Automated Integration of Condition Monitoring with an Optimized Maintenance Scheduler for Circuit Breakers and Power Transformers

Final Project Report

Power Systems Engineering Research Center

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Power Systems Engineering Research Center

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Executive Summary

The effectiveness of expending maintenance resources can vary dramatically depending on the target and timing of the maintenance activities. The state-of-the-art in maintenance management offers at least three basic approaches for making maintenance management decisions:

(1) condition-based maintenance (CBM) initiates a maintenance activity when data from equipment monitors indicates a need;

(2) reliability centered maintenance (RCM) prioritizes maintenance activities based on quantification of likelihood and consequence of equipment failures; and

(3) optimization techniques offer methods for maximizing effectiveness of the maintenance activities subject to constraints on economic resources, available maintenance crews, and restricted time intervals.

In this research project, we developed a comprehensive and cost-effective system-wide maintenance allocation and scheduling system based on automated integration of condition monitoring with an RCM-based optimized scheduler. The maintenance allocation and scheduling system can reduce maintenance costs while increasing equipment reliability. It can also (1) extend equipment life; (2) cut costs for substation design, refurbishment and construction; and (3) ensure high levels of health and safety for operation and maintenance personnel, the public, and the environment.

The research focused on transformer and circuit breaker maintenance, but the system is expandable to other equipment. We focused on circuit breakers and transformers because (1) expenditures for maintenance of this equipment represent a large percentage of maintenance budgets; (2) failures adversely affect system reliability; and (3) monitoring technologies presently exist within substations.

There were two sub-goals of the research project. The first was to develop analytic models and procedures for the maintenance allocation and scheduling system. The second was to create the software necessary for performing automated and continuous integration of data sources when updating maintenance schedules.

There were seven main research products.

1. Failure mode identification: Taxonomies or classifications are essential in identifying the effects of maintenance tasks on failure rates. We provide taxonomies of failure modes associated with power transformers and circuit breakers, respectively, together with maintenance tasks that address those failure modes.

2. Failure rate estimation: Failure rates and time-to-failure reductions from each maintenance task are used in optimizing resources. We developed methods for estimating probabilistic indices (such as failure rate and time to failure for power transformers and circuit breakers) using sequences of condition measurements obtained from either continuous monitoring, or from periodic inspection and testing. These methods also allow calculation of the reduction in failure rate and time to failure for each component.

3. Risk reduction from expected redispatch costs: We extended a previously developed simulator that performs efficient hour-by-hour security assessment for specified contingencies (corresponding to failure of a maintainable line, transformer, or circuit

breaker) over a year. The effect of a specified maintenance task can be quantified based on the cumulative reduction in system risk obtained from it.

4. Mid-term maintenance selection and scheduling: Algorithms and related software applications were created for selecting and scheduling transmission-related maintenance tasks over a budget and labor-constrained time period (e.g., a year) such that the effect of those resources are optimized.

5. Long-term maintenance scheduling: We developed an approach for planning long-term policies associated with inspecting and maintaining power transformers and circuit breakers. Results of this approach serve to provide a list of candidate maintenance tasks as input to the mid-term scheduler.

6. Data integration: A novel data integration method was created to avoid the need to aggregate data into a centralized warehouse but rather to allow users to query multiple, related data sources simultaneously.

7. Software design approach: Multiagent systems use messaging to facilitate communication between software applications, provide for long-term maintainability of the software system, and are particularly effective when data and applications are highly distributed as they are in the asset management problem addressed in this project.

We developed integrated, research grade software in this research.

1. Long-term simulator: This simulator performs hourly security analysis on a power system over a year or more, returning (1) cumulative reliability risk, (2) cost of redispatch to maintain reliability for each contingency for each hour, scaled by the contingency probability, and (3) both measures accumulated over the entire year.

2. Optimizer: The optimizer efficiently selects and schedules tasks over the maintenance planning year. It requires inputs of (1) candidate maintenance tasks; (2) quantified measures of the effect of each task on reliability; (3) maintenance resource requirements for each task, along with any restrictions on when each candidate task can be performed during the year; and (4) the maintenance budget and labor time resources.

3. Data integrator: The data integrator interfaces between the user and any number of remote databases so that data retrievals are made directly into the source without having to maintain a separate, local data warehouse.

The failure likelihood and reliability effects for transmission-level equipment is information that can be used in solving three system-level decision problems: operational security assessment, maintenance planning, and facility replacement planning. Improvements in decisional-analysis simulation tools can be made by capturing the coupling between these inter-related decision problems. We are building upon the research products of this project by designing new simulation capabilities that use the coupling between the three decision problems while interfacing with communications equipment and condition-monitoring hardware. Two investigators in the PSERC project received funding by a recent National Science Foundation Award to take this next step in building simulation tools to support decision-making. Six different companies, including two large utilities, are participating as advisors in the National Science Foundation project. More information about this follow-on project can be found at http://ecpe.ee.iastate.edu/powerweb/auto.htm.

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1. Introduction

A rough estimate of the numbers of power transformers and circuit breakers comprising the US transmission system (138-765 kV) are 150,000 and 600,000, respectively; in addition, there are 254,000 miles of high voltage transmission lines. Total replacement value of the lines alone (excluding land) is conservatively estimated at over $100 billion dollars [1] and triples when including transformers and circuit breakers. Investment in new transmission equipment has significantly declined over the past 15 years. Some of the equipment is well beyond intended life, yet is operated under increasing stress, as load growth, new generation, and economically motivated transmission flows push equipment beyond nameplate limits. Economic operation, and ultimately electric energy price, is heavily influenced by transmission equipment availability, because transmission forced outages require utilization of more expensive generation. And equipment availability is heavily influenced by decisions regarding how to expend resources for maintaining equipment, an issue that becomes more critical as the average equipment age increases.

The technologies employed for condition monitoring over the past decades have been evolving from traditional periodic on-site examination and laboratory analysis to continuous on-line monitoring. Recent technological advancements have made various sensors integrated with substation intelligent electronic devices (IEDs) available to monitor different parameters essential to the health of equipments in operation, for example:

- For power transformers: voltages and load currents, temperatures at different locations, content of certain type of dissolved gases in oil, moisture in oil, oil level and pressure, velocity of oil/air flow, partial discharge activities, insulations, and tap changer positions,
- For circuit breakers: number of operations, contact travel time, static contact resistance, phase currents, coil currents, heater and pump currents, and oil pressure and temperature, and ambient temperature

A major aspect of these above monitoring technologies has been the accumulation of copious amount of data at the field. The monitoring systems monitor these critical parameters continuously, in “real-time”. Usually sampling is from several minutes to seconds. And usually the storage capability of microcomputer based monitoring system is very limited.

The effectiveness of a expending maintenance resources can vary dramatically depending on the target and timing of the maintenance activities. The existing state-of-the-art offers at least three basic approaches for making the decisions associated with identifying maintenance activities: condition-based maintenance (CBM) initiates a maintenance activity when data from monitoring the equipment indicates a need, reliability centered maintenance (RCM) prioritizes maintenance activities based on quantification of likelihood and consequence of equipment failures, and optimization techniques offer methods of maximizing effectiveness of the maintenance activities subject to constraints on economic resources, available maintenance crews, and restricted time intervals. These three approaches are illustrated in the circled part of Fig. 1.1 [2].

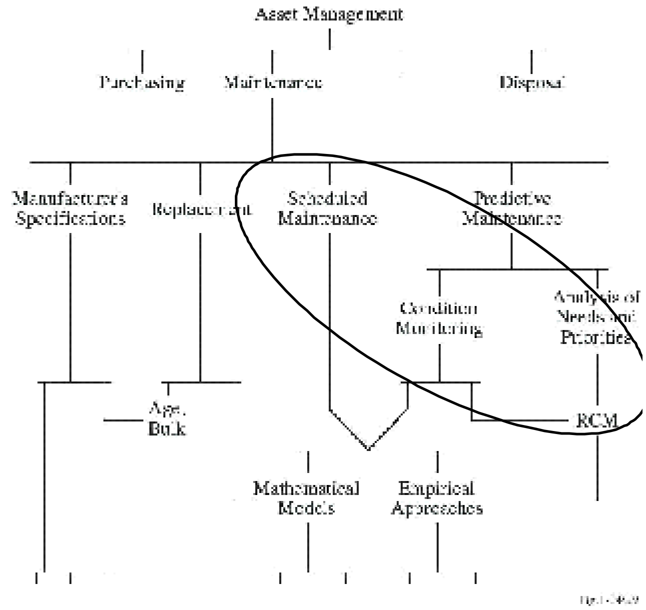

Fig.1.1: Maintenance approach overview

The objective of the work described in this report is to develop a comprehensive and cost-effective maintenance allocation and scheduling system, based on an integration of these three approaches. We have developed a system wide maintenance allocation and scheduling system based on automated integration of condition monitoring with an RCM-based optimized scheduler for transformers and circuit breakers. This framework reduces maintenance costs while increasing equipment reliability to meet the challenges from the increasingly competitive marketplace. It also helps to extend equipment life; cut costs for substation design, refurbishment, and construction; and ensure high levels of health and safety for operation and maintenance (O&M) personnel, the public and the environment.

In order to limit the work to that which can be accomplished within the designated budget and duration, we focused on circuit breakers and transformers for the following reasons: expenditures for the associated maintenance of this equipment represents a large percentage of maintenance budgets; their failure can have significant system reliability impact; and monitoring technologies for each of these equipment types presently exist within substations of PSERC member utilities. There are two subgoals associated with accomplishing the project objective. The first is to develop the analytic models and procedures for using conditions of the monitored equipment in decision making related to a maintenance allocation and scheduling function. The second is to create the software infrastructure necessary for performing automated and continuous integration of the various data sources when updating the maintenance schedules.

The main products of the work described in this report are summarized as follows:

1. Failure mode identification: Chapters 2 and 3 provides taxonomies of failure modes associated with power transformers and circuit breakers, respectively, together with maintenance tasks that address those failure modes. These taxonomies are essential in identifying the effects of maintenance tasks on failure rates.

2. Failure rate estimation: Chapter 4 describes methods of estimating probabilistic indices such as failure rate and time to failure for power transformers and circuit breakers, using sequences of condition measurements obtained from either continuous monitoring or from periodic inspection and testing. These methods also allow calculation of the reduction in failure rate and time to failure for each component. Failure rates and time-to-failure reductions from each maintenance task are used in optimizing resources as described in Chapter 5.

3. Mid-term maintenance selection and scheduling: Chapter 5 presents a set of algorithms and related software applications for selecting and scheduling transmission-related maintenance tasks over a budget and labor-constrained time period (e.g., a year) such that the effect of those resources are optimized. A simulation approach was used that computed risk reduction from maintenance in terms of the expected decrease in redispatch costs.

4. Long-term maintenance scheduling: Chapter 6 provides an approach for planning long-term policies associated with inspecting and maintaining power transformers and circuit breakers. Results of this approach serve to provide a list of candidate maintenance tasks as input to the mid-term scheduler of Chapter 5.

5. Data integration: Chapter 7 describes a novel data integration method that avoids the need to aggregate data into a centralized warehouse but rather provides users with the ability to query multiple, related data sources simultaneously.

