PSERC

Risk-Based Resource Allocation for Distribution System Maintenance

Final Project Report

Power Systems Engineering Research Center

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Power Systems Engineering Research Center

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Executive Summary

Distribution systems are maintenance-intensive so maintenance budgets are a substantial share of costs for distribution businesses. Maintenance budgets are high, in part, due to the size of the systems and the number of people that it takes to properly maintain the system to achieve the appropriate reliability level. Operations and maintenance (O&M) budgets can be reduced through improved efficiency. However, of concern is the effect of such budget reductions on a distribution business' ability to keep its system operating at the desired reliability level. To meet customer needs for affordable and reliable service while complying with regulatory requirements, with limited budgets, it is necessary to find tools and techniques that, when coupled with a sound asset management policy, can be used to optimally maintain distribution systems. Such a policy also extends equipment life to avoid or defer costly capital investments resulting from poor equipment maintenance.

In this project, we have developed a comprehensive and cost-effective maintenance allocation and scheduling system, and have implemented it in software tools. These tools assist in answering three concerns commonly faced by an asset manager:

1. How to identify and justify the resources needed for managing the assets of the entire system.
2. How to allocate the available resources to different maintenance programs.
3. How to select a set of maintenance tasks to be performed within each maintenance program.

Our system allocates resources and schedules maintenance tasks to optimize system reliability by maximizing risk-reduction achieved from those tasks. It uses information obtained from inspection and monitoring to determine the state of the system. Available maintenance tasks are identified, and the risk reduction provided by each is computed. The risk reduction for each task is based on the condition of the component being serviced, the task's effect on improving the component's condition of equipment, and the resulting improvement in reliability indices. The tasks are prioritized, subject to constraints on available resources, using an optimization technique combining integer programming, Lagrange relaxation, and dynamic programming. For this initial development work, the maintenance tasks incorporated so far are associated with wood poles, reclosers, and vegetation management of distribution line right of way. Actually, maintaining these particular assets represents a large percentage of maintenance budgets; furthermore, outages of these assets can significantly affect system reliability. This work can be adapted to most types of distribution equipment.

The essential elements of the maintenance allocation and scheduling system include:

1. <u>Failure mode identification</u>: Taxonomies are essential in identifying the effects of maintenance tasks on failure rates. We determined the taxonomies of failure modes together with maintenance tasks that address those failure modes.
2. <u>Failure rate estimation</u>: Failure rate reductions provided by each maintenance task were used to optimize the allocation of maintenance resources. Methods were developed for estimating the probabilistic failure rate for wood poles and

reclosers using condition measurements obtained from either continuous monitoring or from periodic inspection and testing. These methods also estimate the reduction in failure rate by maintenance task for each component.

3. Risk reduction due to maintenance: Using information on failure rate and its reduction by maintenance task, risk reduction was estimated with a reliability assessment tool developed in this project.
4. Maintenance task selection and prioritization: Risk reduction estimates form a pool of candidate maintenance tasks, along with their resource requirements. The system selects and prioritizes maintenance tasks based on the risk reduction obtained. Constraints on the optimization include the maintenance budget and level of labor resources. An integer programming optimization technique was developed for the selection and prioritization of candidate maintenance tasks.

A degradation-path model to estimate failure probability and probability reduction was developed. This model was applied to wood poles to predict individual pole failure probability based on condition measurements that represent degradation in the pole's residual strength.

A condition assessment technique was developed for reclosers. A check sheet for evaluating a recloser's condition, either in the field or in the shop, is provided. The condition score is then correlated with historical data to provide an estimate of the recloser's failure rate. Maintenance changes the recloser's condition and thus its failure rate. Similar techniques can be applied to other distribution system components.

Research-grade software from this research includes:

1. Reliability evaluation tool: A predictive reliability evaluation tool was developed in Excel. It is used to compute system reliability levels. This software tool also computes sensitivities of reliability metrics to maintenance tasks. When combined with estimates of failure rate reduction obtained from maintenance tasks, the tool computes the risk reduction associated with maintenance. The output of this tool is one input to an optimizer tool that selects and prioritizes maintenance tasks.
2. Optimizer tool: An optimizer processes the inputs of (1) candidate maintenance tasks, (2) effect of each task on reliability (i.e., risk reduction), (3) financial and labor resources needed for each maintenance task, and (4) available resources. The program selects and prioritizes maintenance tasks for the budget cycle.

Follow-on work to this project is needed. The reliability and inspection models developed should be further expanded, verified, and then adapted to other distribution equipment. Specifically, the wood pole degradation path model should be validated for other components with complex failure processes, such as switches and transformers. Similarly, the inspection methods developed for reclosers should be applied to other components, and the resulting failure rate estimates should be verified.

The problem formulation should be further enhanced by considering scheduling issues involved in equipment maintenance. The result will provide a schedule of planned maintenance for a budget period.

The optimal resource allocation strategy sacrifices some accuracy to solve the large-scale problem. Further research involving other optimization techniques will help improve the accuracy of the solution.

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1 Introduction

Both inspection and maintenance of equipment are a critical part of utility expenditures. It is important to ensure that every dollar spent helps improve the reliability and performance of the system. As illustrated in Figure 1.1, the ideal budgetary allocation results when the greatest benefit is obtained for every dollar spent. In this case, the benefit is reliability improvement indicated by relevant reliability indices.

From the asset manager's point of view, a resource allocation within the indicated region in Figure 1.1 is desirable because it is the resource allocation for which the ratio of benefit to allocation is greatest. For larger resource allocations, this ratio falls off, and within the organization, the strength of the argument for obtaining such resource allocations diminishes.

This chapter describes, in detail, the challenge that asset managers face in maintaining their different distribution system assets. A brief review of common utility maintenance practices and their impact on reliability is discussed. A risk-based method of allocating maintenance resources is then proposed. Because of the limited resources available to this project, the methodology developed is limited to reclosers, vegetation, and wood poles. The methods developed for these can be adapted to other distribution equipment.

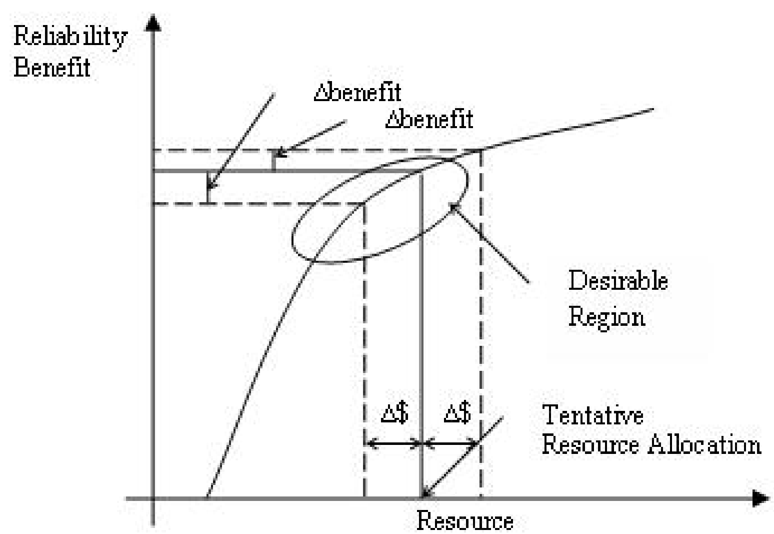

Figure 1.1: Reliability benefit obtained from various resource-allocation levels.

1.1 Asset Management Problem

Asset managers allocate resources among various maintenance activities. They are constrained by limited monetary and labor resources available for a broad array of maintenance activities. This presents a set of challenges to the asset manager that can be broadly classified into three categories.

The first is how to identify and justify the resources needed for asset management. Usually once a year, each asset manager must make a case for the financial and human resources required to manage equipment for which he/she is responsible. His/her argument is best made in terms of the benefit obtained from the resources allocated. This establishes the total resources available to each asset manager.

Each manager must then decide how to allocate the available resources to different maintenance programs. [1] This secondary resource allocation distributes available resources from the first allocation to the different asset management programs. For this, the asset manager must understand how the total benefit from all programs changes as resources are shifted from one program to another.

The third problem is to select a set of maintenance projects[2] to be completed within each program, constrained by the secondary budgetary allocation. A solution to this problem allows the asset manager to compare the benefits of the different maintenance tasks available within a program and choose the best options depending on the resources available.

Apart from the above three issues, there may be a situation where certain parts of the system need to be maintained due to safety or regulatory requirements, regardless of the reliability benefit obtained. Such obligatory tasks also have to be addressed.

In order to find a comprehensive solution to each of the above problems, asset managers need tools to assess the benefit obtained from each maintenance task. Once that is determined, the corresponding cost and labor requirements can be used to judge the usefulness of the activity and prioritize accordingly.

1.2 State of the Art in Power System Maintenance

Before proposing a solution to the asset management problem presented in Section 1.1, a brief review of the state of the art in power system maintenance will be presented. Maintenance of a component reduces its failure rate and, thereby, the frequency and duration of interruptions experienced by customers. Utilities follow different procedures [1] or strategies to maintain different kinds of equipment. These maintenance practices can be broadly classified into two categories: corrective maintenance and preventive maintenance.

1.2.1 Corrective Maintenance

Also known as the run-to-failure strategy, corrective maintenance involves no maintenance of equipment until it fails. Once a component fails, it is replaced with a new or repaired component. This strategy can be disastrous in terms of reliability and can result in costly regulatory penalties. Most utilities have evolved from this method and use one or more of the following preventive maintenance strategies.

1.2.2 Time-Based Preventive Maintenance

Unlike corrective maintenance, preventive maintenance is done on equipment before a failure occurs, thus improving its condition and increasing the time before its next failure. In time-based preventive maintenance, a fixed time period is associated with each piece of equipment, after which it is replaced or maintained. This period is based on

[1] Program: A budgetary category within the asset management group. Programs are typically identified by a geographical region or type of equipment, e.g., tree-trimming, recloser maintenance, wood pole maintenance for a city or county, etc.

[2] Projects: A set of tasks within a particular program, e.g., tree-trimming for three feeders in a city, wood pole maintenance (that may comprise of reinforcement or replacement) for ten segments, etc.

analysis of failure statistics and may use trial-and-error methods, expert judgment, or more analytical methods to estimate the optimal frequency of maintenance that is both economical and reliable at acceptable levels. The use of fixed-time period replacements, however, can lead to sub-optimal use of assets and unnecessary maintenance of equipment. Such strategies do not compensate for different conditions that identical components may experience on a system.

1.2.3 Condition-Based Preventive Maintenance

Condition-based preventive maintenance better allocates resources by using information regarding the current state of equipment to determine when and what kind of maintenance needs to be done. These methods require inspection and monitoring to estimate the piece of equipment's condition and its remaining useful life before maintenance. Examples include dissolved gas tests for transformer oil, recloser operation counters, and visual inspection of feeders for vegetation growth. Condition information is used to predict the probability of component failure and the maintenance that is needed to prevent failure. Relative to time-based maintenance, condition-based methods typically extend the interval between successive maintenances and, therefore, reduce maintenance costs [2]. This method is restricted, however, to equipment whose cost of failure outweighs the inspection and monitoring costs incurred. Improved testing, monitoring, inspection, and data collection methods are needed to accurately predict the state of many power system components.

Condition-based maintenance uses information from equipment inspection and monitoring to estimate the condition of the equipment and schedule maintenance. The method does not, however, consider the effects of component failure or quantify the benefits of preventing failures. Decisions are made solely based on equipment condition, not its relative importance.

1.2.4 Reliability-Centered Maintenance (RCM)

Reliability-centered maintenance (RCM) is a preventive strategy that is being used increasingly by utilities. In this method, condition-based measurements are used to determine the various components that require maintenance. Maintenance projects are then ranked according to their effect on improving selected criteria. One or more reliability indices are usually chosen as the criterion, and maintenance projects are carried out to achieve desired target levels. While traditional maintenance programs, such as vegetation management, recloser maintenance, and maintenance of sectionalizing devices, are considered as discrete and unrelated programs, RCM provides a method to integrate a variety of programs and tasks with a single global objective of improving system performance [3].

1.2.5 Risk-Based Preventive Maintenance

Risk-based preventive maintenance methods further advance RCM [2]. Failure probabilities estimated by condition monitoring methods, along with the failure effects quantified by RCM methods, are used to determine the risk associated with failure of a particular piece of equipment. This risk is combined with the financial and human resource requirements to prioritize maintenance projects in order to maximize risk reduction.

For transmission systems, risk is defined as the time-dependent product of the probability of equipment failure and the consequence of its failure [2]. The consequence of failure is the quantified effect of equipment outage, such as overload of equipment, cascading failures, and low voltage. Risk-based maintenance is thus a form of RCM, with the following specific attributes when applied to transmission systems [2]:

a. Condition information is used to estimate equipment failure probability.
b. Failure consequences are estimated and used in prioritizing maintenance tasks.
c. Equipment failure probability and consequence at any particular time are combined into a single metric called "risk."
d. 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.
e. The prioritization (and thus selection) of maintenance tasks is based on the amount of reduction in cumulative risk achieved by each task.

Selection and scheduling of maintenance tasks are performed at the same time (using optimization algorithms), since the amount of reduction in cumulative risk depends on the time when a maintenance task is implemented.

1.3 Risk-Based Allocation of Distribution System Maintenance Resources

The objective of this work is to develop a similar risk-based strategy to allocate maintenance resources and prioritize maintenance projects for distribution system assets. The work will also provide a solution to the asset management problem discussed in Section 1.1. To do this, certain important differences between transmission and distribution need to be understood before extending the method to distribution systems.

First, unlike transmission systems, which are highly networked, most distribution systems are radial. Hence, the effects of an outage are localized, and the chance of cascading outages is very small. Furthermore, maintenance scheduled in one area can be assumed to be independent of the conditions in another region of the system. This is not the case in transmission systems, where maintenance of a component in one transmission region may restrict a task in another region due to stability constraints.

Second, distribution systems have a much larger number of components than transmission systems. The consequence of failure in most distribution components is thus lower than that in transmission components. This implies a large number of decision variables (candidate maintenance tasks) from which to choose and, hence, the need for optimization techniques that can suitably handle them.

Furthermore, the conditions in a distribution system are relatively constant or predictable compared to those in a transmission network, which can be highly dependent on such variables as network topology, loading, and equipment outages due to maintenance and environmental conditions.

This results in an important distinction in the nature of failure consequences. The consequence of failure of a specific transmission component is time varying and influences the short-term (hourly) as well as long-term (yearly) reliability indices. The failure consequence of a distribution component tends to be constant and thus can be well represented using the long-term or yearly indices.

Figure 1.2 provides an outline of steps involved in the risk-based resource allocation strategy as it applies to distribution systems. Historical outage data and condition measurements are used to develop models that can predict equipment failure rates. The failure models are used to estimate how much each maintenance task will reduce a component's failure rate. The effects of a failure are then related to changes in reliability indices. Failure rate reduction and the associated change in indices are used to compute the risk reduction associated with each maintenance task. Finally, tasks are selected and scheduled to maximize risk reduction subject to the resources available.

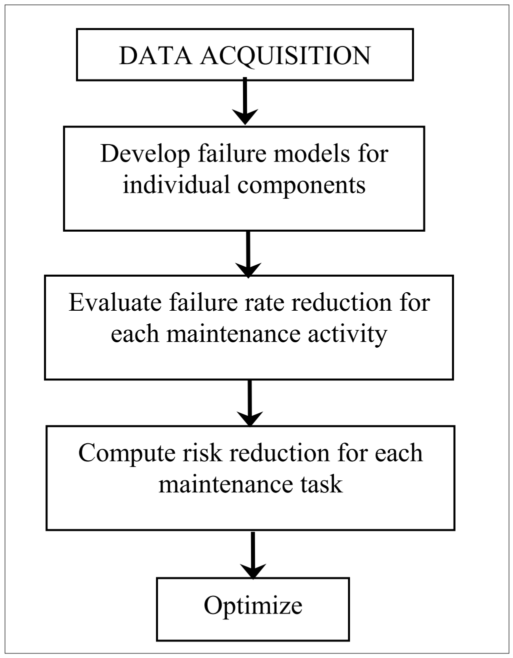

Figure 1.2: Risk-based resource allocation for distribution systems.

1.3.1 Definition of Risk

Every piece of equipment in the distribution system has a finite life, with failure probability that tends to increase with time. Maintenance improves the condition of equipment and thus reduces its likelihood of failure. In defining risk, the following effects of equipment failure will be considered:

a. Customer satisfaction, in terms of the expected number and duration of outages.
b. Revenue lost by the utility due to energy not served.
c. Cost to replace or repair failed equipment.
d. Regulatory or contractual penalties paid by the utility due to missed reliability targets.

Repair and switching times for each component are assumed to be constant, and the distribution network configuration is considered fixed. This allows the reliability effects of each component to be expressed as linear contributions to the overall system indices [4]. These effects are expressed [4], [5] as follows.

1.3.1.1 Effect on customer satisfaction

SAIFI, the system average interruption frequency index, is defined as

> SAIFI = total number of customer interruptions / total number of customers served

for a given time period. For time period Δt, as a function of failure rate $\lambda_{k,l}$, for failure mode l of component k, the contribution of failure mode l of component k to the system SAIFI is

$$SAIFI(t \mid k,l) = \lambda_{k,l}.\Delta t \cdot \frac{n_{k,l}}{N} \tag{1.1}$$

with units of average number of interruptions per customer in time period Δt. The system SAIFI is the sum of these individual SAIFI contributions over all components k and failure modes l.

SAIDI, the system average interruption duration frequency index, is defined as

> SAIDI = sum of customer interruption durations / total number of customers served

for a given time period. The contribution of failure mode l of component k to the system SAIDI is

$$SAIDI\ (t \mid k,l) = \lambda_{k,l}.\Delta t \cdot \frac{\sum_{j=1}^{n_{k,l}} d_j}{N} \tag{1.2}$$

with units of average hours of interruptions per customer in time Δt. The system SAIDI is the sum of the individual SAIDI contributions over all components k and failure modes l.

1.3.1.2 Revenue lost by the utility

$$ENS(t \mid k,l) = \lambda_{k,l}.\Delta t \cdot \sum_{j=1}^{n_{k,l}} P_j d_j \tag{1.3}$$

1.3.1.3 Cost of equipment failure

$$DevRisk(t \mid k,l) = \lambda_{k,l}.\Delta t \cdot Cost(k,l) \tag{1.4}$$

1.3.1.4 Regulatory penalties due to violation of regulatory limits

The effects expressed by equations (1.1) to (1.4) can be directly computed using standard analytical methods [6-9]. However, due to increased regulatory monitoring of reliability indices, it may be necessary for utilities to also estimate the risk of paying penalties that might arise from missed reliability targets. In such scenarios, it becomes necessary to estimate not only the average reliability indices for the system but also the variability in the indices [11] due to events that have low probability of occurrence with substantially high penalties. The risk of penalties associated with each component may be defined as shown in equations (1.5) and (1.6).

$$PBRF(t \mid k,l) = \left\{ \int_{T_F}^{\infty} PBR(SAIFI).f(SAIFI(t \mid k,l))d(SAIFI(t \mid k,l)) \right\}.\Delta t \tag{1.5}$$

$$PBRD(t \mid k,l) = \left\{ \int_{T_D}^{\infty} PBR(SAIDI).f(SAIDI(t \mid k,l))d(SAIDI(t \mid k,l)) \right\}.\Delta t \tag{1.6}$$

where:

- $\lambda_{k,l}$ is the failure rate of component 'k' due to a maintainable failure mode 'l.'
- Δt is the time interval under consideration.
- N is the total number of customers served.
- $n_{k,l}$ is the number of customers affected due to failure of component 'k' in mode 'l.'
- d_j is the duration of the interruption seen by the 'j'th customer due to failure of component 'k' in mode 'l.'
- P_j is the load connected at point 'j.'
- Cost (k,l) is the cost of failure for component 'k' in mode 'l.'
- PBR(SAIFI) is a performance-based penalty for a SAIFI violation beyond threshold T_F.
- PBR(SAIDI) is a performance based penalty for a SAIDI violation beyond threshold T_D.
- $f(SAIDI(t \mid k,l))$ is a probability distribution of SAIDI obtained by non-sequential Monte Carlo simulation for component 'k' in failure mode 'l.'
- $f(SAIFI(t \mid k,l))$ is a probability distribution of SAIFI obtained by non-sequential Monte Carlo simulation for component 'k' in failure mode 'l.'

The time interval 'Δt' is assumed to be one year, so it can be removed from equations (1.1) to (1.6). As discussed in Section 1.3, the consequence of a component's failure is assumed to be constant throughout the year. Unless the component is maintained, the component's failure rate is also assumed to be constant throughout the year. This removes scheduling from the optimization problem, and leaves allocation of resources to programs and selection of maintenance tasks for the year.

Furthermore, the subscript 'l,' indicating the maintainable failure mode, can also be dropped without loss of generality, assuming that each of the equations (1.1) to (1.6) represents the consequences of equipment failure due to a single maintainable failure mode. Thus, the simplified expressions for the risk associated with each component can be correspondingly written, as shown in equations (1.7) to (1.12):

$$SAIFI\ (k) = \lambda(k).\frac{n_k}{N} \tag{1.7}$$

$$SAIDI\ (k) = \lambda(k).\frac{\sum_{j=1}^{n_k} d_j}{N} \tag{1.8}$$

$$ENS(k) = \lambda(k).\sum_{j=1}^{n_k} P_j d_j \tag{1.9}$$

$$DevRisk(k) = \lambda(k).Cost(k) \tag{1.10}$$

$$PBRF(k) = \int_{T_F}^{\infty} PBR(SAIFI).f(SAIFI(k))d(SAIFI(k)) \tag{1.11}$$

$$PBRD(k) = \int_{T_D}^{\infty} PBR(SAIDI).f(SAIDI(k))d(SAIDI(k)) \tag{1.12}$$

The consequence of equipment failure may be expressed as the sum of the quantities defined by equations (1.7) to (1.12). This sum comprises the risk associated with a component's failure. The risk associated with a component varies with its failure probability. If, during the time period under consideration, the failure rate of the component remains constant and is sufficiently low, the failure probability in equations (1.7) to (1.12) can be replaced with the failure rate of the component.

Maintenance reduces the failure rate of a component and thus the risk associated with its failure. The following expressions then can be used to define the effect of maintenance on a component:

$$\Delta SAIFI(k) = SAIFI_B(k) - SAIFI_A(k) = (\lambda_B(k) - \lambda_A(k)) \cdot \frac{n_k}{N} = \Delta\lambda(k) \cdot \frac{n_k}{N} \tag{1.13}$$

$$\Delta SAIDI(k) = SAIDI_B(k) - SAIDI_A(k) = (\lambda_B(k) - \lambda_A(k)) \cdot \frac{\sum_{j=1}^{n_k} d_j}{N} = \Delta\lambda(k).\frac{\sum_{j=1}^{n_k} d_j}{N} \tag{1.14}$$

$$\Delta ENS(k) = (\lambda_B(k) - \lambda_A(k)).\sum_{j=1}^{n_k} P_j d_j = \Delta\lambda(k).\sum_{j=1}^{n_k} P_j d_j \tag{1.15}$$

$$\Delta DevRisk(k) = (\lambda_B(k) - \lambda_A(k)).Cost(k) = \Delta\lambda(k).Cost(k) \tag{1.16}$$

$$\Delta PBRF(k) = \int_{T_F}^{\infty} PBR(SAIFI).f(SAIFI_B(k))d(SAIFI(k)) - \int_{T_F}^{\infty} PBR(SAIFI).f(SAIFI_A(k))d(SAIFI(k)) \tag{1.17}$$

$$\Delta PBRD(k) = \int_{T_D}^{\infty} PBR(SAIDI).f(SAIDI_B(k))d(SAIDI(k)) - \int_{T_D}^{\infty} PBR(SAIDI).f(SAIDI_A(k))d(SAIDI(k)) \tag{1.18}$$

The subscripts 'B' and 'A' used in equations (1.13) to (1.18) correspond to the state of the component before and after maintenance, respectively. Thus, the overall risk reduction obtained from maintaining a component 'k' can be written as a linear combination of each of factors, as shown in equation (1.19).

$$\Delta Risk(k) = \overbrace{\alpha_1.\Delta SAIFI(k) + \alpha_2.\Delta SAIDI(k)}^{Customer\ \ satisfaction} + \overbrace{\alpha_3.\Delta ENS(k)}^{Lost\ \ revenue}$$
$$+ \overbrace{\alpha_4.\Delta DevRisk(k)}^{Cost\ \ of\ \ component\ \ failure} + \overbrace{\alpha_5.\Delta PBRF(k) + \alpha_6.\Delta PBRD(k)}^{\mathrm{Re}\,gulatory\ \ penalties} \tag{1.19}$$

The coefficients (α_i) in equation (1.19) correspond to weights that an asset manager assigns to the different factors based on their relative importance or confidence in their accuracy. By choosing the units appropriately for the coefficients (α_i), the overall risk reduction associated with a component's failure can be represented by a single monetary value.

2 Maintenance Practices

This chapter reviews common maintenance practices for the following distribution components included in the methodology developed in this project: reclosers, vegetation, and wood poles.

2.1 Reclosers

Reclosers are very reliable devices that seldom fail. When failures do occur, however, they can lead to widespread outages and damage that significantly affect reliability indices and costs. Thus, many utilities use time-based preventive maintenance for reclosers, scheduling maintenance for all reclosers on the system every three to five years. Reducing the frequency of maintenance by using a risk-based methodology may significantly reduce recloser maintenance costs.

2.1.1 Failure Modes

Failure of reclosers can occur in four different modes:

a. Failure to open.
b. Failure to close/reclose.
c. False trip.
d. Failure to lockout.

Most failures are caused by improper settings. Causes of recloser failure fit within these four modes, and most can result in more than one type of failure mode.

Causes of recloser failure can be classified as follows:

a. Mechanical moving parts, including linkage, plunger, and contacts.
b. Electrical insulation, including bushings, stringers, and oil.
c. Structural, which addresses the integrity of the tank.
d. Improper setting or placement of a recloser.
e. Electronic, for electronic reclosers.

Preventive maintenance is performed to reduce the probability that these will occur.

2.1.2 Maintenance Practices

All but the very simplest recloser maintenance must be done in a shop; therefore, the recloser must be removed from service. When a recloser is removed, another recently serviced or new one is installed in its place. Since removal is costly, most utilities perform a standard maintenance procedure on each recloser that comes into the shop. The procedure returns the recloser to a serviced condition and reduces its failure rate.

During service of reclosers, oil is replaced or filtered. Mechanical parts, bushings, and stringers are inspected and replaced if they are damaged or excessively worn. Contacts are inspected for wear and replaced if needed. Insulation is tested to reduce the likelihood of internal or external recloser faults. Structural maintenance includes removing rust and repainting the tank can to a specified thickness of paint to reduce the effects of weather. When maintenance is complete, the recloser is tested to ensure that it is operating in accordance with its specified time curves. It is then returned to the warehouse for installation when needed.

2.2 Vegetation

Vegetation-related failures are a large contributor to distribution system interruptions. Utilities spend sizeable portions of their maintenance budgets controlling vegetation. Because of the high cost, utilities must assess the effectiveness of their vegetation maintenance programs.

2.2.1 Failure Modes

Tree growth into power distribution lines is less of a factor in distribution outages that it is in transmission. Most utility tree-trimming programs are effective in keeping growing vegetation away from distribution lines. Tree growth causes about 20 percent of sustained distribution outages, most of which are of short duration. Growth-related failures are maintainable and can be effectively controlled through regular tree-trimming [11].

Tree failures occur when branches or entire trees break and come into contact with the power-carrying conductors, resulting in short-circuited or downed conductors. Trees outside the actual right-of-way may fail and cause outages, which makes maintenance more difficult because utilities have limited authority outside of this area. Tree failure causes about 40 percent of all sustained distribution outages. These faults are often more severe and take longer to repair.

Some tree failures are preventable and thus maintainable, that is, if the tree shows external signs of decay or degradation. If identified, these failures can be corrected by providing structural support or removing dead or weak branches. Other tree failures, such as those caused by severe weather, may cause extensive damage to the distribution network. Such failures, which account for about 40 percent of all tree-related outages [12], are not maintainable.

2.2.2 Maintenance Actions

Corrective maintenance refers to repair activities done to restore the system after a fault. Crews are dispatched to locate the fault and remove the branch or tree from the circuit. They should also clear any overhang that may come in contact with the lines in the near future. Such maintenance is local and is aimed at restoring service to customers in the shortest possible time.

Preventive vegetation maintenance is done before a failure actually occurs and may include the following:

- Tree-trimming, which is the most common vegetation maintenance activity. Most utilities follow a three- to six-year cycle of trimming, whereby a specialized crew identifies vegetation overgrowth and trims to prescribed standards.
- Tree growth regulators. These are chemical agents used to slow vegetation growth rates and are typically used after trimming to slow regrowth.
- Tree removal. Utilities also remove trees that threaten the system, sometimes replacing them with shorter, slower-growing species.
- Spacer and tree cables. Insulated overhead conductors are used in areas requiring higher reliability and in regions where accessing the right-of-way is difficult. These cables allow vegetation to grow closer to the conductors and reduce the number of outages.

2.2.3 Inspection Methods

To identify areas where tree-related outages are likely to occur and to determine the proximity of trees to conductors, utilities have inspection programs to assess vegetation near their circuits. Vegetation is inspected visually, often midway between two tree-trimming cycles. Remote sensing and laser imagery, e.g., light detection and ranging (LiDAR), are also used.

