check heater operability	Repair; replacement	1 month for check
Internal cabinet leak (medium)	Internal cabinet	Deterioration of weather seal / compressor oil leak	Overall breaker operation	Visual inspection	Sealing maintenance	1 year
Trip free fail to operate (medium)	Mechanical parts	Mechanism out of adjustment / subcomponent sticking / loose connection / switch or relay failure	Damage of equipment	Check key measurements/ operational check	Adjustment/ replace / tighten	100 ops/ 1 year

Table A2: Circuit breakers (SF6)

Failure mode (criticality)	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency (typical data)
Fail to close or recluse (medium)	Control circuit	Coil, relay, switch, circuitry failure,	Failure to carry load could lead to catastrophic failure of the breaker	Verify close coil pilot light in station house;	Repair, replacement	N/A
	Charging system	Charging system failure		Operational test of stored energy	Repair, charge	5 years
		Degraded lubrication failure		Lubrication test	Clean and re-lubricate accessible bearing surface	5 years
	Mechanical components	Mechanism binding, worn, out of adjustment, failure; contacts degraded, worn, out of adjustment, failure;		Time and travel test to detect slow closing of mechanism; contact resistance testing	Mechanical maintenance	10 years
		Degraded or contaminated lubrication		Lubrication test	Clean and re-lubricate accessible bearing surface	5 years
	External connection	High resistance external connection		Thermography of external connection points	Remove or clean the blocking item in external connection	3 years
Fail to open or extinguish arc (high)	Control circuit	Coil, relay, switch, circuitry failure,	Failure to carry load could lead to catastrophic failure of the breaker	Verify close coil pilot light in station house;	Repair, replacement /clean and re-	N/A
	Charging system	Charging system failure		Operational test of stored energy	Repair, charge	5 years
		Degraded lubrication failure		Lubrication test	Clean and re-lubricate accessible bearing surface	5 years
	Mechanical components	Mechanism binding, worn, out of adjustment, failure; contacts degraded, worn, out of adjustment, failure;		Time and travel test to detect slow closing of mechanism; contact resistance testing	Mechanical maintenance	10 years
		Degraded or contaminated lubrication		Lubrication test	Clean and re-lubricate accessible bearing surface	5 years
	Interrupter	Interrupter failure		Internal inspection	Interrupter maintenance	Each internal inspection

Table A2: Circuit breakers (SF6)
(continued)

Failure mode (criticality)	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency (typical data)
Gas density lock out switch fail to operate (high)	Control circuit	Coil, relay, switch, circuitry failure	Catastrophic breaker failure if gas pressure drop to the point where contacts arc to tank walls or themselves	Calibration check of density switch to verify lock out signal	Verify low density alarm signal/ repair / replacement	10 years
	Sub-component	Sub-component sticking, worn or fouling				10 years
Auxiliary switch fail to operate (high)	Control circuit	Coil, relay, switch, circuitry failure	Incorrect remote position indication; Improper information to the operating scheme	Verify with operations that breaker position signal is correct after change of state	Repair; Mechanical maintenance	Each breaker maintenance
	Sub-component	Sub-component sticking, worn or fouling				
SF6 tank heater fail to operate (medium)	Heater element	Heater element/ thermostat/ circuit failure	Direct impact on insulation value of SF6, especially at very low temp	Operational check of tank heaters	Repair of heater component	1 year seasonally
Fails to provide required insulating (high)	SF6-Gas	Loss of SF6 gas density	Could lead to flashover, system instability and damage to equipment	Gas density inspection	Measure gas pressure and temperature monthly replace gasket and seals every five years	3 months
		Extreme low ambient temperature		Thermograph inspecion	Maintain thermal insulation and heater circuits	1 year seasonally
		Contamination of SF6 by moisture intrusion		Sample SF6 gas test	Gas filtering; Dehydrate	10 years
	External bushing	External contamination		Visual inspection to detect contamination	Cleaning; lubrication; replacement	Each breaker maintenance
SF6 external leak (medium)	Gasket, seal, casting or fitting	Gasket, seal, casting or fitting failure	Threat to insulation value which could lead to catastrophic failure of breaker	Visual inspection of pressure gauge to verify expected readings	Sealing maintenance	3 months
Trip free fail to operate (medium)	Control circuit	Coil, relay, switch, circuitry failure	Allow breaker to close in on a fault, thus result in damge	Verify proper trip free operation as part of the time and travel testing	Adjustment/ repair	10 years