6. Software design approach: Chapter 8 identifies use of multiagent systems for software design of the developed maintenance selection and scheduling system. Multiagent systems use messaging to facilitate communication between software applications, provide for long-term maintainability of the software system, and are particularly effective when data and applications are highly distributed as they are in the asset management problem addressed in this project.

2. Failure Modes, Maintenance and Condition Monitoring of Power Transformers

The power transformer accounts for a significant percentage of investment in the transmission system, and they usually provide operationally important links. As a result, their failure can have dramatic economic consequences in terms of unit repair and replacement and operational constraints. This chapter summarizes the different ways in which a transformer can fail together with the various maintenance tasks that contribute to preventing or delaying those failures.

2.1 Transformer Failure Modes and Corresponding Maintenance

A failure mode is a characterization of the way a component, process, or system fails, usually in terms of how the failure is observed (in contrast to how the failure is caused). For example, the dielectric breakdown of transformer oil is a failure mode, which may have multiple causes such as oil contamination, oil oxidization, thermal decomposition, and moisture in oil from cellulose decomposition. A contingency is the result of the failure mode, which is usually an outage in the transmission system. One contingency can be caused by different failure modes. And one failure mode may cause different contingencies, according to real condition of the system. Failure modes and effects analysis (FMEA) is an important procedure to identify and assess consequences or risks associated with potential product failure modes. A FMEA typically includes a listing of failure modes, possible causes for each failure, effects of the failure and their seriousness and corrective actions that might be taken [3].

2.1.1 Definition and cost of transformer failures

Failure of transformer is an important cause of transmission outage and sometimes can cause significant loss to the system. A 'failure' of transformer can be defined as [4]:

- A forced outage of the transformer due to major damage of the transformer in service.
- A problem that requires the transformer to be taken to the factory/workshop for repair work.
- An extensive field repair is also regarded as a failure.

Transformer failure does not necessarily imply the 'blue smoke' condition where the component has catastrophically failed. Rather, 'failure' can be defined by a set of measurement values for which engineering judgment results in the action of removing the transformer from service.

Economic consequences of transformer failure can be large, due to the cost of property damage, repair cost, and the business cost due to transmission service interruption. The time to repair and replace a power transformer is also substantial. For example, the repair and replacement of a 345/138 kV transformer normally requires about 12 - 15 months, and if a spare is available, the time needed for replacement of a failed unit is in the range of 8 - 12 weeks [4]. Reference [5] contains a five-year survey (1997-2001) of transformer failure cost worldwide based on available data. Table 2.1

displays the annual transformer claims including total costs, property damage costs, and transmission service interruption costs.

TABLE 2.1: NUMBER AND COSTS OF POWER TRANSFORMERS FAILURES BY YEAR

Year	# of losses	Total costs	Property damage costs	Transmission service interruption costs
1997	19	$40,779,507	$ 25,036,673	$ 15,742,834
1998	25	$24,932,235	$ 24,897,114	$ 35,121
1999	15	$ 37,391,591	$ 36,994,202	$ 397,389
2000	20	$ 150,181,779*	$ 56,858,084	$ 93,323,695
2001	15	$ 33,343,700	$ 19,453,016	$ 13,890,684
Total	94	$ 286,628,811	$ 163,239,089	$ 123,389,722

** Total losses in 2000 includes one claim with a business interruption portion of over $86 million US*

Table 2.1 indicates that transformer failure can result in significant costs. So analyzing the failure modes and developing policies for monitoring and maintaining transformers is an essential task for transformer asset management.

2.1.2 Transformer failure modes and mechanisms

Transformer failure modes can be divided into two groups: maintainable and non-maintainable. There are some failures that cannot be improved with maintenance, such as human error, manufacture and design defects, and bad weather such as lightning or ice storms. These problems generally have a constant failure rate over the transformers lifetime and maintenance cannot reduce the failure rate. In our work we only focus on the failure modes whose probability increases with the service age or operations, so that maintenance can ‘renew’ the corresponding conditions and thus reduce the failure rate. Such failure modes are called ‘maintainable’ failure modes.

During the entire operation time, a power transformer has to withstand numerous stresses. These stresses are of thermal, electrical, and mechanical nature and can result in various problems, such as insulation degradation, partial discharge, hot spots etc. The mechanisms of major failure modes of transformers are described in the following six subsections.

2.1.2.1 Insulation degradation

Insulation degradation can be caused by many reasons, but in most cases it is because of the high thermal and electrical stress around the neighborhood of the insulation material. In oil-immersed transformers, usually the insulation materials are cellulose and mineral oil. Both of them deteriorate under the thermal or electrical stress of transformer in service.

1) Cellulose decomposition

Paper (cellulose) immersed in mineral oil is used as the insulation system for power transformers. The main component of paper is cellulose fiber, a carbohydrate, and the structure of cellulose is a long chain made up of glucose molecules. The number of the molecules in the chain can be 300-750. Under thermal or electromagnetic stress, the long chain may break resulting in the paper becoming brittle. Insulation of the paper is not acceptable if the number of glucose molecules in one chain is less than 200. Also, water is produced internally as the product of oxidation of the cellulose, and water in paper can significantly reduce the dielectric strength of paper.

2) Oil decomposition

Mineral transformer oils are mixtures of many different hydrocarbon molecules, and the decomposition processes for these hydrocarbons in thermal or electrical faults are complex. The fundamental steps are the breaking of carbon-hydrogen and carbon-carbon bonds. Different gases are formed during the decomposition process based on the presence of individual hydrocarbons, on the distribution of energy and temperature in the neighborhood of the fault, and on the time during which the oil is thermally or electrically stressed. IEEE has provided an interpretation of the analysis of dissolved gases (DGA) in oil and standards of determining the condition of the transformer with the DGA test data [6]. Products of oil decomposition might contain combustible gases, which can cause danger to the transformers if they cannot be released properly. In addition, acids are produced as a result of oxidation of the oil, increasing the rate at which the oxidation takes place. Carbon and sludge can also be produced, coating heat transfer surfaces on the core/coil and the tank/radiators, reducing the heat transfer capacity of the system. The operational temperatures are increased, thus accelerating the degradation of the oil or even damaging the transformer. Also the carbon might cause some short circuit between different surfaces.

Insulation deterioration via either cellulose or oil degradation can cause problems such as short circuit within the transformer, extra heating, or partial discharge or arcing between different surfaces. These problems can require that the transformer be removed from service, and in the worst case, they can result in damage to the transformer.

2.1.2.2 Winding failure

Winding failure can be caused by many reasons, including lightning, overload, or short-circuits. Overload and short-circuits caused by low insulation strength can cause extra heat to the winding and may cause damage to the winding. Lightning or external short-circuits can cause current several times to several tens of times as large as the rated load current to flow through the winding conductor. Large amounts of short circuit currents result in mechanical stress on the transformer winding due to the electromagnetic force which is proportional to the square of the short circuit current. The magnitude of the electromagnetic force due to the short circuit current may amount to a few million Newton [7]. This force can deform the arrangement of the winding conductors or even mechanically destroy fixed transformer parts. If the short circuit current is sustained from more than a few cycles, the winding conductors are subjected to extreme heat with potential to melt or fail the paper insulation. Also, if as a result of this force, the high-voltage or low-voltage windings experiences displacement, distortion, or lack of clamping force, the difference in height between windings will increase leading to ampere-turn imbalance and axial force deviation, resulting in intensified vibration.

2.1.2.3 LTC failure

Tap changers usually have a higher failure rate than transformers, although smaller consequences. Improper tap position can cause excessive core loss and consequently excessive heating. Contact coking is a major problem. Initial deposition of carbon on

LTC contacts leads to increased contact resistance, which in turn leads to increased heating and the buildup of carbon. Like transformers, LTCs also experience arcing and overheating problems. Although fault gases are produced even in normal operation, empirical work has revealed that concentration of fault gases in ‘problem’ LTCs are significantly higher than the levels in a trouble-free unit. Therefore, although the underlying principles of DGA analysis, based on establishing maximum threshold concentration for each fault gases, can be applied without modification to the analysis of fault gases formed in LTCs, the selection of the threshold must be empirically determined, based on case historical studies.

2.1.2.4 Partial discharge

Partial Discharge (PD) is an electrical discharge that only partially bridges the insulation between conductors or interfaces within that insulating system or from the sharp edges of energized apparatus parts. It may be induced by temporary over-voltage, an incipient weakness in the insulation introduced during manufacturing, or as a result of degradation over the transformer lifetime. Different classes of defects result in PD activity in oil filled power transformers. These include: bad contacts, floating components, suspended particles, protrusions, rolling particles, and surface discharges [8]. PD is undesirable because of the possible deterioration of insulation with the formation of ionized gas due to this breakdown that may accumulate at or in a critical stress region [9]. This generally involves non-self-restoring insulation that may be subject to permanent damage.

2.1.2.5 Bushing failure

Bushings provide an insulated path for energized conductors to enter grounded electrical power apparatus. Bushings are not only exposed to high electrical stress but also may be subjected to high mechanical stress, affiliated with connectors and bus support, as well. Although a bushing may be thought of as somewhat of a simple device, its deterioration can have severe consequences. The deterioration mechanisms for bushings include a combination of cracking, corrosion, wear and contamination. Failure of a bushing can cause flashover, short circuit and thus outage of the transformer, or even catastrophic events such as tank rupture or violent explosion of the bushing and fire [10].

2.1.2.6 Other failure modes

There are some other failure modes, with low probability, but they can cause outage and even significant damage to the transformer. For example, loss of sealing may cause insulation problems and environmental contamination. Blocking of pressure relief devices might cause combustible gases to accumulate in the transformer tank and, if unrelieved, lead to an explosion. Core vibration can aggravate when core-clamping force is lost, resulting in extra heat and possibly damage of the transformer. Heat exchange devices such as radiators, fans and corresponding pumps should work properly to avoid extra heat within the transformer.

2.2 Typical maintenance activities for transformer

In industry, maintenance always includes two parts: testing and improvements. The first part are all kinds of testing and measurements activities which will be performed routinely, if condition monitoring techniques are not available, such as visual inspection, temperature measurements, DGA test, PD test and commissioning test. In our study, we define the maintenance only as the second part, which is equipment refurbishing or refining power equipments to prevent oncoming failure, based on the judgment of the status of the component in the deterioration process in each failure mode.

Generally, the maintenance activities are consistent with the failure modes listed in section 2.1. It can be classified as the following categories:

a. Insulation improvement

Maintenance activities which could improve the insulation strength mainly are oil filtering or oil degasification. The purposes of oil filtering and degasification are:

1. Remove oxygen and other gases from transformer or LTC oil.
2. Reduce the acid and moisture contents in the transformer or LTC oil
3. Remove metal or other particles in the oil

Other maintenance which might improve insulation conditions also include leaks repair of transformer tank, which is also very important but has much lower frequency comparing with oil filtering and degasification.

b. Mechanical maintenance

Maintenance of mechanical parts of transformer includes the following activities:

1. Repair and cleaning of bushing
2. Inspect and repair the pressure relief blocking
3. Repair or replacement of the heat exchanging devices such as fans, radiators and pumps
4. Rewinding of the transformer
5. Out of service commissioning testing or calibration
6. Overhaul which may include any of above and replacement or repair of any individual component in the transformer.