Some utilities also have inspection activities that extend beyond the right-of-way. These hazard tree programs identify trees that are likely to fail and determine the maintenance needed, including reinforcement or replacement, to avoid failures.

2.2.4 Factors Influencing Failure Rates

A feeder's vegetation-related failure rates are influenced by the following factors [13]:

a. Length of overhead lines.
b. Local density of vegetation, measured in number of trees per mile.
c. Growth and regrowth rates of different species of vegetation.
d. Climate, weather, and other environmental factors.

Since these factors may vary significantly among feeders, it is appropriate to model each individual feeder's failure rate, if data is available.

2.2.5 Vegetation Condition and Modeling

Overhead feeders are repairable systems, and vegetation-related failures are a recurring process. When failures occur, repairs restore the system to a working state. Repair or maintenance decreases the failure rate of the system. However, the system tends to deteriorate as vegetation regrows and clearances decrease. This causes the number of tree-related outages to increase with time, thereby increasing the failure rate.

Vegetation management decreases, but does not totally eliminate, vegetation-related failures. The number of tree-related outages occurring in a unit of time may be used as a measure to estimate the state of the system. If this value is higher than a specified limit, the feeder may inspected to identify areas of maintenance. A low value indicates that no maintenance is required. This method can also be used to determine if the current trimming cycle is adequate.

Information that utilities maintain about tree-related outages is generally obtained from an outage management system. Such information may include the location, date, and time when the outage occurred, the time it took to repair the problem, the number of customers interrupted, and the time when service was restored. There is often, however, no information about the failure mode or maintenance performed.

Parametric failure rate models require information on each of these factors for individual feeders. Because such information is often not available, the use of non-parametric models may be necessary. Non-parametric models only require historical outage information and information about when the feeder was trimmed.

2.3 Wood Poles

Wood poles keep energized conductors and equipment away from the public and the ground, and maintain separation between conductors. Poles also serve as a support platform for equipment such as capacitors, regulators, and reclosers [14].

2.3.1 Decay of Wood Poles

Wood poles decay both internally and externally. Most decay is just below ground level, where moisture, temperature, air, and absence of direct sunlight are most favorable to the growth of fungi. This portion of the pole is also hidden from view and is close to its natural breaking point under strain. Thus, it is the most critical part of the pole and warrants special inspection and maintenance.

Wood pole failures usually occur as a result of physical stress such as wind, ice, or vehicle impact. The tendency of a pole to fail under such stress is related to the strength of the pole at ground level, where almost 90 percent of pole failures occur [15].

2.3.2 Detection and Measurement of Decay

Nondestructive evaluation methods estimate the effective area of the pole cross section at the ground line. Visual inspection is ineffective, since it will not reveal internal decay or decay below this point. Other approaches vary in accuracy and cost. These include acoustic [16] and resistance force [17], sometimes combined with measurements of humidity [18]. Another simple but cost-effective approach is to remove external decay and assess the internal decay by drilling into the pole. This project assumes measurements based on this approach.

2.3.3 Maintenance Practice

The primary maintenance on wood poles is ground line treatment [19], which can provide an economical extension of a pole's physical life. Ground line treatment is recommended under the following conditions:

- Whenever a pole is inspected and the decay is not so far advanced that the pole must be replaced.
- Whenever a pole over five years old is reset.
- Whenever a used pole is installed as a replacement.

Ground line treatment consists of removing the external decay, followed by application of a preservative paste or grease. Then the treated section is wrapped, and the dirt around the pole is replaced.

A decayed pole can be stubbed, whereby the decayed section is simply cut off, if the remaining portion is long enough, strong enough, and in good enough condition. Stubbing costs one-third to one-half the cost of replacing a pole. If stubbing is not possible, the pole must be replaced when its residual strength is below applicable standards.

3 Failure Rate Estimation

This chapter presents models that estimate the failure rates of components, as well as the failure rate reduction achieved by preventive maintenance tasks.

3.1 Recloser

This section discusses the methodology for determining the condition of a recloser while in service. This condition data is then used to estimate the recloser's failure rate.

3.1.1 Condition Assessment

The methodology begins by assessing the condition of the recloser. A scoring sheet that itemizes relevant failure causes is shown in Table 3.1. Each of the criteria on the score sheet contributes to the reliability of a recloser, and most can be improved by preventive maintenance. Those that cannot be improved are still relevant in determining the recloser's condition. These include the age of the recloser, which can only be improved by replacing the recloser, and the duty cycle rate and environmental factor, both of which are a function of placement on the distribution system rather than any maintenance performed.

For some reclosers, each of the criteria can be evaluated while the recloser is in service or from prior maintenance records. A large part of the cost of recloser maintenance is removing it from service, and removing a recloser from service to assess it, without performing maintenance, is never cost-effective. Components that can never be assessed in service are therefore omitted from Table 3.1.

Table 3.1: Recloser score sheet

Criteria	**Weight**	**Score (0 - 1)**
		Pre-Maintenance
Age of Oil		
Duty Cycle Rate		
Environmental Factor		
Oil Dielectric Strength		
Condition of Contacts		
Age of Recloser		
Experience with this Recloser Type		
Condition of Tank		
Sum		
Weighted Average		

Scoring criteria are as follows:

- *Age of Oil* – The oil in a recloser is the most important dielectric in the unit, especially if the contacts are not in a vacuum. The oil helps extinguish arcs as contacts open and close, keeps arcs from occurring between other electrical conductors within the recloser, lubricates most of the moving parts, and is used to raise the trip piston after operation. The average expected life of oil is three years. Oil age thus provides a rough estimate of the oil's dielectric strength without removing the recloser from service.
- *Duty Cycle Rate* – Duty cycle is a measure of the use a recloser has experienced since its last maintenance and is one of the most important criteria for determining when maintenance should be performed again. Duty cycle is a combination of the number of interruptions the recloser has performed, and either the percent of rated interrupting current or the circuit X/R value. NEMA has defined a standard duty cycle for distribution class reclosers [20]. Constant monitoring of every recloser's duty cycle is impractical, so an alternate criterion, duty cycle rate, is defined. To calculate the duty cycle rate, the number of faults a recloser will see per year in a certain location is determined from the historical data used to calculate the utility's SAIFI index. The value of system X/R at the recloser location is determined from system data. Then the NEMA standard duty cycle definitions give the number of operations per duty cycle for that location. Dividing the operations/cycle by the expected operations/ year gives the duty cycle in years/cycle for a recloser at that location. Duty cycle is then compared to expected oil life, whereby duty cycle rate equals the expected duty cycle divided by the expected oil life. This score is high for a high expected remaining duty cycle. If the score is greater than one, then the expected duty cycle is longer than the expected oil life, and the score is entered as one. This score is a function of recloser location on the system and not of the actual recloser condition.
- *Environment Factor* – This criterion is for reclosers in locations that require more frequent maintenance. It consists of a combination of recloser placement and environmental effects on the physical condition of the recloser. For example, a recloser bank protecting a feeder along a coastline will experience air with a much higher salt content than one located farther inland. The salt may cause the dielectric strength of the recloser oil to fall below standards much sooner than normal. This criterion addresses such conditions.
- *Oil Dielectric Strength* – This score is important if the utility's recloser maintenance includes filtering the oil instead of replacing it. The score should be given as the difference between the post-maintenance oil dielectric strength, which is measured as part of maintenance, and the minimum allowable oil dielectric strength, divided by the difference between the new and minimum oil dielectric strengths.
- *Condition of Contacts* – This score is given as a percentage of remaining useful contact life.
- *Age of Recloser* – This is important because, as with all machines, reclosers become less reliable and fail with age. However, reclosers have proven to last for many years, and age has not been shown to be a reliable predictor of failure. Recloser age should still be monitored, though, as one indicator of condition.

- *Experience with this Recloser Type* – This criterion is used to differentiate among failure rates for different manufacturers or models, types, and sizes of reclosers.
- *Condition of Tank* – If a tank has excessive damage, either from nature or handling, the recloser may need maintenance before it is justified by the other factors.

3.1.1.1 Scoring

Recloser assessment begins with selecting the criteria for a particular recloser, as shown in Table 3.1. Different recloser types and models, for example, will use different criteria. Each recloser's score will then be normalized by dividing the score by the maximum possible for the scored criteria. For example, evaluating contacts and oil dielectric strength for many reclosers requires removal from service. These criteria will not be included in the assessment or maximum possible score for those reclosers.

The score for each item is per unit of the remaining state of the recloser criterion. For example, if the contacts are 60 percent of their original size, their score would be 0.60. A recloser that has completed 75 percent of its recommended duty cycle would have a duty cycle score of 1.00 – 0.75 = 0.25, indicating the remaining 25 percent of its duty cycle. The resulting condition score, between 0 and 1, is denoted as x_{cs}.

3.1.1.2 Weighting

The weight column in Table 3.1 represents the influence that a particular condition actually has on the failure rate of a recloser. Weights will be determined in practice by the combined opinion of manufacturers, utility engineers, and field personnel. Certain items are utility dependent, such as the environment factor inspection item.

3.1.2 Failure Rate Calculation

To relate a recloser's condition score to its numerical failure rate, historical failure rate data from a number of systems were compiled for various power system components, including reclosers [21]. From this data, the best, worst, and average failure rates for each component were calculated. The resulting values for reclosers are as follows:

$$\lambda(0) = 0.0025 \text{ (Best)}$$
$$\lambda(1/2) = 0.015 \text{ (Average)}$$
$$\lambda(1) = 0.060 \text{ (Worst)}$$

If no historical data exists for the system to be modeled, then these values can be used. If, however, historical data is available for the system, then that data can, and should, be used to determine recloser failure-rate statistics for that system. Equation (3.1) [22] demonstrates how a system wide average recloser failure rate is calculated:

$$\lambda(1/2) = \frac{Total\ number\ of\ recloser\ failures}{(Number\ of\ reclosers)\, x\, (Time\ period)} \tag{3.1}$$

Ideally, the number of reclosers should be constant over the time period; a failure rate should be calculated for each such period, and then the failure rate for the entire period calculated from these values. The calculations are complicated by the inherent reliability and low failure rates of reclosers. The accuracy of the calculation thus depends on the availability of such data and the time period over which it is available. Some utilities already have systems in place to collect data that can be used to track component reliability. Those that do not must use the best available data while gathering the needed information.

Also from the available data, the lowest and highest failure rates for reclosers on the system become the best, $\lambda(0)$, and worst, $\lambda(1)$, historical failure rates. If the calculated values are not judged to be accurate, then the published [21] values should be used.

From the historical failure rates, coefficients A, B, and C are calculated using equation (3.2) [21]:

$$\begin{aligned} A &= \frac{[\lambda(1/2)-\lambda(0)]^2}{\lambda(1)-2\lambda(1/2)+\lambda(0)} \\ B &= 2\ln\left(\frac{\lambda(1/2)+A-\lambda(0)}{A}\right) \\ C &= \lambda(0)-A \end{aligned} \tag{3.2}$$

These coefficients are recalculated periodically as data becomes available. Equation (3.3) then estimates the failure rate for an individual recloser, based on the coefficients and its condition [21]:

$$\lambda(x) = Ae^{B*x} + C \tag{3.3}$$

where $\lambda(x)$ is the recloser's failure rate, and x is a modified condition score that is calculated from the check sheet score x_{cs} using equation (3.4):

$$x = 1 - \frac{x_{cs} - x_1}{x_0 - x_1} = \frac{x_0 - x_{cs}}{x_0 - x_1} \tag{3.4}$$

If x_{cs} is used directly, then a recloser would need a score of $x_{cs} = 1$ to be assigned the best failure rate on the system, and a score of $x_{cs} = 0$ to be assigned the worst. A recloser with $x_{cs} = 0$ would have completely failed every condition with a score of zero, which is not practical. Instead, the best and worst scores on the system should relate to the best and worst historical failure rates. Thus, x_1 is the worst recloser condition score recorded on the system, and x_0 is the best. The resulting value is subtracted from 1, because a high x_{cs} indicates a low failure rate, and a high x in equation (3.3) must represent a high failure rate.

Equation 3.4 will produce values that are negative when a recloser score x_{cs} is greater than the previous best score or greater than one when x_{cs} is less that the previous worst score. When this occurs, x_{cs} replaces the previous best x_1 or worst x_0 historical score, as shown in equations 3.5 and 3.6. Then x for the recloser is recalculated with the new values as follows:

$$\text{If } x < 0\text{, then } x_{cs} \text{ is the updated } x_0 \tag{3.5}$$

$$\text{If } x > 1\text{, then } x_{cs} \text{ is the updated } x_1 \tag{3.6}$$

3.1.3 Effects of Maintenance

The maintenance tasks associated with each criterion on the score sheet are assumed to bring the score for that criterion to a predetermined value; this may be 1 or something less than 1. New post-maintenance coefficients, equation (3.2), and a new failure rate, equation (3.3), are calculated. Reliability indices for the system being simulated are then computed using the evaluation tool discussed in Chapter 4 and Appendix B. The calculated failure rates should then be calibrated so that the indices correlate with historical indices. A least-squares approach has been suggested for this [21], using the method of gradient descent.

3.1.4 Example

Six years of outage data were obtained from a utility and are used to illustrate the recloser assessment method. Out of 341 reclosers on the system, 23 recloser failures occurred during a 6.44-year period. Equation (3.1) produces an average failure rate $\lambda(1/2)$ of

$$\lambda(1/2) = \frac{23}{341 * 6.44} = 0.010473$$

The best and worst failure rates, $\lambda(0)$ and $\lambda(1)$, respectively, are then calculated. Each recloser on the system failed either zero times or one time during the six-year period. This gives failure rates of

$\lambda(0)$ = 0 failure / 6.44 years = 0.00000
$\lambda(1)$ = 1 failure / 6.44 years = 0.15528

These are too low and too high, respectively, to be practical; therefore, the following published failure rates [21] are used for the best and worst values:

$\lambda(0) = 0.0025$
$\lambda(1/2) = 0.010478021$
$\lambda(1) = 0.060$

Next, the A, B, and C coefficients are calculated using equation (3.2) to be

A = 0.0015321
B = 3.6514524
C = 0.0009679

The resulting equation (3.3) is

$$\lambda(x) := 0.0015321 \cdot e^{3.6514524 \cdot x} + 0.0009679$$

and the relationship of assessment score to failure rate is shown in Figure 3.1.

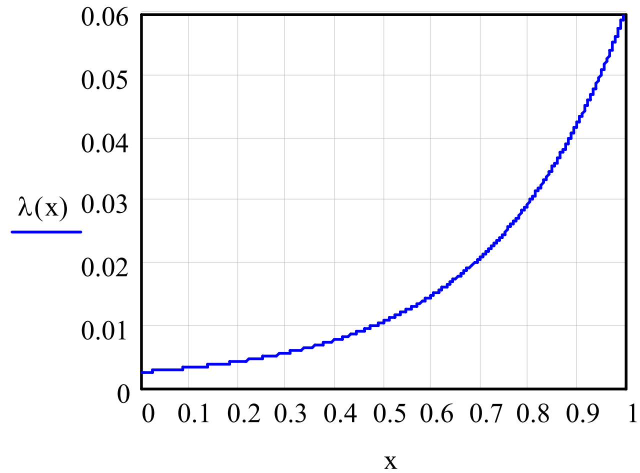

Figure 3.1: Recloser score vs. failure rate.

Best and worst historical scores for reclosers on the system were not available; therefore, the worst (x_1) and best (x_0) scores were assumed to be 0.31 and 0.95, respectively. Table 3.2 then shows actual scores for a recloser that failed while in service. It was considerably past its expected duty cycle. Its condition score x_{cs} was 0.392. Equation (3.4) corrects this to

$$x = \frac{0.95 - 0.932}{0.95 - 0.31}$$

$$x = 0.872$$

which results in a failure rate, equation (3.3), of

$$\lambda(0.872) = 0.038$$

The low condition score, 0.392, as expected, produced a higher-than-average failure rate.

Table 3.2: Condition of typical failed recloser

Criteria	Weight	Score (0 - 1)
		Pre-Maintenance
Age of Oil	20	0
Duty Cycle Rate	20	0.5
Environmental Factor	20	N/A
Oil Dielectric Strength	15	N/A
Condition of Contacts	15	N/A
Age of Recloser	10	0.65
Experience with this Recloser Type	10	0.7
Condition of Tank	5	0.4
Sum	65	25.5
Weighted Average		0.392307692

Next, a recloser in near-average condition was scored, as shown in Table 3.3.

Table 3.3: Score for recloser in average condition

Criteria	Weight	Score (0 - 1)
		Pre-Maintenance
Age of Oil	20	0.33
Duty Cycle Rate	20	0.9
Environmental Factor	20	N/A
Oil Dielectric Strength	15	N/A
Condition of Contacts	15	N/A
Age of Recloser	10	0.65
Experience with this Recloser Type	10	0.9
Condition of Tank	5	0.65
Sum	65	43.35
Weighted Average		0.666923077

This score produced the estimated failure rate of

$$\lambda\left(\frac{0.95-0.667}{0.95-0.31}\right)=0.00867$$

which is close to the system average failure rate of 0.01048.

Finally, Table 3.4 shows scores for a relatively new recloser that underwent scheduled maintenance about a year before it was scored. This is indicated by the age of the oil in the recloser. The recloser is not expected to complete a duty cycle before the oil is due to be changed again.

Table 3.4: Score for recently maintained recloser

Criterion	Weight	Score (0 - 1)
		Pre-Maintenance
Age of Oil	20	0.66
Duty Cycle Rate	20	1
Environmental Factor	20	N/A
Oil Dielectric Strength	15	N/A
Condition of Contacts	15	N/A
Age of Recloser	10	0.95
Experience with this Recloser Type	10	0.9
Condition of Tank	5	0.85
Sum	65	55.95
Weighted Average		0.860769231

The estimated failure rate for this recloser is

$$\lambda\left(\frac{0.95-.861}{0.95-0.31}\right)=0.00351$$

which is close to 0.0025, the best failure rate previously found on the system.

A condition score, x_{cs}, of 0.30, produces an equation (3.4) score, x, of 1.015. This score of 0.30 replaces (equation (3.6)) the previous historical low score of 0.31, and the recloser is assigned the lowest historical failure rate on the system.

3.1.5 Summary

This methodology allows for quantifiable assessment of a recloser's condition. The assessment is designed to be done in the field without removing the recloser from service. The assessment score is converted to an estimated failure rate, which is based on historical data.

The assessment criteria are directly related to maintenance tasks that may be performed on the recloser. Each maintenance task will increase the score for the associated criteria, resulting in a lower calculated failure rate. This method can be adapted to other power system components.

3.2 Vegetation

Another approach to computing failure probabilities is illustrated in Figure 3.2, based on a multi-state Markov probability model, where each of the J states is represented as a deterioration level. Boundary conditions separating J states of deterioration in component k are defined in terms of the measurements $\underline{c}_k(t)$, using the deterioration function $g(\underline{c}_k(t))$. The deterioration function returns a deterioration level j identified by $d_{j-1}<g(\underline{c}_k(t))<d_j$, where the last state $j=J$ represents the *failed* state. State J need not represent the relatively rare catastrophic failure, for which very little data is typically available. Rather, state J represents a set of measurement values for which engineering judgment indicates the component should be removed from service. The particular representation in Figure 3.2 shows $J=4$ deterioration levels, and deterioration level j can be reached only from deterioration level $j-1$. However, the model is flexible so that any number of deterioration levels can be represented, and if data indicates that transitions occur between non-consecutive states (e.g., state 1 to state 3), then the model can accommodate this easily. The transition from level 4 to level 1 stochastically represents the effects of maintenance, and if the decision problem is whether to maintain or not (a deterministic result of the problem), then we would set $\mu_{41}=0$. The steps to implementing this approach are described as follows.

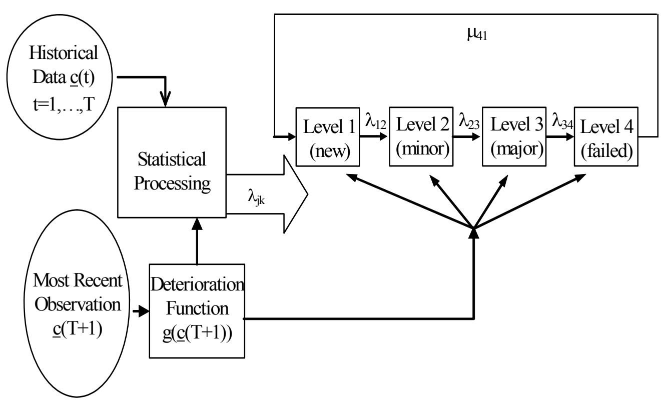

Figure 3.2: Computing contingency probability reductions.

a. Deterioration function: The deterioration function, denoted by $g(\underline{c}_k)$, may be an analytical expression, if one is available, or it may be a set of rules encoded as a program, likely consisting of a nested set of *if-then* statements that returns a scalar assessment value. For the model of Figure 3.2, the assessment value would be a deterioration level 1, 2, 3, or 4.

This represents a flexible and practical way of connecting our approach to the wealth of existing knowledge and experience contained in the industry relative to interpreting condition monitoring measurements. Often, such rules depend not only on the measurements $\underline{c}_k(t)$ but also on the rates of change in such measurements. These rules, together with expertise provided by industry advisors, are used to develop the deterioration functions. For example, a comprehensive compilation of such rules for transformers [23] provides 62 different measurements for characterizing 23 transformer failure modes. Examples, and some of the failure modes they detect, include dissolved gas analysis results on main tank oil (indicating insulation deterioration, deterioration of cooling system, or oil pump failure) and load tap changer oil (indicating oil dielectric weakening), thermography testing (indicating magnetic circuit overheating or bushing overheating), ultrasonic testing (indicating oil pump failure), partial discharge testing (indicating magnetic circuit overheating), and winding and oil temperature measurements (indicating deterioration of the transformer cooling system).

Little has been published on correlating equipment deterioration with operating histories, a fact that stems from the difficulty in obtaining and merging operating and condition data in ways that properly characterize deterioration. Statistical modeling and analysis can be used to capture such trends, however. For vegetation, probabilistic vegetation failure rate models developed in [13, 24], are used to capture deterioration in this failure mode.

b. Transition intensities: Transition intensities between the various states of the model can be obtained from life histories of multiple units of the same manufacturer and model. In the case of Figure 3.2, λ_{12}, λ_{23}, and λ_{34} are needed. Consider a set of condition measurements $\underline{c}(t)=[c_1(t),c_2(t),\ldots,c_K(t)]$ for K similar components taken over an extended period of time $t=0,1,\ldots,T$. For component i, the deterioration function is used to compute the deterioration level indicated by each measurement. This gives the time the component spent in deterioration level j. The mean of the durations for all components is then used as the estimated time spent in state j. Reasonable estimates of the desired transition intensities are obtained by inverting these mean duration times.

Transition intensities computed in this way capture deterioration in the state of the equipment, but they do not capture variations in equipment failure propensity as a function of loading or environmental conditions. To do this, one needs to model the dependency of the transition intensities on these parameters. However, component loading and environmental histories typically reside in database systems (such as control center historians) distinct from component condition histories. This requires a significant effort in data integration.

c. Desired failure probability: For a particular set of transition intensities, the transition probability matrix for the case represented by Figure 3.2 is given by equation (3.7). The state probability vector gives the probability that a component is in any particular deterioration level at a given time and is denoted by p(hT)=[p1(hT) p2(hT) p3(hT) p4(hT)], where h = 1,2,3,…, and T is the time step. If at time t=0 the component resides in deterioration level 1, then the initial state probability vector is p(0)=[1 0 0 0]. The probability of finding the component in any deterioration level at time hT is then given by p(hT)=p(0)Ph. Given that at time t=0 the component's deterioration level is known, this provides the probability of residing in the failed state in any future time interval. We denote this failure probability for component k as pk(c). This probability is a function of the time-dependent physical condition of the equipment c(t).

$$\underline{P} = \begin{bmatrix} 1-\lambda_{12} & \lambda_{12} & 0 & 0 \\ 0 & 1-\lambda_{23} & \lambda_{23} & 0 \\ 0 & 0 & 1-\lambda_{34} & \lambda_{34} \\ \mu_{41} & 0 & 0 & 1-\mu_{41} \end{bmatrix} \tag{3.7}$$

In addition to failure probability, this model provides the ability to predict maintenance-induced probability reduction and expected time to failure, metrics that are important for a number of decision problems. If a particular maintenance task results in renewing a component to deterioration level 1, for example, then if the component is in deterioration level 3, the probability reduction for maintenance task *m, Δp(m,k)*, is given by the last element of the 1×4 row vector resulting from the calculation:

$$[1\ \ 0\ \ 0\ \ 0]\underline{P}-[0\ \ 0\ \ 1\ \ 0]\underline{P}=[1\ \ 0\ \ -1\ \ 0]\underline{P}$$

The expected time to failure is captured by computing first-passage times. First-passage time is the expected value of the time a process will take to transition from a given state *j* to another state *i*, under the assumption that the process begins in state *j*. The remaining life of the component is estimated from this computation. The method of computing first-passage times is provided in [25], [26] discusses this issue from a power system reliability perspective.

3.3 Wood Poles

Wood poles form the backbone of most overhead distribution circuits. Their purpose is to keep conductors and equipment away from the public and the ground, and to maintain separation between conductors. Poles also serve as a support platform for equipment such as regulators and reclosers [14].

For most utilities, the wood pole is one of the most ubiquitous assets, and different maintenance strategies for them can result in significant cost differences. Maintenance planning can be more cost-effective if pole degradation can be predicted. Such predictive capabilities provide the ability to estimate the number of required replacements in the next budget cycle. Pole-specific prediction provides the ability to determine which poles are most likely to need replacement. If degradation information can be transformed to probabilistic failure indicators, e.g., probability of failure and time to failure, then the effect of wood pole maintenance on these indices can be evaluated. These failure indicators can then be used in system-level decision tools, such as reliability evaluation programs, to compare different maintenance-related resource allocations among regions, components, and types of maintenance. This section describes conversion of wood pole condition data gathered from the field into predictive functions and illustrates the use of these functions in developing probabilistic failure indicators.

3.3.1 Degradation Path Model Approach Basis

Wood pole failures occur as a result of physical stresses such as wind, ice, and vehicle impact. The tendency of a pole to fail under such stress is usually related to the strength of the pole at the ground line, where almost 90 percent of pole failures occur [15]. Therefore, the most useful indicator of wood pole condition is its residual strength at the ground line.

This strength is usually measured as the effective area of the cross section at the wood pole ground line. A number of approaches for doing this vary in accuracy and implementation cost. Some approaches described in the literature include acoustic [16], resistance force [17], and combining measurements of resistance force and humidity [18]. Another simple but cost-effective approach is to remove external decay and assess the internal decay pocket by drilling. This method is assumed here.

Figure 3.3 provides a flow chart of the degradation path model approach to convert such condition measurements into probabilistic failure indicators. After obtaining the condition history (1), the component degradation path model (2) is determined, and the lifetime analysis (3) is performed using the actual failure data, or the extrapolated failure data from the degradation path model. These two procedures provide the population degradation path model (4) and the age-based hazard function (5), which are then mapped point by point to get the condition-based failure rate(6), and then the time to failure and the effect of maintenance are estimated. This model is data-driven; more data and better data result in better models and ultimately better decision-making.

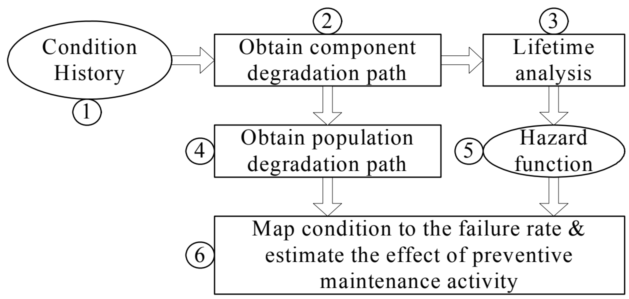

Figure 3.3: Flow chart of degradation model approach.

3.3.2 Degradation Path Model

Let $Rsg_i(t)$ represent the residual strength, in units of N/mm^2, at the ground line of wood pole i, as a function of time t. Because different poles have different initial strengths, the residual strength is normalized as

$$Lspi(t)=1-Rsgi(t)/Rsgi(0) \tag{3.8}$$

where $Lsp_i(t)$ represents the lost strength percentage for pole i at time t.

Wood poles decay continuously; therefore, $Lsp_i(t)$ is non-decreasing over time. If all poles were identical and operated under exactly the same conditions and in exactly the same environment, they would have the same degradation path. But of course, there is a degree of variability in some or all of these factors. This variability in turn causes variability in the degradation path. While different poles have different degradation paths, the general degradation path formed will be quite similar from pole to pole. The degradation-path model thus represents the degradation path of a particular wood pole over time as

$$Lspi(t)=g(t;\beta i0,\beta i1,\ldots,\beta in) \tag{3.9}$$

where $t>0$, and $\beta_{i0},\beta_{i1},\ldots,\beta_{in}$ are the time regression coefficients for pole i. In general, the form of g may be linear, polynomial, or exponential in the coefficients. Condition data from the field are used to obtain the coefficients of this degradation path model. Two kinds of nondestructive measurement data can be used in this model. The best kind involves measurements for multiple poles taken over multiple time instances. Such measurements provide the ability to obtain pole-specific degradation functions. More common, though, is the kind that involves measurements for multiple poles taken at approximately the same time, resulting in a single measurement per pole. Although such data are inferior multiple measurements, they may still be used to characterize degradation functions and, from those, to extract probabilistic failure indicators [27], [28], [29].

