PSERC

Integration of Asset and Outage Management Tasks for Distribution Application

Final Project Report

Power Systems Engineering Research Center

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Integration of Asset and Outage Management Tasks for Distribution Application

Final Project Report

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Power Systems Engineering Research Center

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Executive Summary

Faults in distribution system may cause interruption of power supply to customers. Since distribution systems in general encounter high frequency of faults caused by weather, component wear and other reasons, the need to reduce outage time caused by faults is required for an important reason: better service to customers. Customer requirements on the quality of service are constantly growing. As an example, sensitive loads in modern industry, such as chip manufactures or ore smelters, are very sensitive to interruptions in power supply. The consequence of failure is more severe nowadays than decades before when such sensitive loads were not so prominent. The most direct impact of faults on the utility profit is the loss in customer sales as well as the increase in maintenance expenses.

Reliability indices, defined in an IEEE standard, are used to evaluate the impact of faults on distribution system performance. The System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) are the two most widely used indices. Lower values of SAIDI and SAIFI are associated with higher levels of distribution reliability. However, each reliability index reflects only one or two aspects of system reliability. When analyzing distribution reliability, several reliability indices should be used.

On the other hand, different types of customers have different reliability requirements. The trade-off between the reliability experienced by individual customers and the overall reliability for the whole system should also be considered when estimating outage costs.

This study looked at two ways to improve the reliability of a distribution system. One is to improve the performance of outage management tasks so that the impact of faults can be minimized. The second way is to improve the performance of asset management tasks so that failures occur less frequently and the fault is "prevented".

This study explores the technologies available for both asset management and outage management tasks by addressing the following issues:

- *Lack of data*. Beside voltage and current measurement at substations, few monitoring devices for measurements are installed in a distribution system; this study develops a methodology on how to correlate improvement in the measurement infrastructure with improvement in performance, a crucial decision-making tool for making investment allocations.

- *Ineffective processing of faults and maintenance scheduling caused by inefficient use of operational data.* The fault location practice is currently based on trouble calls and manual switching while maintenance is performed either with a run-to-failure strategy or with a fixed ahead-of-the-time planned schedule which does not require operational data but yields less efficient performance. The study points out how operational data (i.e., measurements from intelligent electronic devices or IEDs) can be utilized for implementing more efficient outage and asset management solutions.

- *Independent planning and operation of asset and outage management tasks.* Those two functions are planned independently, including planning of budgets even though the equipment that may record and collect relevant data from the

field maybe common to both applications. The study ties the two planning function together through risk-based cost analysis, a unique solution for optimized planning of budgets and tasks associated with both outage and asset management simultaneously.

The approaches mentioned above have been implemented on the distribution system model connected to a bus in an IEEE reliability test system. The result shows that the frequency and duration of faults decrease and system reliability improves as a result of the proposed technology deployment and tool improvements.

Additional research issues need to be studied so that the investment in asset management and outage management can provide maximum return. Further research may include:

- *Integrated view of capital investment strategy*. This effort should answer the question of how the investment in monitoring equipment should be allocated among asset management and outage management tasks in a most efficient way, i.e., how to gain the largest return for utilities and the greatest improvement in reliability of the system for the customers. The risk-based assessment of outage cost can be used as the objective of the optimization problem;
- *Post-fault reconfiguration*. The impact of reconfiguration cost after the fault has been located using the outage task needs to be addressed. The following two costs should be compared:
    - The implementation cost of the best scheme for reconfiguration made possible with improvements in the technology and tools proposed in this study
    - Cost of conventional practice: isolate the faulted area and after the replacement or repair is done restore service to the customers that lost power due to the fault.
- *Placement of IEDs in a distribution system*. This topic requires a more comprehensive study of the optimal placement of IEDs. Given a certain amount of capital funds, the research needs to focus on where the measurements should be taken in the system so that the overall accuracy of fault location program is maximized.

Table of Contents

List of Figures

List of Tables

Nomenclature

IED	Intelligent Electronic Device
σ	Standard Deviation
J	Jacobi index
RI	Residual Index
γ	Weighted Deviation
h	Hazard Function
SAIFI	System Average Interruption Frequency Index
SAIDI	System Average Interruption Duration Index
ENS	Energy Not Served
ASIDI	Average System Interruption Duration Index
MAIFI	Momentary Average Interruption Event Frequ
MED	Major Event Day
AM	Asset Management
OM	Outage Management
λ	Failure rate
MTTF	Mean Time To Failure
N	Number of Customers
LT	Total Connected kVA
d	Duration of Outage

1. Introduction

1.1 Background

Faults in distribution system may cause interruption of power supply to customers. Since distribution systems in general encounter high frequency of faults caused by weather, component wear and other reasons, the need to reduce outage time caused by faults is required for several reasons:

- *Better service to customers.* Customers' requirement on the quality of service is constantly growing. As an example, sensitive loads in modern industry such as chip manufacture and ore smelter are very sensitive to interruptions in power supply. The consequence of failure is more severe nowadays than a decade before;

- *Return on investment for utility shareholders*. The most direct impact of faults on the profit is the loss in customer billing, as well as maintenance expense. The concern is how to reduce the outage and repair time so that the service can be restored as soon as possible.

Reliability indices defined in an IEEE standard are used to evaluate the impact of faults on power distribution performance [1]. The System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) are two most widely used indices. The lower the value of SAIDI and SAIFI, the better the performance in terms of reliability. According to a survey done by the IEEE Working group on distribution reliability , in the year 2007, the average SAIDI derived from SAIDIs provided by 153 utilities is 385.94 min/(customer*year), and the average SAIFI is 3.20 /(customer*year) [2].

Currently the improvement in distribution performance is hampered by four major issues:

- Lack of data. Beside voltage and current measurement at substations, few monitoring devices for measurements are installed in a distribution system;

- Aging of equipment. Most of the primary equipment installed in the USA distribution system is pretty old, in some instances over 30-40 years.

- Ineffective fault restoring and maintenance scheduling caused by the lack of data. The fault location is currently based on trouble calls and manual switching [3] while maintenance is performed either with a run-to-failure strategy or with a fixed ahead-of-the-time planned schedule [4]. Nether require operational data;

- Independent planning and operation of asset and outage management. Those two functions are planned independently even though the equipment that may record and collect relevant data from the field maybe common to both applications.

Technologies have been proposed to reduce the frequency and duration of faults. For outage management, effort has been made to better process the trouble calls [5], supplement information from trouble calls with automatic meter reading (AMR) system and other sources [6], and to investigate various methods to locate faults [7]-[9]. For asset management, condition-based maintenance has been proposed to prevent component failure and reduce cost by monitoring real-time electrical quantities and assessing condition of equipment [10, 11].

1.2 Asset Management in Electric Utility Distribution

Today's distribution utilities have to face the challenges of cost, growing demand, environmental concerns, regulatory issues, customer satisfaction and reliability issues. This has given increased importance to the cost effective and efficient use of physical assets. Asset management within an electric power distribution utility involves making decisions about those assets to allow the business to maximize long term profits, while achieving maximum customer satisfaction with acceptable and manageable risks. [12]

The goals of asset management are to reduce spending, improve performance and effectively manage risk, and to find an optimal balance among these. Asset management must consider issues such as aging infrastructure, asset utilization, maintenance planning, automation, reliability and risk management. Asset management can be broadly divided into three main areas: Management, Engineering and Information Processing activities.

Technical aspects of Asset Management include all the Engineering activities mentioned above. Asset Management for large scale complex power systems can be categorized based on the time scale as:

• Short-term asset management: The Main task of short term asset management is to ensure the secure and reliable operation and control of the power system. This focuses on real time system monitoring, tracking asset conditions, and performing fault restoration to improve system's reliability. System monitoring, and tracking of asset conditions, is done through Supervisory Control and Data Acquisition (SCADA) system and Geographic Information System (GIS).

• Mid-term asset management: Mid-term asset management focuses on the maintenance aspects of physical assets. Maintenance is an important part of any asset management activity. Maintenance policies are selected to satisfy both technical aspects (to ensure reliability and safety of supply) and financial aspects (as cost is involved in maintenance activities). Maintenance activities can be divided as emergency (corrective), preventive (scheduled) and predictive (condition based).

• Long term asset management: Long term asset management involves strategic planning activities for network growth, taking into account increasing load, reliability, quality of supply, environmental, and regulatory issues. For radial systems, which make up the majority of distribution systems, the least reliable equipment affects the reliability of the entire system. Hence it is desirable that the decision-making techniques used in strategic planning must consider the condition and performance of the various assets of the system.

1.3 Outage Management in Distribution System

Outage management focuses on detecting, locating and clearing of faults. Currently fault location method can be classified into following categories:

• Trouble call-based approach: The first call implies a potential network failure (fault alert), while additional calls confirm the failure and altogether they form a data base for the outage management tool. Each call is associated with a physical location on the network through the customer-network link. The outage tool analyzes trouble calls that are not associated with known or verified outage, and then group them into probable outages. Logical analysis such as fuzzy logic is then applied to provide an outcome based on a set of rules.

• Impedance-based approach: The impedance is calculated using voltage and current phasors recorded from one or both ends of the feeder where the fault occurs. The location of fault is then provided in terms of distance from one end of a branch. Impedance-based approach has been applied successfully in transmission system, but does not work well in distribution systems, because of the complicated topology and lack of sensors.

• Traveling wave-based approach: Traveling wave method relies on calculation of time for the traveling wave to reach the end of the line. Determining accurately the arrival time of the traveling wave to the sensor is crucial for such methods. As the traveling wave travels at the speed close to speed of light, a difference of 1μS in time will cause an error of approximately 150 meters. As a result, wave detection technique and a high sampling rate are required, which is not available for most distribution systems.

• Model-based approach: Model-based methods assume faulted node and compare the simulated electric quantities (node voltage, line current, etc.) with recorded values. Such methods are favored under the condition of sparse measurements, i.e. field-recorded data are not sufficient to support other methods. System model can be obtained from SCADA and requires no extra investment. The fault location algorithm developed in this work is a model-based algorithm.

1.4 Common Issue between Asset Management and Outage Management

The new technologies in both asset management and outage management use non-operational data, which is recorded in the field by intelligent electronic devices (IEDs), and reveals the current condition of the system. The overlapping IED database use by outage and condition-based asset management makes integration of outage and asset management possible. Today's software solution providers are focusing on packaging applications that will work as a single tool addressing the business processes across the multiple departments in an electric utility. They are providing an integrated set of applications that work together in real time giving enterprise-wide visibility, which helps to improve business processes. Most of the leading software solutions providers for electric utilities cover applications like Customer Care and Billing, Asset and Work Management, Outage and Distribution Management, Supervisory Control and Data Acquisition (SCADA) systems, Geographical Information Systems (GIS), Mobile Work Force Management and Enterprise Business Intelligence.

The expected benefits from the integration include: savings in IED installation expenditures, efficient collection and use of non-operational data, reduced failure cost and better system reliability, and finally more return on investment.

1.5 Report Organization

After an introduction, the report presents the concept of data integration, as well as new solutions for outage management and asset management tasks. The risk based approach to cost analysis and the benefits of integration of the two tasks are discussed next. Future research suggestions and conclusion are given at the end.

2. Concept of Integration

2.1 Introduction

This section focuses on problem definition for the project. The most needed information for distribution system operation was addressed by conducting a survey at the beginning of the project. Concept of integration and the benefit are defined afterward. Technology supported by integration that provides the most needed information is developed in separate sections.

2.2 Conclusion from a Survey

To address the activities that can improve distribution operation, a survey of the improvements needed for distribution systems was conducted in January, 2008. Six utilities participated in the survey. Ten currently not available functions/features that had potential use were listed. Participants were asked to mark the proposed functions/features as very useful, not so very useful, useful, maybe useful, of little use and already available.

The potentially useful functions/features are:

- Automated fault location with high accuracy;
- Fault prediction based on early detection of incipient faults;
- Component failure prediction: next failure, time to failure, consequences;
- Estimation of IEEE 1366 reliability indices;
- Maintenance suggestions to improve reliability, prevent incipient faults, mitigate power quality;
- Line, transformer, component loadings;
- Feeder voltage profiles, including sags;
- Load status: power consumption, switching state;
- Asset management planning;
- Detection, classification and verification of faults, and automated analysis of related fault clearing sequences.

A summary sheet of the survey is provided in Appendix I. According to the results, automated fault location with high accuracy was recognized as the most useful, followed by component failure prediction. Line, transformer and component loadings, and fault prediction are also considered as very useful information by many utilities.

Our project focused on exploring technologies to provide and improve the fault location and component failure prediction by integrating the outage and asset management tasks.

2.3 Concept of Integration

A traditional distribution utility business process approach is illustrated in Figure 1. In this approach, outage analysis is primarily based on inputs from outage detection, telling which customers are connected, and incident verification reporting (IVR), telling which customers have reported loss of power. Asset management is primarily based on off-line data without extensive use of operational and/or condition based non-operational data.

With the development of new technology in fault location and maintenance prediction, system failures may be reduced in terms of frequency and duration.