2.3 Condition Monitoring Techniques for Transformer Failures

The most obvious purpose of transformer monitoring is to determine the condition of the equipment, potentially resulting in various benefits [11]:

(1) Operational status: Determine operational ability/statue of transformer.

(2) Failure prevention: Evaluate condition of transformer, detect abnormal conditions and initiate action to prevent impending failure.

(3) Maintenance support: Evaluate condition of transformer and initiate maintenance only when degraded condition requires maintenance; assist with maintenance planning; judge condition of a larger population of similar/identical transformers.

(4) Life assessment: Evaluate condition of transformer to determine anticipated remaining life; detect abnormal conditions.

(5) Optimize operation: Evaluate functional condition of transformer while extending or maximizing duties imposed on transformer (generally at conditions other than nameplate loading); control the effects of loading regardless of transformer condition.

(6) Commission verification tests: Confirm correct installation conditions and adjustments; evaluate condition of transformer and improve effectiveness and efficiency of verification/acceptance testing; automate collection and preservation of baseline condition data and characteristics.

(7) Failure analysis: Provide information on prior condition of transformer after a failure has occurred.

(8) Personnel safety: Prevent unsafe condition to personnel.

(9) Environment safety: Prevent unsafe condition to environment.

For power transformers, monitoring can take many forms including manual inspections (periodic visual inspections), continuous monitoring with a change in status/condition alarm as the only output (low level alarm), periodic automated monitoring (connection of portable analysis instruments), or continuous on-line monitoring (full time measurement of parameters to assess condition while in service). We review some of these forms in the following five subsections [12, 13, 14].

2.3.1 Operating condition monitoring

Transformer operating condition is mainly determined by its load current and voltage. Maximum loading of transformers is restricted by the temperature to which the transformer and its accessories can be exposed without excessive loss of life. Continuous on-line monitoring of current and voltage at operating frequency coupled with temperature measurements can provide a means to gauge thermal performance. Load current and voltage monitoring can also automatically track the loading peaks of the transformer; increase the accuracy of simulated computer load flow programs; provide individual load profiles to assist system planning; and aid in dynamic loading the transformer. Voltages can be measured easily using the measuring tap of the bushings, and, for current measurements, current transformers either mounted in the bushing domes or external devices can be used. An operating condition monitoring agent can use such loading information to provide one view of transformer operating condition.

2.3.2 Temperature monitoring

Based on temperatures measured at different locations of a transformer, e.g., oil temperature, winding temperature etc., thermal related faults can be identified. There is a direct correlation between winding temperature and normally expected service life of a transformer. The hottest spot temperature of the winding is one of various limiting factors for the load capability of transformers. Insulation materials lose their mechanical strength with prolonged exposure to excessive heat. This can result in tearing and displacement of the paper and dielectric breakdown that will result in premature failures. There is an IEEE guide describes the aging mechanisms and diagnostic techniques in evaluating electrical insulation systems [15]. Conventional winding temperature measurements are not typically direct and have slow response; the hot spot temperature is indirectly calculated from oil temperature and load current measurements. As an alternative, fiber optic temperature sensors can be installed in the winding only when the transformer is manufactured or rebuilt or refurbished. Two main types of sensors are available: optical fibers that measure the temperature at one point, and distributed optical fibers that measure the temperature along the length of the winding. Since a distributed fiber optic temperature sensor is capable of measuring the temperature along the fiber as a function of distance, it can replace a large number of discrete sensors, allowing real-time measurement of temperature distribution. Top oil temperature, ambient temperature, load (current), fan/pump operations, and direct reading winding temperatures can also be combined in algorithms to determine hottest-spot temperature and manage the overall temperature conditions of the transformer.

2.3.3 Dissolved gas-in-oil analysis

An important benefit to transformer monitoring is to the ability to identify the onset of unreliable performance as the end of life approaches. There are a variety of chemical, electrical and physical conditions monitoring techniques that can be applied, but for many companies the basic method is a regular analysis of an oil sample. The dissolved gas-in-oil analysis (DGA) technique was introduced in the mid 1960s and has been widely used throughout industry as the primary diagnostic tool for transformer maintenance, and it is typically key to a transformer owner's loss prevention program [16].

Mechanical and electrical faults may rise following short circuits, local overheating at hot spots or leakage flux and eddy currents in the core, and partial discharge or arcing at areas of high stress. Decomposition products from breakdown of the oil, paper or insulating boards, and glue are transported through the transformer by the coolant oil. Some of these products are low molecular weight gases dissolved in the oil and can be identified by gas chromatography. Others indicating solid degradation includes furans, cresols, and phenols that can be detected by liquid chromatography [17].

Dissolved Gas-in-oil Analysis (DGA) has proven to be a valuable and reliable diagnostic technique for the detection of incipient fault conditions with liquid-immersed transformers by detecting certain key gases. The gases involved are generally CO, CO_2, H_2, O_2, CH_4, C_2H_2, C_2H_4, *and* C_2H_6. The solubility of these gases is dependent on the type of gas, the gassing tendency of the oil and temperature [6]. Laboratory based DGA programs are typically conducted on a periodic basis dictated by the application or transformer type. Oil samples are normally taken at least once a year from the transformer, with samples taken from the top and bottom of the main tank and from the tap changer. Some problems with short gestation times may go undetected between normal laboratory test intervals. Installation of continuous gas-in-oil monitors may detect the start of incipient failure conditions to allow confirmation of the presence of a suspected fault through laboratory DGA testing. This early warning may allow the user to plan necessary steps required to identify the fault and implement corrective actions where possible. Technology exists that can determine gas type, concentration, trending, and production rates of generated gases. The rate of change of gases dissolved in oil is a valuable diagnosis in terms of determining the severity of the developing fault. The application of on-line dissolved gas monitoring considerably reduces the risk of missing the detection or prolonged delay in detecting fault initialization due to long on-site oil sampling intervals [12].

For any given sample the absolute and relative concentrations of fault gases can be used to indicate the type, intensity and location of the fault. Table 2.2 summarized the key gas interpretation method [17]. The decomposition of transformer oil at temperatures ranging from 150 to 500 °C produces large quantities of hydrogen and methane and small quantities of ethylene and ethane. The concentration of hydrogen increases with increasing temperature and exceeds that of methane. At higher temperatures, high concentrations of ethane and ethylene are produced. Ethane concentration is usually higher than ethylene. At the upper end of the temperature range, high concentrations of hydrogen and ethylene and traces of acetylene may be detected. The thermal decomposition of both paper and oil may produce carbon monoxide, but paper is less stable, producing *CO* at lower temperatures than oil. Consequently, the ratio of CO_2/CO is sometimes used as an indication of paper decomposition. Low energy discharges produce mainly hydrogen, with much smaller quantities of methane and trace quantities of acetylene. This may also happen with very low level intermittent arcing. As the intensity of the discharge increases, the concentration of acetylene and ethylene rises significantly. Arcing or continuous sparking may give rise to temperatures of 700 to 800 °C leading to the production of large quantities of acetylene. There is also an IEEE guide available describing the interpretation of gases generated in oil-immersed transformers, operating procedures, and instruments [6].

TABLE 2.2: KEY GAS INTERPRETATION

Key Gas	Characteristic Fault
H_2	Partial Discharge
C_2H_6	Thermal Fault $< 300^{\circ}C$
C_2H_4	Thermal Fault $300^{\circ}C - 700^{\circ}C$
C_2H_2, C_2H_4	Thermal Fault $> 700^{\circ}C$
C_2H_2, H_2	Arcing

For a number of years, on-line sensors for detecting hydrogen (mainly indicative of partial discharge, but also of arcing) have been available on the market, e.g. the Hydran sensor from Syprotec [18]. These sensors are most sensitive to hydrogen, but also measure other combustible gasses to a certain extent. Recently, efforts have been made to develop on-line sensors that measure individual concentrations of several gasses. Such sensors are also to be regarded as warning systems, but they will give a better indication of the type of the fault, and will give warning for heating of cellulose that the previous sensors do not. Examples are the developments made by Micromonitors (metal insulator semiconductor technology) [19].

2.3.4 Moisture-in-oil monitoring

The measurement of moisture in oil is a routine test performed in the laboratory on a sample taken form the transformer. The moisture level of the sample is evaluated at the sample temperature and at the winding temperature of the transformer. This data is vital in determining the relative saturation of moisture in the cellulose/liquid insulation complex that establishes the dielectric integrity of the transformer. Moisture in the transformer reduces the insulation strength by decreasing the dielectric strength of the transformer's insulation system. As the transformer warms up, moisture migrates from the solid insulation into the fluid. The rate of migration depends on the conductor temperature and the rate-of-change of the conductor temperature. As the transformer cools, the moisture returns to the solid insulation at a slower rate. The time constants for these migrations depend on the design of the transformer and the solid and liquid components in use. The combination of moisture, heat and oxygen are the key conditions that indicate accelerated degradation of the cellulose. Excessive amounts of moisture can accelerate the degradation process of the cellulose and prematurely age the transformers' insulation system. There are also different kinds of sensors capable of measuring the moisture content in oil, e.g., HYDRAN 201 sensor.

2.3.5 Partial discharge monitoring

Partial Discharge (PD) is an electrical discharge that only partially bridges the insulation between conductors. Partial discharge in the main insulation often poses a major threat to the function of the transformer. The major causes of the long-term degradation and ultimate failure of this insulation are erosion and tracking due to partial discharges. These discharges can, however, be detected by the application of appropriate diagnostic techniques. The benefits of these techniques are:

- Potential sources of failure can be identified
- Intermittent activity can be located
- Confidence is provided in the continuing safety and reliability of the transformer
- Investment decisions on the replacement or refurbishment of aged transformer can be based on measurement information
- No outage is required

One cause of transformer failures is dielectric breakdown. Failure of the dielectrics inside transformers is often preceded by partial discharge activity. A significant increase either in the partial discharge level or in the rate of increase of partial discharge level can provide an early indication that changes are evolving inside the transformer. Since partial discharge can deteriorate into complete breakdown, it is desirable to monitor this parameter on-line. Partial discharges in oil will produce hydrogen dissolved in the oil. However, the dissolved hydrogen may or may not be detected, depending on the location of the PD source and the time necessary for the oil to carry or transport the dissolved hydrogen to the location of the sensor. The PD sources most commonly encountered are tracking in the insulation, void in solid insulation, metallic particles, and gas bubbles generated due to some fault condition. The interpretation of detected PD activity is not straightforward. No general rules exist that correlate the remaining life of a transformer to PD activity. As part of the routine factory acceptance tests, most transformers are tested to have a PD level below a specified value. From a monitoring and diagnostic view, detection of PD above this level is therefore a cause for an alarm but not generally for a tripping action. To give a correct diagnosis after receiving an alarm signal via sensors or via gas-in-oil sampling, it is necessary to localize and to characterize the PD source.