Degradation Leading to Failure

Loading on a wood pole varies with time as weather conditions (mainly wind and ice) change, so the model should include these conditions [27]. It is possible to use force analysis based on weather modeling to obtain a statistical load model [17], but in this report a simpler model is used. The National Electric Safety Code requires that a pole be rejected when 33 percent of its strength is lost [18]. Based on this requirement, a pole is assumed to fail when its strength falls below a given percentage of its initial strength, denoted by *fp* (failure percentage), to which a value of 33 percent is assigned.

After obtaining a group of $Lsp_i(t)$ curves, interpolation (when the poles have lost more than 33 percent of their original strength) or extrapolation is used to obtain the random variable lifetime (*LT*). The lifetime distribution cumulative function *F(t)*, and the hazard function *H(t)* can be obtained by standard statistical methods [28].

Variability in the degradation level across a pole population at a particular age *t* is best described by a distribution. This distribution is denoted as:

$$\text{Lspd(t)}\sim\text{dist}\{\text{Lspm(t), Lspe(t)}\} \tag{3.10}$$

where

*Lspd(t)*is the degradation distribution at age *t*.
Lspm(t) is the mean of the distribution at age *t*.
Lspe(t) is the standard deviation of the distribution at age *t*.

At each age *t*, the mean *Lspm(t)* is mapped to the hazard function *H(t)* for the decayed population; that is, if the lost strength percentage of pole *i* at an age *t*, $Lsp_i(t)$, equals the lost strength percentage population mean at some age t_1, $Lspm(t_1)$, then the pole *i* failure rate equals $H(t_1)$. This ensures that the condition-based failure rate can be estimated.

After the mean at every age is fit, the following expression is obtained for *Lspm(t)*:

$$\text{Lspm(t)}= \Phi(\text{t}; \alpha0, \alpha1,\ldots, \alpha\text{n}) \tag{3.11}$$

where $t>0$, and $\alpha_0, \alpha_1,\ldots, \alpha_n$ are the time regression coefficients.

The failure probability for any pole of age *t*, defined as $P(T<t)$, is given by the probability that the random variable *Lspd(t)* exceeds *fp*, according to

$$F(t)= P(T\leq t)=P(Lspd(t)>fp) \tag{3.12}$$

Effect of Preventive Maintenance

A maintenance activity on a component subject to degradation may renew the component to a less degraded state, slow the future rate of degradation, or both. For example, a wood pole may be treated by chemical material to slow decay. The effect on degradation can be quantified in the failure rate and time to failure. It is important to note that failure rate and time to failure are population averages.

The lost strength percentage before maintenance is $Lsp_i(t_c)=Lspm(t_0)\rightarrow H(t_0)$, and the lost strength percentage after maintenance is $Lsp_i(t_c)=Lspm(t_1)\rightarrow H(t_1)$. The failure rate reduction, Δh, is

$$\Delta h= H(t_1)- H(t_0) \tag{3.13}$$

and the increase in time to failure, ΔTTF, is

$$\Delta TTF= t_0 - t_1 \tag{3.14}$$

This degradation path model can be used to estimate the condition-based failure rate, failure rate reduction, and increase in time to failure. This information is highly useful in asset management decision making. These procedures are illustrated in Section 3.3.3, together with an application of budget planning and maintenance task selection.

3.3.3 Illustration

Field data consisting of age, initial strength, and one residual strength measurement per pole were obtained for a group of wood poles. The total pole population includes 13,940 poles ranging in age from 1 to 79 years with a mean age of 30 years. Measurements indicated that of the total population, 1,163 poles (8 percent) had begun to decay. These are referred to as the decayed population, ranging in age from 5 to 67 years with a mean age of 37. Figure 3.4 shows the distribution of the number of poles at each age for the decayed population.

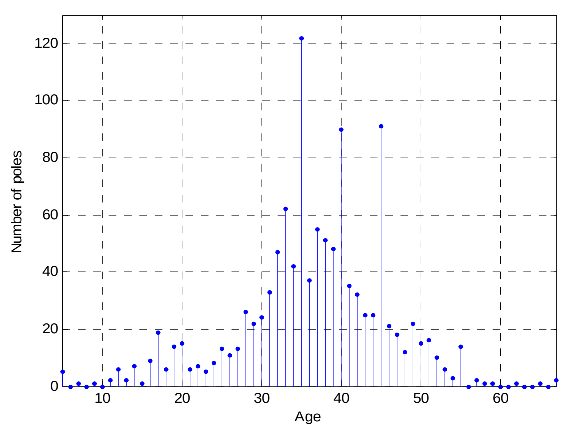

Figure 3.4: Number of poles at every age of the decayed population.

Obtaining the Degradation Path Model

Figure 3.5 plots the lost strength percentage for each pole as a function of pole age *t* for the decayed population. Each point represents a specific pole's degradation level at its given age.

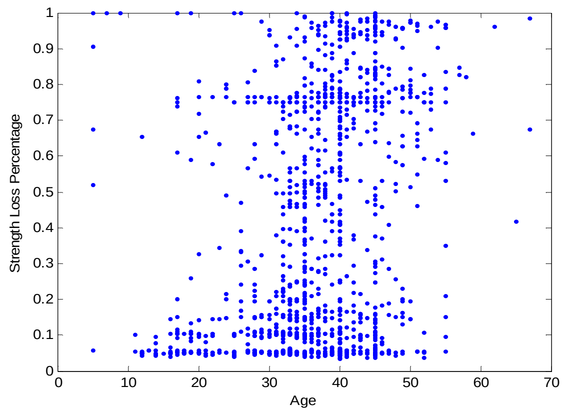

Figure 3.5: Decayed population Lspi(t) plot.

From the data illustrated in Figure 3.5, for each age, the average lost strength percentage was computed using the lost strength percentages for all poles of the given age. The resulting averages are plotted against pole age in Figure 3.6.

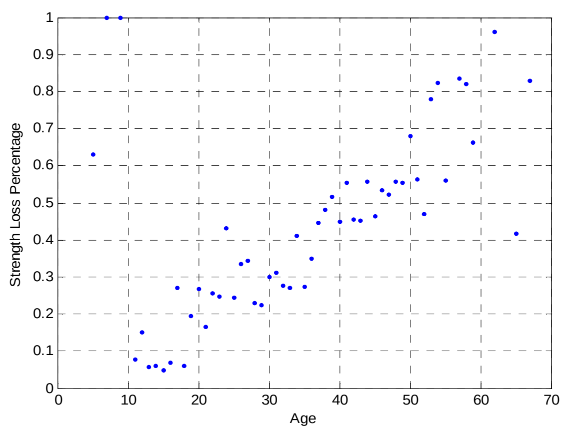

Figure 3.6 The average degradation level at every age.

Figure 3.6 indicates that the average degradation trend of the population is nearly a straight line. Therefore, as shown in equation (3.4), the degradation path for the decayed population is represented using a linear model of the lost strength percentage mean

$$Lspm(t)=a_1*t-a_2 \tag{3.15}$$

where the random variable a_1 is called the *mean strength loss rate*. After removal of several outliers, regression is used to obtain $a_1=0.014418$, and $a_2=0.10683$.

Equation (3.15) characterizes well the lost strength percentage for a pole *once it is known that the pole has begun to decay*. However, as indicated previously, the number of decayed poles is only eight percent of the total population. For very new poles, the percentage of decayed poles is expected to be significantly less than eight percent, and for very old poles, it is expected to be significantly more than eight percent. Figure 3.7 shows a plot of the percentage of decayed poles in the total population as a function of age.

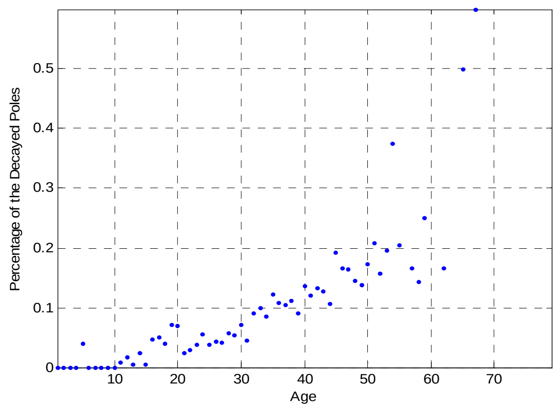

Figure 3.7: Percentage of decayed pole at every age.

Figure 3.7 indicates that the percentage of decayed poles increases almost linearly with age beginning at about ten years. Therefore, after removing several outliers, linear regression is again used to obtain a linear model of the percentage of decayed poles as a function of pole age:

$$Per(t)=0.004*t-0.04 \tag{3.16}$$

$Per(t)$ can also be interpreted as the probability of decay at age t. This information is useful for predicting the number of decayed poles in a system as a function of time.

Figure 3.4 confirms the observation from Figure 3.7 that very few poles begin deteriorating until about ten years old. We also observe from Figure 3.7 and equation (3.16) that the percentage of decayed poles grows with time, indicating that the time at which a pole actually begins to decay is a random variable. We call this random variable the *penetration age* and represent it as b. The reason the penetration age almost always exceeds ten years is due to the chemical treatment applied to each pole prior to installation. This treatment resists decay very well until it is penetrated, at which time the degradation process begins and continues from then on. By inspecting the number of poles having a minimal but non-zero level of strength loss in Figure 2.5, it can be seen that the penetration time ranges from 10 years to about 55 years. This variability is due to the quality of the pretreatment and the pole location and environment.

From Figure 3.6 and equation (3.15), the mean strength loss rate is calculated as $a_1=0.014418$. From Figure 3.7 and equation (3.16), the penetration age b is identified as a random variable. Therefore, for a given value of b, the mean lost strength percentage is expressed as a function of pole age as

$$\mathrm{Lspm}(t)=a_1\times(t-b) \tag{3.17}$$

Because there is only one measurement per pole (and the population degradation rate is used to predict the degradation of each pole), a_1 is fixed and b is a random variable. Implied is that, while the age at which decay begins is unknown, once it begins, the pole will decay at the rate of a_1.

<u>Estimation of Failure Rate</u>

The transformation of equation (3.8) and the measurements are used to interpolate or extrapolate the lifetime of the decayed pole population. After comparing several different distributions, the Weibull distribution is selected, giving a hazard function having the form

$$H(t)=(\beta/\eta)*(t/\eta)(\beta-1) \tag{3.18}$$

The parameters are determined using the maximum likelihood method [28], resulting in $\beta=4.6676$ and $\eta=50.6090$, which is shown in Figure 3.8.

To obtain the failure rate, the degradation ($Lsp_i(t)$) of the pole is measured. The 'condition age' is the age t_a, where $Lspm(t_a)=Lsp_i(t)$, and t is the actual age of the pole. $Lspm(t_a)$ is found from equation (3.15) and substituted into equation. (3.18) to get the failure rate. Failure rate reduction and time to failure increase can then be calculated using equations (3.5) and (3.6).

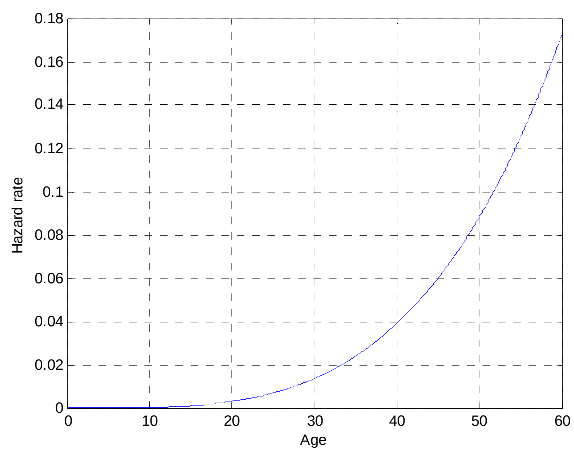

Figure 3.8: Hazard function of decayed poles.

<u>Wood Pole Asset Management Decision Making</u>

<u>Budget Planning</u>

The above information can facilitate asset management decisions for wood poles. An asset manager, in planning financial resources for the next year, must answer the following two questions: How many poles need to be replaced? How many poles need to be treated?

To predict the failed number of poles and thus the number of poles to replace, the strength loss rate a_1 is used to estimate the degradation level of the decayed pole in the future. For example, if a pole i has $Lsp_i=0.3$, it is estimated to reach a strength loss reduction of 0.33 (and therefore fail) within (0.33-0.3)/0.014418 = 2.08 years.

To predict failure times for poles not yet decaying, the randomness at which healthy poles join the decayed population must be accounted for. Equation (3.16) predicts the number of decayed poles. The age distribution of the poles moves forward along the age-axis in the next year, meaning more poles are decaying at that time. Table 3.5 presented the decayed pole percentage, expected number of failed poles, expected number of poles needing chemical treatment for future years 2006 and 2015, and the condition history of 2005, the current year. This data, together with replacement and treatment costs, facilitate development of condition-driven budgets by the asset manager.

Table 3.5: Population predictions

Year	Decayed Pole Percentage	Failed Number of Poles*	Poles Need Treatment
2005	8.156%	541	622
2006	8.479%	549	633
2015	12.012%	644	1030

* Failure does not imply that the pole falls but rather, as defined in Section 3.1, that the strength loss reduction percentage exceeds 33 percent.

Maintenance Tasks Selection

Budget constraints often require asset managers to prioritize maintenance tasks. Useful indicators in this process for poles are the lost strength percentage, condition age, and failure rate of each pole. Table 3.6 provides this information together with the actual age for four selected poles. It is interesting that poles 3 and 4, although nearly the same age, have significantly different condition ages and corresponding failure rates.

Table 3.6: Estimate of failure rate

Pole	Age	$Lsp_i(age)$	Condition Age (years)	Failure Rate (failures/year)
1	10	0	0	0
2	17	0.1025	14.5	0.001
3	39	0.0615	11.7	0.0004
4	42	0.2929	27.7	0.01

Similarly, the effect of maintenance can be estimated. Replacement is assumed to entirely renew the pole, whereas treatment delays further decay by five years but does not improve the condition of the pole. Therefore, both actions result in an increase in time-to-failure, but the effects on failure rate of the two actions are different; while replacement causes immediate failure rate reduction, the failure rate reduction from treatment is not incurred until the next and following years when the treated pole's failure rate remains fixed but the untreated pole's failure rate continues to increase.

For poles without decay in the current year, equation (3.9) is used to estimate the probability of decay in the next year. For example, for pole 1, which is ten years old without decay, the next year's failure rate is $Per(11)*H(1)=0.004*5.2*10^{-8}=2*10^{-10}$, and its time to failure increase is $Per(11)*5=0.004*5=0.02$. For this pole, replacement and treatment have the same effect, because this pole is in good condition to start. For decayed poles, such as pole 2, replacement will renew the pole, so the failure rate reduction is $H(14.5)=0.01$, and the increase in time to failure is its condition age of 14.5

years. Treatment will stop the decay, and the failure rate reduction seen in the next year is *H(15.5)-H(14.5)=0.000*; the increase in time to failure is 5. These procedures were applied to poles 1 through 4, with results summarized in Table 3.7. The results are reasonable: maintenance activities on healthy poles have almost no effect but result in significant benefit on the most decayed poles.

Table 3.7: Estimate of maintenance effect

Pole	Age	Failure Rate Reduction (failures/year)		Time to Failure Increase (years)	
		replace	treatment (per year)	replace	treatment
1	10	$2*10^{-10}$	$2*10^{-10}$	0.02	0.02
2	17	0.01	0.0003	14.5	5
3	39	0.0004	0.00015	11.7	5
4	42	0.01	0.0014	27.7	5

In selecting maintenance tasks, an asset manager should consider not only the effect on failure rate and time to failure but also the consequences of failure in terms of the effect of each candidate maintenance task on system reliability indices such as SAIDI and SAIFI. A risk-based approach has been developed to address this issue [30].

4 Reliability Evaluation for Distribution Systems

The objective of this chapter is to describe the development of a predictive reliability assessment tool that computes the reliability indices of a system and estimates the risk reduction associated with maintaining each component in the system. The tool, whose user manual in Appendix B, is used to determine the relative importance of each component and prioritize maintenance resource allocation. Section 4.1 defines the various parameters used to describe the reliability of distribution system equipment. A description of the various components modeled in the analysis is provided in Section 4.2. Section 4.3 describes the different states associated with protective and switching equipment in response to a sustained or permanent fault, while Section 4.4 describes the algorithm used for analytical reliability evaluation. Section 4.5 describes a Monte Carlo integration method to compute the risk associated with regulatory penalties imposed due to violations of SAIFI and SAIDI limits.

4.1 Parameters Used in Reliability Modeling of Distribution System Equipment

The various components modeled in the distribution system include overhead and underground line segments, protective devices (fuses, reclosers, circuit breakers, sectionalizers) that operate when a fault occurs, and switching devices that are used to reconfigure the system after the fault is cleared. In order to develop a predictive reliability analysis method, mathematical equivalents for each component in the system are required to represent their failure and repair characteristics. Since the indices used to compute the risk reduction are associated with the effects of sustained or permanent faults, temporary faults are excluded from the analysis. The following is a list of parameters used to describe the reliability of distribution system equipment [1], [32].

4.1.1 Permanent Failure Rate (λ_p)

The permanent failure rate is a measure of the expected number of sustained or permanent outages of a component in a fixed duration of time, usually one year. Permanent faults require operating protective devices to clear them. Customers downstream of the protective devices are interrupted and experience an outage duration equivalent to the time taken to repair the fault, or determined by the switching and sectionalizing actions done after the fault is interrupted.

4.1.2 Mean Time to Repair (MTTR)

The mean time to repair (MTTR) a component is the expected time required to repair a permanent fault occurring on the component. It includes the time it takes to identify the failed component, travel to the fault location, isolate the fault, and carry out repairs before service is restored. The MTTR for protective and switching devices, however, is the expected duration of repair for a component that fails to operate in response to a fault.

4.1.3 Protection Reliability (PR)

Protection reliability (PR) of a protective device is the conditional probability that the protective device will operate to clear a fault. In other words, it is the probability of successful operation contingent on a fault occurring. Thus, it is a quantity between zero and one, where the value of one represents 100 percent successful operation upon the occurrence of a fault. Failure to operate may arise from mechanical breakdown or improper settings.

4.1.4 Reclose Reliability (RR)

Reclosers have the ability to repeat open/close actions during a fault. These actions allow time for temporary faults to clear, thus avoiding long outages, and results in reclosers failing in two mutually exclusive modes: failure to open and failure to close. Both are conditional on a fault occurring downstream of the recloser. Reclose reliability (RR) is the probability that a recloser will successfully reclose after it successfully opens in response to a fault.

Failure to open and failure to close are the modes of failure on demand. Protective devices can also fail due to inadvertent operation [33] when there is no fault, but this is not considered here. Inadvertent operation is usually due to a problem in device coordination and is comparatively rare.

4.1.5 Switching Reliability (SR)

Also called the probability of successful switching, the switching reliability (SR) parameter defines the conditional probability that a switching action takes place successfully as a part of the fault isolation scheme. Switching actions may not occur because of mechanical failures, inability to locate a switch, failure of a crew to operate a switch, or conditions such as overloading of feeders. Thus, SR is the probability that switching is performed based on the occurrence of a fault whose MTTR is greater than the time taken to perform the switching operations.

4.1.6 Mean Time to Switch (MTTS)

Mean time to switch (MTTS) represents the average time to operate a switch and isolate a faulted area. This includes both the time to identify the faulted area and the time to operate the switch. In the case of manually operated switches, it also includes the time taken to travel to the switch's location.

4.1.7 Probability of Failure (PF)

In order to compute the reliability metrics for protective and switching devices like fuses, reclosers, and switches, the average number of times the device was expected to operate and the number of times it was successful are required. Since such data may not be available, because such records often are not maintained, device parameters like protection reliability, reclose reliability, and switching reliability may be approximated from the available data.

An approximate value for a devices' probability of failure (PF) is estimated by using the ratio of the number of failures of a particular type of device to its number of operations. Thus, a device's probably of PF may be defined as

$$PF = \frac{Number\ of\ device\ failures}{Total\ number\ of\ device\ operations} \quad (4.1)$$

The total number of device operations in equation (4.1) includes the number of times the device successfully operated and the number of times it failed. Using this failure probability, the reliability metrics for various protective and switching devices can be estimated. In the case of fuses, sectionalizers, and substation breakers, whose primary mode of failure is failure to open, PR is simply the complement of PF, as shown in equation (4.2). A similar expression can be used compute the switching reliability of switches, as shown in equation (4.3).

$$PR = 1 - PF \quad (4.2)$$

$$SR = 1 - PF \quad (4.3)$$

Special consideration needs to be given to reclosers. Since these devices have more than one mode of failure, both the protection reliability and reclose reliability must be computed. If data distinguishing the failure modes is not available, PR and RR can be estimated by using PF. If 'A' is the event that the recloser fails to open in the event of a fault, and 'B' is the event that the recloser fails to reclose, then a recloser has four different states of operation:

$\overline{A}$: Recloser opens when a fault occurs, with a probability of $P(\overline{A}) = PR$ (4.4)

A : Recloser fails to open when a fault occurs, with a probability of

$P(A) = 1 - PR$ (4.5)

$\overline{B}|\overline{A}$: Recloser successfully recloses after opening on a fault, with a probability

of $P(\overline{B}|\overline{A}) = RR$ (4.6)

$B|\overline{A}$: Recloser fails to reclose after clearing a fault, with a probability of

$P(B|\overline{A}) = 1 - RR$ (4.7)

The events described by equations (4.6) and (4.7) depend on the successful opening of a recloser during a fault. From the four possible states of a recloser, it can be observed that those represented by equations (4.5) and (4.7) correspond to recloser failures. Since these are mutually exclusive (a recloser can either fail to open or fail to reclose once opened, but not both), the total probability of recloser failure can be written as

$$PF = P(A) + P(B \cap \overline{A}) \quad (4.8)$$

This can be further simplified as

$$PF = P(A) + P(B|\overline{A}) * P(\overline{A}) = (1 - PR) + (1 - RR) * PR \quad (4.9)$$

Assuming the probability a recloser opens in response to a fault is equal to the probability that it recloses after clearing a fault (PR = RR), and rearranging the above expression, the values of protection reliability and reclose reliability can be obtained as

$$PR = RR = \sqrt{1 - PF} \tag{4.10}$$

4.2 Models Used in the Program

The parameters defined in Section 4.1 are now used in this section to describe the reliability characteristics of distribution system components.

4.2.1 Overhead Line and Underground Cable Segments

Overhead lines and underground cables are modeled as repairable systems. Faults occur on segments that are isolated by protective and switching devices before carrying out repairs. The parameters used to describe segments are as follows: permanent failure rate per mile (λ_p), mean time to repair a fault (MTTR), average cost per failure (COF), which is the cost of repair that results from a failure, and length of the segment.

4.2.2 Fuses, Reclosers, and Breakers

Protective devices are assumed to be located at the upstream node of a segment and are normally closed. Fuses, reclosers, breakers, and sectionalizers are modeled using their probability of failure, protection reliability, reclose reliability, and MTTR.

4.2.3 Switches

Switches are used to reconfigure a system after a fault is interrupted. Normally closed (NC) switches are located at the source, or upstream, node of a segment. Normally open (NO) switches are located on the load, or downstream, node of a segment. Switches cannot interrupt fault currents, so their PR is set to zero.

Switches are modeled by switching reliability and mean time to switch. When a fault occurs, the upstream protective device responds to interrupt the fault. If there were no switches between the faulted segment and the upstream device, the time of outage for all customers downstream of the device is the MTTR of the faulted segment. However, if there is a switch between the faulted segment and the device, it may be beneficial to operate the switch, so that the interrupting device can be reset to restore service to some customers. Switching in this case requires two operations:

- Open the upstream switch nearest to the faulted segment, with a time of MTTS_{swi}.
- Close the previously open device, with a time of MTTS_{dev} for that device.

The total time to complete this sequence is estimated as

$$\mathrm{MTTS}_{\mathrm{seq}} = \mathrm{MTTS}_{\mathrm{swi}} + \left| MTTS_{swi} - MTTS_{dev} \right| \tag{4.11}$$

This equation assumes that all switch and device MTTS values represent base-to-station travel time, so $|\mathrm{MTTS}_{swi} - \mathrm{MTTS}_{dev}|$ is the travel time between the switch and the protective device.

The switching reliability of the protective device represents the probability that the device will actually be reset when desired. A value other than 1 means overloading and mechanical failures.

4.2.4 Sectionalizers

Sectionalizers are used in conjunction with an upstream recloser in cases where fast switching to restore load is required. When a fault occurs, the upstream recloser opens and recloses, allowing sufficient time for the fault to clear. After a predefined number of such operations, the recloser remains open long enough for the sectionalizer to open and then reclose again. This allows customers between the sectionalizer and recloser to avoid a sustained outage. Sectionalizers are modeled using PR, MTTR, MTTS, and SR.

4.2.5 Equivalent Component

In addition to the failures of overhead lines, underground cables and protective equipment, outages also occur for many other reasons, including the following:

a. Transmission outages.
b. Public acts, such as accidents, vandalism, and accidental dig-ins.
c. Failure of other equipment, including lightning arrestors, capacitor banks, transformers, and many others.
d. Utility errors.

Since it would be inappropriate to attribute such outages to any of the equipment listed in subsections 4.2.1 to 4.2.4, they are represented as a separate component with characteristics equivalent to the components and failure modes that are not modeled. This equivalent component will be included at the beginning of every feeder. It represents the combined effects of all other outage causes. Similar to an overhead or underground line segment, the equivalent component is modeled using permanent failure rate (λ_p) and MTTR.

4.3 System Response to Outages

When an outage occurs in a distribution system, the system transitions into one or more states based on events that happen after the outage. This begins with the nearest upstream protective device sensing a fault and operating to isolate it. After a crew is dispatched to repair the fault, the nearest switch upstream of the fault is opened by the crew. This isolates the fewest possible customers while the rest are restored by reclosing the protective device. Further restoration is possible by opening switches downstream of the fault and closing tie switches to connect the isolated region to another feeder or another region of the same feeder. Once the failed equipment is repaired, the system returns to its original state and remains there until the next fault.

In this section, the response of protective and switching devices to a sustained fault are described along with their equivalent models.

4.3.1 Circuit Breaker

A circuit breaker is described by its protection reliability, mean time to repair ($MTTR_B$), switching reliability, and mean time to switch. For a fault with failure rate (λ) occurring downstream of the breaker, its probability of operating successfully and clearing the fault is PR. The repair time of the faulted segment is MTTR, so all the customers downstream of the breaker experience an outage with frequency (PR * λ) and duration of MTTR.

If the breaker fails to operate, the next upstream protective device is expected to operate and clear the fault. The number of customers interrupted is determined by the upstream device. The frequency of such events is given by (1-PR)* λ, and the duration of interruption is $MTTR+MTTR_B$. The probability of the upstream device failing will be neglected in this analysis because the probability of multiple breaker failures is very low. If L_P and L_S refer to the load interrupted when the primary and the secondary (backup) protection device operate, the outcomes of the two states are shown in Table 4.1.

Table 4.1: Protection response of circuit breaker

Circuit breaker successfully clears a fault with failure rate (λ) and repair time (MTTR)	
Frequency	PR * λ
Duration	MTTR
Customers interrupted	Downstream of breaker
Expected cost of failure	PR * λ * COF, where COF is cost of outage on faulted line segment
Expected energy interrupted	PR * λ * MTTR * L_P
Circuit breaker fails to clear a fault with failure rate (λ) and repair time (MTTR)	
Frequency	(1-PR)* λ
Duration	$(MTTR+MTTR_B)$
Customers interrupted	Downstream of backup (next upstream) protective device
Expected cost of failure	(1 - PR) * λ * (COF + COF_D), where COF_D is cost associated with breaker failure
Expected energy interrupted	(1 - PR) * λ * (MTTR + $MTTR_B$) * L_S

4.3.2 Fuse with No Upstream Recloser

A fuse that is not coordinated with an upstream recloser responds like a breaker to a sustained fault. Hence, the states shown in Table 4.2 apply to a fuse.

Table 4.2: Protection response of fuse

Fuse successfully clears a fault with failure rate (λ) and repair time (MTTR)	
Frequency	PR * λ
Duration	MTTR
Customers interrupted	Downstream of fuse
Expected cost of failure	PR * λ * COF, where COF is cost of outage on faulted line segment
Expected energy interrupted	PR * λ * MTTR * L_P
Fuse fails to clear a fault with failure rate (λ) and repair time (MTTR)	
Frequency	(1 - PR) * λ
Duration	(MTTR + $MTTR_F$), where $MTTR_F$ is average repair time for a fuse
Customers interrupted	Downstream of backup protective device
Expected cost of failure	(1 - PR) * λ * (COF + COF_D), where COF_D is cost associated with fuse failure
Expected energy interrupted	(1 - PR) * λ * (MTTR + $MTTR_F$) * L_S

4.3.3 Recloser

As a primary protective device, a recloser's response to a sustained fault is similar to that of a breaker. In the event of a permanent fault, the recloser is expected to open and lockout. Recloser failure occurs when the recloser fails to open during a fault. For a downstream fault with failure rate (λ) and repair time (MTTR), the states shown in Table 4.3 occur for a recloser with protection reliability (PR) and repair time ($MTTR_R$).