Table A3: Reclosers

Failure mode	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency (typical data)
Fail to close or reclose (medium)	Vacuum bottle	Vacuum bottle rupture	Failure to carry load could lead to increased overload risk	Run to failure	Repair, mechanical maintenance; replacement	Run-to-failure
	Control circuit	Control panel, circuit failure		Functional test		2 years
	Battery	Battery or battery charger failure		Load test battery		1 year
	Mechanical	Linkage mechanical failure		Functional test		1 year
Fail to open (high)	Vacuum bottle	Vacuum bottle rupture	Possible breaker damage ; damage to transformer; loss of power	Run to failure	Repair, mechanical maintenance; replacement	Run-to-failure
	Control circuit	Control panel, circuit failure		Functional test		2 years
	Battery	Battery or battery charger failure		Load test battery		1 year
	Mechanical	Linkage mechanical failure		Functional test		1 year
Fails to carry load (medium)	Contact	Contact failure	Out of service, possible re-closer damage	Contact resistance measurement /	Polish the contact surface	5 years
	Bushing connection	Loose or contaminated bushing connection		Thermography inspection	Cleaning the bushing connection	1 year
	Insulation oil	Insulation oil degradation carbon; water		Insulation oil analysis	Filter insulation oil to remove carbon, moisture	10 years
Fails to lock out (medium)	Control panel	Control panel failure	Re-closer damage	Functional test of control panel	Repair the control panel	2 years
	Linkage mechanical	Linkage mechanical failure		Functional test of linkage mechanical	Mechanical maintenance	1 year
Fails to insulate (high)	Bushing	Contaminated bushings	Flashover Damage to bushing. Arc, damage to recloser	Visual inspection	Cleaning. Lubrication	1 year
	Solid insulation	Solid insulation failure		Power factor test	Repair; replacement	5 years
	Insulation oil	Loss of insulation oil		Visual inspection of leak	Sealing maintenance	1 month
	Vacuum bottle	Failed vacuum bottle		Run to failure	Repair, replacement	Run-to-failure

Table A4: Transformers

Failure mode (criticality)	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency (typical data)
Insulation failure (high)	Insulation media (Transformer oil)	Oxidization of oil	Cause corrosion of the various metals within the transformer, particularly the iron	Oil screen test	Oil degasification; Oil filtering of non-pcb contaminated oil. Oil replacement	1 year
		Thermal decomposition of oil	Breakdown of the oil resulting in carbon formation, sludge and insulation deterioration. Possible catastrophic failure, winding to winding or winding to tank			
		Contamination from moisture				
	Bushing	Solid insulation failure /moisture ingress /external contamination	Possible catastrophic failure/ personal safety	Power factor of bushing / visual inspection	Replacement, cleaning and greasing	6 year
Fail to transform voltage (high)	Insulation media	Turn to turn short	System instability. Loss of load and risk of cascading	DGA(Dissolved Gas Analysis)	Oil degasification; Oil filtering of non-pcb contaminated oil	1 year
	Winding	Open winding		Resistance test	Rewind of transformer	1 year for test
	Internal bolted/compression	Connection loose		Vibration analysis	Off line repair	1 year for analysis
	Core	Shifted core				
	External bushing connection	High resistance		Thermogragh inspection		
Loss of sealing (High)	Conservator	Moisture ingress, oxidization, corrosion	Possible catastrophic failure, low oil level alarm	Visual inspection / signals of leaks	External examination for oil leaks	1 month
	Insulation media (oil)	Gasket failure/weld fatigue			Sealing/ refilling	On demand
Pressure relief device block (high)	Pressure relief device	Corrosion, moisture ingress	Cannot release the pressure during internal fault	Visual inspection	Repair the blocked relief device	6 year
Winding overheat (Medium)	Winding	Excessive overloading, failure of cooling system or temperature devices	Winding resistance increase. Damage of winding	Thermogragh inspection	Inspection of cooling system. Winding temperature device test	6 year

Table A4: Transformers
(continued)

Failure mode (criticality)	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency (typical data)
Failure of cooling system (high)	Fans	Block, wrong direction, deterioration	Threat to useful lifetime of transformer. Can cause outage. Affects capacity	Thermograph alarm scan or cooling system operability test	Repair or replacement	6 years
	Pumps	Block, wrong direction, deterioration		Vibration test	Repair failed pumps	1 year for test
	External heat radiation	External heat radiation restriction		External visual inspection	Remove blocking items such as bird nets.	1 year for inspection
	Temperature gauge and control circuit	Failure to operate		Function test	Calibration	6 years
Earthing malfunction (medium)	Neutral earthing	Earthing disconnected with the earth or resistance too large	Induced circulating currents	Grounding test	Repair, replace	NA
Looseness of fastenings (medium)	Connections and fastenings	Looseness of fastenings	Loss of sealing, mechanical strength, etc	Check the tightness of fastenings	Fastening	1-10 years
Surge arrester fail to operate (medium)	Surge protection facilities	Moisture ingress/ aging	Possible internal damage to the transformer and bushing	Power factor of surge arrester	Replacement	6 years
Sudden pressure relay trip fail to operate (high)	Sudden pressure relay trip	Subcomponent failure/ control circuit failure	Reenergize faulted transformer and destroy it/ personal safety	Functional test	Repair, replacement	6 years
Malfunction Breather system (medium)	Breather system	Block or cannot filtrate moisture or other contamination	Oil deterioration, overheat	Visual inspection	Remove the blocking items	6 months
Malfunction Buchholz (medium)	Buchholz	Wrong settings. Deterioration of age.	Damage of facilities	Commissioning test	Repair, replace	6 years