Localization of partial discharges is made acoustically using different methods for triangulation. This requires deep knowledge of wave propagation in different types of materials/liquids and is a task for highly qualified experts. Each PD occurring within the insulation produces a low-amplitude mechanical pulse, which propagates to the tank wall where it can be detected by an appropriate sensor. The output of the sensor will be proportional to the energy content of the forcing function (pulse). Because the sensor contains a resonant crystal, it will oscillate at its natural frequency. The amplitude of these oscillations will then decay exponentially due to the mechanical damping inherent in the crystal. Consequently, each pulse arriving at the transformer tank wall will result in a “burst” type signal from the transducer. One burst is produced for each PD detected. The number of oscillations contained within each burst is determined by the amplitude of the forcing function (pulse from the PD) that excited the crystal. An accounting of the number of these oscillations, which occurs within a 1 s interval, or a set number of cycles, contains information relative to both the number of discharges that occurred within that time interval as well as their amplitude. The amplitude of the mechanical pulse is attenuated as it propagates through the insulation and oil during its journey to the tank wall. Consequently, the oscillation count rate will be at its maximum when the sensor is at its closest proximity to the source. This effect enables the operator not only to detect the presence of PDs, but also to estimate the approximate location of their source. There is an IEEE guide [20] describes the instrumentation, test procedures, and results interpretation for the acoustic emissions detection of partial discharges in power transformers.

Noise suppression in a substation environment poses the largest challenge to accurate PD detection. Characterization of the type of PD, e.g., void in main insulation or metal particle, can be made by using Phase Resolved Partial Discharge Analysis (PRPDA [21]). This is a modern PD measuring system that performs both data acquisition and data processing of conventionally detected PD signals. The PD pulses are presented with respect to charge intensity, phase position and number of pulses. The obtained patterns form a “fingerprint” which is indicative of a certain type of defect. The transformer needs to be de-energized a certain period of the investigations.

There are other types of monitoring methods available, e.g. insulation power factor, static charge in oil, pump/fan monitoring etc. With enough on-line monitoring information, developing transformer failure modes can be detected well before they lead to catastrophic transformer/system failures.

Based on an extensive review of literature and some other useful resources, Table 2.3 summarizes typical major transformer failures and corresponding condition monitoring techniques and maintenance activities [22]. Also for each condition monitoring technique, the feasibility of online monitoring is listed. Table 2.4 summarizes typical failure modes, causes, effects as well as corresponding maintenance activities for power transformer.

TABLE 2.3: FAILURE MODES OF TRANSFORMER AND CORRESPONDING CONDITION MONITORING TECHNIQUE AND MAINTENANCE ACTIVITIES

Failure mode	Condition monitoring technique	Maintenance	Online monitoring
Cellulose insulation degradation	Degree of Polymerization Fluid analysis (furan test, oxygen and moisture test)	N/A	Yes Yes
Oil decomposition	DGA analysis Fluid analysis	Oil refinement (Filtering, Dehumidify, Degas)	Yes Yes
LTC failure	DGA analysis Internal inspection	Oil refinement Replacement of worn parts	Yes No
Partial Discharge	Partial discharge (acoustic and electric signal testing) DGA analysis	Repair after location of the partial discharge	Yes Yes
Bushing failure	Power factor test Visual inspection	Replacement, cleaning and greasing	No Yes
Short turns or open winding circuits	Resistance test Winding ratio test	Rewind of transformer	No No
Loss of sealing	Visual inspection	Repair, replacement	Yes
Pressure relief blocking	Visual inspection	Repair the blocked relief device	Yes
Heat exchange devices failure	Thermography, Function test, Vibration test	Repair or replacement	Yes No

TABLE 2.4: TRANSFORMER FAILURE MODES, CAUSES, EFFECTS AND MAINTENANCE ACTIVITIES

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

Table 2.4 (continued)

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

2.4 Representative Commercial Transformer Monitoring Products

Although there are a variety of factors that may cause transformer failures, some transformer components, e.g. bushings, cooling system and control equipment require little more than routine visual inspection and operational testing [1]. Most on-line, computer-based, integrated monitoring systems use a combination of sensors to provide real-time monitoring of important transformer functions/parameters, such as: thermal performance, gas-in-oil, moisture-in-oil, partial discharges etc. These systems are now commercially available, and some of them are described in the following 5 subsections.

2.4.1 Siemens Advanced Transformer Monitoring and Control System

Siemens PTD, Inc. has developed a system for continuously monitoring in-service transformers [23]. Applications can be layered on top of the automation system to monitor transformer performance with a real-time communications interface to the SCADA/EMS dispatcher. Utilizing field sensors, distributed PLC architecture, and information from existing substation IEDs, the system offers the following features:

- Continuous thermal monitoring of transformer parameters
- Advanced control of fan banks
- Trending and archiving of transformer data
- Intelligent alarming of transformer performance to the SCADA/EMS dispatcher.

The Siemens Advanced Transformer Monitoring and Control System is a “substation-centric” system designed to provide enhanced monitoring and control of T/D substation transformers.

2.4.2 Serveron TrueGas™ Transformer Gas Analyzers

TrueGas Transformer Gas Analyzers [24] are on-line gas chromatographs with built-in computer processing and remote data communications. TrueGas analyzers continuously sample, measure, and display the concentration of eight transformer fault-indicating gases.

2.4.3 GE Syprotec Systems

The HYDRAN® 201i System [25] consists of on-line instruments to monitor and detect key-fault gases dissolved in dielectric oil. This monitoring system provides transformer owners with decision-making information.

The HYDRAN® MULTI 2010 System [26] is an online gas-in-oil detector that analyzes and monitors incipient fault gases developing in transformer oil. The system measures the concentration of acetylene gas in addition to a combined incipient fault gas reading of hydrogen, carbon monoxide, and ethylene.

The AQUAOIL® 400 System [27] is a stand-alone unit for field installation on a transformer valve. It allows the user to monitor online the relative humidity in the oil and its changes during load variation. Online monitoring of moisture in transformer oil is an essential element for the evaluation of the overall condition of transformers.

[1] Some typical transformer testing will be addressed in report 2.

2.4.4 Mitsubishi Electric Transformer Monitoring System

The Mitsubishi system [28] consists of sensors and monitoring equipment that analyze the sensor data and provide early warning of abnormal operation. The system monitors the following items:

- Dissolved Gases. Dissolved gases are extracted from the transformer oil and the concentrations of six gases (CO, H_2, CH_4, C_2H_2, C_2H_4, C_2H_6) are measured as well as the total combustible gas content. These data are used to provide early warning of local heating, discharge and other abnormalities.
- Partial Discharge. A high-frequency current transformer detects partial discharge and acoustic emission (AE) sensors mounted on the wall of the transformer tank detect the associated ultrasonic vibrations. The time delay between the discharge detection (by the current transformer) and ultrasonic detection makes it possible to detect whether the discharge is inside or outside the transformer, and if inside, whether or not it occurred in the transformer tank.
- Oil Temperatures. Resistance thermometer bulbs check the temperatures of the main transformer oil, the load voltage regulator oil and the ambient temperature, and the detected values are compared against specified ranges.
- Oil Level Monitoring. Potentiometers on the shaft of conservator-type oil gauges monitor the oil level in the main transformer and load voltage regulator tank. The measured oil levels can be compared against the oil levels predicted on the basis of oil temperature.
- On-Load Tap Changer Operating Characteristics. The drive shaft torque during tap changing is measured by a rotary-transformer-type torque sensor. A current sensor measures the current of the motor drive mechanism. Torque and current waveforms are monitored and compared against standard values for each of the six operating modes corresponding to the combination of tap changing command signals and tap positions to verify correct tap changer operation and to resolve the cause of any malfunction that may arise.

2.4.5 Alstom MS2000 Monitoring System

A transformer monitoring system based on field bus technology and process control software was described in [29]. The great modularity of Alstom MS2000 monitoring system can easily be focused on the customer’s needs. Depending also on their monitoring “philosophy”, it is possible to propose a personalized set of sensors and functionalities. A multitude of different measuring quantities of the monitoring system is shown in table 2.5.

TABLE 2.5: MEASURING QUANTITIES OF ALSTOM MS 2000 MONITORING SYSTEM

Active Part	Conservator	Bushings	Cooling Unit	Tap Changer
Gas-in-oil contend	Oil level	Voltages, Overvoltages	Oil temperature in/out cooler	Tapping position
Oil level in Buchholz relay	Humidity	Load Currents	Air temperature in/out cooler	Power consumption of motor drive
Moisture in oil		Oil pressure	Ambient temperature	
Oil temperature, Hot spot temp			Operating condition of pumps and fans	

Those above representative commercial transformer condition monitoring products mostly are stand-alone and focusing on only individual transformer. Due to the communication bandwidth limitation of EMS/SCADA, these individual transformer-based monitoring systems can only pass few monitoring data (or warning signal) to the central control room for later analysis.

2.5 Conclusions

Transformers deteriorate in different ways under different working conditions and stresses. Monitoring of transformer conditions and identification of failure modes is important to the maintenance engineer, to make decisions on maintenance activities and frequencies. This chapter addresses issues about transformer failure modes and condition monitoring techniques. Typical transformer failure modes along with their causes as well as corresponding maintenance activities are summarized. Various transformer condition monitoring techniques, such as: operating condition monitoring, temperature monitoring, dissolved gas-in-oil analysis (DGA), moisture-in-oil, partial discharge (PD) etc., are also described.

3. Failure Modes, Maintenance and Condition Monitoring of Circuit Breakers

The utilities face an economical challenge during the industry de-regulation process, and have to make survival decisions on asset management. They are forced to get the most out of the devices they already own through more effective operating policies, including improved maintenance programs. Several maintenance programs are reported in literature so far, emphasizing the importance of condition monitoring of the devices [30]. Recent trend in maintenance approaches is to maintain the device according to its condition. Mathematical models, like probabilistic maintenance models, look promising but they demand an extensive relationship among condition monitoring techniques, failure probabilities, and maintenance tasks of the device. The intention of this report is to identify possible methods of establishing above mentioned relationship, which can be used for future development of a real application in maintenance planning.

This chapter starts with a brief history of developments in circuit breaker (CB) condition monitoring techniques. Then, circuit breaker failure modes and various maintenance schemes are discussed. Condition monitoring options are discussed in detail in the following section. As a whole, this chapter gives a basic idea about the relation between failure modes, maintenance actions and condition monitoring options, which is very essential for developing a probabilistic maintenance model.

3.1 History of Circuit Breaker Condition Monitoring Techniques

Preventive maintenance heavily depends on the information obtained from condition monitoring. Technology developments offer various condition monitoring techniques which directly (or indirectly) affects the existing maintenance policies. Data acquisition systems, signal processing techniques and expert systems made the condition monitoring techniques much more refined and accurate as well. This section gives an account of CB monitoring techniques development in the following categories:

- From de-energized to energized
- From manual to automatic (online)
- From periodic to continuous monitoring
- From limited to advanced diagnostic analysis

3.1.1 From de-energized to energized

Routine inspection and maintenance usually requires the circuit breaker to be disconnected from all electric power flow, which is both costly and time-consuming. New measurement techniques allow breakers to be tested while remaining in service.