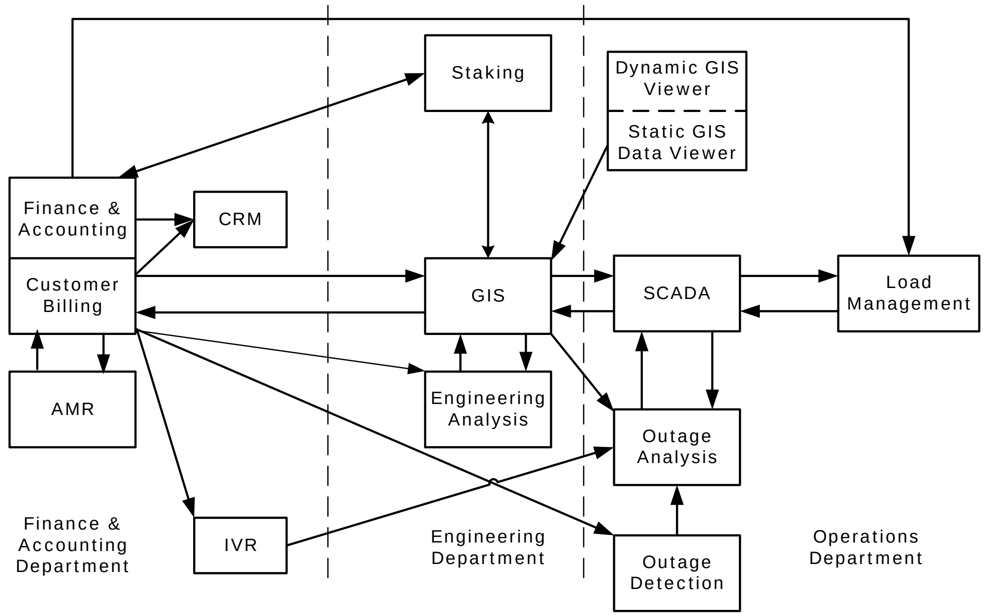

Figure 2.1 Traditional Distribution Utility Business Process

One of the constraints to implement those technologies is the availability of data. Condition-based maintenance, for instance, requires real-time field-recorded data, for example voltage, load current, etc to perform the condition assessment. On the other hand, to implement a model-based fault location algorithm, an accurate system model is required, including system topology, on/off status of switching devices, parameters of components, etc. [9]

Technologies have been proposed to reduce the frequency and duration of faults. For outage management, effort has been made to better process the trouble calls [5], supplement information from trouble calls with AMR system and other sources [6], and to investigate various methods to locate faults [7],[8],[9]. For asset management, condition-based maintenance has been proposed to prevent component failure and reduce cost by monitoring real-time electrical quantities and assessing condition of equipment [10, 11].

The new technologies in both asset management and outage management use non-operational data, which is recorded in the field by intelligent electronic devices (IEDs), and reveals the current condition of the system. This paper considers the overlapping of IED database use by outage and condition-based asset management and proposes the concept of integration of asset management and outage management tasks. The expected benefits from integration include: savings in IED installation expenditures, efficient collection and use of non-operational data, reduced failure cost, better system reliability, and finally more return on investment.

From the discussion above it can be concluded that the flow of data required to improve the business processes is no longer as shown in Fig.1. Outage management and asset management now share the need for certain data and models. It is more efficient to generate an integrated database. Integrating the outage and asset management tasks through the use of data and models of common interest should enhance the efficiency and effectiveness of the overall business process because it prevents either duplication or lack of investment in installing monitoring devices, and collecting and storing data. This strategy of using extensive field data provides two benefits:

- Due to improved maintenance, primary equipment will fail less frequently, reducing the number of forced outages;
- Due to more precise location of a faults and better prediction of the equipment "health", outage restoration practices will be far more efficient and effective.

The benefit can be evaluated from two aspects:

- System reliability. This is reflected by the impact on reliability indices.
- Return on investment. This is measured by optimization in capital and operating expense.

The improved business process should explore the correlation of outage management task with the task of risk-based management of equipment assets leading to optimized equipment maintenance practices. This will reduce the risk of outages, as measured by reliability indices, energy not served, cost of failure, or other measures. The optimization may be implemented using an asset management concept that selects and schedules maintenance tasks to minimize outage risk.

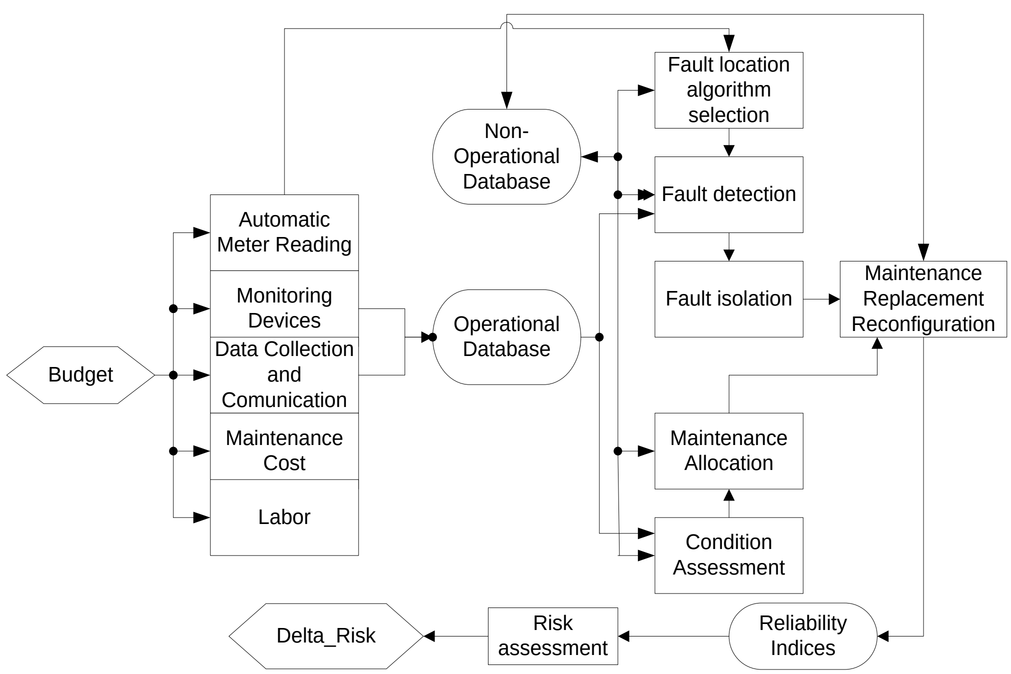

Figure 2.2 Integrated Asset and Outage Management Tasks

The integrated asset and outage management tasks are shown in Fig.2. Fault location and condition assessment retrieve field-recorded operational and non-operational data, as well as system models and configuration data from a common database. Based on this data, the reduction in failure cost is evaluated in an integrated risk-based assessment program.

2.4 Conclusion

In this section, the result from a survey that was conducted at the beginning of this project is reported. The new approach to integration of asset management and outage management is introduced and will be explored in following sections. The concept how the integration is realized and implemented is also briefly discussed.

3. Optimized Fault Location

3.1 Introduction

This section focuses on new applications in outage management. Computer-based fault location program and the practice of inspection in the system by field crew are considered as two parts of a fault location task. Stochastic process is introduced in fault location program to improve the robustness of the algorithm to imperfect input data. Scheduling and dispatch of field crew is determined by the result of fault location algorithm and risk analysis.

3.2 Overview of Fault Location Approaches in Distribution System

The outage management includes two main aspects: fault location and restoration. Electrical faults are detected and isolated by protective devices. Outage time can be reduced if the location of fault can be determined quickly. Fault location in distribution system is more difficult than in transmission system for the following reasons:

- The topology of distribution system is more complicated. The structure of the system can be radial, loop or mixed.
- It is common to have laterals on the line. Even if the distance of the fault point to a node is acquired, it is still hard to tell at which lateral it is located. As a result, the fault location algorithms may have multiple solutions.
- The data available is limited. Most frequently used are the fundamental frequency voltage and current data obtained from substations at feeder supply transformers. Compared to the complexity of the task, the information provided by this data quite often is not sufficient.
- The load and fault resistance have major impact on fault location accuracy.

In general, the fault location approaches can be classified into the following categories: impedance-based, model-based, superimposed components based, traveling wave based and artificial intelligence based.

3.2.1 Impedance-based approaches

The impedance-based approaches calculate fault location from the apparent impedance seen looking into the line from one end (single-terminal) or both ends (two-terminal). The phase-to-ground voltages and currents in each phase must be measured.

The precondition is that the fault resistance is assumed to be zero. In practical cases the fault resistance can not be ignored. As a result, the accuracy of single-terminal method is not optimal. In two-terminal approaches, the effects of fault resistance can be minimized or eliminated. The impact of load current can be minimized by measuring pre-fault data.

Other impedance-based approaches include negative and zero sequence impedance calculation. Such approaches are devoted to estimating fault location in radial systems.

3.2.2 Model-based approaches

Such approaches are based on the idea of the integration of network information with distribution automation information. The principle of such approaches is finding the similarity between simulated and measured fault signals.

To achieve such a goal, the following data is needed: Pre-fault and post-fault voltages and currents from the nodes in the system, the topology of the system and status signals from the equipment (the state of relays, etc.) The accuracy of the system model determines the performance of the method. The fault signals can be voltage or current. Fault in each lateral of the same fault type is simulated using the system model, and the fault location is assumed to be the one whose simulation result matches the field-recorded fault signals the best.

Such approaches can provide a single solution to the problem, i.e. the distance to the fault point from a node and lateral. Their application does not confine to radial systems. It is understandable that the more data from system nodes is available, the more accurate the approach. The voltage and current data from the nodes of the system is very limited, and may not be available to the current outage management system.

3.2.3 Superimposed components based approaches

Such approaches first calculate the superimposed voltage, and then inject it at the assumed fault point. If the point is correct, the sound phase injected currents at the actual fault point will be around zero.

To calculate the superimposed voltage (difference between pre and post-fault voltage), the pre-fault and post-fault data is needed. Such approaches are confined only to calculation of the fault location on radial distribution lines.

3.2.4 Traveling wave based approaches

Traveling wave based approaches were firstly utilized in transmission line fault location. The principle of traveling wave approaches is to record the traveling waves (either the fault wave itself or the wave of the signal injected to the lines) and calculate the distance of fault from the locator according to the time recorded. The fault locators were classified as Type A, B, C and D according to their mode of operation.

As the speed of electro-magnetic wave is close to the speed of light, data acquisition devices with high sampling rate is required. The line parameters are needed to calculate the accurate wave speed. For the two-ended measurement, the synchronization of both data acquisition devices is required. The traveling wave approaches have not been widely applied in distribution system, because of the cost, inaccuracy caused by equipments along the line, and because it is relatively easy to used this technique only on systems with simple topology and few laterals.

3.3 Constraints of Fault Location Approaches

3.3.1 Types and volume of data

Except for the model-based approaches, all fault location approaches above has the defect of inflexibility of input data. Very few information other than field-recorded data is used. For distribution system with few sensors installed and poor data quality, the accuracy of such approaches is not guaranteed.

The model-based approaches are flexible in number of inputs, which make it better than other approaches. However, selection of the faulted node is based on errors between simulated values and recorded values. The errors actually come not only from calculation but also from measurement error, model error, etc. In this section a new algorithm is developed to deal with such problems.

3.3.2 Error in field-recorded data

As mentioned in the introduction, the availability of filed data at the distribution level is not as good as at transmission level. The imperfection of field data has two aspects:

- Insufficiency: sensors placed in distribution systems for protection and monitoring purpose are very few because of the lack of instrument transformers and communication facilities along feeders. In addition, data from available sensors are mostly phasors or just magnitudes that are not time-synchronized.
- Inaccuracy: data recorded in the field is prone to errors due to unreliable communications and potential calibration problems with the sensors.

A fault location algorithm implemented in distribution systems must be able to deal with the poor data condition. A model-based algorithm may be selected to deal with the insufficiency of data, but data processing technology is needed for dealing with the inaccuracy of data. Data error needs to be analysis carefully before any method is proposed to reduce the impact of error.

The data required for the fault location algorithm proposed in this paper are phasors from the feeder root and scalars from some nodes in the distribution system. Data acquired may be “contaminated” in two steps: at the sensor and during transmission. A/D conversion, phasor calculation and electro-magnetic interference (EMI) are all possible sources of error. The model of acquired data may be represented as:

$$\hat{X} = X + e(X) = X + [(G-1)\cdot X + D(X) + x] \qquad 3.1$$

where:

$\hat{X}$ is the contaminated data;

G is the gain ratio;

e(X) is the total error inserted;

X is the true value of the electric quantity;

D(X) is the offset associated with X;

x is the random error (white noise).

The error consists of three parts: gain factor G, offset D and random error x. The first part is proportional to the true value of data, which comes from differences in the calibration of measured value, caused by the ratio of instrument transformer, voltage reference in A/D conversion, etc. Offset is a constant value introduced mostly by the difference in the ground voltage and random error x may come from various sources such as instrument transformer saturation or EMI. Although it is hard to predict the random error, it is reasonable to assume that it has a normal distribution:

$$\frac{x}{x_n} \sim N(0, \sigma^2) \tag{3.2}$$

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} \cdot \exp\left(-\frac{x^2}{2\sigma^2}\right) \tag{3.3}$$

where

x_n is the rated value of *X*;

$p(x)$ is the density function of *x*;

σ^2 is the variance of *x*.