Table 4.3: Protection response of recloser

Recloser successfully clears a fault with failure rate (λ) and repair time (MTTR)	
Frequency	PR * λ
Duration	MTTR
Customers interrupted	Downstream of recloser
Expected cost of failure	PR * λ * COF, where COF is cost of outage on faulted line segment
Expected energy interrupted	PR * λ * MTTR * L_P
Recloser fails to clear a fault with failure rate (λ) and repair time (MTTR)	
Frequency	(1 - PR) * λ
Duration	(MTTR + $MTTR_R$)
Customers interrupted	Downstream of backup protective device
Expected cost of failure	(1 - PR) * λ * (COF + COF_D), where COF_D is cost associated with recloser failure
Expected energy interrupted	(1 - PR) * λ * (MTTR + $MTTR_R$) * L_S

4.3.4 Fuse with Upstream Recloser

Fuses are coordinated with upstream reclosers to allow temporary faults to clear by opening and reclosing, thus saving the fuse. The fuse is described by its protection reliability (PR_F) and repair time ($MTTR_F$), and the recloser is described by its protection reliability (PR_R), reclose reliability (RR_R), and repair time ($MTTR_R$). For a permanent fault downstream from the fuse, with fault failure rate λ and repair time MTTR, the following mutually exclusive events can occur:

a. Recloser opens and recloses, and the fuse opens, causing an outage to customers downstream of the fuse. The frequency of such a situation is given by (PR_F* RR_R * PR_R * λ), and the duration of interruption is MTTR.
b. Recloser opens and recloses, but the fuse fails to open. The recloser locks out, interrupting customers downstream of the recloser. The frequency of such a situation is given by ((1 - PR_F) * RR_R * PR_R^2 * λ), and the duration of the interruption is (MTTR + $MTTR_F$).
c. Recloser opens and recloses, the fuse fails to open, and the recloser fails to open, causing the fault to be interrupted by the next device upstream of the recloser and interruptions to all customers downstream of that device. The frequency of occurrence of this event is ((1 - PR_R)*(1 - PR_F) * RR_R * PR_R * λ), and the duration of interruption is (MTTR + $MTTR_F$ + $MTTR_R$). The probability of this event, however, is very low and will be neglected in this analysis.
d. Recloser opens but fails to reclose, causing interruptions to customers downstream of the recloser. The frequency of this event is ((1 - RR_R) * PR_R * λ), with an outage duration of (MTTR + $MTTR_R$).
e. Recloser fails to open and the fuse opens, interrupting customers downstream of the fuse. The frequency of the event is given by: (PR_F * (1 - PR_R) * λ), while the duration of outage experienced by the customers downstream of the fuse is MTTR. This is an event when the failure of the recloser goes unnoticed since the fuse successfully operates to clear the fault. It must be included in the analysis, however, to completely describe the coordinated fuse/recloser combination.

f. Recloser fails to open, and the fuse fails to open, resulting in the fault being cleared by the next device upstream of the recloser. The frequency of this occurrence is given by $((1 - PR_F) * (1 - PR_R) * \lambda)$, which is a very low and will be neglected in this analysis. The interruption duration is $(MTTR+MTTR_F+MTTR_R)$.

These six states completely describe a fuse coordinated with a recloser when a sustained fault occurs downstream of the fuse. These events are summarized in Table 4.4.

Table 4.4: Protection response of fuse with upstream recloser

Recloser opens and recloses, and fuse clears the fault with failure rate (λ) and repair time (MTTR)	
Frequency	$(PR_R*RR_R*PR_F*\lambda)$
Duration	MTTR
Customers interrupted	Downstream of fuse
Expected cost of failure	$PR_F*RR_R*PR_R*\lambda*COF$ (COF is cost of outage on faulted line segment)
Expected energy interrupted	$PR_F*RR_R*PR_R*\lambda*MTTR*L_P$ (L_p is load downstream of fuse)
Recloser opens and recloses, fuse fails to clear the fault, and recloser opens to clear the fault with failure rate (λ) and repair time (MTTR)	
Frequency	$((1-PR_F)*RR_R*PR_R^2*\lambda)$
Duration	$(MTTR+MTTR_F)$
Customers interrupted	Downstream of recloser
Expected cost of failure	$((1-PR_F)*RR_R*PR_R^2*\lambda)*(COF+COF_D)$, where COF_D is cost associated with failed fuse.
Expected energy interrupted	$((1-PR_F)*RR_R*PR_R^2*\lambda)*(MTTR+MTTR_F)*L_S$, where L_S is load downstream of recloser.
Recloser opens and recloses, fuse fails to open, and recloser fails to open to clear the fault; this event is not modeled due to very low probability	
Recloser opens but fails to reclose, causing outage to all downstream customers	
Frequency	$((1-RR_R)*PR_R*\lambda)$
Duration	$(MTTR + MTTR_R)$
Customers interrupted	Downstream of recloser
Expected cost of failure	$((1-RR_R)*PR_R*\lambda)*(COF+COF_D)$, where COF_D is cost associated with failed recloser.
Expected energy interrupted	$((1-RR_R)*PR_R*\lambda)*(MTTR+MTTR_R)*L_S$, where L_S is load downstream of recloser
Recloser fails to open in response to the fault, and fuse opens to clear the fault	
Frequency	$(PR_F*(1-PR_R)*\lambda)$
Duration	MTTR
Customers interrupted	Downstream of fuse
Expected cost of failure	$(PR_F*(1-PR_R)*\lambda)*(COF)$
Expected energy interrupted	$(PR_F*(1-PR_R)*\lambda)*(MTTR)*L_P$, where L_P is load downstream of fuse
Recloser fails to open and fuse fails to open; this event is not modeled due to very low probability	

4.3.5 Sectionalizer with Upstream Recloser

Sectionalizers are switches that are coordinated with an upstream recloser. In response to a sustained fault, they open while the recloser is open to isolate the fault. If the sectionalizer fails to open, the coordinated recloser opens again, locking out to isolate the fault. A sectionalizer is described by its protection reliability (PR_S) and repair time ($MTTR_S$). When a permanent fault with failure rate (λ) and repair time (MTTR) occurs downstream of the sectionalizer, the following mutually exclusive events can happen:

a. Recloser opens to clear the fault and sectionalizer opens to isolate the faulted segment. The frequency of such an event is (PR_R * PR_S * RR_R * λ), with an outage duration of MTTR to the customers downstream of the sectionalizer.
b. Recloser opens, but the sectionalizer fails to open. The recloser opens and locks out, interrupting customers downstream of the recloser. The frequency of such an event is ((PR_R)^2 * (1-PR_S) * λ) with an outage duration of (MTTR+ $MTTR_S$).
c. Recloser opens and sectionalizer opens, but the recloser fails to reclose, causing sustained interruptions to all customers downstream of the recloser. The frequency of this event is: (PR_R * PR_S * (1 - RR_R) * λ), with interruption duration of (MTTR + $MTTR_R$).
d. Recloser opens but sectionalizer fails to open. The recloser then recloses and fails to open again. The fault is interrupted by the backup protection device upstream of the recloser. This event has a very low frequency of occurrence
e. ((1 - PR_R) * (1 - PR_S) * PR_R * λ), and is neglected in this analysis. The duration of interruption for this event is (MTTR + $MTTR_S$ + $MTTR_R$).
f. Recloser fails to open, so the fault is cleared by the backup protective device. All customers downstream of the backup device are interrupted. The frequency of this event is ((1 - PR_R) * λ), while the duration of interruption is MTTR + $MTTR_R$.

Table 4.5: Protection response of sectionalizer with upstream recloser

Recloser opens, sectionalizer opens to isolate the fault, and recloser recloses	
Frequency	$(PR_R * PR_S * RR_R * \lambda)$
Duration	MTTR
Customers interrupted	Downstream of sectionalizer
Expected cost of failure	$(PR_R * PR_S * RR_R * \lambda) * COF$ (COF is cost of outage on faulted line segment)
Expected energy interrupted	$(PR_R * PR_S * RR_R * \lambda) * MTTR * L_P$ (L_p is load downstream of sectionalizer)
Recloser opens, sectionalizer fails to open, and recloser opens again and locks out to clear the fault	
Frequency	$((1-PR_S) * PR_R^2 * \lambda)$
Duration	$(MTTR+MTTR_S)$
Customers interrupted	Downstream of recloser
Expected cost of failure	$((1-PR_S) * PR_R^2 * \lambda) * (COF+COF_D)$, where COF_D is cost associated with failed sectionalizer
Expected energy interrupted	$(((1-PR_S) * PR_R^2 * \lambda) * (MTTR+MTTR_S) * L_S$, where L_S is load downstream of recloser
Recloser opens, sectionalizer fails to open, and recloser fails to open again to clear the fault. This event is not modeled due to very low probability	
Recloser opens, sectionalizer opens to isolate the fault, but recloser fails to reclose, causing outage to all downstream customers	
Frequency	$((1-RR_R) * PR_S * PR_R * \lambda)$
Duration	$(MTTR + MTTR_R)$
Customers interrupted	Downstream of recloser
Expected cost of failure	$((1-RR_R) * PR_S * PR_R * \lambda) * (COF+COF_D)$, where COF_D is cost associated with failed recloser
Expected energy interrupted	$((1-RR_R) * PR_S * PR_R * \lambda) * (MTTR+MTTR_R) * L_S$, where L_S is load downstream of recloser
Recloser fails to open	
Frequency	$(1-PR_R) * \lambda$
Duration	$MTTR+MTTR_R$, where $MTTR_R$ is recloser's expected repair time
Customers interrupted	Downstream of backup protection device
Expected cost of failure	$((1-PR_R) * \lambda) * (COF+COF_D)$, where COF_D is failure cost associated with failed recloser
Expected energy interrupted	$((1-PR_R) * \lambda) * (MTTR+ MTTR_R) * L_T$, where L_T is load downstream of backup device

4.3.6 Switching

After these devices operate, distribution circuits are switched to isolate the faulted portion of the system and restore power to as many customers as possible in the shortest possible time. In the previous sections, protective devices and their fault responses were modeled. In this section, two such switching modes are modeled: upstream isolation and backfeeding, or downstream, isolation.

4.3.6.1 Upstream Isolation

In an upstream isolation scheme, the upstream switch nearest to the fault is opened after the fault is interrupted. The interrupting device is then reset (closed). This reduces the outage duration to those customers between the switch and interrupting device. If there is no upstream switch, or if it is not opened, all customers downstream of the interrupting device will experience an outage duration equal to the time taken to repair the fault. If SR_D and SR_S are the switching reliabilities of the device that interrupted the fault and the upstream switch operated to isolate the faulted area, respectively, then $SR_{seq}= SR_D * SR_S$ represents the switching reliability of the switching sequence. The equivalent switching time required to open the switch and close the protective device is as follows:

$$\mathrm{MTTS}_{\mathrm{seq}} = \mathrm{MTTS}_{\mathrm{swi}} + \left| MTTS_{swi} - MTTS_{dev} \right|$$

The customers that are restored by switching experience an equivalent outage duration given by

$$MOT_{seq} = SR_{seq} * MTTS_{seq} + (1 - SR_{seq}) * MTTR\ hours$$

where MTTR is the time taken to repair the fault. Table 4.6 describes the states associated with upstream switching done after a sustained fault.

Table 4.6: Switching response for upstream isolation

Switching sequence is successful	
Frequency	$SR_{seq}\lambda$
Interruption duration for customers downstream of switch	MTTR
Interruption duration for customers downstream of protective device and upstream of switch	$MTTS_{seq}$
Expected energy restored (switching restores some of load that was interrupted by the protective device)	$\lambda * SR_{seq} * MTTS_{seq} * L_{swi}$, where L_{swi} is load restored by switching
Switching sequence fails	
Frequency	$(1-SR_{seq})\ \lambda$
Interruption duration for customers downstream of switch	MTTR
Interruption duration for customers downstream of protective device and upstream of switch	MTTR
Expected energy restored	None

4.3.6.2 Backfeeding

Another method of reducing the outage duration experienced by customers during a sustained interruption is through backfeeding. Normally open switches are closed, while normally closed switches are opened, to provide alternative paths for service to customers. Thus, when a sustained outage occurs, the nearest NC switch downstream of the fault is opened, and an NO switch located further downstream of the circuit is closed, restoring power to the segments in between the switch pair. NO switches may connect to other parts of the faulted feeder or to an adjacent feeder when closed. The expressions for the expected outage duration and energy restored are similar to those for upstream switching.

If SR_{NO} and SR_{NC} are the switching reliabilities of the NO switch that is closed and the NC switch that is opened, respectively, then $SR_{seq}= SR_{NC}*SR_{NO}$ represents the switching reliability of the sequence to restore service to customers downstream of the NC switch,. The equivalent switching time is

$$\mathrm{MTTS}_{\mathrm{seq}} = \mathrm{MTTS}_{\mathrm{NC}} + \left| MTTS_{NC} - MTTS_{NO} \right|$$

The outage duration for restored customers is

$$MOT_{seq} = SR_{seq} * MTTS_{seq} + (1 - SR_{seq}) * MTTR\, hours$$

where MTTR is the time to repair the fault. Table 4.7 describes the states associated with downstream switching done after a sustained fault.

Table 4.7: Switching response for downstream isolation

Switching sequence is successful	
Frequency	$SR_{seq}\lambda$
Interruption duration for customers upstream of NC switch	MTTR
Interruption duration for customers restored downstream of NC switch	$MTTS_{seq}$
Expected energy restored (switching restores some load interrupted by protective device)	$\lambda * SR_{seq} * MTTS_{seq} * L_{swi}$, where L_{swi} is load restored by switching
Switching sequence fails	
Frequency	$(1-SR_{seq})\,\lambda$
Interruption duration for customers upstream of NC switch	MTTR
Interruption duration for customers downstream of NC switch	MTTR
Expected energy restored	None

4.4 Analytical Reliability Evaluation

Analytical evaluation of reliability is a predictive method in which each contingency is simulated, and its effect on each of component in the system is determined and weighted by the probability of the contingency. This gives the expected (average) values for the frequency and duration of outages caused by each contingency. The expected cost of equipment failure and expected energy not served are also computed, as required by the formulation for risk reduction of Section 1.3.1.

An enumerative analysis algorithm, in which the failure consequences of each component are weighted by its failure probability, is used to compute system reliability indices. The following is a brief description of the algorithm:

a. For a feeder, determine the protective and switching device locations, and the number of customers and load interrupted when each operates in response to a fault.
b. Select a contingency and evaluate its outage effects (number of customers interrupted, duration of interruption, energy not served, and cost of the failure) on the feeder by determining the following:
   (1) The device that interrupts the fault.
   (2) Switching actions that reconfigure the feeder and restore some customers.
c. Weight the outage effects of the contingency by the probability of its occurrence and update the outage effects on the feeder.
d. If the component failed is an overhead line segment or a recloser, determine its sensitivity to maintenance by the following:
   (1) For a line segment, recompute the number of customers affected, customer hours interrupted, energy not served and cost of failure using the failure rate of the overhead line segment under consideration after maintenance.
   (2) For a recloser, determine the same quantities for reduced failure probabilities or improved PR and RR due to maintenance.

The difference in the outage effects before and after maintenance can then be used to determine the risk reduction associated with maintenance.

e. Repeat steps 2 to 4 until all contingencies have been simulated.

In step 4, the change in reliability indices for reclosers and wood poles is performed for every component on the system, thus identifying the risk reduction for every recloser and wood pole on the feeder. Vegetation maintenance is assumed to be done on an entire feeder, so the risk reduction for vegetation growth is computed for the entire feeder.

Maintenance performed on a pole influences the failure rate of the overhead line segment it supports. Hence, the risk reduction due to maintenance on a particular pole is determined by the sensitivity of the reliability indices to maintenance on the corresponding segment. Reliability indices are linearly dependent on the failure rate of the pole, so sensitivities can be computed using the difference in indices before and after maintenance.

It can also be shown that the reliability indices of a feeder change linearly with respect to the vegetation-related failure rate of the feeder. If the failure rate of all overhead line segments is changed by the same proportion, which corresponds to the failure rate reduction due to vegetation maintenance, then the change in reliability indices can be predicted using a linear relationship.

For a recloser, however, two parameters quantify its reliability [34]: protection reliability and reclose reliability. Furthermore, a recloser may have to function in one or more of the following ways during a sustained fault:

a. As a primary protective device in the event of a fault occurring directly downstream,
b. In conjunction with a downstream fuse for a fault downstream of the fuse.
c. In conjunction with a sectionalizer, interrupting the fault and then reclosing after the sectionalizer opens.

The reliability indices are not linearly related to PR and RR, and can be deduced from expressions in Table 4.3, Table 4.4, and Table 4.5. The reliability indices, however, can be approximated with less than 5 percent error, as varying linearly, by assuming that the recloser's PR and RR are equal.

If reliability indices vary linearly with failure rates, the risk reduction associated with maintaining each component can be obtained by computing the reliability indices before and after maintenance.

4.5 Regulatory Penalty Risk Evaluation

The definition of risk in Section 1.3.1 includes regulatory penalties. A method to determine the regulatory penalty risk associated with the failure of a component is described here.

The computation of regulatory risk uses information obtained from the analytical evaluation. The reliability indices, SAIDI and SAIFI, and the failure rates, computed before and after maintenance of a component, are used as inputs. Because the indices are assumed to be linear, the equations of the straight lines for SAIFI and SAIDI as a function of the component failure rate can be determined.

For wood poles and vegetation, a vector of random numbers 'u_n' is created in which 'n' represents the number of years the simulation is carried out. Assuming a Poisson distribution for the number of times a component fails in a given year, the number of failures in each of the 'n' years can be determined by solving equation (4.12), where x(i) is the number of failures in year 'i':

$$u_n(i) = \frac{\lambda^{x(i)} e^{-\lambda}}{x(i)!} \tag{4.12}$$

By using the number of times the component fails in a particular year, instead of its failure rate, SAIFI and SAIDI can be computed using the linear relationships between the indices and the failure rate of the component. Thus, for a set of random numbers drawn for a component, the number of times it fails each year and the corresponding SAIFI(k) and SAIDI(k) indices for each of the years can be determined. Since the numbers drawn are random, SAIFI(k) and SAIDI(k) are also random. Similarly, random variations of SAIFI(k) and SAIDI(k) can be determined using the failure rate of the component after maintenance. Since SAIFI(k) and SAIDI(k) are randomly distributed with unknown distributions, statistical methods can be used to suitably fit parametric equations that represent their distributions. But this is a cumbersome process and not an attractive solution, especially if the number of components is very large. If there are *m* components in a system, *4m* curve-fitting procedures (for SAIFI and SAIDI, before and after maintenance) would be needed to evaluate the expected risk.

Using the Monte Carlo integration [35] instead, the complex integral defined in equation (3.11) can be reduced to a more convenient summation, as shown in equation (4.13).

$$\begin{aligned} PBRF(k) &= \int_{T_F}^{\infty} PBR(SAIFI).f(SAIFI(k))d(SAIFI(k)) \\ &\approx \frac{1}{n}\sum_{i=1}^{n} PBR(SAIFI(x_k(i)) \end{aligned} \tag{4.13}$$

A similar expression can be developed for SAIDI.

These expressions are evaluated for each component before and after maintenance to determine the reduction in regulatory penalty risk obtained by maintaining each component. To draw a comparison between the curve-fitting method proposed in the literature [11] and this Monte Carlo integration, the lognormal distribution is used as suggested in [11]. However, the distributions were highly skewed, and the lognormal fit does not accurately represent the risk of events with low probability and high consequences, especially for equipment with very low failure rates. The fit improves for higher failure rates, but variability in the reliability indices also increases. This provides erroneous estimates for the risk of penalties associated with component failure.

Because the Monte Carlo integration method does not make an assumption about the distribution of variability in the indices, it represents low probability events with greater accuracy. The Monte Carlo integration method was also found to take about 30 to 40 percent less computation time than the conventional curve-fitting method. The drawback of the Monte Carlo technique, however, is that the accuracy of solution depends on the length of the simulation period, and it requires a very large sample to achieve significant accuracy.

The method to compute the regulatory penalty risk reduction for wood poles and vegetation-related outages is summarized as follows:

a. Input the failure rate of the component before and after maintenance, and the resulting SAIFI and SAIDI values before and after maintenance.
b. Determine the straight line equations for SAIFI and SAIDI as functions of the failure rate of the component.
c. Specify the number of years to simulate.
d. Determine the number of times the component fails each year by drawing uniform random numbers for each of the simulated years, as in equation (4.12).
e. Determine SAIFI and SAIDI for each of the simulated years by using the linear relationship between the failure rate and the reliability index, replacing the failure rate with the number of times the component fails during each year.
f. Express the variability in SAIFI (or SAIDI) indices due to the variability in the component's failure each year as a probability distribution.
g. Compute risk as an expectation of the probability distribution and the penalty curve PBR(SAIFI), as in equation (4.14), where PBR(SAIFI) is a piecewise linear function that describes the penalty as a function of the SAIFI for the year.

$$PBRF(k) = \int_{T_F}^{\infty} PBR(SAIFI).f\big(SAIFI(k)\big)d\big(SAIFI(k)\big) \tag{4.14}$$

h. Keep in mind that equation (4.14) gives the risk of penalty before maintenance. Repeating the computation using the failure rate after maintenance provides the risk of penalty after maintenance. Risk reduction is the difference in risk before and after maintenance.

To illustrate the variability in SAIFI from maintaining wood poles and vegetation, probability plots obtained using this method are shown in Figure 4.1 to Figure 4.4. For this illustration, it was assumed that the failure rate of the component is halved after maintenance. Similar plots can also be obtained for SAIDI.

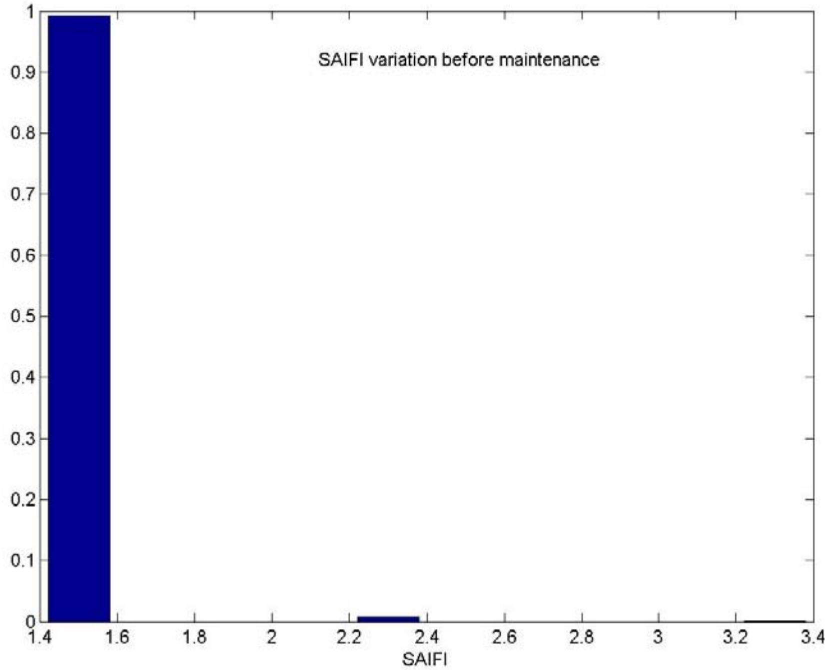

Figure 4.1: Variation in SAIFI before maintenance of wood pole.

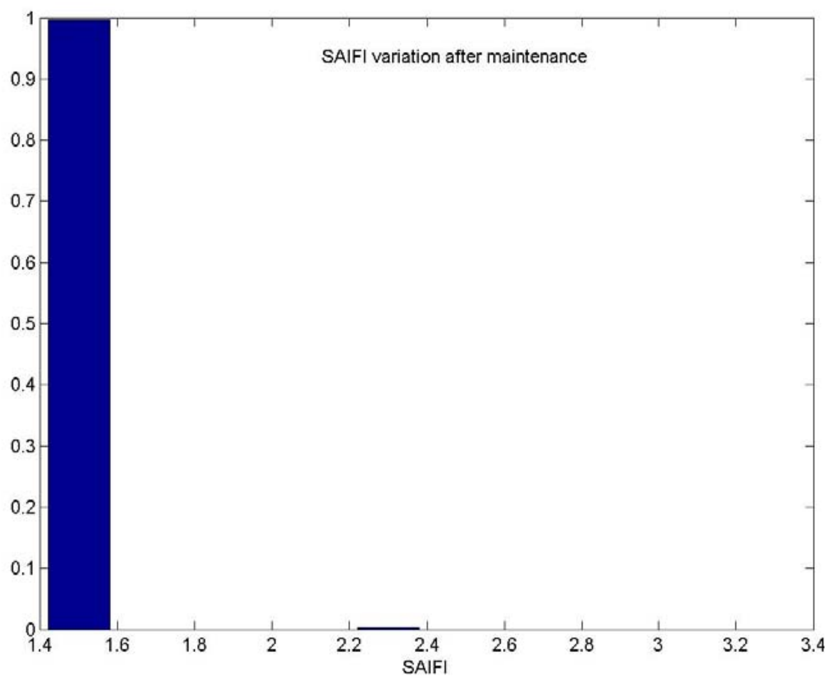

Figure 4.2: Variation in SAIFI after maintenance of wood pole.

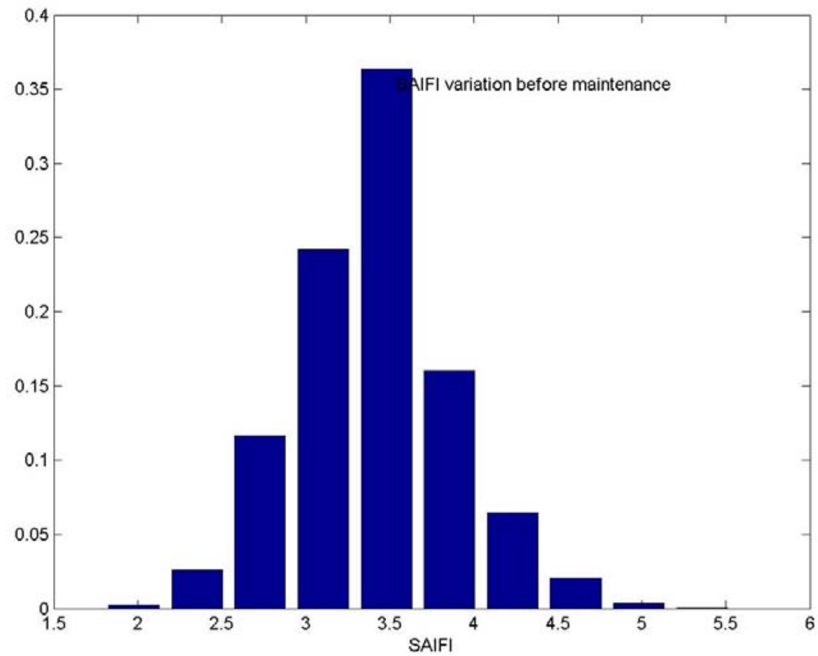

Figure 4.3: Variation in SAIFI before tree-trimming.

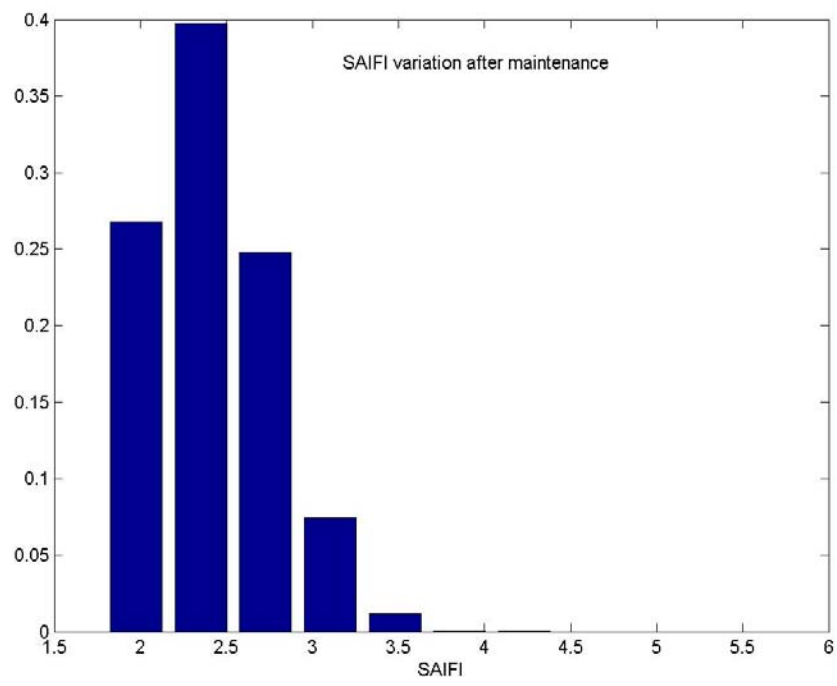

Figure 4.4: Variation in SAIFI after tree-trimming.

These figures illustrate that maintenance not only improves the expected values of the indices but also reduces the risk of low probability, high consequence events.