For instance, some portable test devices collect common signals in the control circuitry of breaker through a standard socket. Data is collected while the breaker is in-service, and breaker is operated either manually or remotely during the test [31]. Sensors are also used in monitoring the vibration of the breaker. Sensors are attached outside the breaker cubicle to collect vibration signatures during the breaker operation [32]. Most recent developments even claim the capability of not touching the equipment under monitoring at all, such as corona camera and infrared meters [33], [34]. Corona camera is able to take the snapshot of the equipment and detect corona in the insulation. Infrared meter is able to read the temperature of the equipment non-intrusively. Obviously, the more advanced techniques are used, the less interference during the monitoring of the equipment.

3.1.2 From manual to automatic (online)

Further developments in data acquisition system reduce the involvement of the maintenance staff in the maintenance activities. For example, the test of partial discharge includes taking the equipment out of service and building a test circuit. Right now, the online partial discharge monitoring is available, and data are collected automatically [35]. Another example is that contact erosion is related to the time integral of arc current(s) interrupted. Monitoring the performance and condition of circuit breakers therefore requires the use of on-line transient recording equipment. Such equipment, in the form of oscillographic type fault recorders, has been widely used on EHV transmission systems [36]

3.1.3 From periodic to continuous monitoring

Regular inspection requires that the technician makes periodic travel and performs the test and maintenance activities at the local substation. With the development in data communication, data can be sent directly to central control house through either fiber-optic network or wireless network, which allows immediate data processing and archiving [37].

3.1.4 From limited to advanced diagnostic analysis

Maintenance decisions are generally based on the empirical knowledge. With the developments of data processing and analysis techniques, much more accurate decision aid tools are available. For the signature analysis of the circuit breaker condition, initially, maintenance staff just compared the newly recorded signature with the old reference, and made judgment based on the observed waveform difference. Right now, signal processing, expert system, neural networks and etc, are used in analyzing the data, supporting the decision making process [38].

3.2 Typical Circuit Breaker Failure Modes

This section presents typical failure modes of circuit breakers. Most of the circuit breaker failures are associated with failure of operating mechanism. The function of the operating mechanism is to open or close the breaker contacts upon a command. Operating mechanism consists of various components such as operating rod, springs, valves, latches, cams, rollers, bolts, washers etc. All these components should work in desired way in order to operate the breaker correctly.

Circuit breaker failures and their effects are discussed in detail in references [39] and [40]. CIGRE working group A3.12 conducted a failure survey focusing on control system reliability on circuit breakers [41]. The study objective was to receive information on which failure modes, components and causes appear most frequently. Readers are advised to go through the mentioned references to know more about the failures of different varieties of CBs (e.g. Oil, Air Blast, SF_6 etc). Typical failure modes are selected, and listed in table 3.1, starting with a few important definitions.

TABLE 3.1: TYPICAL FAILURE MODES OF CIRCUIT BREAKER

(1)	Breaker does not open the circuit to interrupt current
(2)	Circuit breaker opens and then closes again
(3)	Circuit breaker opens and then repeatedly closes and opens
(4)	Fault or load current is not interrupted, and the circuit breaker interrupter has a major failure
(5)	Breaker fails to provide required dielectric isolation of contacts immediately after the opening operation
(6)	Circuit is unintentionally interrupted with possible safety and economic damage issues
(7)	Breaker does not close the circuit to conduct current
(8)	Breaker does not close the circuit to conduct current in one or more poles
(9)	Circuit is unintentionally closed with possible safety and economic damage issues
(10)	Breaker does not conduct current with resulting thermal damage to contact assemblies
(11)	Short circuit on power system or unintentional energization of components
(12)	Phase-to-ground fault on the power system with possible safety and economic damage; interruption required to power system
(13)	Phase-to-phase fault on the power system with possible safety and economic damage; interruption required to power system components
(14)	Circuit is unintentionally closed with possible safety and economic damage issues; may result in a major failure of circuit breaker
(15)	Circuit is unintentionally closed with possible safety and economic damage issues; major failure of circuit breaker interrupter
(16)	Loss of insulating medium to environment
(17)	Operation of power system with a circuit breaker that is incapable or has reduced capacity to perform its functions
(18)	Defective closed, opened, or stored energy indicator, causing operator to undertake inappropriate actions

3.3 Standard Maintenance Tasks and Procedures for Circuit Breakers

Correspond to the typical failure modes listed in section 3.2, the following are typical maintenance activities in practice for circuit breakers [42].

1) Operating Mechanism

- Clean all insulating parts from dust and smoke.
- Clean and lubricate operating mechanism and apply suitable grease for the wearing surfaces of cams, rollers, bearings etc.
- Adjust breaker-operating mechanism as described in the manufacturer's instruction book.
- Make sure all bolts, nuts, washers, cotter pins etc. are properly tightened.
- After servicing the circuit breaker, verify whether the contacts can move to the fully opened and fully closed positions or not.

2) Contacts

- Check the alignment and condition of the contacts and make adjustments according to the manufacturer's instruction book.
- Check if the contact wear and travel time meet specifications.

3) Insulating Medium and Arc Extinction

- Tightening oil/gas pressure seals.
- Check governor and compressor for required pressure.
- Oil conditioning and painting.

In addition, replacement of following components is necessary according to their condition.

- Arc chute and nozzle parts if damaged.
- Governors and compressors if worn or malfunctioning.
- Contacts if badly worn or burned.
- Oil if dielectric strength drops below an allowable limit and if any arc products are found in the oil.

3.4 Various Condition Monitoring Techniques

A condition monitoring technique is usually designed for evaluating one unique condition, and the information collected to evaluate such condition can be called monitoring parameters. Condition monitoring is playing a major role in taking accurate maintenance decisions. It allows the maintenance crew to get a clear picture of the condition of the breaker, which in turn helps to come up with more optimal maintenance programs.

This section presents some important monitoring parameters and groups them according to the subassemblies they belong to, such as operating mechanism, contact, control circuit, etc (Table 3.2). Such an arrangement facilitates the correlation between condition monitoring technique and the failure rate of one specific component. The operating environment for the circuit breaker is not a negligible factor in evaluating the overall condition either. The involved information for operating environment is classified as either system information or environment information. A more detailed list of monitoring parameters for various failure modes can be found in references [40] and [43].

In some cases, one monitoring parameter may be used to evaluate the condition of more than one component of a circuit breaker. Trip coil current is a good example of such a parameter. The “in-continuity” of trip coil current may indicate an open or shorted trip coil or a control circuit failure, and the drop time of the trip coil current may reveal the lubrication condition of the trip latch or trip mechanism.

CBs vary greatly in their voltage class, installation, location, external design characteristics and most importantly, in the method and the medium used for the current interruption. Another fact is that CBs owned by the utility may be from different manufacturers and purchased at different time. A wide variance in condition monitoring techniques can be anticipated under such circumstances. It is impossible to list all the available monitoring techniques (may be up to hundreds) in this report. The techniques introduced here are the most-widely documented by the industry [39], [40] and [43].

TABLE 3.2: MONITORING PARAMETERS FOR CIRCUIT BREAKER

Operating Mechanism (Break Timing, vibration analysis)	
– Movement of release mechanism – Stored energy pressure (such as air pressure) – Position of stored energy springs	– Full travel indication – Mechanism travel and over travel – Ambient Temperature
Contact (Contact Resistance Test, Infrared monitoring of contact temperature)	
– Contact temperature – Contact erosion and interrupter wear	– Contact travel distance – Contact Resistance
Control Circuit (Circuit Breaker Signature Analysis)	
– Control circuit current – Close coil current – Trip coil current – Auxiliary contact timing	– X & Y relay timing – DC voltage – Charging motor – Heater
Arc extinction and insulating medium (air, oil, vacuum, SF6) (Partial discharge, oil condition)	
– Water content (Air) – Temperature (All) – Relative humidity of compressed air – Dielectric (Oil) – Insulating medium level (liquids) – Color, purity (Gas, Oil)	– Vacuum-Integrity Over-potential (Vacuum) – Density (Gas, Oil) – Pressure (Air) – Moisture (Gas) – Partial discharge
System (DFR recorder)	
– Number of breaker operation – Power system disturbance – Fault level, and condition	– Primary voltage – Primary current
Environment	
– Severe weather conditions (Temperature, moisture, dirt)	

3.4.1 Condition monitoring of the operating mechanism

From the energy storage point of view, the mechanisms that are used in today's circuit breakers fall under the spring, pneumatic or hydraulic categories [43]. Spring mechanisms obtain their energy either by manually charging the springs, or by electrically charging the springs by means of a motor. Pneumatic mechanisms are fitted with compressed-air storage reservoirs. The energy storage of hydraulic mechanisms is compressed nitrogen. Malfunction of charging motors, compressors and pumps may cause the operating mechanism to lose its energy, which results in operational failures of circuit breakers.

From the mechanical operation point of view, the mechanisms are either of the cam or of the four bar linkage type. Inappropriate or inadequate lubrication of the mechanism, trip latch surface wear, deteriorated bearings, or deformation of trip latch flat surfaces may cause the increase of operating time, or even ‘stuck condition’. The mechanism linkage failure between operating mechanism and interrupters may also prevent the breaker from proper operation.

Sometimes when the temperature of mechanism cabinet drops below required limit and the lowering temperature lasts several hours, the breaker may also fail to operate. The monitoring of mechanism temperature will be discussed in the next section with the monitoring of contact temperature.

The condition monitoring choices for operating mechanism are generally physical techniques. For stored energy, the simplest way is to monitor the spring position. For mechanism wear and deterioration problems, timing test is used to measure the trending of the movement and detect any potential problems. Monitoring of charging motors, gas compressors and hydraulic pumps is also important to avoid operational failures of circuit breakers.

3.4.1.1 Breaker timing test

Breaker timing test provides dynamic information about the operating mechanism, which include mechanical links and interrupter contacts. The test typically monitors the contact travel, speed, wipe and bounce during the entire cycle of opening and closing operation. A transducer is mechanically attached to the moving part of the mechanism, which measures the displacement of contacts with respect to travel time, and electrically connected to a timing set. These results are compared to the last test and to the manufacturers' recommendations.

The transducers can be either contact or non contact type [43]. Contact type transducers are physically connected to the component being measured, and examples are sliding resistors, linear or rotating resistor potentiometers, step travel recorders etc. Non-contact transducers are those such as optical motion sensors, proximity sensors, Light-To Voltage (LTV) sensors, etc. that do not require a physical connection between the sensor and the moving part.

High and medium voltage breakers can benefit from this test. A permanent data recorder connected with the transducer and further data analysis is an inevitable step before a full-fledged online technique is available. The disadvantage of the technique is that it is not applicable to molded case breakers and/or low voltage breakers.

3.4.1.2 Vibration analysis

Vibration patterns can be used to detect mechanical malfunctions, excessive contact wears, maladjustments, other irregularities and failures [44]. Due to the physical movement of the operating mechanism and contacts in a short period of time during the breaker operation, the moving parts vibrate at a variety of frequencies. These frequencies are governed by the nature of the vibration sources, and can vary across a very wide range or frequency spectrum. If one of the mechanism components start to fail, its vibration characteristics change, and vibration analysis is all about detecting and analyzing these changes.

Accelerometers mounted on the arcing chamber and operating mechanism, are used to record the vibrations. Great expertise is necessary in interpreting the vibration characteristics.