The approaches for reducing the impact of data error are:

- Cancel out the gain and offset parts of data error by doing simple processing operations such as subtraction or division;
- Rely more on accurate data and less on inaccurate data;
- Detect and eliminate bad data when data error exceeds the threshold.

Methodology for implementing such approaches is described in the following section.

3.4 Fault Location Algorithm Capable of Dealing with Imperfect Data Condition

The merits of the algorithm proposed as a distribution system fault location method are as follows:

- It deals with the reality of insufficient measurements in distribution system, although the accuracy of the algorithm is affected by the number and placement of the measurements.
- It minimized the impact of fault impedance on the accuracy by considering fault as a special load connected to the faulted node.
- It takes into account the characteristics of distribution system: non-transposed feeders, single-phased line sections and nodes, and radial topology.

3.4.1 Data requirement

The proposed fault location algorithm is based on the one published in [16]. Some improvements are made for handling insufficient and inaccurate data. Following is a detailed description of data requirements.

a.) Electric quantities

Voltage and current phasors from a feeder root and voltage magnitudes from sparse measurements at some nodes of the system are needed. Both pre-fault and fault values are required.

b.) Feeder database

The topology information is required to build the model of the system. The line parameters, transformer locations and nominal power for each transformer must be provided.

c.) Load

The changes of loads connected to the secondary side of transformers according to voltage variations are estimated in load modeling. A generic static load model presented in reference [13] is used in the fault location algorithm.

$$S = P_n(\frac{V}{V_n})^{np} + jQ_n(\frac{V}{V_n})^{nq} \qquad 3.4$$

where

S: power consumed by load when voltage magnitude is V;

P_n, Q_n : nominal active and reactive power;

np, nq : active and reactive power exponents.

d.) Measurement information

Location of voltage measurements and the standard deviation σ of measurement error are needed.

3.4.2 Methodology

The flow chart of proposed fault location algorithm is shown in Figure 3.1. The algorithm consists of four steps: Pre-fault load flow calculation, estimation of applicability, fault simulation and faulted node selection. The four steps will be described separately in the following sections.

Processing of data takes place in the step of estimation of applicability where the data condition is estimated using $J(\hat{X})$ detection test [14]. If the number of recorded data points and accuracy cannot satisfy the requirements for implementing the algorithm, bad data is removed from input values. The procesure is repeated until the data is good enough for the algorithm to be executed or no more data can be removed and the program is terminated.

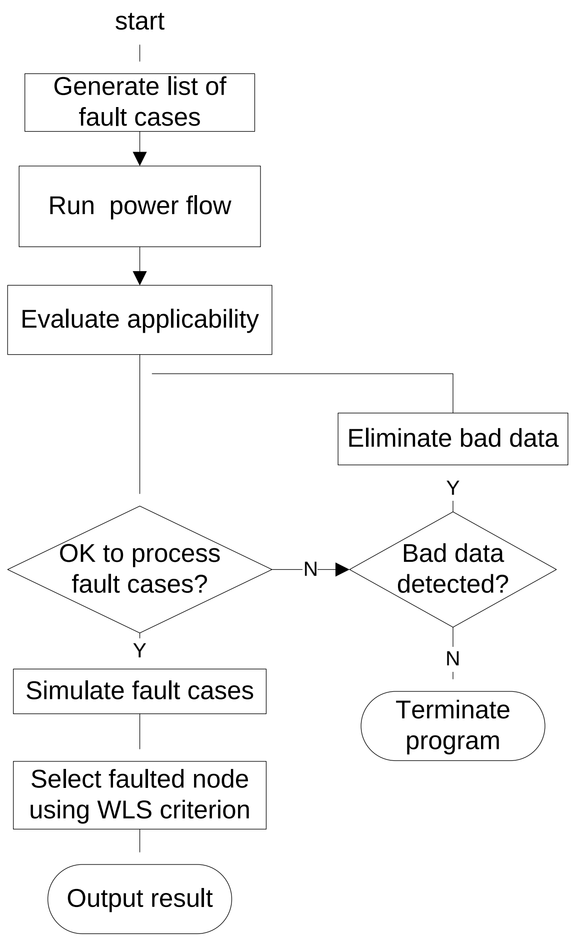

Figure 3.1 Flow chart

a). Power flow solution

The load flow algorithm for radial system described in [15] is used to calculate pre-fault voltage magnitudes. Fixed-impedance model is used for load modeling. In the initial stage, all node voltages are assigned with voltage recorded at the root of feeders. Back-sweeping to update branch currents using 3.5 and 3.6 and forward-sweeping to update node voltages using 3.7 is done in each iteration. The stopping criterion for iterations is defined by 3.8.

$$I_{j\_n}^{(k)} = Z_{L\_n}^{-1} \cdot V_n^{(k-1)} \quad 3.5$$

$$I_{b\_i}^{k} = \sum I_{b\_p}^{(k)} + I_{j\_n}^{(k)} \quad 3.6$$

$$V_n^{(k)} = V_m^{(k)} - Z_{b\_i} \cdot I_{b\_i}^{(k)} \quad 3.7$$

$$\max\{|V_n^{(k)} - V_n^{(k-1)}|\} < \varepsilon \text{, } n=1,\ldots, N \quad 3.8$$

where

k is the number of iteration;

$I_{j\_n}^{(k)}$ is the injection current at node n;

Z_{L_n} is the three phase load impedance matrix at node n;

$V_n^{(k)}$ is the node voltage of the down-stream node of branch i;

$I_{b\_i}^{k}$ is the branch current of branch i, which flows from node m to node n;

$I_{b\_p}^{(k)}$ is the branch current of branch p, which flows out from node n;

Z_{b_i} is the three phase line impedance matrix for branch i;

ε is the threshold for change in node voltage.

N is the total number of nodes.

b). Estimation of applicability

The $J(\hat{X})$ detection test from [14] is applied to estimate the condition of data, i.e. if the number and accuracy of voltage measurements are good enough for a reliable output.

Calculated value of voltage magnitude at node i from pre-fault load flow calculation is designated as $|V_{i,pre}^{cal}|$, while field-recorded value is designated as $|V_{i,pre}^{meas}|$. Weighted difference J_i is defined as (V_N is the rated voltage):

$$J_i = \left(\frac{|V_{i,pre}^{cal}| - |V_{i,pre}^{meas}|}{V_N \cdot \sigma_i} \right)^2 \qquad 3.9$$

The J index is the summation of J_i:

$$J = \sum J_i \qquad 3.10$$

Reliability index of field-recorded data is defined as:

$$RI = \frac{\sqrt{J - m}}{\sqrt{2m}} \qquad 3.11$$

where m is the number of redundant measurements. For the proposed algorithm, load flow calculation relies only on voltage and current phasors at feeder roots, m is the total number of voltage measurements.

The value of J_is and RI reveal the condition of data. Large value of individual J_i indicates that data from measurement i is very likely to be bad data and should be eliminated; Large value of RI indicates that either the number of measurements are not enough for a reliable output, or bad data exists, or sever error exists in system model, such as wrong topology or load information.

J_i and *RI* are used as double criteria. If J_i *<25* stands for all J_i s, and if *RI<3*, the data condition is considered as acceptable, and the program will proceed to fault simulation. If for one or two J_i *>25*, data from the corresponding measurements will be eliminated and

RI will be recalculated. If the criteria can not be met by eliminating bad data, the program is to be considered not applicable under the current data condition.

c). Fault-case simulation

A list of fault cases is generated according to the affected area. All nodes within the affected area are considered as a suspect faulted node. Fault-case simulation is executed for each case, and the calculated value of node voltage magnitudes at nodes with voltage measurements are recorded.

The algorithm for fault case simulation is similar to pre-fault load flow algorithm. Fault is considered as a special load connected to the faulted node, as is shown is Figure 3.2. The total injection current is the summation of fault current and load current.

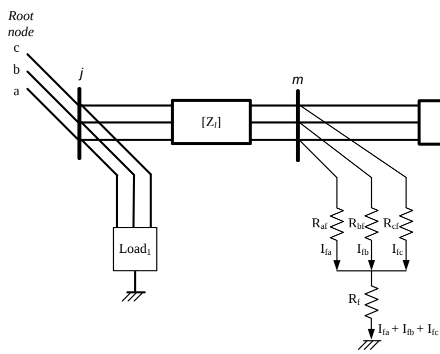

Figure 3.2 Current injection from a fault at node m

The equivalent impedance of the fault is not of interest. The fault current is calculated at the end of every iteration and added as current injection caused by fault at the faulted node using 3.12 and 3.13:

$$I_f^{(k)} = I_f^{(k-1)} + (I_{rn}^{df,meas} - I_{rn}^{df,cal}) \qquad 3.12$$

$$I_{j\_n}^{df,(k)} = I_{j\_nl}^{df,(k)} + I_f^{(k)} \qquad 3.13$$

where

$I_f^{(k)}$ is fault current;

$I_{rn}^{df,meas}$ is the current measured at feeder root;

$I_{rn}^{df,cal}$ is the calculated current at feeder root;

$I_{j\_n}^{df,(k)}$ is the injection current at faulted node n;

$I_{j\_nl}^{df,(k)}$ is the injection current from load connected to n.

The flow chart for fault case simulation is shown in Figure 3.3.

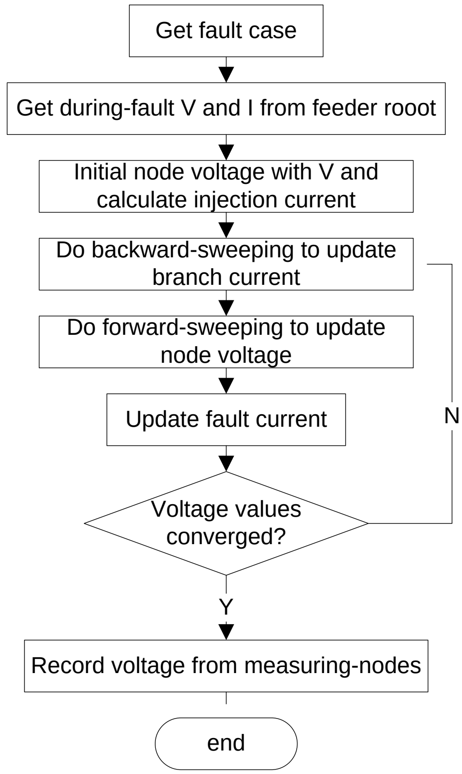

Figure 3.3 Flow chart for fault-case simulation

d). Faulted node selection

The likely fault location is selected taking into account all analyzed nodes during the fault location process. Weighted-deviation is used for locating the fault.

For each analyzed node, the during-fault magnitude deviation between measured and calculated voltage sags is computed:

$$\delta_k^j = \left\| \Delta V_k^{j,cal} - \Delta V_k^{j,meas} \right\|, k = 1,\ldots m;\ j = 1,\ldots np \tag{3.14}$$

where

$\Delta V_k^{j,cal}$ is the difference in three-phase pre-fault and during-fault voltage magnitudes (voltage sags) calculated at node k considering node j as the faulted node;

$\Delta V_k^{j,meas}$ is the three-phase voltage sags measured at node k;

m is the total number of voltage measurements;

np is the total number of fault cases simulated.

The weighted-deviation is calculated as

$$\gamma_j = \sum_{k=1}^{m} (\delta_k^j / \sigma_k)^2 \tag{3.15}$$

The faulted node is the one with the smallest value of γ_j.

$$n_f = j \mid \gamma_j = \min\{\gamma_s\}, s = 1...np \qquad 3.16$$

e). Description of the error-impact reduction

The algorithm is capable of minimizing the impact of offset error and random error.

The offset error is removed by the calculation of voltage sags—offset from pre-fault and during fault data cancels out in subtraction.

As the selection of faulted node relies on the weighted-deviations, the contribution of data from less accurate measurements is reduced in proportion with the variance of the random error, which means that data more likely to have high random error has a lower impact on the result.

The proportional error is not considered in the proposed algorithm.

3.4.3 Simulation results

a). Description of the test system

A 13.8 kV, 134-node, overhead three-phase primary distribution feeder is used as the test system. Figure 3.4 shows the topology of the feeder.

Root voltage and current are recorded at node 1.

Four voltage measurements are placed in the system, at node 30, 48, 103 and 118 respectively. They are marked as measurement 1- 4 respectively.

The algorithm reported in [16] and the algorithm proposed in this paper are implemented and the results are compared.