For reclosers, Section 4.4 shows that the reliability indices are approximately linearly dependent on protection reliability or reclose reliability. Unlike the wood pole or vegetation sensitivities, which are functions of failure rate, the recloser's PR is a probability between zero and one. Hence, the risk of penalties associated with recloser failure can be simulated using a Bernoulli distribution of parameter PR. For each year simulated, PR is determined in the following manner:

a. Either assume a fixed number of faults per year. Or, if the distribution of the number of faults occurring downstream of the recloser is known, randomly generate the number of faults per year.
b. Generate Bernoulli-distributed random numbers, either zero or one, for parameter PR, to represent recloser failure or operation for each of the fault.
c. Remember that the average number of times the recloser operates is the PR for the specified year.

Using the estimated PR for each simulated year, and the straight line equations for SAIFI and SAIDI as functions of PR, the reliability indices are computed. Using the Monte Carlo integration of equation (4.13), the corresponding risks of penalties before and after maintenance are computed. This method is summarized as follows:

a. Input PR before and after maintenance, and the resulting reliability indices, SAIFI and SAIDI, before and after maintenance.
b. Determine the straight line equations for SAIFI and SAIDI as functions of PR.
c. Specify the number of years to simulate.
d. Determine recloser PR for each year:
    (1) Assume a fixed number of faults per year. Or, if the distribution of the number of faults occurring downstream of the recloser is known, randomly generate the number of faults per year.
    (2) Generate Bernoulli-distributed random numbers, either zero or one, for parameter PR, to represent recloser failure or operation for each of the fault.
    (3) Keep in the mind, that the average number of times the recloser operates is the PR for the specified year.
e. For the estimated PR, calculate the annual reliability indices SAIFI and SAIDI using their straight line equations.
f. Express the annual variability in SAIFI and SAIDI as probability distribution functions.
g. Using equation (4.14), calculate the risk of penalty before maintenance. Repeat for the risk of penalty after maintenance.
h. Remember that risk reduction is the difference in risk before and after maintenance.

To illustrate the variability in SAIFI and SAIDI from maintaining reclosers, probability plots obtained using this method are shown in figures 4.5 through 4.8.

The method developed for wood poles and vegetation-related failures can also be applied to failures of overhead and underground conductors. The method for reclosers can be similarly extended to other protective equipment, such as circuit breakers and fuses.

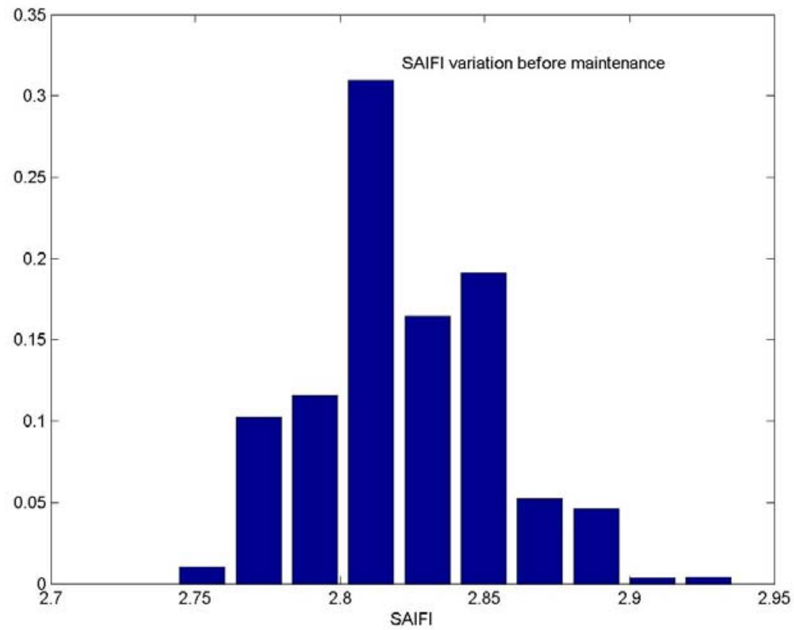

Figure 4.5: Variation in SAIFI before recloser maintenance.

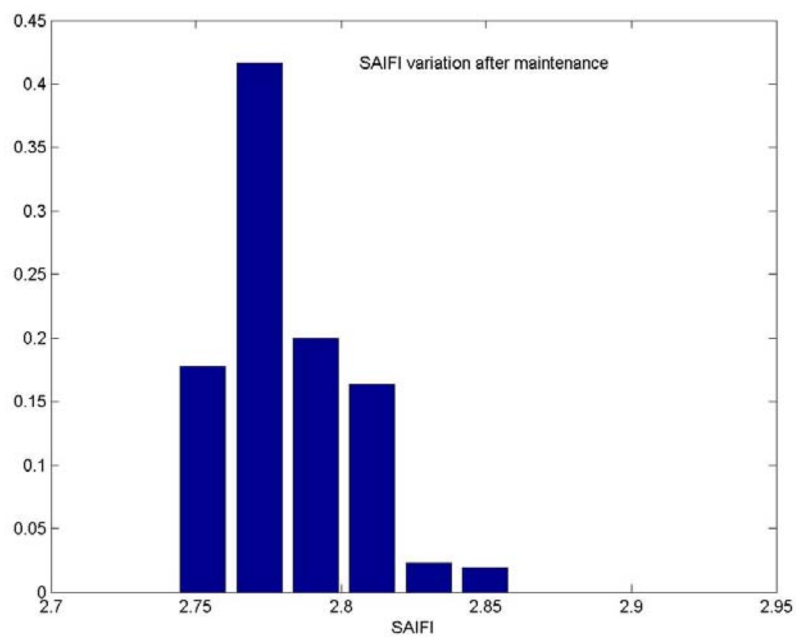

Figure 4.6: Variation in SAIFI after recloser maintenance.

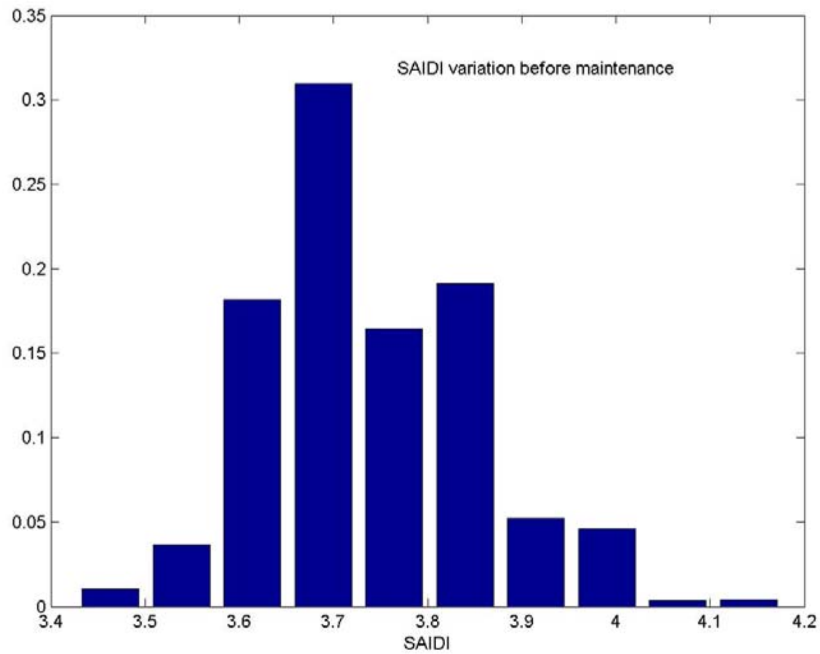

Figure 4.7: Variation in SAIDI before recloser maintenance.

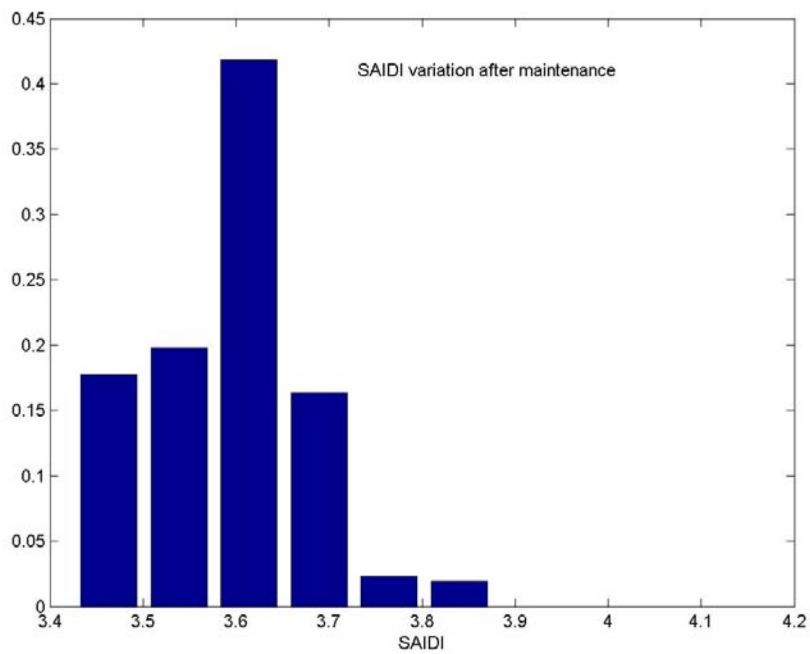

Figure 4.8: Variation in SAIDI after recloser maintenance.

4.6 Validation of Reliability Assessment Tool

The reliability evaluation tools developed in Sections 4.2 to 4.6 are validated using the IEEE test system [36]. Figure 4.9 shows the test system of four radial distribution feeders. The number of customers and corresponding loads connected to each load point are shown in Table 4.8. Table 4.9 provides the lengths of each feeder section. The overhead line failure rate is 0.065 failures/km-yr, and the average repair time is five hours. The transformers in the system are modeled as lines, with a failure rate of 0.015 failures/year and average repair time of 200 hours. Switching time (MTTS) is assumed to be one hour. All protective and switching devices are assumed to operate with 100 percent reliability. Transformers and corresponding line segments are reduced to a single equivalent component using the failure rate and repair time expressions for series connected components [31].

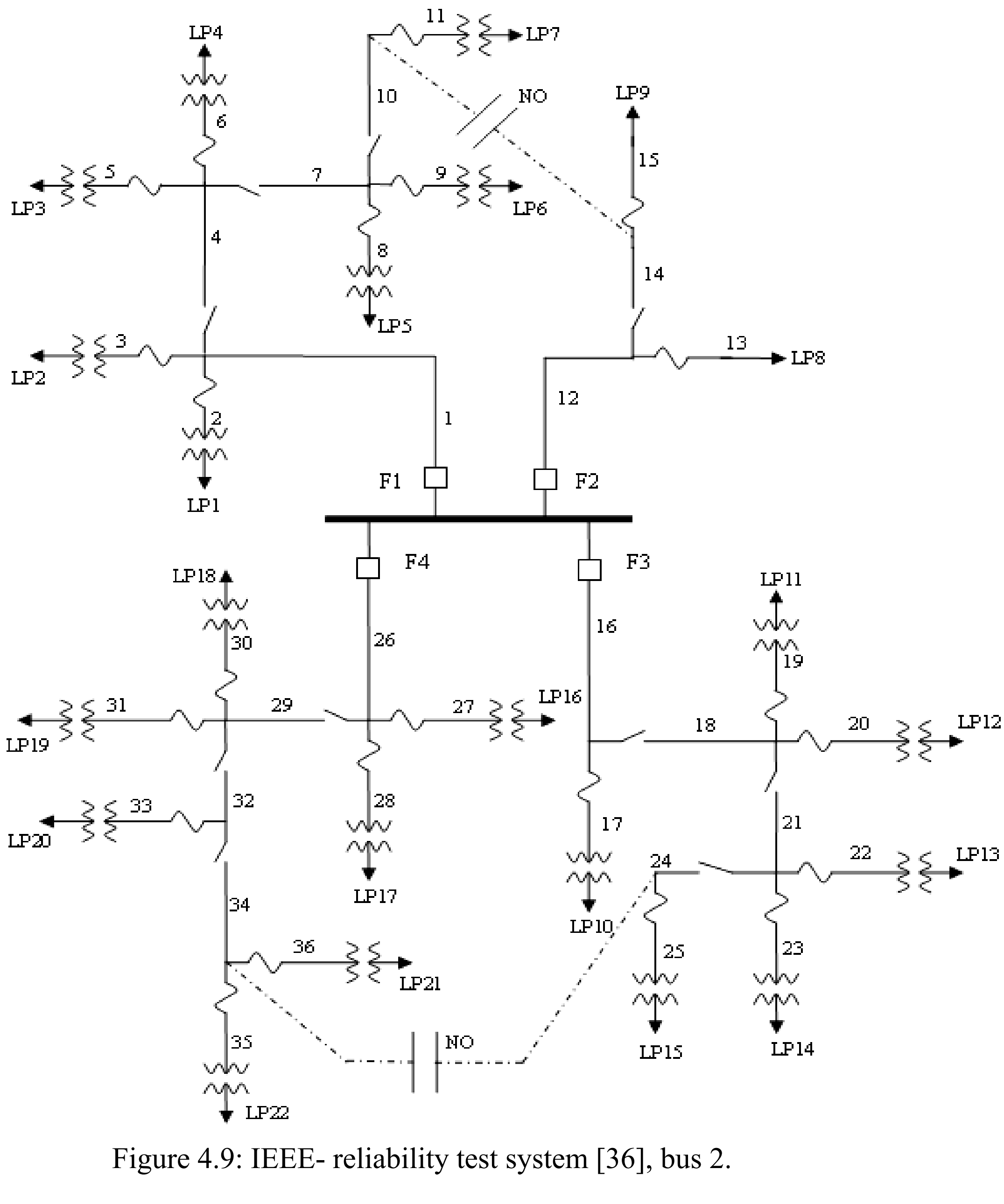

Figure 4.9: IEEE- reliability test system [36], bus 2.

Table 4.8: Customer data

Feeder	Load Points	Load/Point (kW)	Number of Customers/Points	Customer Type
1	1-3	535	210	Residential
1	4-5	566	1	Institution
1	6-7	454	10	Commercial
2	8	1000	1	Industrial
2	9	1150	1	Industrial
3	10-11	535	210	Residential
3	12	450	200	Residential
3	13-14	566	1	Institution
3	15	454	10	Commercial
4	16	454	10	Commercial
4	17-19	450	200	Residential
4	20-21	566	1	Institution
4	22	454	10	Commercial

Table 4.9: Lengths of feeder section

Length (km)	Feeder Section Numbers
0.60	2 6 10 14 17 21 25 28 30 34
0.75	1 4 7 9 12 16 19 22 24 27 29 32 35
0.80	3 5 8 11 13 15 18 20 23 26 31 33 36

As shown in Table 4.10, the reliability indices computed by the reliability evaluation tool exactly match those provided in [36]. Further validation was also performed on two actual distribution feeders using the results obtained from the reliability evaluation software, DRIVe, developed by EPRI and Iowa State University. The reliability indices computed by the reliability tool were found to be in close agreement with those predicted by DRIVe.

Table 4.10: Reliability indices for the ieee- reliability test system, bus 2

Feeder #	SAIFI (customers/year)		SAIDI (customer hours/year)		ENS (kWh/year)	
	Predicted	RBTS*	Predicted	RBTS*	Predicted	RBTS*
1	0.248	0.248	3.618	3.620	13172.06	13172
2	0.140	0.140	0.523	0.520	1122.06	1122
3	0.250	0.250	3.624	3.620	11203.20	11203
4	0.247	0.247	3.605	3.610	12248.36	12248
System	0.248	0.248	3.613	3.610	37745.68	37746

* Reliability indices given in [36].

5 Optimization

This chapter describes a risk reduction optimization problem and its corresponding solution. The reliability evaluation tool developed in Chapter 4 first computes the risk reduction introduced by each candidate maintenance task. Then the results for each task are combined with the resource consumed, resulting in triplets comprised of the candidate task risk reduction, financial cost, and labor cost. These triplets are the inputs to the optimizer. The optimization problem is presented in Section 5.1. Possible solution methods are summarized in Section 5.2. Finally, Section 5.3 describes the solution method selected and implemented in this project.

5.1 Problem Statement

In the problem statement, the following terms are used:

P is the number of maintenance categories.

$p=1,\ldots P$ is the index over the set of categories.

N_p is the number of candidate components within category p.

$k=1,\ldots,Np$ is the index over the set of candidate components within category p.

M_k is the number of maintenance tasks for component k.

$l=1,\ldots,M_k$ is the index over the set of maintenance activities for component k.

The risk reduction related to each candidate preventive maintenance task is *ΔRisk(k,l)*. Resource requirements for each task are represented by cost, *Cost(k,l)*, and labor, *Labor(k,l)*. Therefore, each task it is associated with a triplet: *{ΔRisk(k,l), Cost(k,l),* and *Labor(k,l)}*. For every task, variable *Iselect(k,l)* reflects whether the task is selected (1) or not (0). The triplets are input to the optimizer, which identifies the values of *Iselect(k,l)* for all tasks that maximize the risk reduction subject to the resource constraints. *Budget(p)* is the budget assigned to maintenance category *p*. *TotLabor(p)* is the available labor, in person-hours, in maintenance category *p*. *Totbudget* is the total budget for all categories.

The optimization formulation has two steps. The first is the task selection subproblem, selecting tasks within resource constraints in each maintenance category. The second is the budget planning subproblem, allocating budgeted resources to the maintenance tasks.

The formulation of the task selection subproblem is as follows:

$$Max: \sum_{k=1}^{N_p} \sum_{l=1}^{M_k} \Delta Risk(k,l) Iselect(k,l) \tag{5.1}$$

Subject to the following constraints:

$$\sum_{k=1}^{N_p} \sum_{l=1}^{M_k} Sel(k,l) Cost(k,l) \le Budget(p) \tag{5.2}$$

$$\sum_{k=1}^{N_p} \sum_{l=1}^{M_k} Sel(k,l) Labor(k,l) \le \mathrm{TotLabor}(p) \tag{5.3}$$

$$\sum_{l=1}^{M_k} Iselect(k,l) \le 1, k = 1,2,\ldots N \tag{5.4}$$

The objective, equation (5.1), is to maximize the total risk reduction. The constraint, equation (5.2) represents the budget constraint, and equation (5.3) represents the available labor resource constraint. The constraint represented by equation (5.4) indicates that each component is maintained at most once during the time frame.

This task selection subproblem is a low-level formulation of the maintenance optimization problem for a specific category p of maintenance tasks. Its results are used in a higher-level problem. Task selection is solved repeatedly, increasing the budget each time by a specified increment until all candidate tasks in each category are selected, or available resources are exhausted.

Task selection is repeated for each category *p=1.,,,P*, resulting in a risk-reduction vs. budget table for each category, as illustrated with example data in Table 5.1. Tasks are selected, as illustrated by the binary strings in Table 5.2, where element k of a string indicates whether task k is performed (1) or not (0). Each cell in Table 5.2 corresponds to the cell in the same position in Table 5.1.

Table 5.1. Risk reduction vs. budget

Budget ($1,000)	Risk Reduction from Different Categories		
	Wood Pole	Recloser	Tree-Trimming
0	0	0	0
1	4.2	3.75	2.25
…	…	…	…
9	19.8	13.5	14.4
10	20.7	13.5	15
…	…	…	…

Table 5.2. Decision variable code table

Budget ($1,000)	Profit from Different Categories		
	Wood Pole	Recloser	Tree-Trimming
0	000…000	000…000	000…000
1	010…100	101…001	100…010
…	…	…	…
9	100…110	110...101	010…101
10	110…011	111…100	110…110
…	…	…	…

Cells in the risk-reduction table are denoted by $Cat\_\Delta Risk(i,x_i)$, corresponding to category i with budget allocation $x_{i.}$ To obtain the maximum risk-reduction within the total budget constraint, the budget planning subproblem is solved. This subproblem is formulated as follows:

$$Max: \sum_{i=1}^{c} Cat\_\Delta Rist(i, x_i) \tag{5.5}$$

Subject to the following constraints:

$$\sum_{i=1}^{C} x_i \leq TotBudget \tag{5.6}$$

$$x_i = 0,1,\ldots \forall i = 1,\ldots \tag{5.7}$$

5.2 Possible Solution Methods for Task Selection Subproblem

The task selection subproblem is an integer programming problem that is known for its difficulty. Three different solution methods were tried: prioritization, branch and bound, and enhanced linear programming relaxation (ELPR) with the Lagrangean relaxation plus heuristic method (LRH). All three are summarized here, and the ELPR-LRH method is selected because it provides a better solution without a significant increase in computation time.

5.2.1 Prioritization Method

For optimization using prioritization, the cost-effectiveness ratio index is defined as

$$R = \frac{\Delta Risk(k,l)}{Cost(k,l)} \tag{5.8}$$

The prioritization algorithm is as follows:

a. Obtain *R* for each candidate task.
b. Rank all candidate tasks by R.
c. For maintenance tasks on the same component, select the task with the highest ranking and eliminate all others from the list.
d. Select tasks from the top of the ranking list until the cost limit is reached, available labor resources are used up, or the reliability target is reached. This algorithm is very fast and easy to perform, but there is no elegant way to apply constraints (5.3) and (5.4).

5.2.2 Branch-and-Bound Method

Most integer programming optimizations are solved with the branch-and-bound method. This technique is a mature and 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 integers. The process continues until a branching point is reached where there are no more real-valued variables. The algorithm terminates at this point.

Computation time for the branch-and-bound method increases exponentially with problem size, and it will not solve a large-scale problem, like the task selection problem, in a reasonable time. Sometimes stop criteria are introduced, such as errors between upper and lower bounds, or maximum number of nodes searched. But it is still a time-consuming method for large-scale problems.

5.2.3 ELPR-LRH Method

The method used in this project to solve the task selection subproblem combines the enhanced linear programming relaxation method with the Lagrangean relaxation plus heuristic method. ELPR ignores the 0-1 integer constraint while introducing a new constraint, $0 \le x_i \le 1$. Lagrange relaxation retains the 0-1 integer constraint but relaxes all other resource constraints; LRH improves Lagrange relaxation with a heuristic. Figure 5.1 illustrates the ELPR-LRH algorithm.

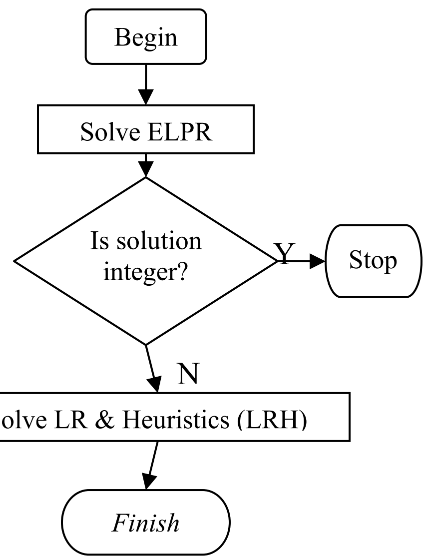

Figure 5.1: Flowchart of ELPR-LRH optimization method.

The task selection sub-problem is represented in standard integer programming form as

$$Max: \ z = cx \tag{5.9}$$

Subject to the following constraints:

$$Ax \le b \tag{5.10}$$

$$x \in \{0,1\} \tag{5.11}$$

The ELPR is solved using the general linear programming algorithm. If the solution is an integer, then the solution is optimal, and the algorithm stops. If the solution is not an integer, the following LRH is solved as follows:

$$Max: \ z(\lambda) = (c - \lambda A)x + \lambda b = c'x + \lambda b \tag{5.12}$$

Subject to the following constraint:

$$x \in \{0,1\} \tag{5.13}$$

In equation (5.12), c is the reliability risk-reduction benefit and c' is the net benefit after deducting the cost of the resources. The optimality criterion for equation (5.12) is simple: if the net benefit of a task is positive, then select it. The difficulty in solving the problem represented by equations 5.12 and 5.13 is obtaining the Lagrange multiplier λ. One approach suggested in the literature is the subgradient method [37], [38], but this is computationally intensive, and can experience convergence problems. Therefore the ELPR's optimal dual solution is used, which provides a good estimate of the Lagrange multiplier, as indicated in [39], and confirmed by numerical experiments performed in this project. This approximate method is a fast and stable way to obtain the Lagrange multiplier.

Sometimes the Lagrangean solution is infeasible or not good enough, e.g., too many tasks are selected; therefore, some heuristic methods are used to improve the Lagrange solution. For this project, a simple heuristic is performed after the solution of the Lagrange relaxation: if it is infeasible, then the least net benefit decision variable is removed until all the constraints are satisfied. If there is residual resource left, then the largest net benefit decision variable among the unselected group is chosen until a constraint is violated.

5.3 Solution Methods for Budget Planning Subproblem

The ELPR-LRH algorithm solves the basic integer programming problem, which addresses the third question posed in the introduction, Section 1.1: to select a set of maintenance projects to be completed within each program, constrained by the budget allocation. The dynamic programming (DP) method is used to answer the budget planning subproblem, which addresses the first and second problems in Section 1.1: how to identify and justify the resources needed for asset management, and how to allocate the available resources to the different maintenance programs. DP is chosen because it provides not only the optimal policy but also the optimal policies of the subproblems [40].

Illustrations of typical results obtained from these algorithms are given in Figures 5.2 and 5.3. The curve in Figure 5.2 provides the asset manager with a direct view of the relationship between the reliability risk-reduction benefit and the maintenance budget. It allows a solution to the first problem regarding the total maintenance budget.

The DP solution also gives the optimal allocation of the budget among different categories, as shown in Figure 5.3. For example, with a total budget of \$12,000, the manager can allocate \$3,000 to the recloser category, \$4,000 to the wood pole category, and \$5,000 to the tree-trimming category. This addresses the second problem. Finally, using the information in Table 5.2, the manager decides which tasks should be performed to solve the third problem.

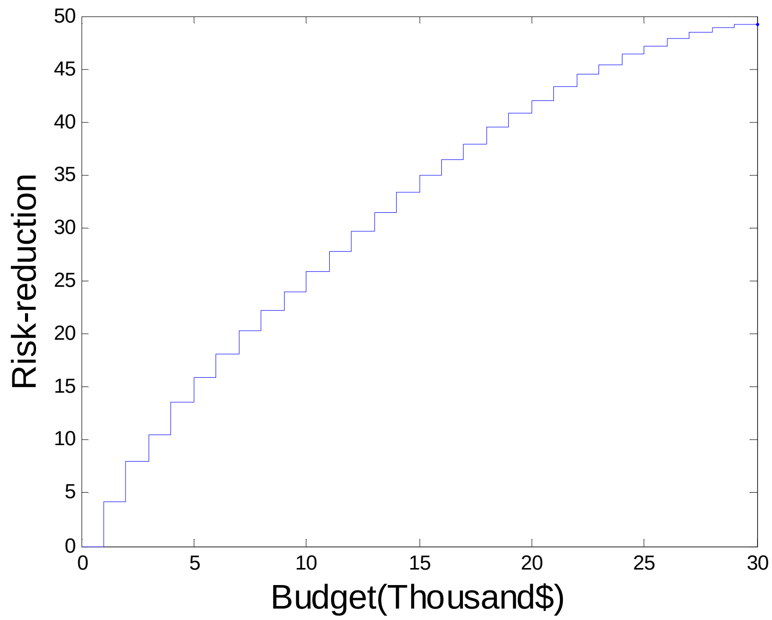

Figure 5.2: Reliability benefit vs. budget.

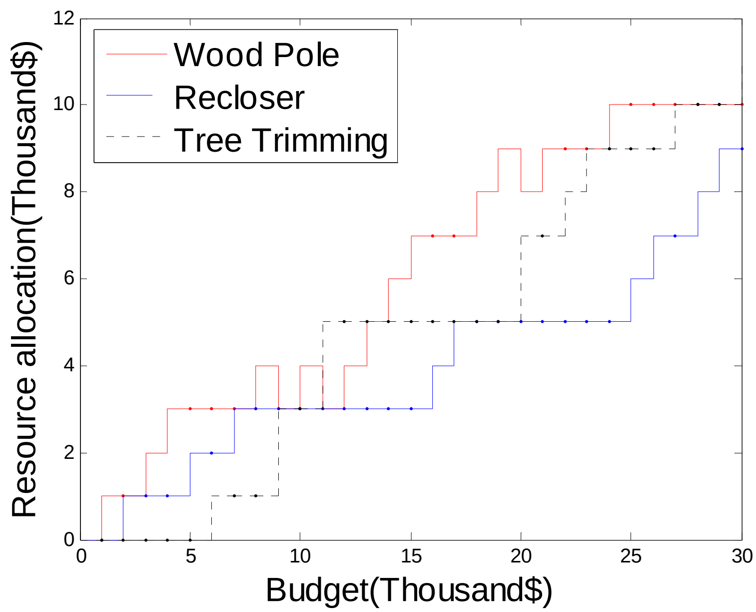

Figure 5.3: Resource splitting curve for different categories.

5.4 Summary

The techniques described in Chapter 5 provide the optimal budget for all assets, the allocation of the budget to different maintenance categories, and the selection of projects within those categories. Different maintenance categories with different characteristics, e.g., some needing scheduled outages and load transfers, while others do not, can be addressed with new categories with special constraints. Additional maintenance categories to account for other types of equipment can also be added. If maintenance for a period is to focus on certain categories, these can be weighted to bias task selection to those categories. If contractors perform certain types of maintenance for a company, this strategy can provide guidance to the asset manager on appropriate contractor pricing.

6 Illustration

Data from an actual distribution system is used in this chapter to illustrate the proposed risk-based resource allocation strategy developed in the previous chapters. The system has 66 feeders, each classified as either urban or rural, and is divided into three operating regions.