3.4.2 Condition monitoring of the contacts

The core of the circuit breaker operation is the current-carrying system, especially the contacts. Contacts may fail to conduct continuous or momentary current (while already closed) caused by [40].

- High-resistance of contacts

- Ablation of contacts
- Broken or missing contacts; deterioration of parts in the current carrying circuit; bolted joints, sliding, rolling, or moving of the main contacts; spring failure.

Contacts may fail to interrupt due to the insufficient contact opening, and the ‘contact travel’ is used to detect the problem. Usually this parameter is not measured directly, but the travel of the mechanism connected to the contacts is measured directly. For example, the travel of grounded end of the insulated operating rod can be used to measure the contact travel, or the timing test discussed in the above section can be used to measure the contact travel.

The current-carrying capacity of contact is limited largely by the temperature rises. One effect of excessive temperature rise is to cause deterioration of the electrical insulation, owing to ageing and to the differential expansion between the conductors and the surrounding insulation. This deterioration eventually results in failure, usually when the equipment is subject to undue stress of some kind. Therefore, the temperature monitoring is also an important technique in telling the contacts condition.

Following are the usual techniques in practice to monitor the condition of breaker contacts.

3.4.2.1 Breaker contact resistance test

Breaker contact resistance test is used to monitor the condition of breaker contact wear and deterioration. A DC current, usually 10 or 100 amps is applied to the contacts. The voltage across the contacts is measured and the resistance can be calculated using Ohm’s Law. Resistances of about 200 micro-ohms are normal, although manufacturers routinely publish their own design limits. This value is trended over time to assess deterioration. Maximum limits can be obtained from manufacturers. More about this test can be easily found in the literature [45].

The advantage of this technique is that resistance values can be trended over time to detect potential failures before the breaker contacts deteriorate significantly. There are disadvantages of this technique as well. Normal resistance meter cannot be used due to the resistance being in the order of micro-ohms.

3.4.2.2 Monitoring of temperature

Monitoring of temperature is to verify temperature-rise limits being exceeded for a time period beyond acceptance. Large changes in contact temperature may be due to broken contacts fingers, excessive burning of the main contact, material degradation, oxide formation, weak contact springs, improperly or not fully closed contacts etc. Temperatures at different components within the breaker and ambient temperature need to be monitored. For example, a high potential temperature monitoring system developed by ABB distribution in 1992 selected 12 points in circuit breaker cubicle including three sensors (one for each phase) placed at the connection of the droppers to the bus-bar, three at the upper breaker contacts, three at the lower breaker contacts and three at the cable connections [46]. The temperature rises of the different components should be referred to the ambient air temperature.

Besides the traditional way of temperature monitoring, infrared monitoring technique is also available in the market [34]. This technique can avoid direct contact with the equipment under monitoring by taking the snapshot of the thermal condition or reading the temperature directly from a thermal meter. The infrared monitoring device is small and portable which will be a good choice during an on-site visit.

3.4.3 Condition monitoring of the control circuit

The failure percentage of the control circuit is rated second to the operating mechanism among all the circuit breaker assemblies. The condition monitoring techniques are relatively easy to develop since it is the secondary circuit. A shunt can be mounted at certain places of the circuit, and electrical parameters of current and voltage are recorded. These collected parameters are called the signature of circuit breaker. There are portable testing devices available in the market to collect the display the control circuit signatures [31]. The following are the typical control circuit signals that can be monitored in practice [47].

- Trip coil current
- Close coil current
- DC supply voltage
- A, B auxiliary contacts
- X & Y coils
- Trip initiation
- Close initiation

3.4.4 Condition monitoring of the arc extinction and insulating medium

Circuit breaker insulation includes vacuum, gas (such as air & SF_6), liquid and solid insulations. Gases are used both for both arc extinction, and to provide electrical insulation between contacts when the circuit breaker is in the open position. Particles, temperature, electrode area and surface flashover will all have influence on the gas insulation. Monitoring options are gas pressure or density as appropriate for ambient temperature, moisture content, compressed air water content and temperature or relative humidity of compressed air etc.

Vacuum insulation may be influenced firstly by the presence of gases absorbed on the electrode and solid insulating surfaces within the vacuum, and, secondly by the emission of charged particles from these surfaces. Loss of vacuum can be detected with periodic vacuum-integrity over potential test.

The only insulating liquid used extensively for CB is mineral oil, manufactured from petroleum, and the major disadvantage of the mineral oil is that carbonization of the oil occurs and that there is also an inherent fire risk. Impurities (such as water content), oil volume and operation frequency, etc may also influence the functioning of oil insulation. A complete list of testing methods and monitoring parameters for oil can be found in IEEE standards [48] and [49]. Solid insulation usually faces both electric and mechanical stress.

3.4.4.1 Partial discharge test

Partial discharge (PD) test is used to monitor the condition of insulation [50]. Localized electrical discharges may occur, owing to ionization in cavities or voids with the solid insulation or within gas bubbles in insulating liquids; discharges may also occur along dielectric surfaces. Such internal discharges only partially bridge the insulation between the conductors, and, although they involve only small amounts of energy, they can lead to the progressive deterioration of the dielectric properties of the insulating materials. This is particularly true for the oil-impregnated-paper insulation of high-voltage bushings.

Standard test procedures to detect PD are reported in IEEE standard 1291-1993 [51]. PD allows quick and more informed decisions. However, expert knowledge and statistical analysis are required to set the PD thresholds. Other techniques that test the insulation includes power-factor test, external & internal corona test, high potential test (for motor), and oil dielectric test [40].

3.5 Conclusions

Recent trend in maintenance approaches is to maintain the device according to its condition. Mathematical models, like probabilistic maintenance models, look promising but they demand an extensive relationship among condition monitoring techniques, failure probabilities, and maintenance tasks of the device. This chapter starts with a brief history of circuit breaker condition monitoring techniques. Then it identifies typical failure modes and maintenance actions of circuit breaker. Finally, it describes various condition monitoring techniques that are widely used in industries.

4. Transformer and Circuit Breaker Failure Modes and Failure Probability

4.1 Introduction

Physical assets are subjected to a variety of stresses. These stresses cause the asset to deteriorate by lowering its resistance to stress. Eventually this resistance drops to the point at which the asset can no longer deliver the desired performance – and so it fails. Both power transformer and circuit breakers are critical and capital intensive asset within a power system. Due to the limited capital investment for new facilities, many transformers and breakers are close to or beyond their designed life. As these components age beyond their expected life, there is a risk of an increasing number of catastrophic failures. There is a great deal of focus on maintenance and life extension of aged transformers to maximize the return on investments. This naturally leads to the use of reliability centered maintenance (RCM) approach where equipments with higher failure probabilities are given higher priority in maintenance. Thus failure probability estimation of equipment is required in maintenance asset management.

Exposure to stress for transmission system equipment, is measured in a variety of ways including, for example, average percent loading, average temperature, operating cycles, number of operations, calendar time, or running time. In [52], six types of patterns are given that represent most kinds of aging and deterioration, as shown in Fig. 4.1. Pattern A is the well-known bathtub curve. It begins with a high incidence of failure (known as infant mortality) followed by a constant or gradually increasing failure probability, then by a wear-out zone. Pattern B shows constant or slowly increasing failure probability, ending in a wear-out zone. Pattern C shows slowly increasing failure probability, but there is no identifiable wear-out age. Pattern D shows low failure probability when the item is new, then a rapid increase to a constant level, while pattern E shows a constant failure probability at all ages. Pattern F starts with high infant mortality, which drops eventually to a constant or very slowly increasing failure probability. For a random failure, the failure probability in any short time interval, assuming that the device has been working up to that time, is constant. The time until failure is exponentially distributed and the hazard rate has the same shape of Pattern E. Because random failure modes have constant failure probabilities, maintenance has no influence. These types of failure modes, then, are not maintainable. Failure modes associated with human error or natural disasters, e.g., earthquakes, tornadoes, etc., are of this sort.

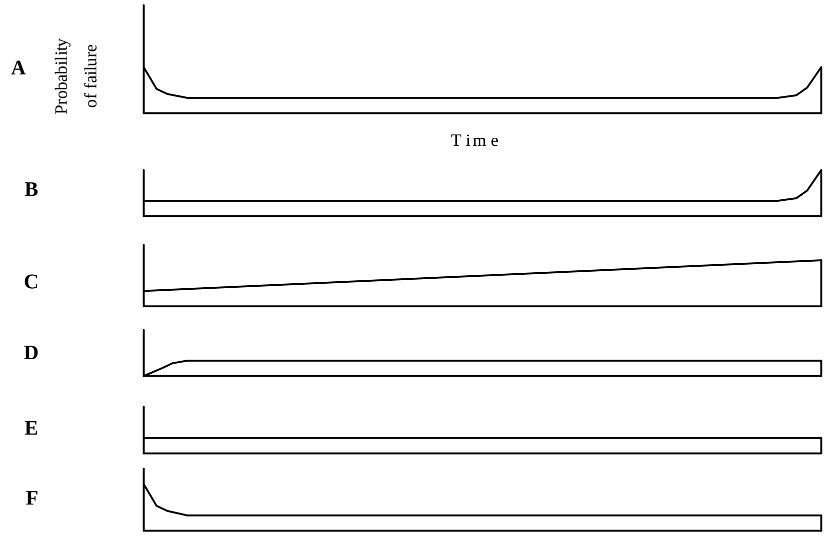

Fig.4.1: Probability of failure caused by aging and deterioration

Curve A is commonly used to model component deterioration, and we adapt it here for modeling failure modes associated with power transmission equipment. We assume in this project the existence of such a hazard model for each failure mode contributing to the failure of a piece of equipment. Such hazard models may be estimated based on typical component lifetimes, or they may be obtained from statistics characterizing the performance of a large number of similar components.

4.2 General Approach to Failure Rate Estimation

4.2.1 Definition of failure rates

The information obtained from various (on-line) condition monitoring techniques is a characterization of equipment state and therefore contains information useful in estimating failure probability. However, this information, and its characterization of the equipment state, is point-wise in time, i.e., instantaneous, and it is equipment-specific. It is therefore useful in estimating instantaneous failure probabilities for specific equipment. Although such probabilities are what is needed in the kind-of mid-term decision-making addressed in this chapter, it is important to distinguish them from the more common time-average, and sometimes equipment-average, failure probabilities typically used in long-term planning decision-making.

In this section, we present models for linking the transformer and circuit breaker condition monitoring information to their time-dependent failure probability. We begin by providing some underlying, and basic concepts in equipment reliability. Let T be a random variable representing the time from when the equipment is put into operation at time t = 0 until the time when a failure occurs. The equipment may be either new or used when it is put into operation. In many cases the equipment will be removed and repaired, and then placed into operation after a refurbishment or a failure has been corrected. The uncertainties in the time to failure T may be described by the distribution function (cumulative density function) $F(t) = \Pr(T \le t)$, or the probability density function $f(t) = dF(t)/dt$. The probability density function $f(t)$ may be expressed as:

$$f(t)\Delta t \approx P(t < T \le t + \Delta t) \tag{4.1}$$

Hence, $f(t)\Delta t$ is approximately equal to the probability that the equipment will fail in the time interval $(t,\ t + \Delta t)$. The survivor function, which gives the probability that equipment will not fail up to time t, is given by:

$$R(t) = \Pr(T > t) = \int_t^{\infty} f(t)dt \tag{4.2}$$

The equipment's life distribution is often most effectively characterized by the so-called failure rate, or hazard function, which is the conditional probability of failure. The failure rate function $h(t)$ may be expressed as:

$$h(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} \Pr[t < T \le t + \Delta t \mid T > t] \tag{4.3}$$

If we consider the equipment that has survived the time interval (0, t), i.e. $T > t$, then the probability that the equipment will fail in the time interval $(t,\ t + \Delta t)$ is approximately $h(t) * \Delta t$.