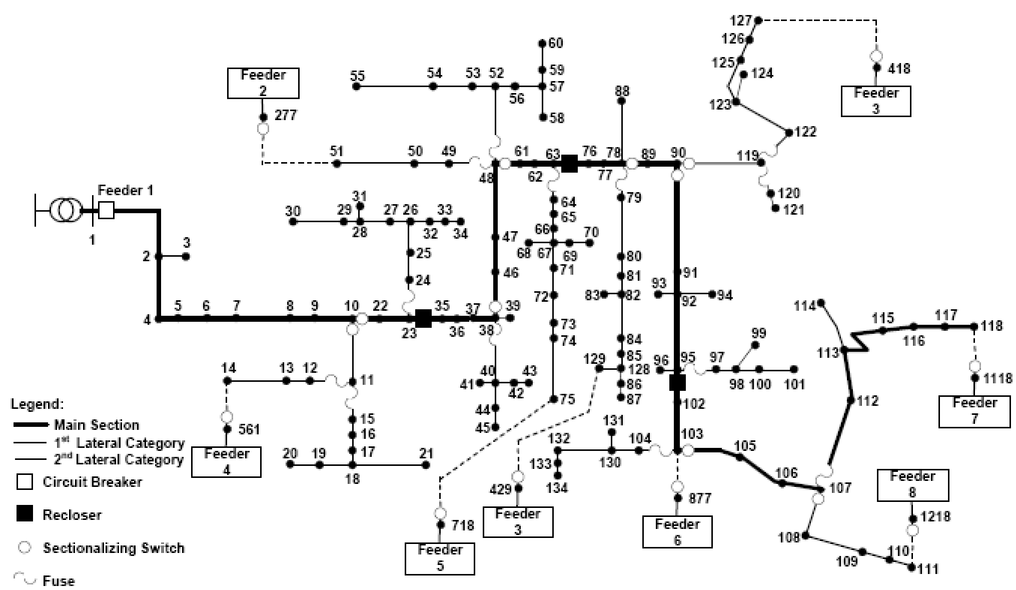

Figure 3.4 Test system

b). Case study

Case 1: perfect condition

In this case, the field-recorded data are not contaminated by errors. Fault scenarios are listed in Table 3.1.

Table 3.1 Fault scenarios for Case 1

Faulted node	***Fault type***	***Fault resistance (Ω)***
17, 36, 42, 107	A-G	1
63, 90	A-G	10
5, 77	A-B-C	5
86	A-B	1

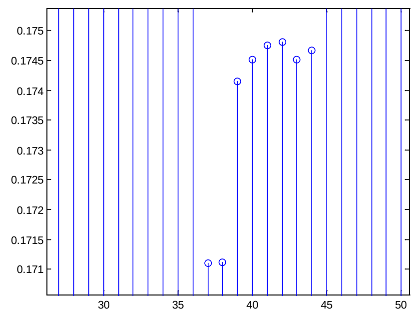

Figure 3.5 Nodes with smallest deviation index γ_j

Both the algorithm reported in [16] and the proposed algorithm give correct result for all scenarios. Figure 3.5 shows the smallest γ_j calculated for fault occurring at node 36.

Case 2: Bad data

A-G fault at node 36 is simulated, but pre-fault and during-fault voltage magnitude recorded by measurement 2 (node 48) are added with errors of 20% and 15%. Variances of random error σ_i for all voltage measurements are 0.01.

The faulted node selected by the algorithm proposed in [16] is node 48, which is incorrect.

J_i and RI calculated by the proposed algorithm are listed in Table 3.2. J_2 is very large, indicating that data from measurement 2 are bad data and should be eliminated. RI after bad data elimination is less than 3, and the program continues with data from measurement 1, 3 and 4.

Table 3.2 J_i and RI

J_i	***RI***
0.1213 398.7 0.1374 0.1151	Before data removal: 7.027 After data removal: 0.6638

The faulted node selected by the proposed algorithm after bad data elimination is node 36. The proposed algorithm selected the right node again.

Case 3: Data with errors

A-G fault at node 36 is simulated. Errors with density function from equation 3.3 is generated according to σ_i of the measurement and added to the true value of the measured pre-fault and during-fault quantities. Four data conditions are designed and ten sets of data are generated and fed to fault location program for each data condition. Data condition and the times that the fault location program provides correct output are listed in Table 3.3.

Table 3.3 List of data condition and result

Measurements	σ_i	***Correct times***
1, 2, 3, 4	0.01, 0.01, 0.01, 0.01	10
1, 2, 3, 4	0.01, 0.1, 0.01, 0.01	10
1, 2, 3	0.01, 0.01, 0.01	10
1, 3, 4	0.01, 0.1, 0.01	8

The outputs for the two cases where the selected node is wrong are 39 and 33.

3.5 Dispatch of field crew based on result of fault location program and outage cost assessment

3.5.1 Problem Definition

Using the model-based fault location algorithms, the nodes are ranked by the probability of being the faulted node. Under some condition (inaccurate data, high fault resistance, unsatisfying placement of measurements, etc.) the first node may not be the nearest node to the faulted point (Simulation Result in [16]). But usually the correct node is among the top n nodes. Sometimes these top n nodes are in two areas. The question is: How do we dispatch field crew to inspect along the feeders?

Other things being equal, the area with higher probability of fault should be inspected first, so that the time to locate fault is minimized. However, temporary faults take a large proportion in faults occurring in distribution system, and the probability of temporary faults developing into permanent faults (component failure) increases exponentially with time needed to clear the fault, which means that customers to the downstream of fault point may experience longer outage if fault is not cleared in time. In that case, other things being equal, area with more loads or with important customers connected should have a priority in fault inspection.

Scheduling the field crew to inspect fault should consider the conditions mentioned above. An optimization problem is formed accordingly, with risk formed as the summation of probability that fault is in the area multiplied by outage cost of this area during fault location period:

$$Risk = \sum P_i \cdot Cost_i \tag{3.17}$$

Formulation of optimization problem:

$$\textit{Objective: min \{Risk\}} \tag{3.18}$$

$$s.t. \quad N_{labor} \leq N_{labor.\max} \tag{3.19}$$

where N_{labor} is the labor assigned to find the faulted node.

3.5.2 Procedure

Index i is used to designate suspicious in the following discussion. The procedure is shown in Figure 3.6.

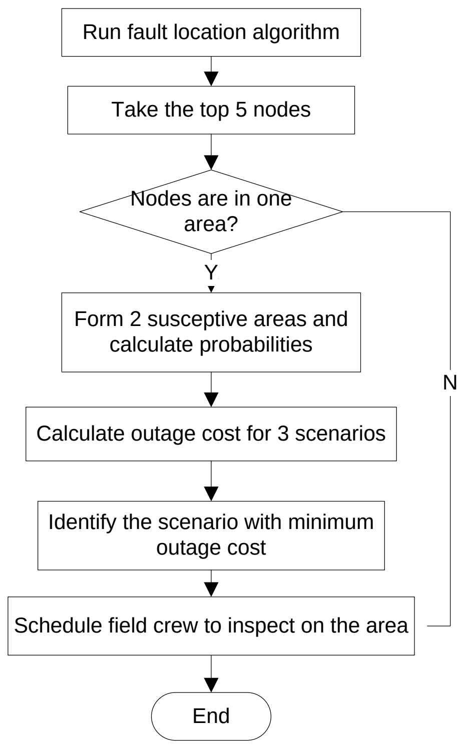

Figure 3.6 Flow chart of program for dispatch of field crew

Step 1: Form 2 suspicious areas and calculate probability for each area that the fault is within this area.

The processing starts with running voltage-measurement-based fault location algorithm. The top 5 nodes are extracted and classified. If they belong to two physically separated areas, the possibility of fault happening in each area is calculated using the following equation:

$$P_i = \sum_{\substack{k=1\\k\in I_i}}^{n} e^{\frac{1-k}{4}} \Big/ \sum_{1}^{n} e^{\frac{1-k}{4}} \qquad 3.20$$

Here the probability is calculated as the summation of the confidence the nodes are among top n and are in area i. Confidence of the nodes is considered decreasing exponentially with the ranking. P_i is the probability that fault is in area i, and *k* is the kth node determined by the program as being in area i.

Step 2: Estimate time to locate fault.

The function of estimating the time needed to locate a fault in area i is:

$$t_i(D_i, N_{labori}) = a_1(D_i / N_{labori}) + a_0 \qquad 3.21$$

Step 3: Calculate *Risk* for different scenarios.

1). Go to area I and if fault is not found, go to area II.

$$\begin{aligned} Risk = P_1 \cdot \{\beta_1 \cdot \frac{N_1}{N} \cdot t_1 + \beta_2 \cdot \frac{L_1}{L_T} \cdot t_1 + \beta_3 \cdot \frac{L_1'}{L_T} \cdot t_1\} + P_2\{\beta_1 \cdot \frac{N_2}{N} \cdot (t_1 + t_2) \\ + \beta_2 \cdot \frac{L_2}{L_T} \cdot (t_1 + t_2) + \beta_3 \cdot \frac{L_2'}{L_T} \cdot (t_1 + t_2)\} \end{aligned} \qquad 3.22$$

The formulation of risk function will be discussed in Section 5.

$\beta_1 \sim \beta_3$ are coefficients of 3 components that form the risk function;

N_1, N_2 are numbers of customers connected to area I and II;

N is the total number of customers;

L_1, L_2 are connected kVA from area I and II;

L_1', L_2' are connected kVA from area I and II by prioritized customers;

L_T is total connected kVA;

t_1, t_2 are estimated time to locate fault in area I and II.

The prioritized customers (sensitive customers) refers to the customers that demand uninterrupted power supply more than the ordinary ones. Special contracts are signed between utilities and these customers (e.g. hospitals, schools, electron chip manufactures, etc.) so that when the quality of service does not meet the requirements (too many times of interruptions or hours of outage) penalty to utilities is added.

2). Go to area II and if the fault is not found, go to area I.

The calculation of cost in this case is similar to case 1 and is not described in detail.

3). Assign $N_{labor.1}$ to area I and $N_{labor.2}$ to area II at the same time.

$$Risk = P_1 \cdot \{\beta_1 \cdot \frac{N_1}{N} \cdot t_1 + \beta_2 \cdot \frac{L_1}{L_T} \cdot t_1 + \beta_3 \cdot \frac{L_1'}{L_T} \cdot t_1\}$$
$$+ P_1 \cdot \{\beta_1 \cdot \frac{N_2}{N} \cdot t_2 + \beta_2 \cdot \frac{L_2}{L_T} \cdot t_2 + \beta_3 \cdot \frac{L_2'}{L_T} \cdot t_2\} \quad 3.23$$

Obviously, the minimum risk appears when all available labor is dispatched.

$$N_{labor.1} + N_{labor.2} = N_{labor.\max} \quad 3.24$$

Substitute (10) into (9) and eliminate variable $N_{labor.2}$. The constraint is now transformed into: $0 \le N_{labor.1} \le 1$.

3.5.3 Case study

The extended distribution system connected to bus 4 of IEEE reliability test system (RBTS4) is used as a test model [17]. The system is divided into 7 subsystems (feeders), and each subsystem can be disconnected by circuit breakers installed at feeder root.

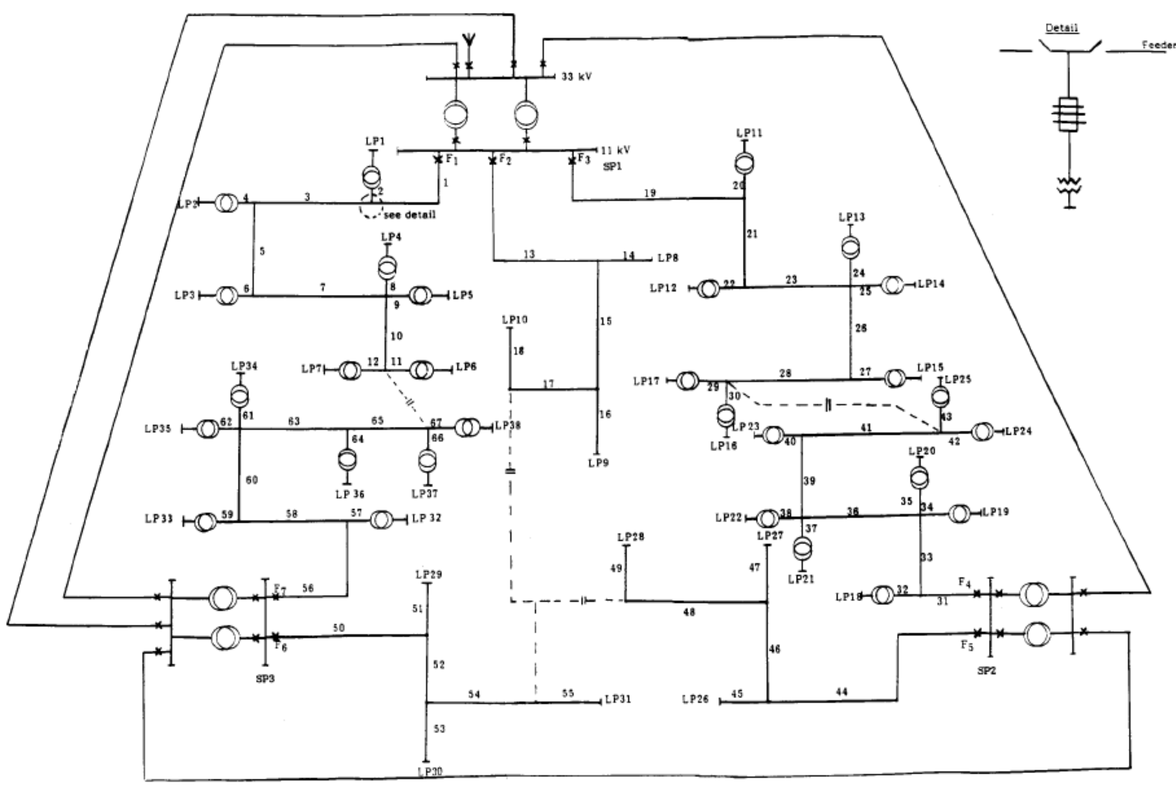

Figure 3.7 Distribution system for RBTS Bus 4

The lists of suspicious faulted nodes are acquired by implementing voltage-based fault location algorithm, with voltage magnitudes recorded at node 6, 11, 18, 27, 32, 49, 51 and 64.