Figure 6.1 shows the steps to implement this method. Historical outage data and network topology, including load and customer information, obtained from the utility's outage management system (OMS), are the primary inputs. They are used to compute the historical reliability indices, and to develop the statistical models to predict the failure characteristics of distribution equipment and evaluate the effects of maintenance. They also provide the basis for modeling various distribution components for the predictive reliability evaluation, and a reference or benchmark for the predictive reliability evaluation method.

The predictive reliability evaluation is followed by the computation of risk reductions for various maintenance tasks, which are then optimized to provide the asset manager with solutions to resource allocation problems. This chapter describes the results obtained from the historical analysis, predictive analysis, and risk reduction computation (shaded boxes in Figure 6.1) for the example feeder.

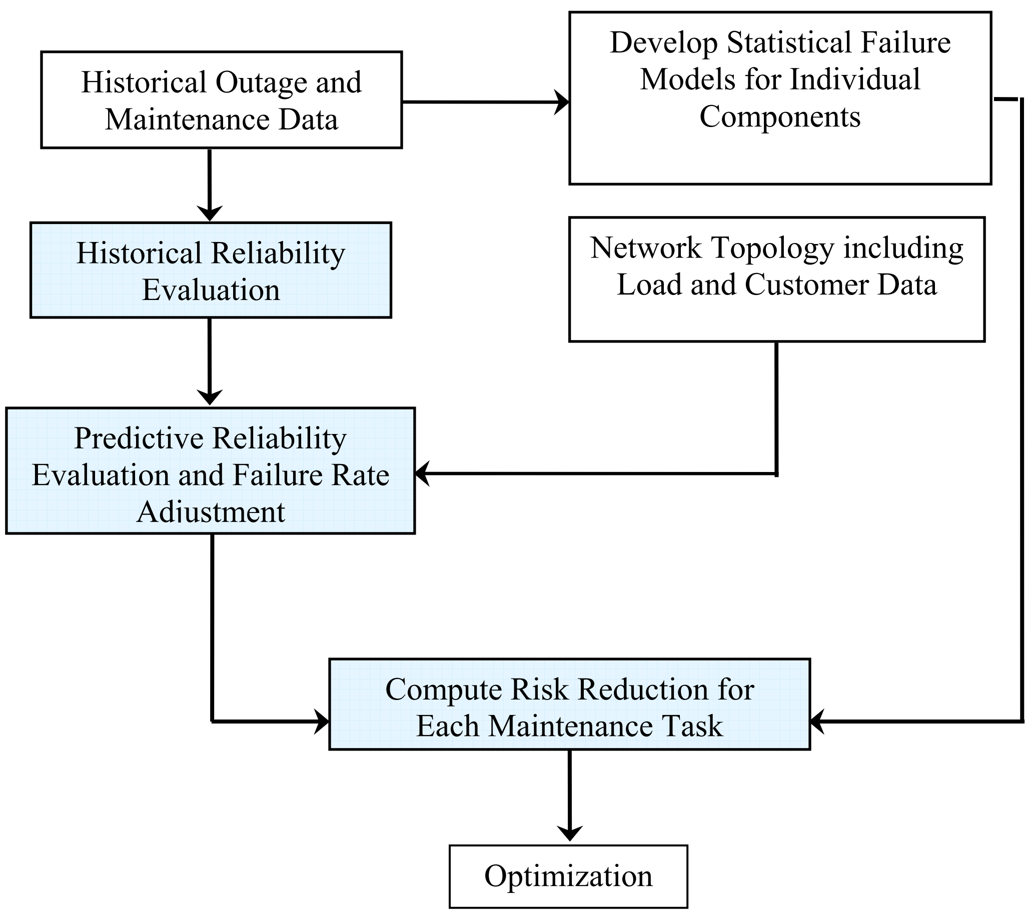

Figure 6.1: Risk-based resource allocation implementation.

6.1 Historical Reliability Evaluation

Outage history is used to calculate SAIFI and SAIDI [41] for a five-year period from 2000 to 2004. They provide a reference to compare with those obtained from the predictive analysis. The outage history analysis also forms the basis for the average failure rate and outage duration estimation used in the predictive analysis presented in later sections. Storm-related extreme weather events are excluded. Outages of less than one minute are classified as temporary, while those of one minute or longer are classified as sustained. Sustained outages are further classified into two categories:

a. Outages caused by overhead or underground line failures, including those caused by weather, vegetation, animals, overloads, and component failure, including switches, reclosers, fuses, sectionalizers, and substation breakers.
b. Outages due to other causes, including transmission failure, public interference, failures of lightning arrestors and distribution transformers, utility maintenance personnel errors, and other events.

Table 6.1 summarizes the historical reliability indices for all causes of outage. Tables 6.2 and 6.3 present the indices by category 1 and 2. Table 6.1 values are the sum of the corresponding indices in Table 6.2 and Table 6.3.

Table 6.1: Overall historical reliability indices for distribution system

Region	SAIFI (2000-2004)	SAIDI (2000-2004)
Total	1.489	1.919 Hours
Region 1	1.625	2.047 Hours
Region 2	1.280	1.676 Hours
Region 3	1.315	1.857 Hours

Table 6.2: Historical indices—overhead, underground, and device failures

Region	SAIFI (2000-2004)	SAIDI (2000-2004)
Total	0.869	1.316 Hours
Region 1	0.836	1.358 Hours
Region 2	0.952	1.339 Hours
Region 3	0.839	1.074 Hours

Table 6.3: Historical indices—outages caused by miscellaneous failures

Region	SAIFI (2000-2004)	SAIDI (2000-2004)
Total	0.620	0.603 Hours
Region 1	0.789	0.689 Hours
Region 2	0.328	0.337 Hours
Region 3	0.476	0.783 Hours

6.2 Predictive Analysis

Before predicted indices are used, they must correlate with historical indices. Predicted indices are calibrated by adjusting component failure rates and repair times.

6.2.1 Failure and Repair Parameter Estimation for Predictive Analysis

To predict the reliability indices of a distribution system, the assessment tool must have values for failure rates and mean time to repair for each component modeled: overhead lines, underground cables, fuses, reclosers, breakers, sectionalizers and switches. To estimate the failure rate of overhead lines, the total number of sustained overhead outages observed during the 2000–04 period was divided by the number of overhead circuit miles and the number of years, as shown in equation (6.1).The average repair time is computed from the repair times for each of the sustained faults during the same period, as shown in equation (6.2).

A similar procedure was followed for under-ground cables. Table 6.4 summarizes the estimated average failure rates and repair times for overhead lines and underground cables.

$$\lambda_p = \frac{Total\ number\ of\ sustained\ interruptions}{Total\ circuit\ miles * number\ of\ years} \quad \text{faults / mi-yr} \qquad (6.1)$$

$$MTTR = \frac{Total\ repair\ time}{Total\ number\ of\ sustained\ interruptions} \qquad (6.2)$$

Table 6.4: Reliability parameter estimates for overhead lines and underground cables

Component	Category	Phase	Average Failure Rate (failures/mile-year)	MTTR (hours)
Overhead Line	Urban	3-Phase	0.0632	1.75
		2-Phase	0.8043	1.75
		1-Phase	2.1268	2.00
	Rural	3-Phase	0.0983	1.75
		2-Phase	0.1323	2.50
		1-Phase	0.4543	2.00
Underground Cable	Urban	3-Phase	0.0672	3.25
		2-Phase	6.7692	0.50
		1-Phase	0.3922	3.75
	Rural	3-Phase	0.0116	2.15
		2-Phase	0.0000	0.00
		1-Phase	0.4156	3.50

The reliability parameters for protective and switching devices is ideally computed from the average number of times the device is expected to operate and the number of times it is successful. However, these were not available in the outage database. Instead, the failure probability was estimated from available data using equation (6.3).

$$PF = \frac{Number\ of\ device\ failures}{Total\ number\ of\ device\ operations} \qquad (6.3)$$

Reliability metrics for protective and switching devices can be estimated from PF. For fuses, sectionalizers, and substation breakers, whose primary mode of failure is fail to open during a fault, protection reliability is the complement of PF, as described in Section 4.1.7 and shown in equation (6.4).

$$PR = 1 - PF \tag{6.4}$$

Similarly a switch's switching reliability is estimated by equation (6.5).

$$SR = 1 - PF \tag{6.5}$$

For reclosers, two failure modes are possible: failure to open, and failure to reclose. Protection reliability and reclose reliability are estimated as described in Section 4.1.7 and shown in equation (6.6).

$$PR = RR = \sqrt{1 - PF} \tag{6.6}$$

The calculated reliability measures for protective and switching devices are tabulated in Table 6.5. The mean time to switch for each is assumed to be one hour, based on the field experience of the switching personnel. Because the switching times of the protective devices are not known, it is assumed that the $MTTS_{dev}$ is one hour, the same as the $MTTS_{swi}$. For this example, it is assumed that all switching failures are due to a switch failing to do the intended operation. Protective device reliability is then 100 percent, and the probability for the switching sequence is SR of the switch alone.

Table 6.5: Reliability parameter estimates for protective and switching devices

Component	Category	Protection Reliability (PR)	MTTR (hours)	Reclose Reliability (RR)	Switching Reliability (SR)
Fuse	Urban	0.970	1.13	0.000	1.00
	Rural	0.950	1.50	0.000	1.00
Recloser	Urban	1.000	1.75	1.000	1.00
	Rural	0.975	1.75	0.975	1.00
Switch	Urban	0.000	2.00	0.000	0.60
	Rural	0.000	1.50	0.000	0.73
Sectionalizer	Urban	1.000	1.75	0.000	1.00
	Rural	0.950	1.75	0.000	1.00
Substation Breaker	Urban	0.988	1.75	0.000	1.00
	Rural	0.985	2.00	0.000	1.00

6.2.2 Results

Using the values listed in Table 6.4 and Table 6.5, predictive analysis was performed. However, the indices predicted did not agree with those from the historical analysis, as shown in Table 6.2. To correct this, the component failure rates and mean time to repair values are adjusted in a two-stage process [1].

First, the failure rates for the urban and rural regions are varied linearly (in this case, decreased), keeping the repair times constant, until the predicted SAIFI values matched those from the historical analysis. Then the MTTR of the urban and rural regions are varied until the predicted SAIDI values nearly equal those from the historical analysis. The adjusted failure rates and the repair times of overhead and underground lines are shown in Table 6.6.

In this procedure, the protective and switching device parameters in Table 6.5 were held constant for two reasons. First, the utility personnel involved in the project were confident that the reliability estimates for protective and switching devices were close to the actual values experienced in the system. Second, it was observed that the predicted indices were not very sensitive to variations in protective and switching parameters, as shown in Table 6.5. This is confirmed in a published sensitivity analysis [42].

The predicted indices obtained using the adjusted failure rates and repair times are summarized in Table 6.7. These are very close to the historical indices in Table 6.2.

Table 6.6: Adjusted failure parameters for overhead and underground line segments

Component	Category	Phase	Average Failure Rate (failures/mile-year)	MTTR (hours)
Overhead Line	Urban	3-Phase	0.0155	1.25
		2-Phase	0.2010	1.25
		1-Phase	0.5317	1.50
	Rural	3-Phase	0.1180	1.00
		2-Phase	0.1590	1.75
		1-Phase	0.5450	1.25
Underground Cable	Urban	3-Phase	0.0168	2.75
		2-Phase	1.6923	0.50
		1-Phase	0.0980	3.25
	Rural	3-Phase	0.0140	1.50
		2-Phase	0.0000	0.00
		1-Phase	0.4990	2.75

To include the miscellaneous failures of Table 6.3, the failure rate and repair time of the equivalent component at the sending end of every feeder is adjusted until the predicted indices are nearly equal to total indices in Table 6.1. For the test feeder, equivalent component failure rates of 0.4 faults/year for urban and 0.7 faults/year for rural, and repair times of 1.25 hours for urban and 1.00 hours for rural provide the indices in Table 6.7, which are in close agreement with those in Table 6.1.

Table 6.7: Reliability indices using adjusted failure rates and repair times

Region	SAIFI		SAIDI	
	Predicted	Historical	Predicted	Historical
Total	0.901	0.869	1.337	1.316
Region 1	0.892	0.836	1.409	1.358
Region 2	0.910	0.952	1.231	1.339
Region 3	0.917	0.839	1.318	1.074

Table 6.8: Reliability indices using adjusted failure rates and equivalent component

Region	SAIFI		SAIDI	
	Predicted	Historical	Predicted	Historical
Total	1.428	1.489	1.930	1.919
Region 1	1.534	1.625	2.082	2.047
Region 2	1.298	1.280	1.723	1.676
Region 3	1.305	1.315	1.810	1.857

6.2.3 Discussion

Calibration of failure rates and repair time for lines and cables is a multidimensional problem, since each component has two adjustable parameters. Because only two system indices per region (SAIFI and SAIDI) are computed, the problem is under-constrained;

therefore, more than one set of parameter values can yield historical indices. Reference [1] suggests a least-squares approach using the method of gradient descent to determine one or more such values. Combining such an approach with the experience and judgment of utility engineers may be most effective.

The extent of adjustment needed to the input data is influenced by various factors. An important one is the accuracy of the initial estimates. For the example system, the adjustment to the estimates for the urban regions is higher than for the rural regions. Because the estimated average failure rate and repair times for the rural region are determined over a large area, with about 1,400 miles of conductors, they tend to better represent the actual observed indices. In contrast, the urban regions are estimated over a much smaller region (about 170 conductor-miles) and, hence, are less accurate. Similar conclusions can also be drawn from the initial estimated failure rates in Table 5.4. The estimated failure rate for urban two-phase underground cables is unusually high. The initial estimate in this case is influenced by the short cable length rather than the number of outages. The 0.03-mile cable had one outage during the five-year period, resulting in a failure rate estimate of 6.7692 failures/mile-year. Also, the number of outages on the three-phase system was lower than the one-phase and two-phase outages, which explains the lower three-phase failure rates.

The predictive analysis estimates steady-state, long-term, reliability indices, while the historical indices reflect recent performance, which may not be representative of the steady-state values. Hence, the predicted reliability indices tend to be closer to those from the historical analysis when a longer period of outage data is used.

The granularity, or extent of modeling, also influences the predicted indices. Predictive analysis using individual failure rates for three-phase, two-phase single-phase lines resulted in estimates much closer to historical values than when one failure rate was used for all lines regardless of phase.

In summary, predicted indices are closer to historical indices when the system is modeled at a sufficient level of granularity, and the input failure estimates accurately reflect each component's tendency to fail. Thus, it is important to first validate input data with historical indices as described here.

6.3 Computation of Risk Reduction

In the previous section, the predictive reliability algorithm was implemented on the example system, and estimated failure parameters were adjusted to ensure that the predicted indices match historical indices. The predictions thus correlate well with the actual system reliability, and can be used to calculate the benefits of maintenance and associated risk reduction. In this section, risk-reduction computations are performed for the example system. The results are then provided to an optimizer to allocate resources, as discussed in Section 1.1.

Table 6.9 lists the available maintenance tasks. Three categories are considered: wood poles, reclosers, and tree-trimming. Each category has its own labor pools. There are 5,026 wood poles on the system, so there are 5,026 candidate tasks in the wood pole category. There are 252 candidate tasks in the recloser category and 66 candidate tree-trimming tasks. This produces a total of 5,344 triplets. The risk reduction introduced by each is calculated, and the financial and labor costs are obtained. These are input to the optimizer.

Table 6.9: Failure modes and corresponding maintenance activities

Contingency	Failure Modes	Maintenance Activity	Maintenance Level	Cost of Failure
Distribution line outage	Tree contact	Tree-trimming	Feeder-based	\$500/ outage
	Pole failure	Pole treatment and replacement	Segment-based	\$200
Recloser failure	Failure to open and failure to reclose	Minor maintenance, major maintenance, and replacement	Component-based	\$25,000

Regulatory penalties are assumed to be as follows:

- \$25,000 if a feeder SAIFI exceeds 3.0 sustained outages/customer-year
- \$75,000 if a feeder SAIDI value exceeds 3.5 h/customer-year

Coefficients for the various contributing factors are assumed to be as follows:

- Customer satisfaction 100.00
- Lost Revenue 10.00
- Cost of component failure 1.00
- Regulator penalties 0.01

Each utility will specify these coefficients to represent the relative importance, or the relative confidence in the values computed, for each. The total risk reduction obtained from maintaining a component is given by equation (6.7).

$$\begin{aligned}\Delta Risk(k) &= \overbrace{100.(\Delta SAIFI(k) + \Delta SAIDI(k))}^{Customer\ \ satisfaction} + \overbrace{10.\Delta ENS(k)}^{Lost\ \ revenue} \\ &+ \overbrace{\Delta DevRisk(k)}^{Cost\ \ of\ \ component\ \ failure} + \overbrace{0.01.(\Delta PBRF(k) + \Delta PBRD(k))}^{Regulatory\ \ penalties}\end{aligned} \quad (6.7)$$

6.3.1 Recloser Maintenance

No statistical failure models were found for reclosers, so a simpler deterministic approach is used for risk-reduction calculations. As shown in Table 6.9, three different activities are considered for recloser maintenance: minor maintenance (oil change), major maintenance (recalibration), and replacement. Reclosers are modeled by their protection reliability and reclose reliability. As discussed previously, these are assumed to be equal, which gives a linear relationship between reliability indices and PR.

In this example, recloser reliability before maintenance is assumed to be the average value estimated by the predictive analysis developed in Section 6.2.1. In reality, however, each recloser will have its own PR. These differences can be modeled using statistical models of Section 3.1 to determine each recloser's failure rate.

PR after maintenance is also assumed to be deterministic. After minor maintenance, PR is assumed to be improved by 0.005. Similarly, major maintenance improves PR by 0.0125, and replacement improves it by 0.025. Full implementation of the recloser model of Section 3.1 will require incorporation of the model into the software, which is beyond the scope of this project.

Figure 6.2 illustrates the risk reduction obtained from recloser maintenance. Three levels of maintenance—minor, major, and replacement—of five reclosers were chosen to demonstrate the benefits of maintenance versus their cost and labor resource requirements. To simplify the example, reclosers were assumed to be in identical condition before maintenance. This figure shows that despite identical initial conditions, the risk and corresponding risk reduction obtained from maintenance vary significantly for the five reclosers and thus should be included when prioritizing maintenance tasks. The figure also shows that the risk reduction obtained from a lower-level maintenance task can be greater than that obtained from a higher-level, more expensive maintenance task on another recloser. This demonstrates the importance of using these decision-making methods to optimize the use of available resources.

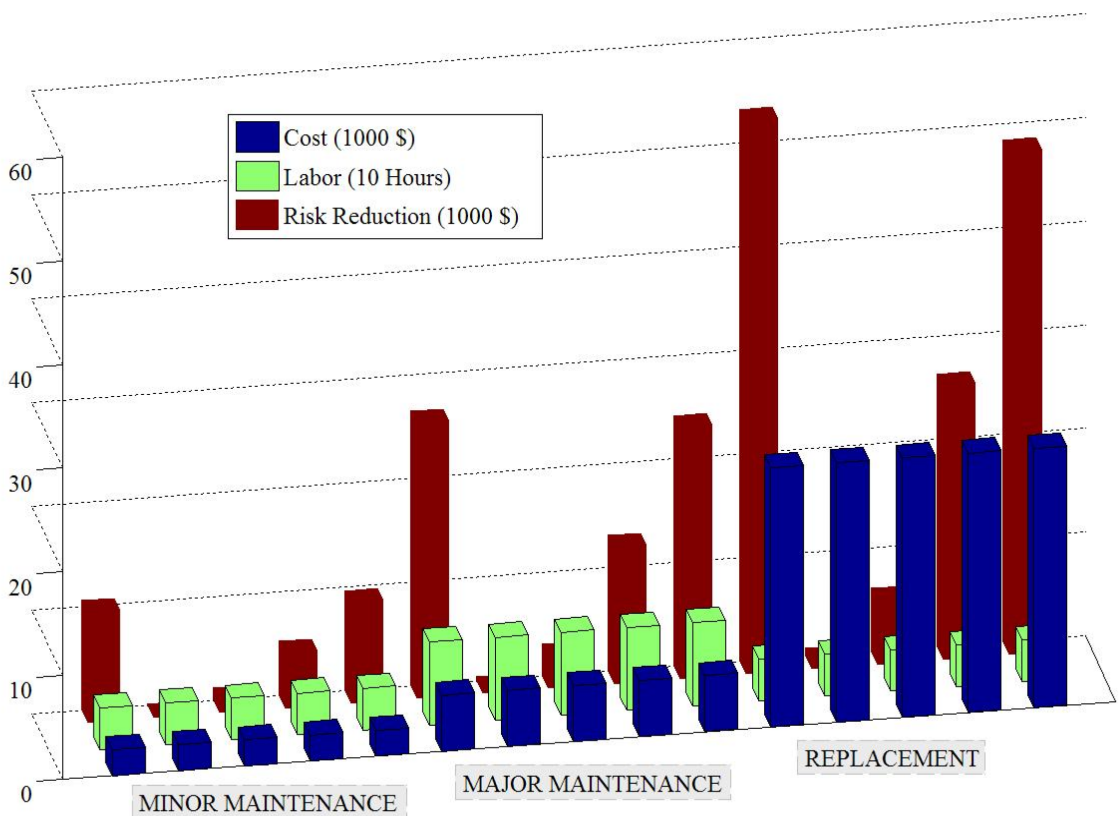

Figure 6.2: Risk reduction due to maintenance on reclosers.

6.3.2 Wood Pole Maintenance

The risk-reduction computation for wood poles is done for each pole. Data was not available for the example system, however, so pole maintenance was computed by line segment, and segments needing maintenance were chosen randomly. Degradation in a pole's mechanical strength on each segment was drawn from a uniform random generator that produces values between 0 and 0.3. A 0.3 value, or 30 percent degradation, represents pole failure.

Regression expressions [43] estimate failure rates before maintenance:

$$con\_age = \frac{con + a_2}{a_1} years \tag{6.8}$$

$$h = \frac{b}{a^b} * (con\_age)^{b-1} \tag{6.9}$$

where

- 'con' is the degradation in pole mechanical strength.
- 'con_age' is the conditional age estimate for the pole, based on its condition.
- 'a_1' and 'a_2' are linear regression coefficients [43] that determine the relationship between the degradation level 'con' and the condition age as follows:
    - $a_1 = 0.014418$
    - $a_2 = 0.10683$
- 'h' is the pole failure rate derived from the Weibull hazard function shown in equation (6.9) with these parameters [43]:
    - a= 50.6090
    - b= 4.6676

As indicated in [43], two separate maintenance activities are considered for wood poles. Pole reinforcement is assumed to reduce a pole's failure rate to 1/4th its value before maintenance. Pole replacement reduces the pole's failure rate to that of a new pole. The risk reduction associated with pole reinforcement and replacement is then calculated as described in Section 4.4.

Figure 6.3 illustrates the risk reduction obtained from maintaining wood poles, considering reinforcement and replacement. It may seem surprising that the risk reduction associated with maintaining wood poles is lower that the expenses involved in maintaining them. However, it may be noted that the average life span of a typical wood pole extends typically in tens of years while that of a recloser is only a few years. Since, the formulation of risk looks at the potential benefits of maintenance over the next year, it is unable to capture the benefits of maintenance done on wood poles.

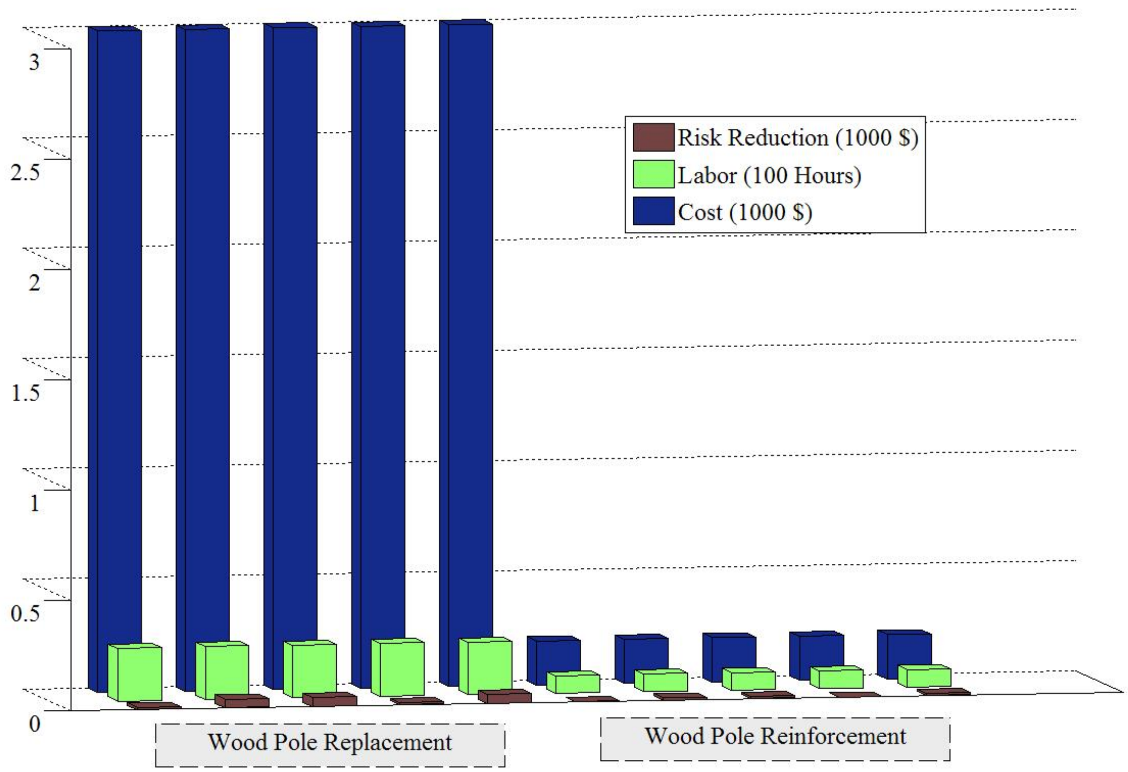

Figure 6.3: Risk reduction obtained due to wood pole maintenance.

6.3.3 Tree-Trimming Maintenance

When data such as tree-density and precipitation are available, existing models [13] can estimate the vegetation-related failure rate for each feeder. These were not available for the example system. Instead, it was assumed that 35 percent of overhead failures were caused by vegetation. Thus, the total overhead failure rate of each feeder is multiplied by 0.35 to obtain the vegetation-related failure rate before maintenance. This failure rate is then reduced to 40 percent of its original value to get the failure rate after maintenance.

Figure 6.4 illustrates the potential benefits obtained by implementing tree-trimming programs on distribution feeders. It may be noted that the cost of maintenance in this case is proportional to the length of the feeder. The cost of performing tree-trimming in the case of Feeder 2 is nearly twice that of Feeder 3, even while the risk reduction obtained may be comparable.

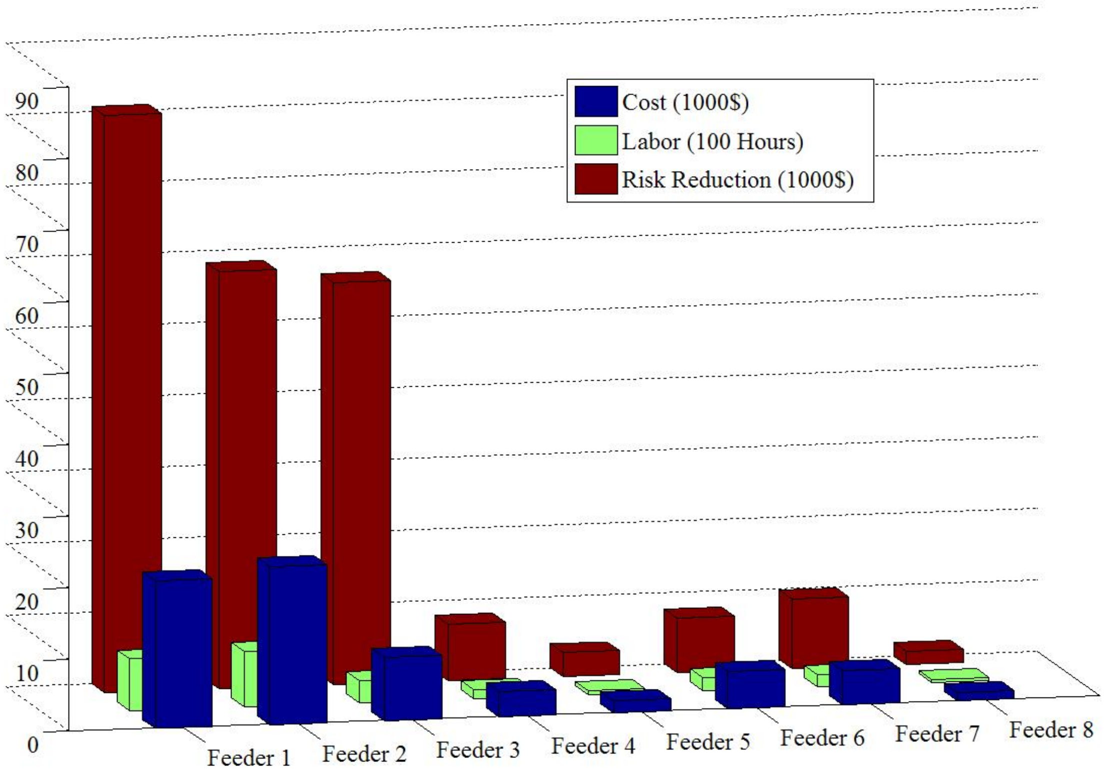

Figure 6.4: Risk reduction due to tree-trimming at a feeder level.