It is only necessary to know one of the functions $h(t)$, $f(t)$, $R(t)$ in order to be able to deduce the other two, as illustrated in Fig. 4.2 [53].

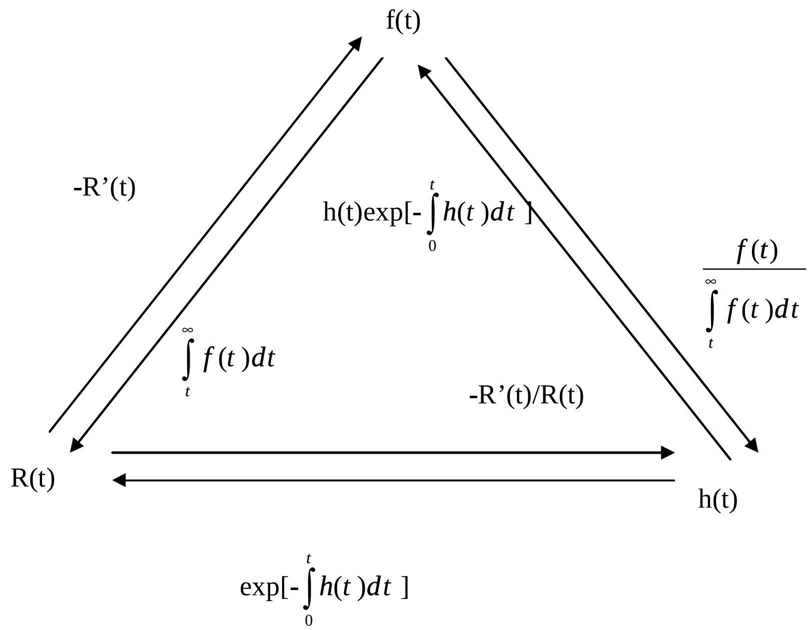

Fig. 4.2: Relationships between h(t), f(t), and R(t)

4.2.2 Overview of failure rate estimation

Methods of estimating the proximity of equipment to failure usually depend on available data. Based on the available data source of the failure rate estimation, we can classify the methods of failure rate estimation as the following categories: 1) Failure based estimation; 2) Loading based estimation and 3) Condition based estimation. Categories 1 and 3 can be applied to both transformers and circuit breakers where as category 2 is exclusive for power transformers.

4.2.2.1 Failure based estimation

Failure based estimation uses recordings of failures spanning multiple components over an extended time period. It is one of the most commonly used methods of calculating the failure probability. It can be classified into two categories: parametric and non-parametric estimation. For parametric estimation, an underlying parametric distribution needs to be assumed. The non-parametric method estimates the cumulative density function of time to failure from interval and right-censored data, without having to assume the underlying parametric distribution. One can go beyond the estimation of failure rate if appropriate data is available. For example, reference [54] reported dependencies of ABCB failure rates with respect to age, voltage level, manufacturers and operating interventions, which obviously requires a huge data base of breaker outages.

4.2.2.1.1. Non-parametric Hazard Function Model

The most direct way of estimating failure rate in reliability analysis, is to use the failure data, which is the observation of failure of a group of equipments in a period of time. In order to get the hazard function for power transformers, a procedure was provided for estimation of $h(t)$ as a so-called central failure rate in [55]. For a specific kind of power transformer (make, model, and voltage level, etc.), suppose we have recorded enough transformer life data in a system. In interval $[t_i, t_{i+1})$ [2], let N_i denote the number of power transformers survived at t_i, F_i how many transformers failed, and C_i the number of power transformers that were censored. However we cannot know precisely the exact time of every occurrence. It is prudent to group even precise data over every interval $[t_i, t_{i+1})$ to increase the number of events observed. This helps to overcome the random effects in estimation of $h(t)$. It is clear that the number of transformers surviving until t_{i+1} is:

$$N_{i+1} = N_i - F_i - C_i \tag{4.4}$$

Every censored transformer should be treated as a removed one, assuming that exact times of failure or removal are known. The "end of observation" time, t_{ij}, for the j-th transformer in interval $[t_i, t_{i+1})$ is defined as:

[2] Typically the time interval for estimating power transformer failure rate ranges from one to two years.

$$t_{ij} = \begin{cases} t_{ijf}, & \textit{if jth transformer is observed to fail} \\ t_{ijc}, & \textit{if jth transformer is removed (censored)} \\ t_{i+1}, & \textit{if jth transformer survives till } t_{i+1} \end{cases} \tag{4.5}$$

Then the total amount of time of exposure to risk of all power transformers, TR_i, during interval $[t_i, t_{i+1})$ is:

$$TR_i = \sum_{j=1}^{N_i} (t_{ij} - t_i) \tag{4.6}$$

The estimated central failure rate in interval $[t_i, t_{i+1})$ is defined as:

$$\tilde{h}_i = F_i / TR_i \tag{4.7}$$

If we did not know the exact time of failure or removal, it would be reasonable to assume that all failures and removals are expected at the middle of the interval $[t_i, t_{i+1})$. Then the estimated central failure rate in $[t_i, t_{i+1})$ can take the form:

$$\hat{h}_i = \frac{F_i}{(t_{i+1} - t_i)(N_i - (F_i - C_i)/2)} \tag{4.8}$$

Although expression (4.8) is not as precise as (4.7), it is more precise than the estimation frequently use in engineering applications for the failure rate:

$$\bar{h}_i = F_i / [(t_{i+1} - t_i) N_i] \tag{4.9}$$

With reasonably precise recordings of the failure or removal times of the transformers, we can use equations (4.7) or (4.8) to estimate the time-dependent failure rate, h_i, as illustrated in Fig. 4.3.

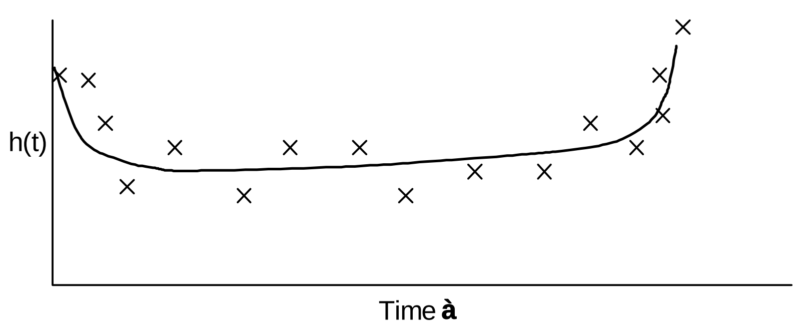

Fig. 4.3: Bathtub Curve

4.2.2.1.2. Parametric Hazard Function Model

The parametric estimation method [56] requires an assumption that the deterioration process follow a specific distribution. The objective is then to estimate the parameter(s) of the distribution using the field data. Weibull distribution has been widely used to model the hazard function for many types of equipment, because it is capable of representing many different forms. The Weibull probability density function is:

$$f_T(t) = \begin{cases} \dfrac{b\, t^{b-1}}{a^{b}} \exp\left[-\left(\dfrac{t}{a} \right)^{b} \right], \; t, a, b > 0 \\[2ex] 0, \; otherwise \end{cases} \tag{4.10}$$

β is called the shape parameter because it determines the shape of the distribution. And the parameter α is called the scale parameter because it determines the scale. Typically β is between 0.5 and 8.0. As β increases, the mean of the Weibull distribution approaches α and the variance approaches zero. Fig 4.4 illustrates this feature by appropriately varying the shape and scale parameters.

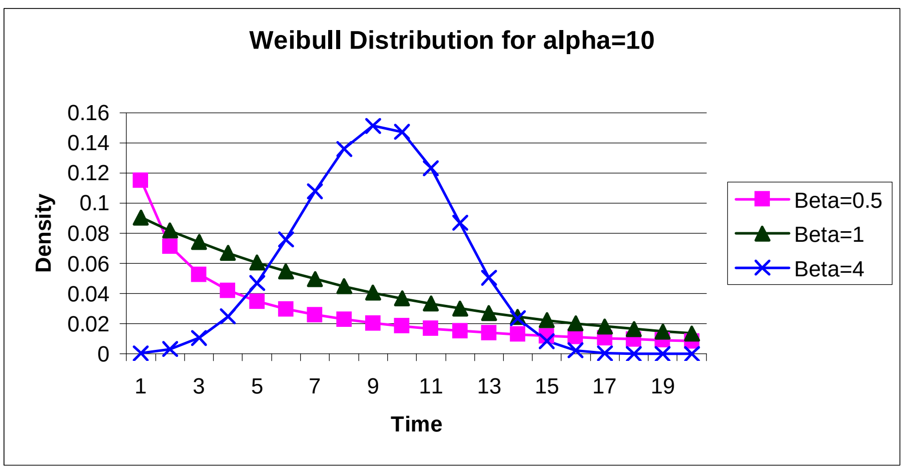

Fig. 4.4: Weibull Distributions

The Weibull hazard function is:

$$h(t) = \frac{b\, t^{b-1}}{a^{b}}, \quad t > 0 \tag{4.11}$$

If $b < 1$, the failure rate is decreasing; if $b = 1$, the failure rate is constant at a value of $1/a$; if $b > 1$, the failure rate is increasing; the higher the value of β, the faster the failure rate is increasing.

References [57, 58] report investigations into the feasibility of representing failure rates of transformers or other components using the Weibull distribution, with failure data. Through experience and numerous data gathered by researchers and engineers, the transformer failure rate (hazard function, h_i) has been shown to follow the so called "bathtub curve", as shown in Fig 4.3. The bathtub curve depicts equipment life in three stages. During the first stage, failure rate begins high and decreases rapidly with time. This stage is known as the infant-mortality period, and it has decreasing failure rate. The infant mortality is followed by nearly constant failure rate period, which usually lasts for the longest period of time. Finally, the curve ends with an increasing failure rate. This is the period of aging. This bathtub curve can be well modeled by the Mixture Weibull, comprising two or three Weibull distributions each of which have well-tuned and unique scale and shape parameters.

4.2.2.2 Loading condition based estimation: Hottest-spot Temperature Model

Loading information was first used to estimate the remaining life of transformer [59, 60]. It was mainly used to estimate life of the cellulose insulation, because cellulose life is directly related with the temperature of the windings and thus the loading history of the transformer. IEEE has provided the mathematical model linking transformer dielectric life to its winding hottest-spot temperature in [61]. It indicates that experimental evidence shows that the relation of insulation deterioration to time and temperature follows an adaptation of the Arrhenius reaction rate theory that has the following form:

$$\text{Per unit life} = 9.80\times10^{-18} EXP^{\left[\frac{15000}{\Theta_H+273}\right]} \tag{4.12}$$

where Θ_H is the winding hottest-spot temperature in unit of °C.