Scalars applied in equation 3.20 through 3.24 are listed below:

Table 3.4 Scalars

a_1	a_0	β_1	β_2	β_3	$N_{labor.\max}$
0.5	0.5	0.25	1	2	4

Case 1: Suspicious faulted nodes are 32, 34, 40, 42 and 37

The list is obtained by feeding the fault location algorithm with simulated result of an A-ground fault at node 40, with high fault impedance of 100 ohm.

It can be seen from the list that although fault location algorithm failed to identify the faulted node because of high fault resistance, the suspicious nodes are all in one area, which is feeder 4, and the faulted node (node 40) appears in the third place. In this case all available field crew should be sent to feeder 4.

Case 2: Suspicious nodes are 2,32,34,40,42, no sensitive loads

The list is obtained under the same faulted condition as in Case 1 but an error of -7% was added to voltage magnitude recorded at node 6 and 11.

The fault location algorithm provided a list of nodes in 2 areas: area I includes feeder 1 and area II includes feeder 4. Probability of each area being the faulted area is: $P_1 = P(Area = 1) = 0.31, P_2 = P(Area = 2) = 0.69$. The confidence indicates that the possibility that fault happened in area II is bigger. Table 2 shows the feeder and load information of the two areas needed to perform the outage cost assessment assuming that no sensitive load is connected in either area.

Table 3.5 Feeder & load information

	N_i	L_i	L_i'	t_i	P_i
i =1	1100	3.51	0	3.5	0.31
i=2	1300	4.01	0	3.75	0.69
Total	4779	24.58	--	--	--

Table 3.6 Risk calculated for the three scenarios

	Scenario A	Scenario B	Scenario C
Risk	0.3626	0.2731	0.3002
Description	Dispatch entire crew to inspect feeder 1, if fault is not found, go to feeder 4	Dispatch entire crew to inspect feeder 4, if fault is not found, go to feeder 1	Dispatch 1 crew to feeder 1 and 3 to feeder 4 at the same time

Risk calculated for each scenario is recorded in Table 3. Scenario B has the smallest risk value, which means that inspecting feeder 4 first is the best choice. The results match the fault scenario generated in simulation.

Case 3: Suspicious nodes are 21, 13, 22, 14, 15; No sensitive loads

Two areas are formed: area I as feeder 3 and area II as feeder 2. Table 4 shows the feeder and load information, and Table 5 records risk calculated for each scenario. This is a case where the probabilities of two areas being the faulted area are very close to each other. Connected load (MVA) and size of areas are similar too, but the number of customers in area I is much larger than area II. The "customer satisfaction" part of outage cost plays an important part in this case and scenario 1 is selected.

Table 3.7 Feeder and load information

	N_i	L_i	L_i'	t_i	P_i
i =1	1080	3.465	0	3.75	0.4981
i=2	3	3.5	0	4.15	0.5019
Total	4779	24.58	--	--	--

Table 3.8 Risk calculated for the three scenarios

	Scenario A	Scenario B	Scenario C
Risk	0.2375	0.2683	0.25139
Description	Dispatch entire crew to inspect feeder 3, if fault is not found, go to feeder 2	Dispatch entire crew to inspect feeder 2, if fault is not found, go to feeder 3	Dispatch 2 crew to feeder 2 and 2 to feeder 3 at the same time

Case 4: Suspicious nodes are 21,22,14,16, 23; Sensitive load 9 is connected in area I

Table 3.9 Risk calculated for the three scenarios

	Scenario A	Scenario B	Scenario C
Risk	0.3316	0.3166	0.3142
Description	Dispatch entire crew to inspect feeder 3, if fault is not found, go to feeder 2	Dispatch entire crew to inspect feeder 2, if fault is not found, go to feeder 3	Dispatch 2 crew to feeder 2 and 2 to feeder 3 at the same time

Compared with Case 3, it is obvious that even though the number of customers in area II is much smaller, the importance of the load requires better attention. Scenario C is selected so that feeder 2 can be inspected earlier.

3.6 Conclusion

A new fault data processing method based on fault location algorithm is proposed in this section. The accuracy of the fault location algorithm is improved under the condition of imperfect (insufficient and/or inaccurate) data. The work order for dispatching the field crew for field inspection uses the list of suspicious nodes produced by fault location algorithm. This approach is capable of providing an optimized solution for crew-dispatch while minimizing the outage cost.

4. Condition-based Component Maintenance

4.1 Introduction

This work addresses one of the major challenges faced by utilities; allocating the resources for preventive maintenance of the distribution system, while maintaining the system reliability. Motivation for this work is from [18] and [19] where authors propose preventive maintenance schemes for distribution system. One of the novel ideas presented in these works is analyzing the component reliability indices based on several criteria attributed to the component, which can be measured or observed periodically. This is a significant advancement in distribution reliability analysis and the work is developed based on this discussion. This work uses '*hazard rate*', the conditional failure rate (given the component survived until this moment) based on the statistical analysis, as a tool to measure the condition of components. The following sections illustrate the technique.

4.2 Identifying the Criteria for Equipment Condition Assessment

In order to wisely allocate the predictive maintenance budget, it is not only important to identify the condition of the component but also it is important to identify is the issues affecting the component's condition, which are defined as the component *failure modes*, if a component is performing badly. The utility will be monitoring and observing certain properties of the component. Out of the monitored properties it is important to identify the properties (criteria) associated with each failure mode. For a distribution power transformer failure modes identified by [20] are presented in Table 4.1.

Table 4.1: Failure Modes of a Power Transformer

1	Winding insulation and conductor failure		6	Core Failure
2	Insulation decomposition and degradation		7	Over-temperature
3	Partial Discharge		8	Pressure relief diaphragm broken
4	Bushing failure		9	Transformer auxiliary equipment troubles
5	Internal Arcing			

As a part of this work, analysis has been done for power transformers and circuit breakers [20]. This gives a detailed methodology to identify the criteria of power transformers (e.g.: oil condition, winding condition, noise, tank condition etc.) and circuit breakers. These criteria are practical as they are based on the manufacturer equipment database, historical failure causes and maintenance activities. A similar approach could be taken to find the criteria of other components. Table 4.2 shows the criteria for a distribution power transformer.

Table 4.2: Criteria for a Power Transformer [20]

		Criterion
General	1	Age of the Transformer
	2	Experience with Transformer Type
	3	Noise Level
	4	Transformer Loading Condition
	5	Core & Winding Losses
Winding Condition	6	Winding Turns Ratio
	7	Condition of Winding
	8	Condition of Solid Insulation
	9	Partial Discharge (PD) Test
Oil Condition	10	Gas in Oil
	11	Water in Oil
	12	Acid in Oil
	13	Oil Power Factor
Physical Condition	14	Condition of Tank
	15	Condition of Cooling System
	16	Condition of Tap Changer
	17	Condition of Bushing
	18	Hot Spot Temperature
	19	Faults Seen by the Transformer
	20	Geographical Location

Not all criteria have same importance when it comes to healthy functioning of a component. Therefore criteria should be weighted based on their importance [18]. Once the criteria for a component are identified, using historical failure causes and manufacturer databases, each criterion is weighted to the scale of 0 to 1. Weighting is based on the following,

a) Effect the failure mode has on the failure of a component, $\left(W_i^E\right)$

This component of the weight would be allocated by experience by the utility engineers.

b) Number of maintenance / replacement needed for a failure mode during life of a component, $\left(W_i^M\right)$

This component of the weight is defined as,

$$W_i^M = \frac{\text{Total no. of maintenance \& replacement needed for a criterion during life of a component}}{\text{Total no. of maintenance \& replacement of all criteria during life of that component}} \tag{4.1}$$

The weight can be defined as,

$$W_i = \frac{\alpha W_i^E + \beta W_i^M}{(\alpha + \beta)} \tag{4.2}$$

where α and β are scaling parameters. Based on knowledge and judgment of the utility engineers, the weights can be changed adaptively.

4.3 Probability Distributions for the Criteria

Once criteria for a component are identified, the next step is to establish a methodology to mathematically represent the condition of each criterion. This work uses a statistical approach to determining the condition of each criterion. Based on historical data, a probability distribution model would be developed for each criterion. It can be seen that the Weibull distribution is best suited for this analysis for the following reasons:

- Small samples are sufficient to predict the failure model accurately [21]
- Scale and shape parameters allow the users to not only scale the distribution, but also to change the shape of the distribution. Hazard rates, increasing with time, decreasing with time and constant with time can be modeled using the Weibull distribution.

This work therefore uses the Weibull distribution to model the hazard rates of the criteria. Barnes, et al, have developed a hazard rate function for the age of the transformer in [22]. Figure 1 show their hazard rate and the hazard rate found by Weibull distribution. It can be seen that the hazard rate found by the Weibull distribution is very much similar to the finding from [22].

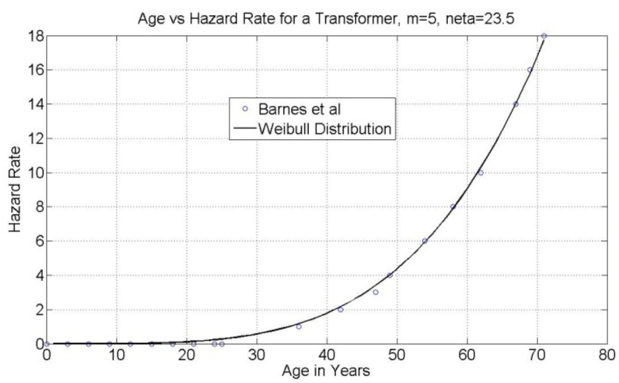

Figure 4.1 Hazard Rate Recalculated Using Matlab

For non-conventional criteria like experience with transformer type, the following example could be used for the analysis. It should note that the hazard rate is not a function of time, but a function of failed transformers. Let,

T – Total Number of Transformers Handled
F – Total Number of Transformers Failed
S – Total Number of Similar Type of Transformers Handled
S_F – Total Number of Similar Type of Transformers Failed
S_U – Out of Failed Same-Type of Transformers, No. of Transformers with Failure Reason Unknown

The shape and scale parameters are modeled as,

$$m = \frac{S_U}{S_F}, \eta = \frac{S_F}{F} \tag{4.3}$$

Thus the hazard rate is,

$$h(S_F) = T \times \frac{m}{\eta}\left(\frac{S_F}{\eta}\right)^{m-1} \tag{4.4}$$

4.4 Hazard Rate Model for Components

Once the hazard rate models for all the criteria of a component are known, the next step would be to find the component hazard rate. To calculate the hazard rate of a component at a given time *t*, different approaches have been taken in literature. This analysis uses a typical reliability approach. Based on the physical architecture and the correlation to other criteria, a series-parallel reliability model is developed. If a particular criterion has a direct impact on the proper function of the component (or represents a failure mode), then that component would be connected in series with the other criteria. If a set of criteria collectively represent a single failure mode, then they would be connected in parallel. For the power transformer discussed in Table 1, the reliability model developed is shown in Figure 4.2.