6.4 Optimization

6.4.1 Three Level Questions

The optimization procedure solves the task selection problem first and then the budget planning problem. It is common practice in industry, however, to first set the total maintenance budget and then distribute that budget to the maintenance categories. The solution for the example system is presented in that order. More examples are presented in the Optimizer User Manual in Appendix C.

Figure 6.5 displays the calculated risk reduction for the example system versus the total maintenance budget, which is the solution to the budget-planning problem. Each increment of the budget is allocated to the activities that produce maximum risk reduction. This plot addresses the Level 1 question of how much to spend on all maintenance activities. The key to answering this question is the amount of risk reduction obtained for each increment of maintenance spending, which is the slope of the Figure 6.5 curve (ΔRisk_reduction/Δbudget) at a given budget level. As spending increases, the slope decreases. The asset manager can identify a ratio below which no further maintenance spending is justified. For example, Figure 6.5 indicates that the reliability benefit per additional dollar spent is low when the total budget increases beyond $1,000k. The ratio is much better for maintenance budgets up to about $500k.

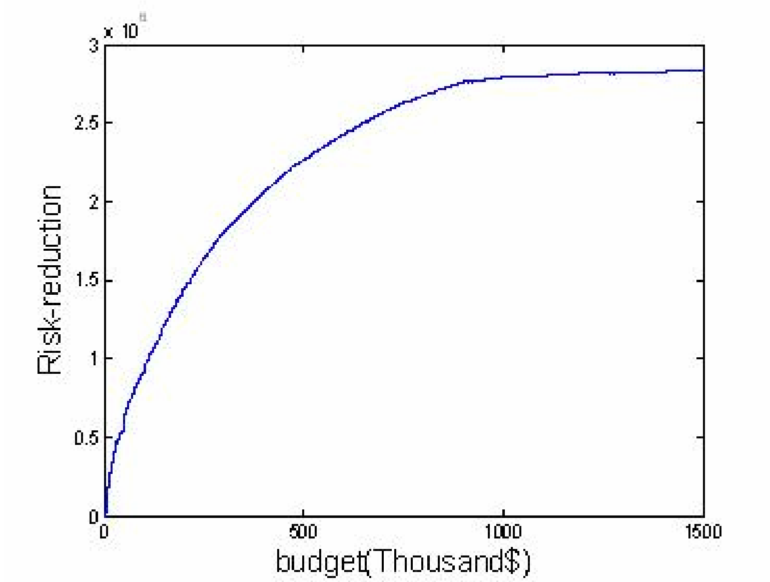

Figure 6.5: Budget vs. risk reduction.

Figure 6.6 displays resource allocation vs. total budget, which is the result of solving the Level 1 problem for various values of total budget. This identifies the optimal budget split among maintenance categories. For example, the figure indicates that for a budget of \$500k, maximum risk reduction is achieved by allocating about \$240k each to recloser maintenance and tree-trimming, and only about \$20k to wood pole maintenance. Wood pole maintenance spending should remain relatively small for budgets below about \$850k. Then wood pole spending increases for budgets exceeding \$850k, when risk reduction from additional spending on recloser maintenance or tree-trimming is minimal.

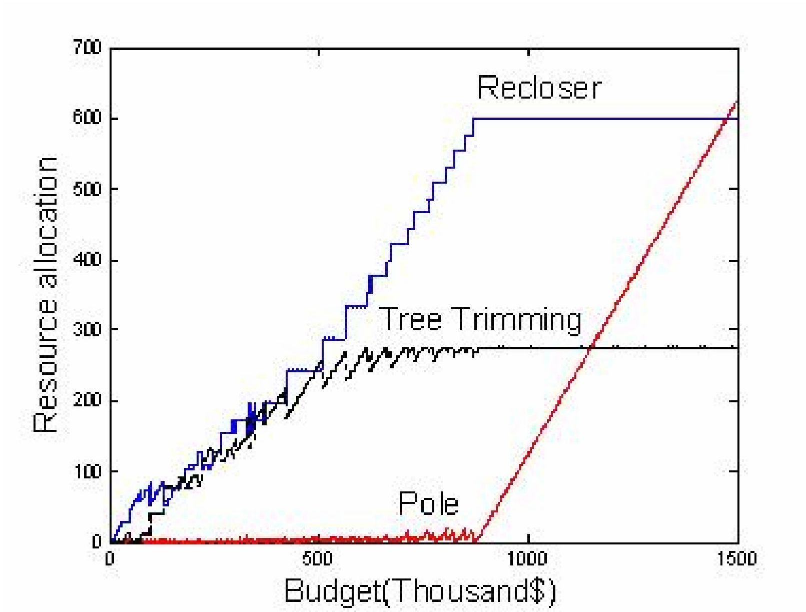

Figure 6.6: Budget-splitting curve for different tasks.

6.4.2 Labor Sensitivity Analysis

Labor constraints are included in Figure 6.5 and Figure 6.6. It is also useful to modify the labor constraints to see if increased or decreased labor spending results in different spending decisions. This information provides the basis for increasing or decreasing the number of maintenance crews.

Figure 6.7 shows the results of this analysis. The lower curve is the same as Figure 6.5, with existing labor constraints. The middle curve reflects the addition of one new recloser maintenance crew. The upper curve represents no labor constraints at all. The curves show that additional labor resources provide no significant improvement until a budget of about \$300k is reached. If a desired ΔRisk_reduction/Δbudget occurs at a budget level below \$300k, then labor reduction may be in order. Likewise, if a desired ΔRisk_reduction/Δbudget occurs for a higher budget level, then increased labor should be considered. Complementary information may be obtained by plotting risk-reduction against labor for a fixed monetary budget.

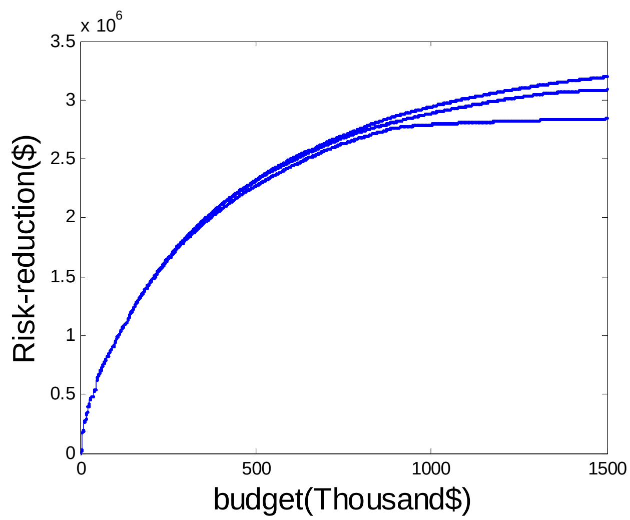

Figure 6.7: Labor sensitivity.

7 Conclusions

7.1 Summary

Distribution system reliability and asset management are assuming greater importance as utilities try to control costs while maintaining service quality. Equipment maintenance and associated reliability improvements are important not only to ensure that equipment lasts as long as it should but also to ensure customer satisfaction and retention, manage operating costs, and comply with relevant service quality regulations. Advanced strategies like reliability-centered maintenance are being adopted by utilities to manage their vast amounts of assets.

Preventive maintenance reduces the failure probability of a component and, hence, reduces the risk due to failure of the component. Each preventive maintenance task has both financial and labor costs. The objective of this project is to maximize risk reduction obtained from maintenance, within the available budget and labor constraints.

In the work presented in this report, the following applies:

- Available reliability evaluation techniques are reviewed
- Utility maintenance strategies are reviewed.
- A risk-based resource allocation method is developed.

The proposed method uses information obtained from inspection and monitoring to determine the state of the system. Available maintenance tasks are identified, and the risk reduction provided by each is computed. The risk reduction for each task is based on the condition of the component being serviced, the task's effect on improving the component's condition of equipment, and the resulting improvement in reliability indices. The tasks are prioritized subject to the constraints on available resources using an optimization technique combining integer programming, Lagrange relaxation, and dynamic programming. The method is demonstrated in Section 6 using data from an actual distribution system.

This method assists in answering the three concerns commonly faced by an asset manager:

1. How to identify and justify the resources needed for managing the assets of the entire system.
2. How to allocate the available resources to different maintenance programs.
3. How to select a set of maintenance tasks to be performed within each maintenance program.

A degradation-path model to estimate failure probability and probability reduction was developed. This model was applied to wood poles to predict individual pole failure probability based on condition measurements that represent degradation in the pole's residual strength.

A condition assessment technique was developed for reclosers. A check sheet for evaluating a recloser's condition, either in the field or in the shop, is provided. The condition score is then correlated with historical data to provide an estimate of the recloser's failure rate. Maintenance changes the recloser's condition and thus its failure rate. Similar techniques can be applied to other distribution system components.

7.2 Conclusions

The risk-based approach to maintenance scheduling integrates information obtained from inspection and monitoring of distribution system assets with their failure characteristics to estimate failure rates. The failure rate combined with the consequences of failure determines risk. Computing the risk reduction provided by each maintenance task allows the asset manager to weigh the benefits against the cost. This method combines maintenance activities into a single objective of maximizing system performance with minimal allocation of resources. It is a comprehensive strategy that results in optimal utilization of resources and enhanced system performance.

A reliability evaluation tool was developed in Chapter 4. It is deliverable in the form of a spreadsheet that can be used to estimate the reliability of a feeder and the benefits of reliability improvement schemes such as automation, introduction of reclosers or sectionalizing devices, and feeder reconfiguration. The User Manual for the spreadsheet is included as Appendix B to this report.

To include all distribution maintenance activities, both failure models and inspection methods are needed for each component under consideration. This method is highly data-intensive and requires detailed information about the equipment's condition obtained from inspection, monitoring, and maintenance records. Some of the data is available in a utility database, but these are usually designed for bookkeeping and inventory, and are not readily accessible for failure analysis. The problem may be compounded by insufficient or inaccurate data or significant changes to the network configuration. Because risk-reduction computations depend on accurate component failure-rate estimations, the accuracy of the entire method depends on the quality of condition and historical data available. But with the correct data, even though the number of devices in a distribution system is very large, the strategy can be effectively used to solve the resource allocation problem in a reasonable time and with sufficient accuracy.

7.3 Further Work

The reliability and inspection models developed should be further expanded, verified, and then adapted to other distribution equipment. Specifically, the wood pole degradation path model should be validated for other components with complex failure processes, such as switches and transformers. Similarly, the inspection methods developed for reclosers should be applied to other components, and the resulting failure rate estimates should be verified.

The problem formulation should be further enhanced by considering scheduling issues involved in equipment maintenance. The result will provide a schedule of planned maintenance for a budget period.

The optimal resource allocation strategy sacrifices some accuracy to solve the large-scale problem. Further research involving other optimization techniques will help improve the accuracy of the solution obtained.

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Appendix A: Distribution Reliability Metrics

A brief review of some of the standard definitions and indices used in distribution reliability evaluation are provided in this appendix. The definitions provided here are found in the current Draft Guide for Electric Power Distribution Reliability Indices IEEE P1366-2003 [44].

Definitions

1. **Connected Load**: The connected transformer kVA, peak load, or metered demand on the circuit or portion of circuit that is interrupted.
2. **Interrupting Device:** An interrupting device interrupts the flow of power, usually in response to a fault. Restoration of service or disconnection of loads can be accomplished by manual, automatic, or motor-operated methods. Some interrupting devices include: transmission circuit breakers, feeder breakers, line reclosers, fuses, sectionalizers and motor-operated switches.
3. **Interruption:** The loss of service to one or more customers connected to the distribution portion of the system as the result of one or more component outages.
4. **Interruption Duration:** The time period from the initiation of an interruption to a customer until service has been restored to that customer.
5. **Momentary Interruption:** A single operation of an interrupting device that results in a voltage zero.
6. **Momentary Interruption Event:** An interruption of duration limited to the period required to restore service by an interrupting device. Switching operations must be completed within a specified time of 5 minutes or less. If a reclosing device operates multiple times within 5 minutes of the first operation, then all of the momentary interruptions are classified as a momentary interruption event.
7. **Outage:** The state of a component when it is not available to perform its intended function due to some event directly associated with that component. An outage may or may not cause an interruption of service to customers, depending on system configuration.
8. **Planned Interruption:** Loss of electric power that results when a component is deliberately taken out of service at a selected time, usually for the purposes of construction, preventative maintenance or repair. If it is possible to avoid the interruption, then it is classified as a planned interruption.
9. **Planned Outage:** The state of a component when it is not available to perform its intended function due to a planned event directly associated with that component.
10. **Sustained Interruption:** Any interruption not classified as a part of a momentary event, which would be any interruption lasting more than five minutes.

Reliability Indices

The most common reliability indices used by utilities are SAIDI, SAIFI, CAIDI, and ASAI [31]. Most of them are based on averages of customer reliability that weight each customer equally. The following are five of the most common reliability indices used for distribution systems as defined in the IEEE Guide for Electric Power Distribution Reliability Indices (IEEE 1366-2003):

1. System Average Interruption Frequency Index (SAIFI):

The system average interruption frequency index (SAIFI) indicates how often the average customer experiences a sustained interruption over a predefined period of time for a given area in the system:

$$SAIFI = \frac{Total\ number\ of\ customers\ interrupted}{Total\ number\ of\ customers\ served} \tag{A.1}$$

For a fixed number of customers, the only way to improve SAIFI is to reduce the number of sustained interruptions.

2. System Average Interruption Duration Index (SAIDI):

System average interruption duration index (SAIDI) indicates the total duration of interruption for the average customer during a predefined period of time, commonly measured in customer minutes or customer hours of interruption:

$$SAIDI = \frac{Total\ duration\ of\ all\ customer\ interruptions}{Total\ number\ of\ customers\ served} \tag{A.2}$$

SAIDI can be improved by reducing the number of interruptions or the duration of the interruptions.

3. Customer Average Interruption Duration Index (CAIDI):

The customer average interruption duration index (CAIDI) represents the average time taken to restore service to the customers:

$$CAIDI = \frac{Total\ duration\ of\ all\ customer\ interruptions}{Total\ number\ of\ customers\ interrupted} \tag{A.3}$$

CAIDI can be improved by reducing the length of interruptions by faster crew response time and repair times.

4. Average Service Availability Index (ASAI):

The average service availability index (ASAI) represents the fraction of time that a customer has received power during the defined reporting period. Higher ASAI values reflect higher levels of reliability [31]:

$$ASAI = \frac{Customer\ hours\ service\ availability}{Customer\ hours\ service\ demand} \tag{A.4}$$

5. Customer Average Interruption Frequency Index (CAIFI):

The customer average interruption frequency index (CAIFI) gives the average frequency of sustained interruptions for those customers experiencing interruptions (each customer is counted only once, regardless of how many interruptions they experienced):

$$CAIFI = \frac{Total\ number\ of\ customer\ interruptions}{Total\ number\ of\ customers\ interrupted} \qquad \text{(A.5)}$$

Appendix B: User Manual for Reliability Evaluation Tool

The following document describes in detail the usage of the reliability evaluation tool discussed in Chapter 4.

The spreadsheet was developed in Microsoft Excel. To use it, macros must be enabled. In Excel, go to Tools>Macro> Security and set the Security Level to “low.” Click “OK.” Close Excel and restart it. Then go to Tools> Customize> Toolbars and check the box for Visual Basic. Then add the resulting VBA toolbar to the tools:

The reliability evaluation software comes as a zip file that contains the following files:

1. A folder named “Backup” with the updated Visual Basic macros and user-forms.
2. Spreadsheets for six individual feeders: Feeder1, Feeder2….Feeder6. Each describes the topology of one feeder in the distribution system being analyzed. Table B.1 describes the layout of these spreadsheets. To create or add new feeders to the existing system of six feeders, copies of any of the feeder files can be used.
3. Special function files:
   a. Automate_Control.xls: provides the interface and platform for performing reliability evaluation on the entire distribution system. It can also be used to assign failure and repair parameters to various feeders (urban or rural). Please do not rename, delete or move this file from the folder.
   b. Master_file.xls: Contains the default values of failure and repair parameters of various distribution components. Sheet 1 stores all the default values for the rural feeders. Sheet 2 stores the values for urban feeders. Please do not rename, delete or move this file from the folder.
   c. Results_summary.xls: Updates the results obtained from a reliability evaluation done on the entire system. It also computes the sensitivities of the various reliability indices when maintenance is done on a particular component. Please do not rename, delete or move this file from the folder.

Table B.1: Feeder Topology Spreadsheets

One line of data for each feeder segment		
Col. No.	**Column**	**Description**
A	Segment#	Unique identifier for each segment of feeder; first segment for each feeder is the equivalent component discussed in section 4.2.5.
B	From node #	Node number that marks beginning of segment

C	To node #	Node number that marks end of segment
D	Upstream segment#	Upstream segment of segment
E	Protection zone	Column left blank (output of program)
F	Switching zone	Column left blank (output of program)
G	Ht above the ground	Column left blank (output of program)
H	Over/ under flag	Takes values "“Over"” or "“Under"” or "“-"” for overhead line segments, underground cables, and equivalent segment, respectively
I	Length	Length of line segment in kft (1000 ft)
J	Load A	Load connected to Phase A in kWh
K	Load B	Load connected to Phase B in kWh
L	Load C	Load connected to Phase C in kWh
M	No. of customers	Customers connected to segment
N	Permanent failure rate before	Failure rate of segment before maintenance (failures/mile-year)
O	Permanent failure rate after	Failure rate of segment after maintenance (failures/mile-year)
P	Cost of failure	Cost of failure on segment ($)
Q	MTTR	Average repair time of segment (hours)
R	Phase	Phase configuration of segment
S	Protective device #	For segments with protective device, contains unique identifier for protective device
T	Segment#	Same as column A
U	Type	BRK/ FUS/ REC/ SWI/ SZL
V	Upstream segment #	For a “CLOSED” device, same as column D; for an “OPEN” switch, same as column A
W	PR	Value between 0.00 and 1.00
X	RR	Value between 0.00 and 1.00
Y	MTTS	Average time to perform switching (hours)
Z	SR	Value between 0.00 and 1.00
AA	Status	CLOSED/ OPEN
AB	Close to node	For a “CLOSED” device, same as column B; for an “OPEN” switch, same as column C

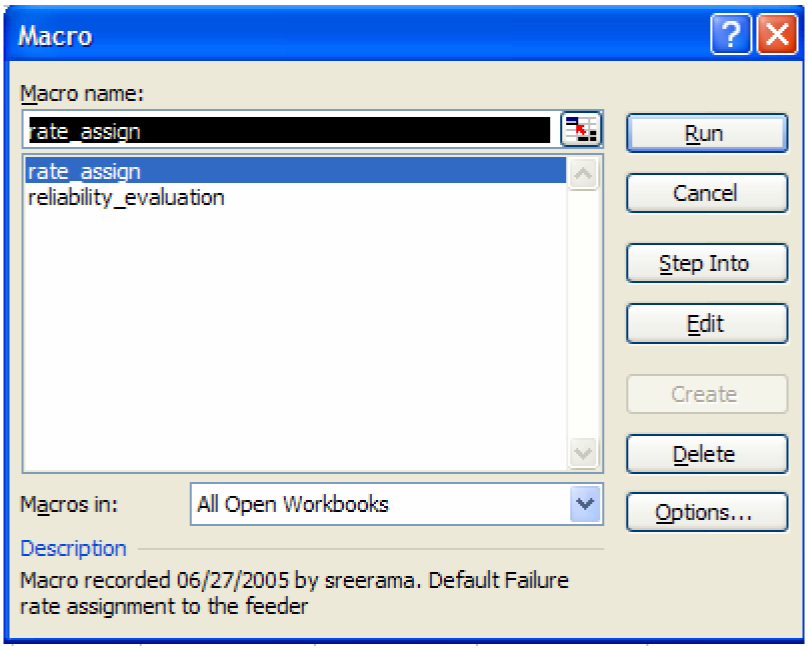
AC	MTTR of device	Average repair time of device (hours)
AD	Cost of device failure	Cost of failure of device ($)
AE	Expected number of customers affected before maintenance	Column left blank (output of program)
AF	Expected number of customers hours interrupted before maintenance	Column left blank (output of program)
AG	Expected energy interrupted before maintenance	Column left blank (output of program)
AH	Expected cost of failure before maintenance	Column left blank (output of program)
AI	Expected number of customers affected after maintenance	Column left blank (output of program)
AJ	Expected number of customers hours interrupted after maintenance	Column left blank (output of program)
AK	Expected energy interrupted after maintenance	Column left blank (output of program)
AL	Expected cost of failure after maintenance	Column left blank (output of program)
AM	SAIFI(i)	SAIFI of the feeder after maintenance done on segment ‘i’ (output of program)
AN	SAIDI(i)	SAIDI of the feeder after maintenance done on segment ‘i’ (output of program)
AO	Delta SAIFI(i)	Improvement in SAIFI due to maintenance on segment ‘i’ (output of program)
AP	Delta SAIDI(i)	Improvement in SAIDI due to maintenance on segment ‘i’ (output of program)
AQ	Delta ENS(i)	Improvement in energy not served (ENS) due to maintenance on segment ‘i’; column left blank (output of program)
AR	Delta COF(i)	Reduction in cost of failure (COF) due to maintenance on segment ‘i’; column left blank (output of program)
AS	PRa(Recloser)	Recloser protection reliability after maintenance; value between 0.00 and 1.00 (only for reclosers)
AT	RRa(Recloser)	Recloser reclose reliability after maintenance; value between 0.00 and 1.00 (only for reclosers)
AU	Delta SAIFI(i)	Improvement in SAIFI due to maintenance done on recloser (output of program)
AV	Delta SAIDI(i)	Improvement in SAIDI due to maintenance on recloser (output of program)
AW	Delta ENS(i)	Improvement in ENS due to maintenance on recloser; column left blank (output of program)
AX	Delta COF(i)	Reduction in COF due to maintenance on recloser; column left blank (output of program)

NORMAL MODE OF OPERATION:

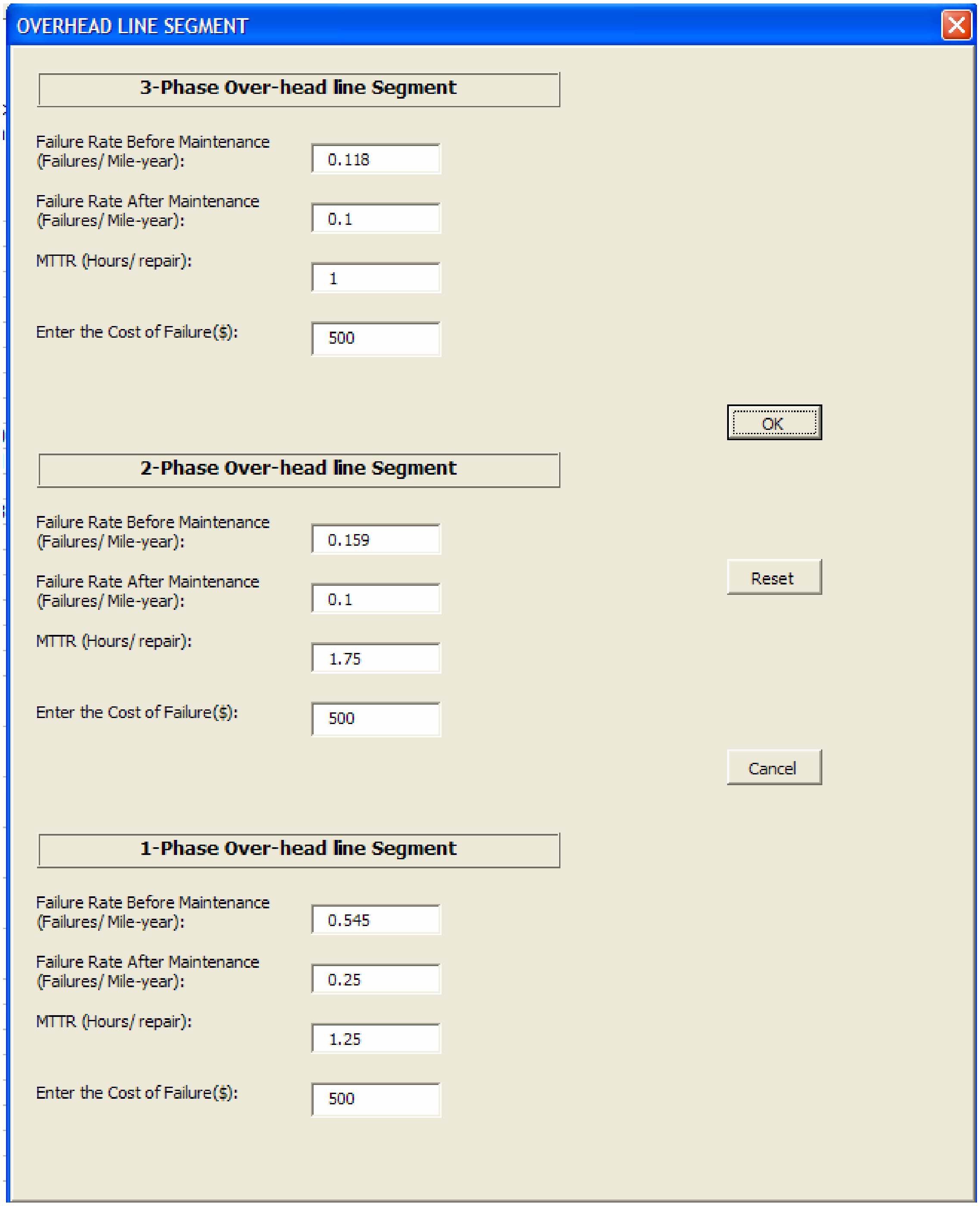
The basic mode of using the reliability evaluation tool is at the feeder level. The following macros are available in this mode.

To assign default failure and repair parameters for each feeder:

Go to Tools>Macro> Macros, select rate_assign and press Run. Alternatively, press [Ctrl + d].