Table A5: LTC (other than what is given in Table A4)

Failure mode (criticality)	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency (typical data)
Fail to regulate voltage (high)	Shaft couplings, drives, components and fixings	Inadequate design; poor quality control in manufacture or site assembly;	Limited system instability. loss of drive and synchronization between diverter and selector; arching faults in selector and/or diverter	Inspect and test operate LTC drive mechanism	Manual operation of the tap changer Clean, lube	6 years
	Contact support components	Component ageing or fatigue	Loss of contact; major failure of tap changer/ transformer	Oil anlaysi	Burnishing motor contactor	Each internal LTC inspection
	Pyrolytic carbon growth	Infrequent use of tap changer	Selector drive failure of misalignment; gassing in selector and/ or arching fault. Possible major fault	Inspection, commissioning test	Burnishing motor contactor	Each internal LTC inspection
	Load reversing switch	Load reversing switch failure	Limited system instability	Partial discharge to detect faulty reverse switch	Repair	I year for test
Operation slow or incomplete (high)	Diverter	Component deterioration	Slow or incomplete operation of diverter, arching fault in diverter; major failure of tap changer/ transformer	Commissioning test. Recording or the time for a complete tap change	Operation test Recording or the time for a complete tap change	1year
Tap changer lock on low vacuum fail to operate (medium)	Tap changer lock on low vacuum	Sub-component failure / control circuit failure	Continued operation of the changer could result in catastrophic failure	Functional test	Repair	3 years

Table A6: Transmission lines

Failure modes	Components	Failure cause	Failure effect	Detection	Maintenance Activity	Frequency (typical data)
Fail to transfer energy	Insulator	Contamination, or deterioration of insulation	Flashover, shortage, line outage; Shortage System instability, overload and cascading	Visual inspection; insulation test	Greasing or cleaning	Depends on the environment
	Line conductors	Proximity of trees and buildings with respect to conductor clearances		Visual inspection	Tree trimming,	Depends on the environment
		Line sag because of ice covering, hot weather		Visual inspection	Adjustment	1 year
	Vibration dampers	Aging deterioration		Functional test	Replacement	1 year
Loss increase	Line conductors	Broken strands because of ageing , deterioration	Resistance increase, loss increase; system overload, instability	Resistance test	Repair, replacement	1 year
	Jointing	Jointing resistance too large		Visual inspection	Cleaning, replacement	1 year
Surge	Surge protector	Surge protector does not operate properly	Facility damage, flash over	Inspection; functional test	Protector maintenance	1 year
Earthing fail to operate properly	Earthing (towers)	Resistance too large	Unbalanced power flow	Resistance test	Earthing maintenance	1 year

Table A7: Cables

Failure modes	Components	Failure cause	Failure effect	Detection	Maintenance activity	Frequency (typical data)
Loss of insulation ability	Sheath	Ageing and moisture ingress	Loss of insulation ability; line outage; system instability	Commissioning test	Replacement	Depends on the environment
	Oil	Deterioration, leakage, moisture ingress		Oil testing	Oil change	1 year
	Assisted cables	Loss of sealing ability		Pressure test	Replacement	
Loss of connectivi ty	Termination	Application or ageing	Loss of connectivity	Visual inspection	replacement	1 year

Table A8: Other

Equipment	Components	Failure mode	Failure cause	Failure effect	Maintenance Activity	Frequency (typical data)
CT	Insulation resistance	Insulation failure	Ageing, loss of contact	Loss of insulation	Test of insulation resistance	
VT	VT oil	Oil deterioration	Deterioration, leakage, moisture ingress	Loss of insulation	Oil testing	
Substation	Power supply batteries	Short of capacity	Ageing or application	Short of capacity in an emergency	Visual inspection and tests	
	Intercell connection	Corrosion, loss of contact	Dirt and grit attached on the intercell connection	Loss of contact, corrosion	Greasing	
Relay	Relay	Malfunction	Wrong settings, ageing, application	Wrong action, or no action during faults	Commission test	

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