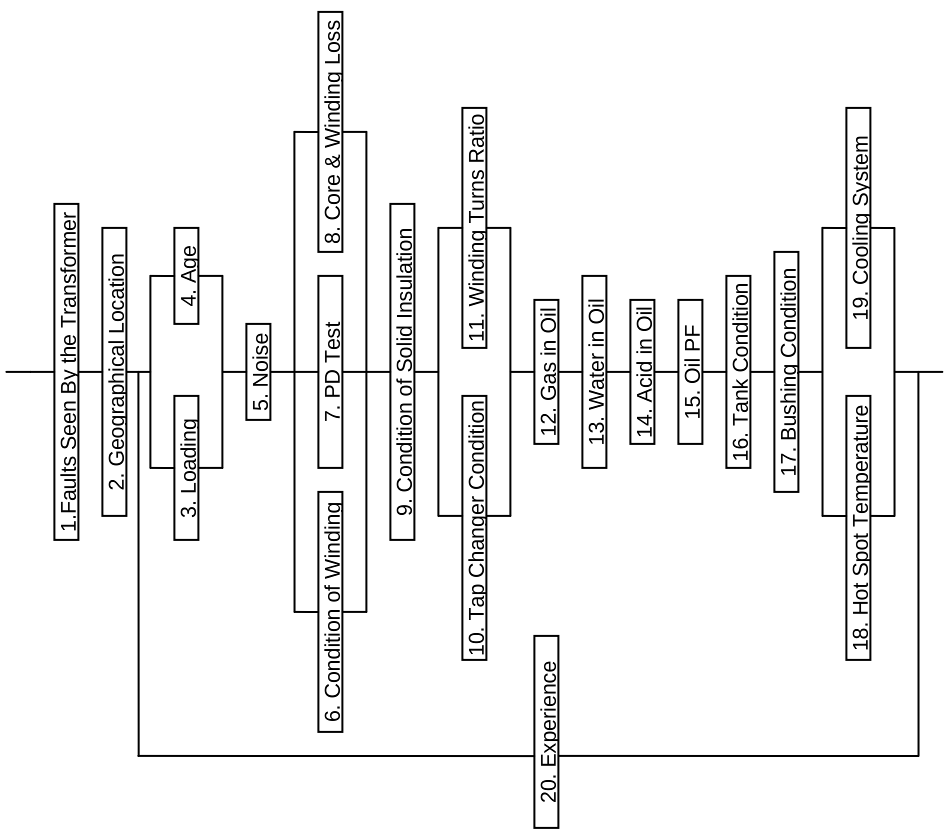

Figure 4.2 Series-Parallel Reliability Model for Power Transformer

The hazard rate for a power transformer is calculated as follows. Let $R_1(t), R_2(t), \ldots, R_n(t)$ and $Q_1(t), Q_2(t), \ldots, Q_n(t)$ be weighted reliabilities and failure distributions for each criterion (for the transformer case, $n = 20$). If the actual hazard rate of a criterion is $Q_i^A(t)$ (this is obtained from the hazard rate model of that criterion), then the weighted hazard rate (Q_i) is given by,

$$Q_i(t) = W_i(t) \times Q_i^A(t).$$

The weighted reliability (R_i) of the same criterion is given by,

$$R_i(t) = 1 - Q_i(t).$$

For simplicity we reproduce Figure 4.2 with just the numbers in Figure 4.3.

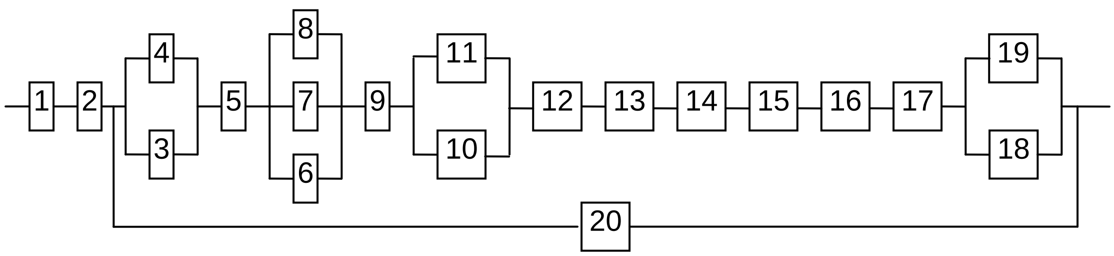

Figure 4.3 Series-Parallel Model for Transformer Criteria

For analytical purposes, the model would be simplified into a single block. The following example shows the mathematical relationship of combining criteria 6, 7, and 8 into one single block,

$$\begin{aligned} R_{parallel}(t) &= 1-(1-R_6(t))(1-R_7(t))(1-R_8(t)) \\ &= R_6(t)+R_7(t)+R_8(t)-R_6(t)\cdot R_7(t)-R_7(t)\cdot R_8(t)-R_8(t)\cdot R_6(t)+R_6(t)\cdot R_7(t)\cdot R_8(t) \end{aligned} \quad 4.5$$

Similarly, series criteria could be combined into one single block, and the following example shows the combination of criteria 12, 13, 14, 15, 16, and 17.

$$R_{series}(t) = R_{12}(t)\cdot R_{13}(t)\cdot R_{14}(t)\cdot R_{15}(t)\cdot R_{16}(t)\cdot R_{17}(t) \quad 4.6$$

By using the scale and shape parameters of the Weibull distribution it is possible to calculate the reliability and hazard rate. In case the distribution is not known the following relationship for the hazard rate and reliability function could be used:

$$h(t) = -\frac{1}{R(t)}\frac{dR(t)}{dt} \quad 4.7$$

4.5 Allocate the required level of maintenance for each component

Distribution system performance can be degraded both by controllable events (e.g., maintenance of components and tree trimming) and uncontrollable events (e.g., lightning and accidents). When the performance of a utility is considered, it is not rational to measure the performance by the uncontrollable events. Therefore in this analysis the reliability indices that are used would include only the events that can be controlled. The subscript 'C' will be used to indicate that the reliability indices are calculated based only on the controllable events.

Once the condition of each component is computed, based on the performance / reliability requirements (required $SAIDI_C$, required $SAIFI_C$, required $CIME_C$, and maximum allowed ENS_C etc.) the utility should be able to schedule its maintenance. As a part of this work we have developed an algorithm to achieve the required improvement of each component in such a way that the total cost of improving the condition of components in the system is minimized.

Uninterrupted power supply has a strong correlation with System Average Interruption Duration Index (SAIDI), thus in most performance analyses SAIDI is given a high significance [23], [24]. Motivation for this work is from [25], in which the author proposes performance based rates based on SAIDI, where utilities are rewarded or penalized based on their performance in meeting the required reliability and power quality indices [25]. Figure 4.4 illustrates the scheme proposed in [26].

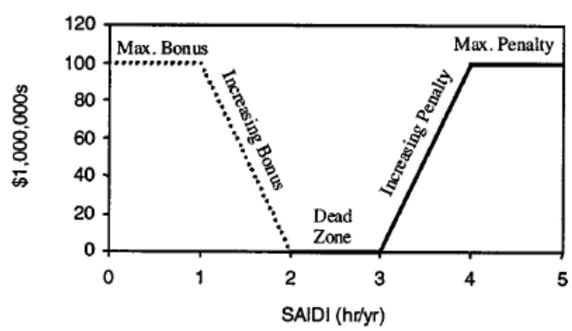

Figure 4.4 PBR Vs. SAIDI [25]

Even though the components have time dependent hazard rates, especially with aging of the component, most utilities use constant hazard rates [26]. This work is based on time dependent hazard rates to achieve more accurate analysis.

Most North American distribution systems are radial; thus the model analyzes radial systems, dividing the system into zones which are physically not connected except at one supply point. Since these zones are not connected, failure in a zone will not affect the others, as shown in Figure 4.5. Thus each zone could be considered as an independent module.

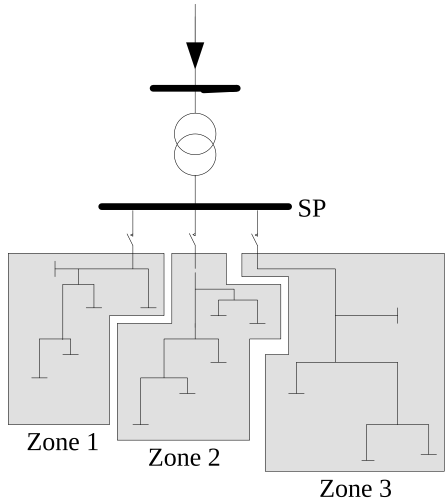

Figure 4.5 Radial Distribution System with Zones

In this analysis we assume that the Supply Point (SP) has almost zero unavailability, which is reasonable as most of the supply points have redundant components to compensate for any component failure. Most utilities make sure that the supply points are maintained appropriately so any failure in these supply points will not interrupt the power supply.

As a part of this work an algorithm has been developed to achieve the required improvement of each component in such a way that the total cost of improving the condition of all components in the system is minimized [27]. We want to allocate reliability in a least-cost manner, and will thus use an approach given in [28]. The cost model is taken similar to that of [28] with the same argument.

$$\min z = \sum_{\forall i} c_i x_i^2 \tag{4.8}$$

x_i is the increase in average hazard rate of zone i and $c_i x_i^2$ is cost of increasing the average hazard rate by x_i. Since PBR's are calculated based on the SAIDI, our aim is to decrease the system SAIDI below a desired value. Because of financial limitations, we do not want to improve the SAIDI beyond the desired value. Thus the constraint for the problem is:

$$\sum_{\forall i} \left(x_i \frac{\sum_{\forall j} d_j}{N} \right) = \Delta S \tag{4.9}$$

This results in the optimal component reliability allocation:

$$h_k^* = W_k \times \left(h_i + \frac{\Delta S \cdot \alpha_i}{c_i \cdot \sum_{\forall j} \left(\frac{(\alpha_j)^2}{c_j} \right)} \right) \qquad 4.10$$

where

h_k^* - Allocated hazard rate for component *k* in zone *i*

h_i - Actual hazard rate of zone *i*

h_l - Actual hazard rate of component *l* in zone *i*

ΔS - Required improvement in SAIDI for the system

α_i - Interruption duration seen by zone *i* due to the failure of component *k*

$$W_k = (r_k \cdot h_k) \Big/ \sum_{\forall l} (r_l \cdot h_l) \qquad 4.11$$

r_k - Risk associated with the failure of component *k*

The optimal component allocated hazard rate may not always be in the valid region of practically achievable hazard rates for components. Thus the optimal solution is not always feasible. In order to incorporate the limitations on hazard rates, we can modify the allocated hazard rates using the suboptimal routine given in Figure 4.6.

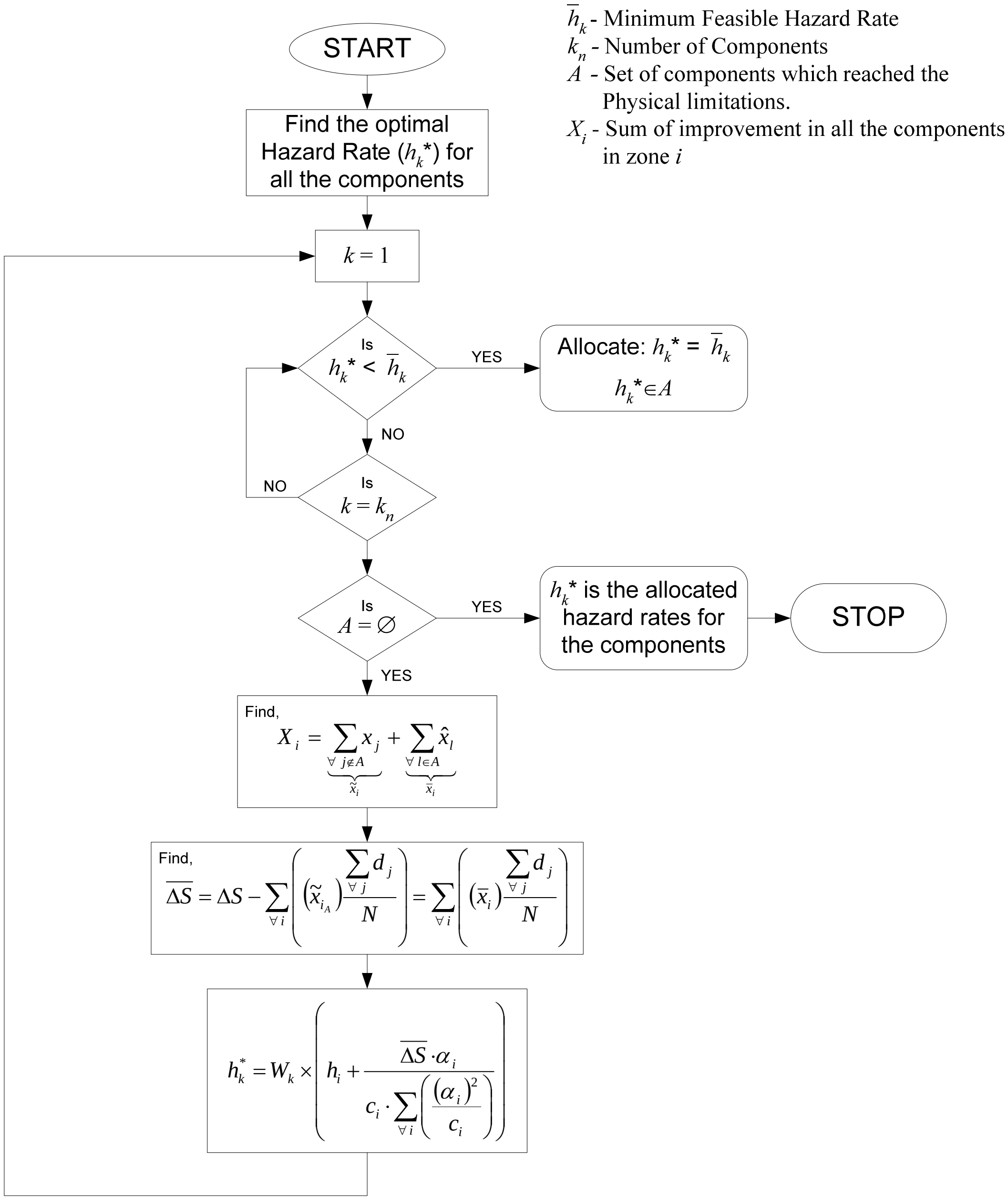

Figure 4.6 Suboptimal Routine

In order to check the accuracy of the method, the system shown in Figure 5.7 was simulated in commercial Milsoft Windmil software. System SAIDI before the maintenance and system SAIDI achieved by maintenance, assuming required SAIDI is achieved, was calculated. The results are as follows:

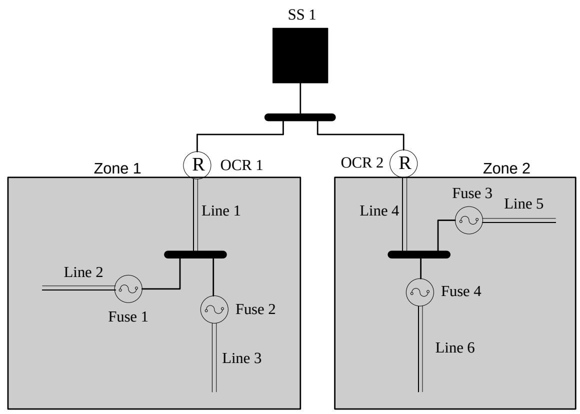

Figure 4.7 System with two zones

Outage and switching data for the system shown in Figure 4.7 are given in Tables 4.3 and 4.4.