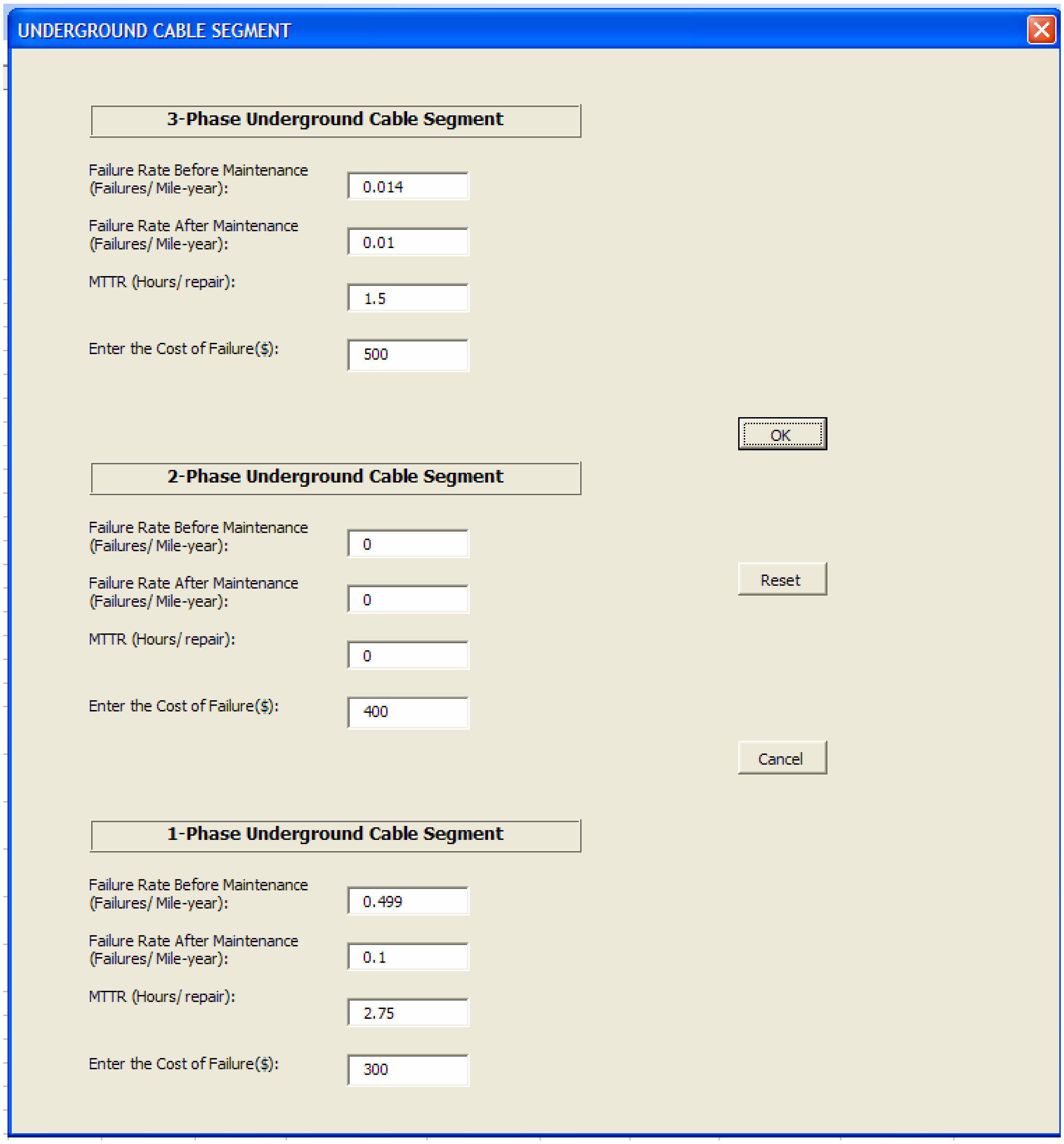


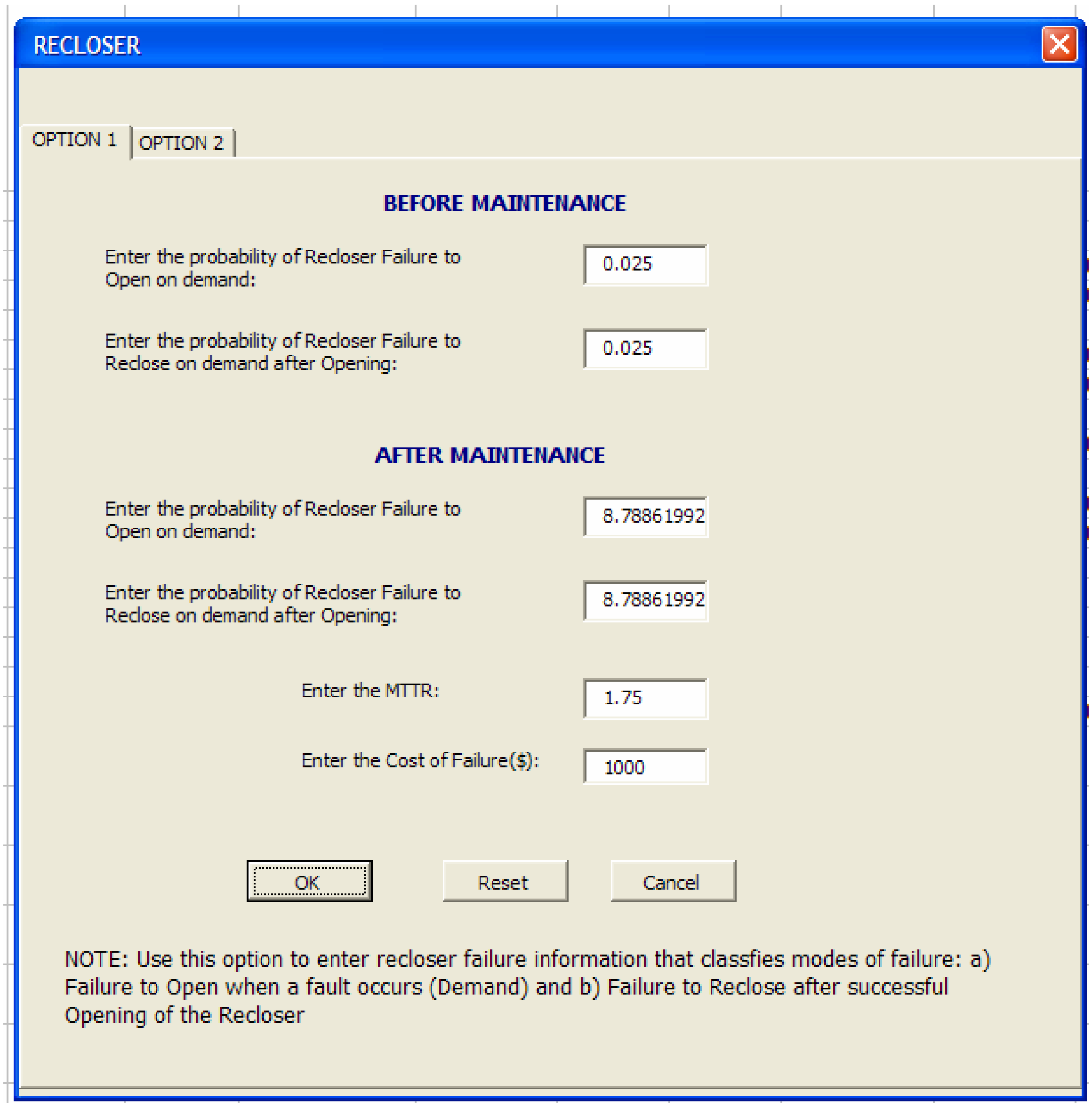
Upon execution, failure and repair parameters are assigned to various distribution system components, as shown in the following figures. The default values that appear are drawn from the Master_File.xls. They can be changed in the interfaces shown. Parameters for individual components and segments are changed directly in the spreadsheet.



Using the line and cable interfaces shown, failure rates before and after maintenance, mean time to repair (MTTR), and cost of failure (COF) can be input for three-phase, two-phase and one-phase line segments. The failure rates are the average number of sustained or permanent failures expected in a unit mile length. Values for failure probabilities should be between 0.00 and 1.00. MTTR is entered in h, and COF has the units of US$.

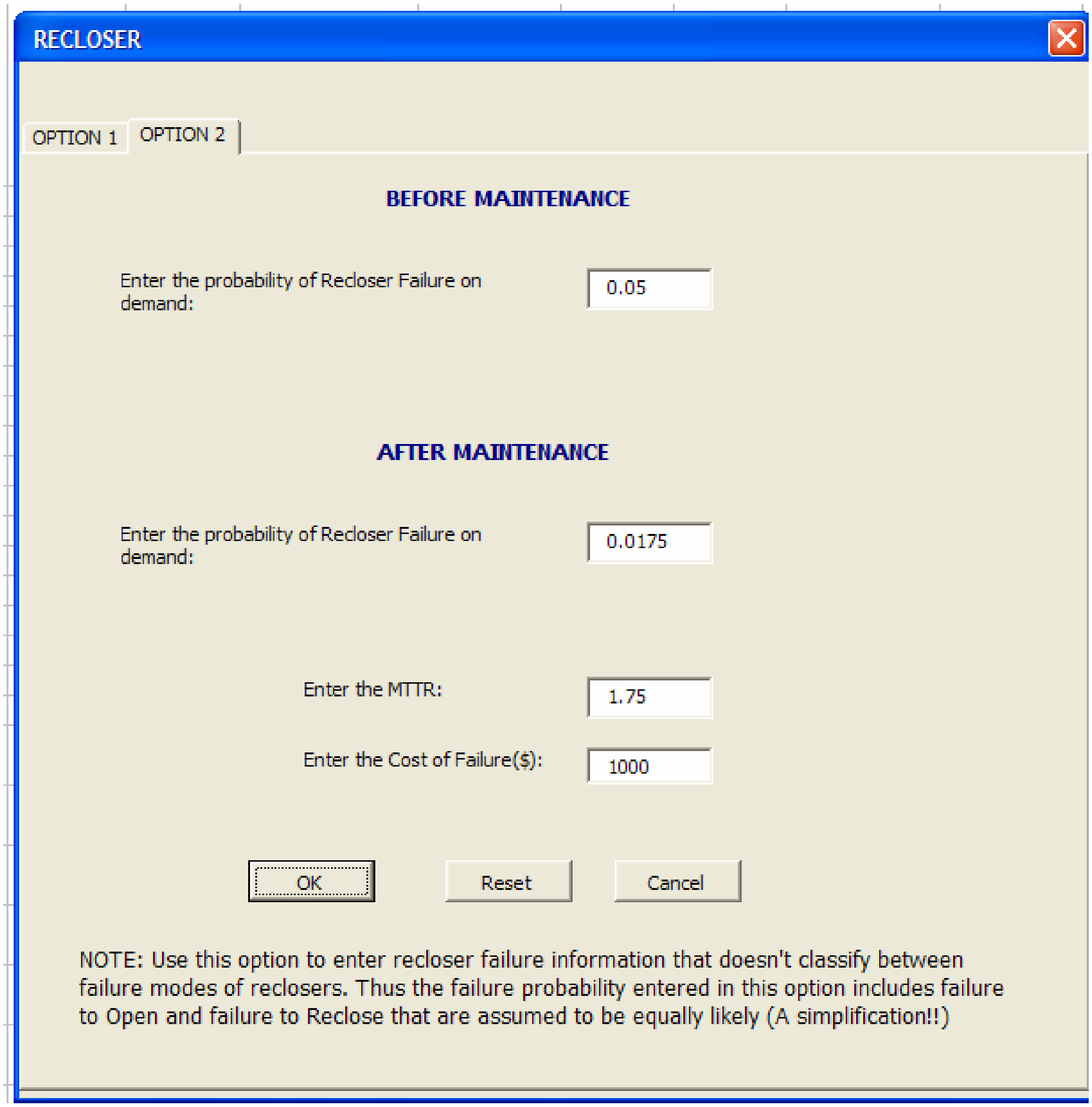
Once all values are entered, they are applied to the feeder by clicking 'OK.' Clicking 'Reset' restores the default parameters stored in the Master_File.xls. 'Cancel' sets all parameters to zero.


UNDERGROUND CABLE SEGMENT
3-Phase Underground Cable Segment
Failure Rate Before Maintenance (Failures/ Mile-year):
0.014
Failure Rate After Maintenance (Failures/ Mile-year):
0.01
MTTR (Hours/ repair):
1.5
Enter the Cost of Failure($):
500
OK
2-Phase Underground Cable Segment
Failure Rate Before Maintenance (Failures/ Mile-year):
0
Failure Rate After Maintenance (Failures/ Mile-year):
0
MTTR (Hours/ repair):
0
Enter the Cost of Failure($):
400
Reset
Cancel
1-Phase Underground Cable Segment
Failure Rate Before Maintenance (Failures/ Mile-year):
0.499
Failure Rate After Maintenance (Failures/ Mile-year):
0.1
MTTR (Hours/ repair):
2.75
Enter the Cost of Failure($):
300

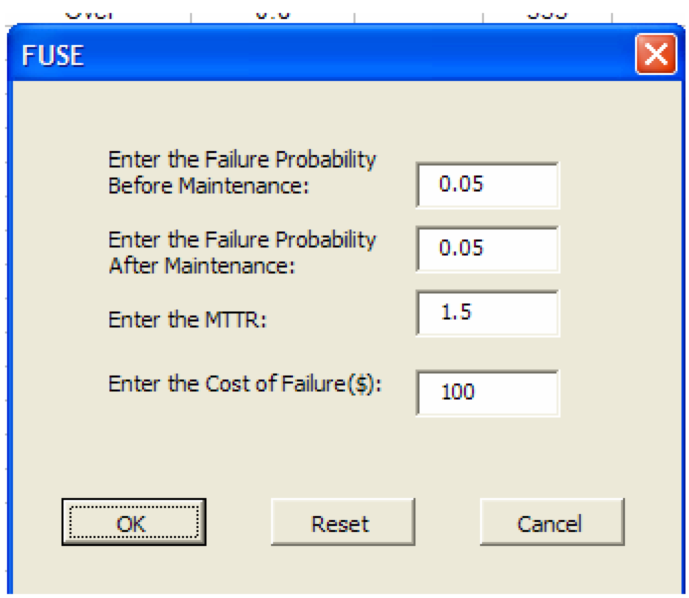


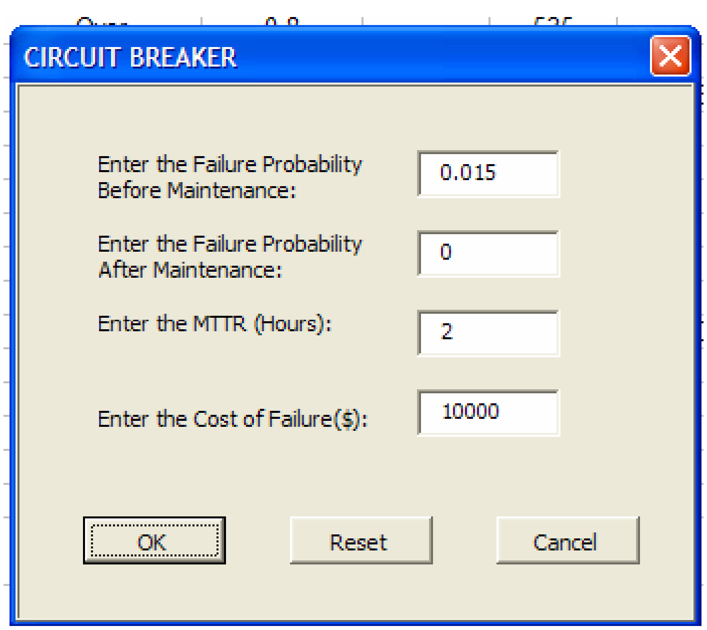
To enter data for reclosers, the user has two options. Option 1 requires the user to input the probability that a recloser fails to open in the event of a fault, and the probability that a recloser fails to reclose once it has cleared a fault. Also required are the probabilities of failure after maintenance and the recloser's MTTR and COF.

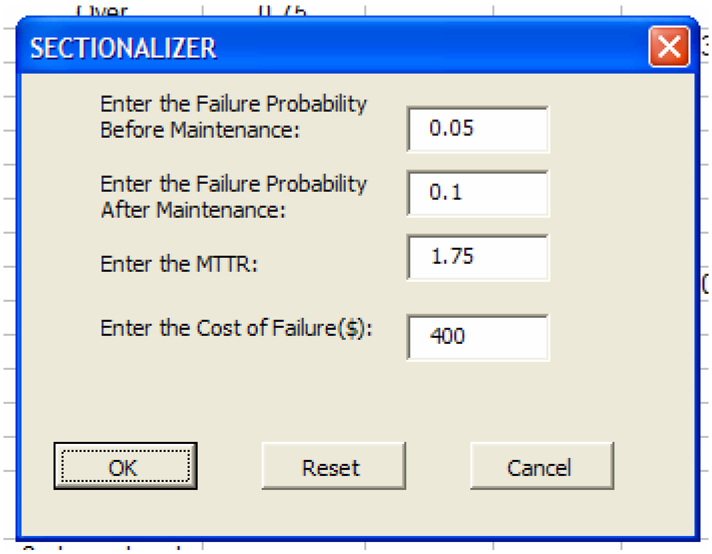
If information characterizing individual failure modes is not available (i.e., failures cannot be classified as failure to open or reclose), Option 2 can be used to enter the overall failure probability of the recloser.

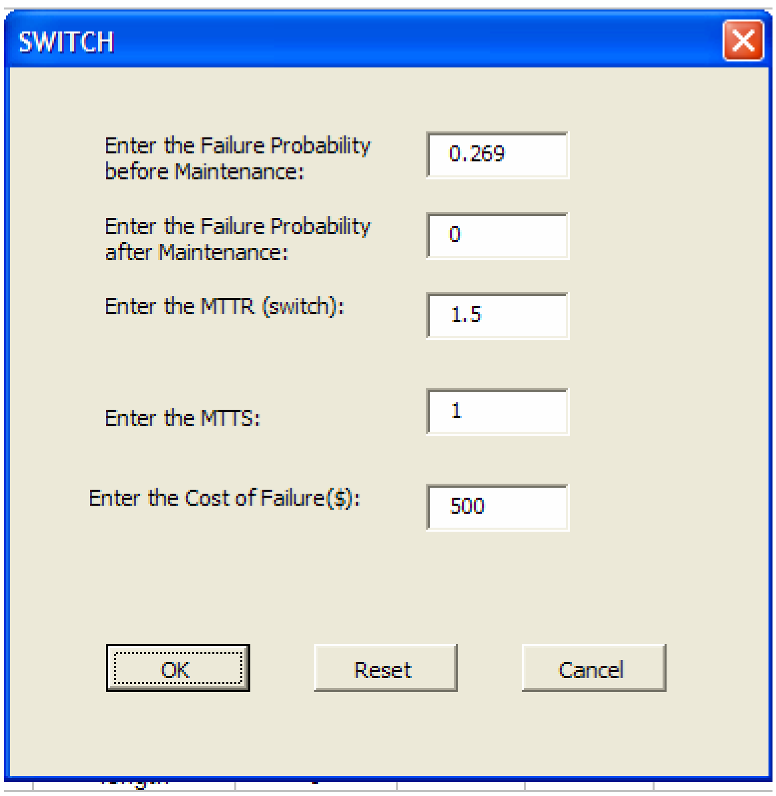


The interface for fuses, circuit breakers, and sectionalizers is similar to that for reclosers. These components have only one failure mode—failure to open in response to a fault.


FUSE
Enter the Failure Probability Before Maintenance:
0.05
Enter the Failure Probability After Maintenance:
0.05
Enter the MTTR:
1.5
Enter the Cost of Failure($):
100
OK
Reset
Cancel


CIRCUIT BREAKER
Enter the Failure Probability Before Maintenance:
0.015
Enter the Failure Probability After Maintenance:
0
Enter the MTTR (Hours):
2
Enter the Cost of Failure($):
10000
OK
Reset
Cancel



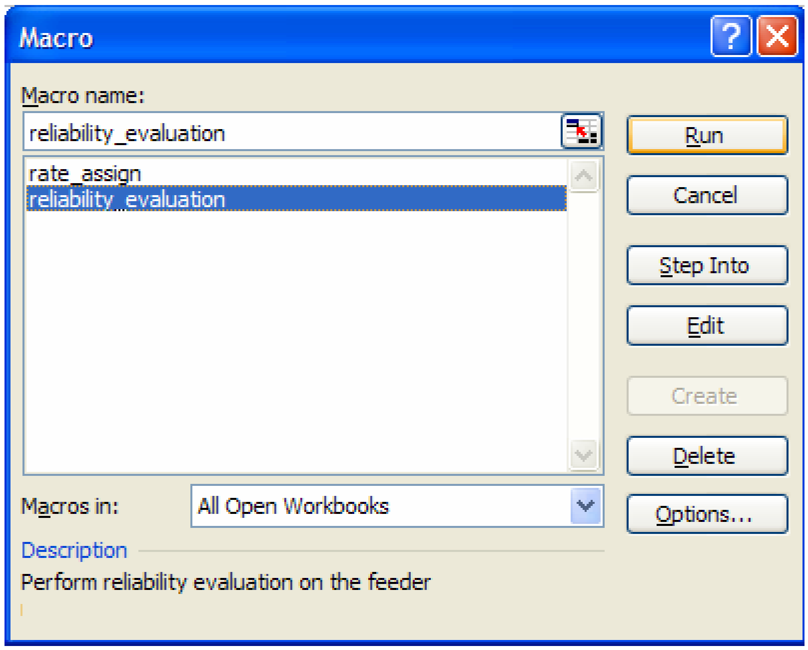


In the switch interface shown, switch failure probability is the probability that a switch fails to switch when needed. The MTTR and mean time to switch (MTTS) represent the average repair and switching times, in h.

The switching characteristics of protective devices are not included in the rate_assign macro. The values MTTS and switching reliability (SR), the probability that a device is switched when required, are entered in the spreadsheet in columns 25 and 26, respectively.

To compute the reliability of the feeder:

Go to Tools>Macro> Macros, select reliability_evaluation, and press Run. Alternatively, press [Ctrl + r]. This computes the reliability indices of the feeder and the corresponding sensitivities due to maintenance. Outputs appear in the spreadsheet, as indicated in Table B.1.

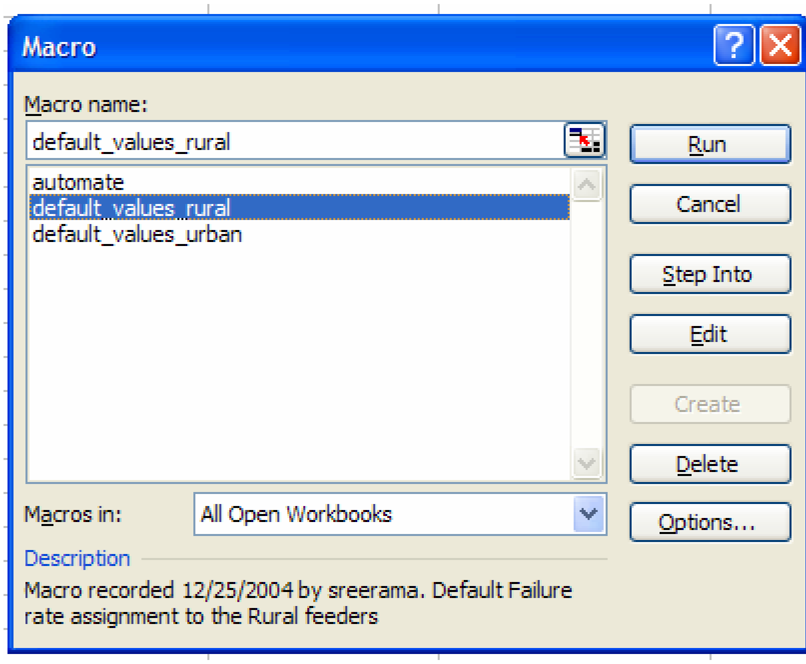


AUTOMATED MODE OF OPERATION:

In the automated mode, failure and repair parameters can be assigned to feeders grouped as rural or urban feeders. Reliability evaluation can also be performed on the entire system. These functions can be performed using the Automate_Control.xls spreadsheet provided. Open the file Automate_Control.xls.

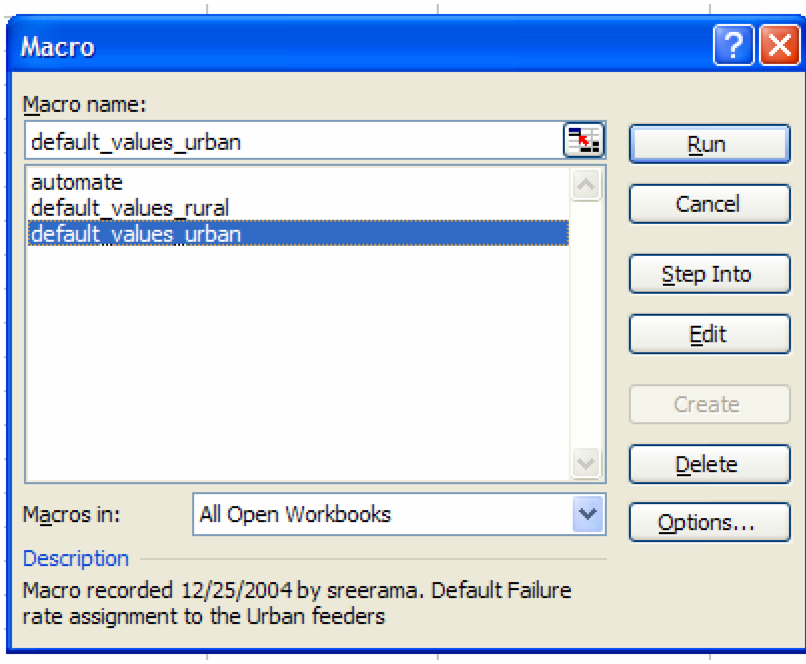
To assign default failure and repair parameters for all rural feeders:

Go to Tools>Macro>Macros, select default_values_rural and press Run. Alternatively, press [Ctrl + r]. Enter the reliability parameters as they were entered in the rate_assign macro.



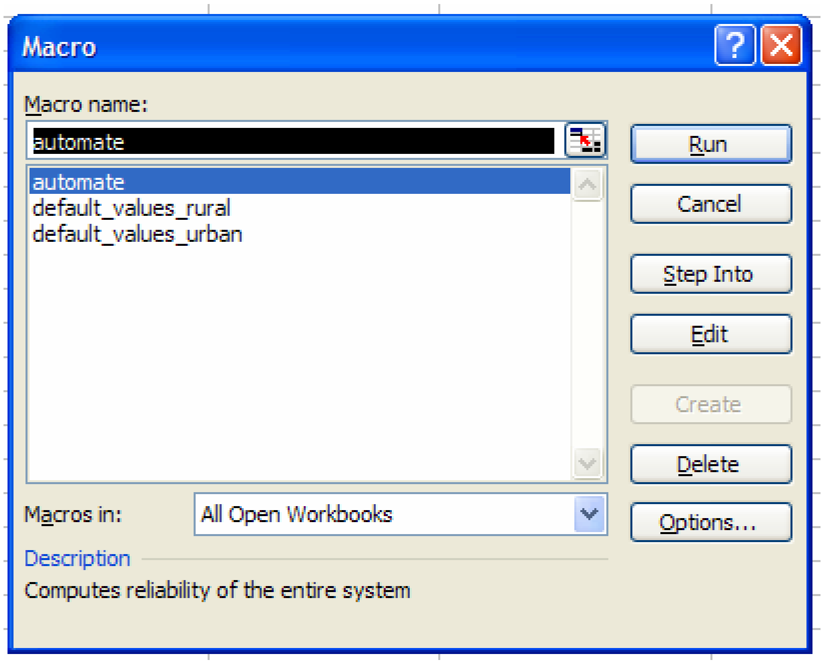
To assign default failure and repair parameters for all urban feeders:

Go to Tools>Macro>Macros, select default_values_urban and press Run. Alternatively, press [Ctrl + u]. Enter the reliability parameters as they were entered in the rate_assign macro.

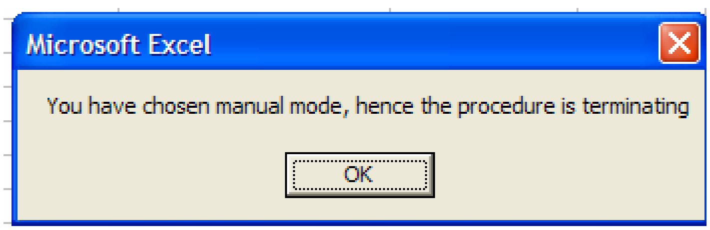


To compute the reliability of the entire system:

Go to Tools>Macro> Macros, select automate, and press Run. Alternatively, press [Ctrl + a]. This requires the user to input the value of '1' if reliability evaluation for the entire system is desired and '0' if not.



If '0' is entered, the program execution is terminated and is followed by the message below.



Appendix C: User Manual for the Optimizer

The optimizer is written in Matlab and compiled into executable file. The following files are contained in a compressed file, RDRA.zip, which contains the following:

/RDRA //root directory
/RDRA/DATA/recl.dat //recloser candidate triplets
/RDRA/DATA/tree.dat //tree-trimming candidate triplets
/RDRA/DATA/pole.dat //wood pole candidate triplets
/RDRA/optconFiguredat //user configuration file
/RDRA/task.exe //solves the task selection subproblem
/RDRA/budget.exe //solves the budget planning subproblem

In the optconFiguredat, the user can set the available resource, budget step size, and maximum budget for the study. An example of this file is as follows:

unit=1000; *%UNIT=1000$*
maxbudget=2000; *%so the total budget = maxbudget*unit*
pole_labor=16000; *%person hour for wood pole category*
recl_labor=1600; *%person hour for recloser category*
trim_labor=9600; *%person hour for tree-trimming category*

In the recloser (recl.dat), tree (tree.dat), and pole (pole.dat) data files, the inputs are the candidate triplets: {risk-reduction, money cost, labor cost}.

pole

	1	2	3	4	5	6
1	65.41888	3000.0	24.0	16.35472	200.0	8.0
2	16.40943	3000.0	24.0	4.10236	200.0	8.0
3	190.98087	3000.0	24.0	47.81504	200.0	8.0
4	51.39968	3000.0	24.0	12.84992	200.0	8.0
5	302.15175	3000.0	24.0	75.53794	200.0	8.0
6	38.16557	3000.0	24.0	9.54139	200.0	8.0
7	17.76203	3000.0	24.0	4.44051	200.0	8.0
8	177.27813	3000.0	24.0	44.31953	200.0	8.0
9	128.68019	3000.0	24.0	32.17005	200.0	8.0
10	21.50145	3000.0	24.0	5.37536	200.0	8.0
11	51.37194	3000.0	24.0	12.84299	200.0	8.0
12	16.58348	3000.0	24.0	4.14587	200.0	8.0
13	110.37174	3000.0	24.0	27.5774	200.0	8.0
14	11.52335	3000.0	24.0	2.88084	200.0	8.0

Figure C.1. Input file of pole candidate tasks.

Each line of data has two triplets, corresponding to two levels of maintenance activities for each device.

The two executable files, task.exe and budget.exe, solve the task selection and budget planning subproblems. After running the task.exe file, there will appear two new .dat files in /RDRA/data. One is the risk-reduction vs. budget table (ptable.m) and the other is the corresponding task selection table (pole_Iselect.m for pole, etc.).

0	0	0
5128.68931	0	0
8249.06255	0	0
10265.19511	0	17914.27853
11885.73384	0	17914.27853
13184.874	0	17914.27853
14238.80502	170568.2246	17914.27853
15152.66377	170568.2246	17914.27853
16002.20306	170568.2246	17914.27853
16793.92338	170568.2246	17914.27853
17509.169	170568.2246	17914.27853
18169.79678	259236.9347	17914.27853
18791.77688	259236.9347	74086.0633

Figure C.2. Risk reduction versus budget table (ptable.m).

35***	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
36***	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
37***	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
38***	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
39***	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
40***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
41***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
42***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
43***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
44***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
45***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
46***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
47***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
48***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
49***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
50***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
51***	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0

Figure C.3. Task selection table (trim_select.m for tree-trimming).

Budget.exe creates two files, which appear in the directory /RDRA/DATA/. One, totrisk.dat, is the total risk-reduction vs. budget. The other, split.dat, is the budget split.