Table 4.3 Outage Duration Data

Element	Hazard rate	Outage Duration , Time to			No of Customers
		Fix	Find problem	Travel	
Substation	0	5.0	1.0	0.25	0
OSR	0	1.0	1.0	0.25	0
Line 1	0.4	2.0	1.0	0.25	100
Line 2	0.6	2.0	1.0	0.25	300
Line 3	0.2	2.0	1.0	0.25	400
Line 4	0.4	2.0	1.0	0.25	350
Line 5	0.6	2.0	1.0	0.25	200
Line 6	1.0	2.0	1.0	0.25	400
Fuses	0.01	3.0	1.0	0.25	0

Table 4.4 Switching Data

Element	Time to close	Time to open	Time to bypass
Fuse	0.5	0.3	0.2
OCR	0.5	0.3	0.2

Let (arbitrary selection),

$$c_1 = 1 \,\&\, c_2 = 10$$

All equipment has limitations on the minimum physically achievable SAIDIs and Table 4.5 shows these limitations.

Table 4.5 Limitation on Minimum Achievable SAIDI

Equipment	Line1	Line2	Line3	Line4	Line5	Line6	Fuse
$SAIDI_{Min}$	0.04	0.06	0.02	0.04	0.06	0.10	0.001

Step 1: Using Windmil the initial SAIDI of the system is calculated to be 3.5211

Step 2: Using the optimization technique the allocated hazard rates for the required SAIDIs are calculated using MATLAB, and they are shown in Table 4.6. In this example we are trying to achieve 5 different system SAIDIs.

Table 4.6 Allocated hazard rates to achieve the required system SAIDI

Element	Allocated Hazard Rates for the required SAIDI.				
	SAIDI = 3.25	SAIDI = 3	SAIDI = 2.5	SAIDI = 2	SAIDI = 1
Line 1	0.3153	0.2373	0.0811	0.0400	0.0400
Line 2	0.4730	0.3559	0.1217	0.0600	0.0600
Line 3	0.1577	0.1186	0.0406	0.0200	0.0200
Line 4	0.3930	0.3866	0.3737	0.3100	0.1461
Line 5	0.5895	0.5799	0.5605	0.4650	0.2192
Line 6	0.9825	0.9664	0.9342	0.7749	0.3654
Fuse1	0.0079	0.0059	0.0020	0.0010	0.0010
Fuse2	0.0079	0.0059	0.0020	0.0010	0.0010
Fuse3	0.0098	0.0097	0.0093	0.0077	0.0037
Fuse4	0.0098	0.0097	0.0093	0.0077	0.0037

Step 3: The system was simulated with the allocated hazard rates, assuming that the allocated hazard rates were achieved by preventive maintenance for each case. It can be seen from Table 4.7 that the actual SAIDI achieved, assuming the required hazard rates are reached by preventive maintenance, are very close to the required SAIDI.

Table 4.7 Windmil Simulation Results of Achieved SAIDI

Required SAIDI	Actual SAIDI with allocated hazard rates
1	1.0000
2	2.0000
2.5	2.4998
3	3.0001
3.25	3.2499

4.6 Optimize the Improvement of the Criteria for a Component

Once the required improvement of a component is found (from the previous work), it is important for the utility to know which criteria to improve and by how much. This work is to determine how to improve the criteria of a component in an optimal way.

From Figure 4.2 it can be seen that not all the criteria have physical meaning for failure. Some of the criteria represent a single physical criterion. Thus it is important to identify the failure modes when we develop the maintenance schedule. Table 4.8 shows the different failure modes for a power transformer and how the general criteria are classified into failure modes.

Table 4.8 Failure Modes of Power Transformer

Failure Mode	Affecting Criteria	Topology
Winding	1. Condition of Winding (6) 2. PD Test (7) 3. Core & Winding Loss (8)	Parallel
Insulation	1. Condition of Solid Insulation (9)	-
Tap Changer	1. Tap Changer Condition (10) 2. Winding Turns Ratio (11)	Parallel
Oil	1. Gas in Oil (12) 2. Water in Oil (13) 3. Acid in Oil (14) 4. Oil PF (15)	Series
Tank	1. Tank Condition (16)	-
Bushing	2. Bushing Condition (17)	-
Cooling System	1. Hot Spot Temperature (18) 2. Cooling System (19)	Parallel

When a failure mode has criteria is series topology, the hazard rate of the j^{th} failure mode for can be found to be,

$$h_j(t) = -\sum_{\forall i} \frac{1}{R_i(t)} \frac{dR_i(t)}{dt} \quad i = 1,2,\cdots number\ of\ criteria \tag{4.12}$$

On the other hand, if a failure mode has criteria in parallel topology, the hazard rate of j^{th} mode for can be found to be,

$$h_j(t) = \frac{\prod_{\forall i} F_i(t)}{1 - \prod_{\forall i} F_i(t)} \sum_{\forall i} \left(\frac{1}{F_k(t)} \frac{d\left(F_i(t)\right)}{dt} \right) \quad i = 1,2,\cdots number\ of\ criteria \tag{4.13}$$

In general we can assume failure of each mode is independent of the others. Thus the hazard rate of the component would be,

$$h_c(t) = \sum_{\forall j} h_j(t) \tag{4.14}$$

Not all failure modes can be improved (eg. age of the transformer, physical location etc) thus we will divide the criteria into those that can be improved and those that cannot. Let x_j be the improvement in the modes which can be improved. Thus if we want to achieve the required hazard rate the h_c^* then the following equation can be formed.

$$h_c^* = h_c(t) + \sum_{\forall j \in I} \left(x_j(t) \right) \tag{4.15}$$

Where,

$h_c(t)$ - Hazard rate of the component c at time t

I - The set of failure modes for component c

The cost of improving a failure mode as a function of improvement in reliability (x_j), is mostly not known. Thus it is assumed that the cost of improvement has the following relationship. If the relationship is known then that known relationship would be used.

$$f(x_j) = co_j x_j^2(t) \tag{4.16}$$

The objective of the optimization problem is

$$\min \sum co_j x_j^2(t) \tag{4.17}$$

with a constant,

$$\sum_{\forall j} x_j(t) = h_c^*(t) - h_c(t)\left(= \tilde{h}_c(t)\right) \tag{4.18}$$

Using the Lagrangian multiplier, the optimum solution can be formed as,

$$x_j^*(t) = \frac{\tilde{h}_c(t)}{co_j \sum_{\forall j}\left(\frac{1}{co_j}\right)} \tag{4.19}$$

The above relationship will optimize the cost of maintenance for a given component. Since non conventional criteria like experience with the transformer are used it may be necessary to calibrate the model. This will be verified in the numerical analysis.

4.7 Maintenance Scheduling

Once the optimal maintenance requirement for each component is found, the next step is to schedule the maintenance. It may be economically competitive to replace the component rather than maintaining it, especially those components that are near failure. Thus budgetary calculations should be done at this stage comparing maintenance with replacement. Maintaining a component will improve its reliability. If the component is faulty, replacement of the component will improve its reliability by a huge margin. Even though the replacement cost may be higher than the maintenance cost, in the long run replacement may be cost-effective. In addition to the standard budgetary calculations it is important to include a comparison between the remaining life of the component by maintenance and the maintenance cost versus the investment.

If replacing the component is cost effective, then the utility should take necessary action to replace the component. On the other hand if the analysis shows it is cost effective to maintain the component, go to the next step.

This step is similar to the previous step. Here we want to ensure that the required maintenance will not exceed the budget limitations. Out of the components which were not replaced, the components performing badly get preference over the others, as they are the major contributors to the poor system performance. If the maintenance cost is within the allocated budget, the component will be scheduled for maintenance.

These two steps are based on utility guidelines and practice, so this work does not elaborate further on these two steps. We do, however, present a technique to improve the reliability in case neither of these steps canbe achieved for the whole system or part of the system, i.e. the budget constraints limit the maintenance and replacement of components.

4.8 Equipment Derating

One of the ways to extend the life of a component (reduce the failure rate of the component) is to derate it. By derating, stress/heat related failures can be minimized. After studying the condition of a component based on the hazard rate, and by inspecting it, the utility could decide whether to derate the equipment (if the component is defective) or decommission the component. Once the component is derated / decommissioned the system should be reconfigured to serve the whole load without overloading system components. In this section we present a technique to derate components to achieve a desired (allocated) hazard rate.

The following expression is used to find the relationship between derating and hazard rates [19].

$$h_2 = h_1 \exp K\left(\frac{1}{T_1} - \frac{1}{T_2}\right) \qquad 4.20$$

If the manufacturer provides the relationship between the change in temperature and current flow through the component, then that relationship should be used. Otherwise we can use generalized relationships; some examples of which are given in Table 4.9.

Table 4.9 Relationship between current and temperature rise

Component	Relationship
Overhead Lines	$I^2 = K(T_{conductor} - T_{ambient})$[28]
U/G Cables	$(T_{conductor} - T_{ambient}) = T = R_{TH}(I^2 R)$[28]
Transformer	$(T_{conductor} - T_{ambient}) = T = (P_\Sigma / A_T)^{0.833}$ [29]

Where,

K - Proportionality constant.

R_{TH} - Total thermal resistance between conductor and the air.

R - Electric resistance of the conductor.

P_Σ - Total transformer losses.

A_T - Surface area of the transformer.

If the utility decides to derate the component we could use the following rule of thumb [22]

"8% Reduction in loading will double the expected lifetime;

similarly 8% increase will halve the lifetime"

The relationship between the lifetime and the hazard rate is dependent on the reliability distribution model. It could be presumed that the doubled lifetime will result in doubling the Mean Time To Failure (MTTF). Since the Weibull distribution is used as the failure distribution for most of the components, the following relationship is formed, using the shape parameter (β) of the Weibull distribution.

$$I_{derated} = \sqrt{\frac{K_{\lambda}}{K_{\lambda} - \ln\left(\frac{h_{allocated}}{h_{rated}}\right) I_{rated}^{2}}} \times I_{rated} \qquad 4.21$$

Using the rated current before derating and 92% of that rated current, K_{λ} could be found,

$$K_{\lambda} = 0.6931\beta\left(\frac{I_{rated}^{2} \times I_{92\%}^{2}}{I_{rated}^{2} - I_{92\%}^{2}}\right) \qquad 4.22$$

Where, $I_{92\%}$ is the 92% of the rated current I_{rated} .

If the hazard rate of a component is higher, it may be uneconomical to derate the component as it may already be in the faulty region. In this case the component will be operated at its rated value, but its owner must be ready to replace the component at its failure. It is important to find the critical hazard rate for this decision making; past failure data is necessary.

Once all these processes are completed, the new system reliability indices will be the input for the risk calculations, and this will give a quantitative analysis on how the maintenance reduced the risk in the system.

4.9 Conclusions

Increased distribution system reliability has very high value in the restructured energy industry. A critical component in distribution reliability is preventive maintenance. In this work we have presented a historical statistics-based maintenance scheduling technique. This work uses time varying hazard rate functions for the system components. In order to minimize the total maintenance cost an optimal algorithm is used to rank the components from most vital to least vital. If budget constraints limit maintenance, a component derating and system reconfiguration is presented to maximize system reliability.

5. Risk-based Assessment for Improved Reliability and Related Benefits from Data Integration

5.1 Introduction

The benefit of integration of asset and outage management is estimated by means of improvement in reliability. How to evaluate distribution network reliability is a topic of interest in our project. For both utility and customers, it is convenient to estimate cost of failures (outages) which reflects the reliability issue ([29]-[32]). The work presented next introduces a method to evaluate cost of outages in a distribution system.

Most of current cost evaluation methods focus on customer interruption cost, because outages of system components will directly lead to failure of power supply to customers, and cause loss of revenue to utilities. Methodologies used in cost evaluation or assessment also vary. The method proposed in this report considers both customer interruption cost and cost of generation and transmission. Risk-based assessment is used because it better reveals the association between outage cost and system reliability.

5.2 Effect of Asset Management Tasks on Outage properties

Asset management tasks focuses mainly on the condition of system components, i.e. transformers, reclosers and wood poles. Failure rate λ, mean time to failure (*MTTF*) and other parameters that are associated with maintenance also have impact on some reliability indices. Following is a discussion of the reliability indices and the effects on the outage properties [33]:

1. Effect on customer satisfaction:

$$SAIFI(k) = \lambda(k)\frac{n_k}{n} \qquad 5.1$$

$$SAIDI(k) = \lambda(k)\frac{\sum_{j=1}^{n_k} d_j}{n} \qquad 5.2$$

2. Revenue loss of utility

$$ENS(k) = \lambda(k)\sum_{j=1}^{n_k} P_j d_j \qquad 5.3$$

3. Cost of equipment failure

$$DecRisk(k) = Cost(k)\{\lambda(k) + (1+r)^{-MTTF}\} \qquad 5.4$$

5.3 Effect of Outage Management Tasks on Outage Properties

Outage management task focuses on the identification, isolation and restoration of faults. Duration of an interruption d_i, number of momentary interruptions IM_i, and number of interrupted customers for each momentary interruption N_{mi} are all sensitive to the accuracy of fault location and correct operation of isolation and system reconfiguration.

Penalty for sensitive customers and generation loss are considered along with customer satisfaction and revenue loss. Following is a list of those reliability indices and the effects they have:

1. Effect on customer satisfaction:

$$SAIDI(i) = \frac{\sum_{j=1}^{n_i} d_j}{n} \qquad 5.5$$

2. Revenue loss of utility

$$ASIDI(i) = \frac{\sum_{j=1}^{n_i} d_j \cdot L_j}{L_T} \qquad 5.6$$

3. Penalty for important (prioritized) customers with special contract of uninterrupted power supply

- Temporary interruptions:

$$MAIFI(i) = \frac{\sum_{j=1}^{N_{mi}} IM_i}{N} \qquad 5.7$$

- Loss of power: equation 5.6.

4. Generation Loss and cost of reconfiguration

$$MED(i) = \{SAIDI(i) \mid SAIDI(i) \geq T_{MED}\} \qquad 5.8$$

The generation loss is neglected when the duration of fault is short. However, when a major event happened and the transmission of power from generation to distribution system via transmission system changes for a considerable amount of time, cost of generation loss is also considered. Also, when outage lasts for a long time, reconfiguration is needed to get at least important customers connected.

5.4 Definition of risk

Reduction in risk is comprised of two parts: reduction from maintenance and reduction from refining fault location and hence other outage management tasks.

The consequence of equipment failure can be expressed as the weighted sum of the quantities provided in 5.1-5.4 and comprised the “Risk” associated with a component’s failure. Reduction in risk obtained from maintaining a component can be expressed as follows:

$$\begin{aligned}\Delta Risk_{AM}(k) = {} & \alpha_1 \cdot \frac{\partial SAIFI(k)}{\partial \lambda(k)} \cdot \Delta\lambda(k) + \alpha_2 \cdot \frac{\partial SAIDI(k)}{\partial \lambda(k)} \cdot \Delta\lambda(k) + \alpha_3 \cdot \frac{\partial ENS(k)}{\partial \lambda(k)} \cdot \Delta\lambda(k) \\ & + \alpha_4 \cdot \left[\frac{\partial DevRisk(k)}{\partial \lambda(k)} \cdot \Delta\lambda(k) + \frac{\partial DevRisk(k)}{\partial MTTF(k)} \cdot \Delta MTTF(k) \right]\end{aligned} \qquad 5.9$$

The subscript “AM” represents asset management-oriented risk function.

Similar to expression $\Delta Risk_{AM}(k)$, the consequence of failure from the impact of outage management can be comprised of weighted sum of the quantities provided in 5.5-5.8. Risk reduction in one interruption event is expressed as follows:

$$\Delta Risk_{OM}(i) = \beta_1 \cdot \frac{\partial SAIDI(i)}{\partial d(i)} \cdot \Delta d(i) + \beta_2 \cdot \frac{\partial ASIDI(i)}{\partial d(i)} \cdot \Delta d(i) + \beta_3 \cdot \left[\frac{\partial MAIFI(i)'}{\partial IM_i'} \cdot \Delta IM_i' + \frac{\partial MAIFI(i)'}{\partial N_{Mi}'} \cdot \Delta N_{Mi}' + \frac{\partial ASIDI(i)'}{\partial d(i)'} \cdot \Delta d(i)' \right] + \beta_4 \cdot \frac{\partial MED(i)}{\partial d(i)} \cdot \Delta d(i) \qquad 5.10$$

Factors with a ’ takes into consideration only the contribution of sensitive loads. Again, the subscript “OM” represents outage management-oriented risk function.

The overall reduction of risk obtained in a reporting period is expressed as a linear combination of $\Delta Risk_{AM}(k)$ and $\Delta Risk_{OM}(i)$:

$$\Delta Risk = \Sigma \Delta Risk_{AM}(k) + \Sigma \Delta Risk_{OM}(i) \qquad 5.11$$

Taking partial derivatives in equation 5.9 and 5.10 and ignoring high order components in the Tailor extension, $\Delta Risk_{AM}(k)$ and $\Delta Risk_{OM}(i)$ can be expressed in another way by component parameters and features of outage:

$$\Delta Risk_{AM} = \Sigma\{\alpha_1 \cdot \frac{n_k}{n} \cdot \Delta\lambda(k) + \alpha_2 \cdot \frac{\sum_{j=1}^{n_k} d_j}{N} \cdot \Delta\lambda(k) + \alpha_3 \cdot (\sum_{j=1}^{n_k} P_j d_j) \cdot \Delta\lambda(k) + \alpha_4 \cdot DevCost(k)[\Delta\lambda(k) + (1+r)^{-MTTF} \cdot (1-(1+r))^{-\Delta t}]\} \qquad 5.12$$

$$\Delta Risk_{OM} = \Sigma\{\beta_1 \cdot \frac{\sum_{j=1}^{n_i} \Delta d(j)}{n} + \beta_2 \cdot \frac{\sum_{j=1}^{n_i} L_j \Delta d(j)}{L_T} + \beta_3 \cdot [\frac{\sum_{j=1}^{n_i'} L_j \Delta d(j)}{L_T} + \frac{N_{Mi}'}{N} \Delta IM_i' + \frac{IM_i'}{N} \cdot \Delta N_{Mi}'] + \beta_4 \cdot \frac{\sum_{j=1}^{n_i''} \Delta d(j)}{N}\} \qquad 5.13$$

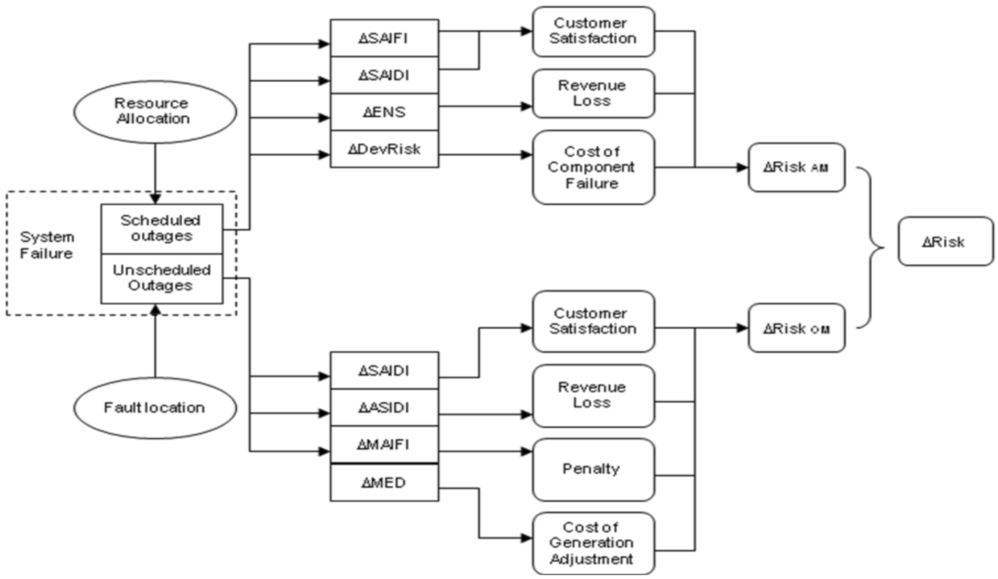

Figure 5.1 Assessment of Risk-reduction

Following is an example showing how the cost of outage is calculated.

The reliability indices for each feeder are given in [17] for the RBT4 distribution system. Reliability indices for feeder 1 are listed below in table 5.1. If by data integration and application of new approaches proposed in section 3 and 4, the failure rate λ of components can be reduced by 10%, MTTF of components increased by 10%, the duration of outage reduced by 10%, and the cost of maintenance reduced to \$4500, the new reliability indices are listed in table 5.2.

The reduction in risk calculated using equation 5.11- 5.13 is 1673.66, which is 14.6% of the cost before integration.

Table 5.1 Reliability indices given in [17]

SAIFI times/(customer.yr)	**SAIDI** hr/(customer.yr)	**ENS** kWhr/yr	**ASIDI** hr/yr	**Maint. Cost** $	**Cost of Outage**
0.302	3.47	12196	0.32315	5000	11468.4

Table 5.2 New numbers: $E(\Delta\lambda/\lambda)$= -10%, E $(\Delta MTTF/MTTF)$=10%, $E(\Delta d/d)$= -10%

SAIFI times/(customer.yr)	**SAIDI** hr/(customer.yr)	**ENS** kWhr/yr	**ASIDI** hr/yr	**Maint. Cost** $	**Cost of Outage**
0.2718	2.8107	10470	0.26175	4500	9794.74

5.5 Conclusion

This section presents a method for evaluating cost of outage that can be used to assess the benefit of the outage and asset management integration studied in this project. The formulation of cost of outage reflects not only the revenue loss but also the combined impact of outage to the customers and serving utility. The selection of the reliability indices makes the cost explicit and easy to calculate.

6. Future Research

Several issues are addressed but not covered in our research. Future work may include:

- Integrated view of capital investment strategy. This effort should answer the question how the investment in monitoring equipment should be allocated among asset management and outage management tasks in a most efficient way, i.e. how to gain the largest return for utilities and the greatest improvement in reliability of the system for the customers. The risk-based assessment of outage cost can be used as the objective of the optimization problem.
- Post-fault reconfiguration. The impact of reconfiguration cost after the fault has been located using outage task needs to be addressed. The implementation cost of the best scheme for reconfiguration made possible with improvements in the technology and tools proposed in this study needs to be compared to the cost of conventional practice: isolate the faulted area and after the replacement or repair is done restore service to the customers that lost power due to the fault.
- Placement of IEDs in a distribution system. This topic requires more comprehensive study of the optimal placement of IEDs. Given a certain amount of capital funds, the research needs to focus on how the measurements be placed in the system so that the overall accuracy of fault location program is maximized.

7. Conclusion

This project explores a method to improve distribution system reliability. The traditional distribution utility business processes are analyzed, and the new technologies for outage management and asset management are addressed and discussed. Considering the constraints that hamper deployment of new technologies, the integration of asset management and outage management tasks is proposed in a way that can take advantage of the new technologies.

This project results in the following contributions:

- Approach to the integration of asset management and outage management tasks is able to deal with the constraint of insufficient data when implementing new technologies;
- A risk-based assessment approach to outage cost improves system reliability. The outage cost is formed by taking into account customer satisfaction, utility interest and other factors hence providing more comprehensive information than reliability indices;
- Introduction of stochastic processing in fault location algorithm improves the robustness to imperfect data. A voltage-measurement based fault location algorithm capable of detecting major errors in operational and nonoperational data, and showing higher accuracy than other algorithms when data is insufficient and inaccurate is proposed and tested;
- Definition of an optimized fault location process combines the fault location technique and dispatch strategy for field crews, and determines how to inspect fault in a system based at the minimum risk;
- The proposed method optimizes the resources for preventive maintenance of the distribution system while maintaining system reliability. The component reliability indices are analyzed based on the several criteria attributed to the component which can be measured or observed periodically and then the preventive maintenance is scheduled using risk analysis.

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Appendix: Summary Sheet of the Survey

Information Needs Survey for Distribution Systems-- Summary Sheet

Integration of Asset and Outage Management Tasks for Distribution Applications

PServ Project T-36

Total Participants: 6

Item	Information provided	How useful?					
		Very	***Not very much***	***Useful***	***Maybe useful***	***Little***	***Already have this***
1	Automated fault location with high accuracy	4					2
2	Fault prediction based on early detection of incipient faults	2	2	2			
3	Component failure prediction: next failure, time to failure, consequences	2	3			1	
4	Estimation of IEEE 1366 reliability indices			2	3	1	
5	Maintenance suggestions to improve reliability, prevent incipient faults, mitigate power quality		1	4	1		
6	Line, transformer, component loadings	2	3		1		
7	Feeder voltage profiles, including sags		3	1	2		
8	Load status: power consumption, switching state		2	2	1		1
9	Asset management planning			1	4		1(unclear)
10	Detection, classification and verification of faults, and automated analysis of related fault clearing sequences	1	3				1