Given the transformer MVA loadings and the ambient temperature, the ultimate steady state top oil temperature rise q_u over ambient temperature is computed as:

$$q_u = q_{fl}\left(\frac{K^2+1}{R+1}\right)^n; \qquad K = \frac{S}{S_{rated}} \tag{4.13}$$

where q_{fl} is transformer top oil temperature rise over ambient temperature at rated load, K is the ratio of MVA loading to transformer nameplate rating. R is the ratio of loss at rated load to no-load loss; n is exponential power of loss versus top oil temperature rise.

For transient temperature calculations, the top-oil temperature rise over ambient after t hours is:

$$q_0(t) = q_u(1-e^{-t/t_0}) + q_i e^{-t/t_0} \tag{4.14}$$

where t_0 is oil thermal time constant for rated load, and q_i is the initial top oil temperature rise over the ambient temperature. The HST rise above top oil temperature rise can then be estimated as:

$$q_g(t) = q_{g(fl)} K^{2m} \tag{4.15}$$

where $\theta_{g(fl)}$ is hottest-spot conductor rise over top oil temperature at rated load, m is the exponential power of winding loss versus winding gradient. Finally the HST of the transformer after t hours is

$$q_{hst}(t) = q_0(t) + q_g(t) + q_a(t) \tag{4.16}$$

where $q_0(t)$ is the ambient temperature. If the initial top oil temperature q_i is unknown, then it can be estimated base on the knowledge of load cycle information using an iterative method [60]. And then the life expectation of transformer, with respect to the cellular decomposition, can be computed.

4.2.2.3 Condition based failure rate estimation

Since power transformers and circuit breakers are crucial and expensive equipment in transmission systems, they usually are well maintained and consequently have very high reliability. So in reality transformer and breaker failures are relatively rare, and it is difficult to obtain statistically significant failure data. Also, loading information is only one of the numerous factors contributing to the failure of transformer. On the other hand, condition data which tracks the deterioration of various failure modes is readily accessible for many power transformers and breakers. In this section, we briefly describe a traditional degradation model to use such data to develop instantaneous failure rates.

A degrading failure mode is one that can be traced to an underlying degradation process. When it is possible to measure degradation, such measures often provide more information than failure-time data for purposes of assessing and improving product reliability [56]. If the actual physical degradation cannot be observed directly then measures of product performance degradation (such as dissolved-gas-in-oil analysis or DGA) may be used. Control circuit data can be used to observe the deterioration of circuit breaker as it reveals the information about both control circuit and part of operating mechanism. However, it is necessary to relate the control circuit data to breaker's health in terms of conditions (e.g. condition 1, condition 2, etc.). This is analogous to the classification of transformer condition based on DGA analysis. In the case of transformers, there exist specific standards (e.g. IEEE standards) which give a clear classification of gases. For circuit breaker, there are no such specific standards to classify breaker control signals into different conditions. Various industries have their own set of rules and procedures to categorize circuit breaker condition. Since, control circuit data are basically signals, probability distributions can be used in characterizing the breaker condition. Bayesian approach can be used to update the distribution of control signals as the new data becomes available. Once we have the condition of the breaker, we can find the transition rates between states using Markov model, and hence the failure rate of the breaker. The outline of the procedure is discussed more in section 4.4.

4.2.2.3.1. Degradation as a function of time

When degradation can be characterized as a function of time, a failure level (or a performance threshold) is defined, and the variation of the degradation variables is plotted versus the service time (or operation cycles). Fig 4.5 shows examples of three general shapes of degradation curves in arbitrary units of degradation and time: linear, convex, and concave. The horizontal line at degradation level of 0.6 represents the level at which the failure would occur. Randomness can be introduced, using probability distributions to describe variability in initial conditions and model parameters. Reference [62] has provided a method of using a semiconductor sensor to detect the by-product of transformer insulation deterioration and then finding the most appropriate by-product to be used as the degradation variable by setting up the relationship between measurements and service time. A natural next step is to estimate the parameters of the degradation model.

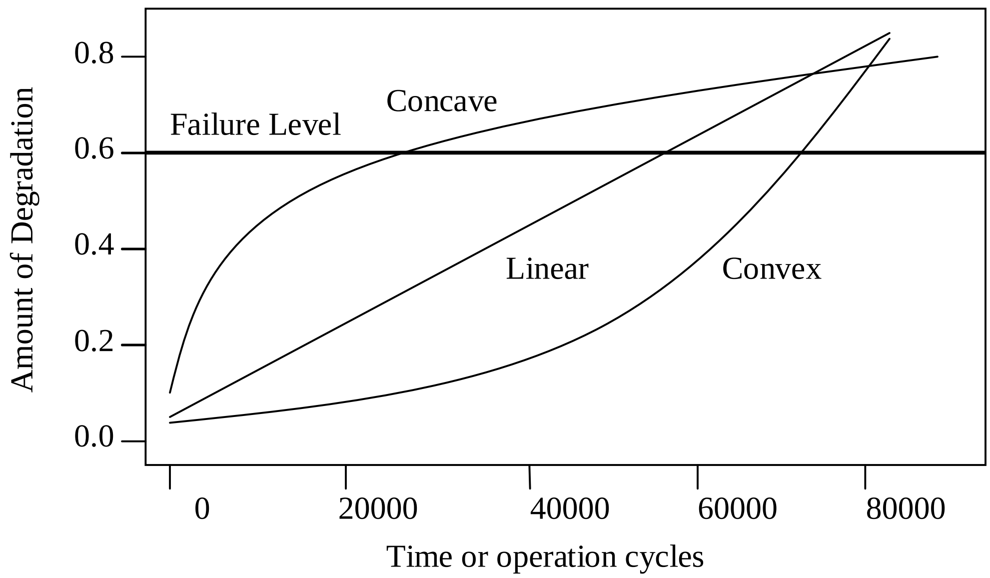

Fig. 4.5: Possible shapes for univariable degradation curves.

4.2.2.3.2. Hazard function model

A conceptual description of the deterioration process is effectively communicated using the hazard function. Consider the hazard function for a typical transmission equipment failure mode as shown in Fig. 4.6. In Fig 4.6 we observe that there are 4 deterioration levels corresponding to four different failure rate areas. Consider that the effect of a maintenance task could be to move the deterioration level from 3 to 1. The benefits from doing so are quantified in two ways: the failure probability is lowered by Δp, and the life is extended by Δt. The relative magnitudes of these two benefits depend on where the component is on the curve when the maintenance is performed. If the component is far to the right, then $\Delta p/\Delta t$ is large. If the component is far to the left, $\Delta p/\Delta t$ is small.

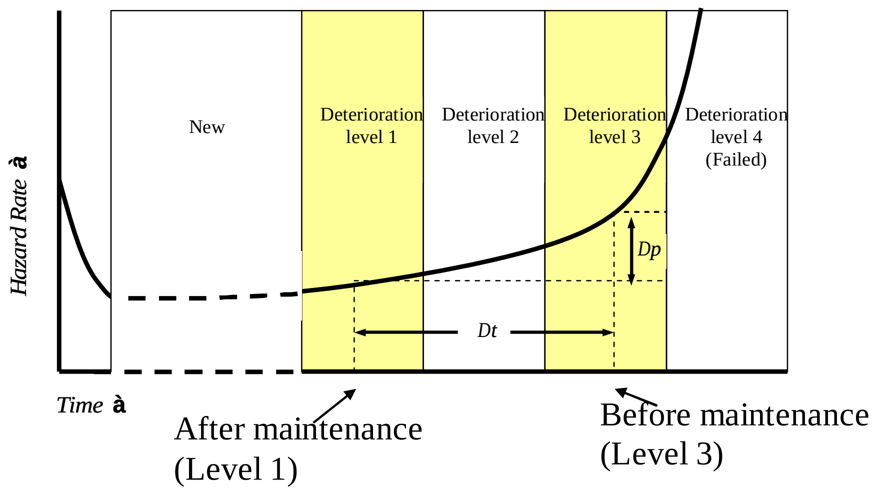

Fig. 4.6: Maintenance-induced improvements in failure probability and time

4.2.2.3.3. Markov models

Although the hazard function provides for a good depiction of how maintenance affects these two important reliability metrics, Δp and Δt, obtaining the hazard curve can be difficult with limited data; in addition, this approach requires that the continuous hazard function be discretized. We have found a method based on Markov models [63, 64] to be more attractive. This method uses a multi-state Markov model [65] adapted from [66] to compute failure rates from condition measurements.

Markov models provide an elegant and effective means of representing certain kinds of so-called “memory-less[3]” random processes, and degradation processes for many kinds of transmission equipment fall into this category, since the likelihood of being in any particular state in the next time period depends only on the state in which it resides in the current time period and not on the path of states taken to reach the current state. Although the deterioration process of component is continuous, we may discretize it in order to apply a continuous-time Markov chain (i.e., a continuous-time/discrete state Markov process) to it. Here we assume that we have the ability to characterize boundary conditions of different states of deterioration in terms of the condition measurements, via a specific deterioration function. Then we use the measurement data to estimate transition time between different states and thus calculate time to failure from each state, and also the benefit from maintenance, which is the failure rate reduction or the life extension of the transformer. This model, illustrated in Fig. 4.7, is more fully described in section 4.3.4.

[3] A “memory-less” random process is one for which the conditional probability distribution for the future state of the process is independent of the past states of the process. In other words, the present “summarizes” the entire history of the process, i.e., all of the information contained in the values taken by the random variables of the past are contained in the random variable of the present.

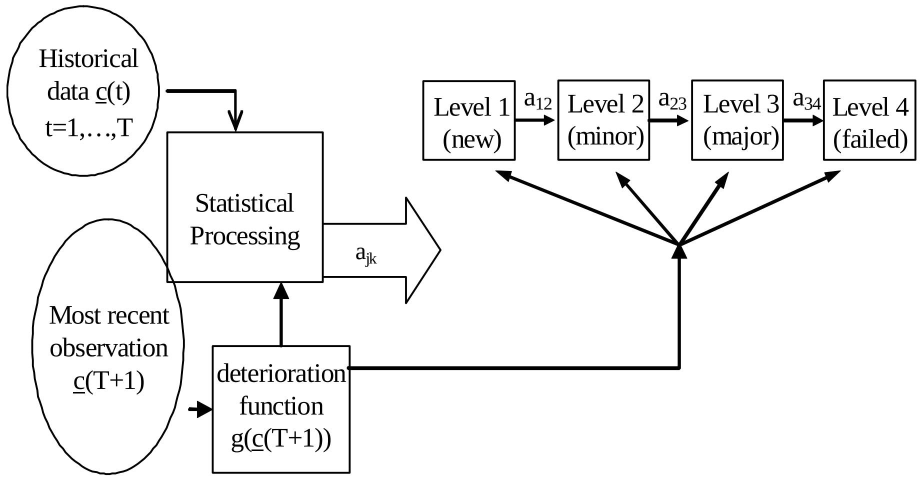

Fig. 4.7: Computing Contingency Probability Reductions

4.3 Failure Rate Estimation of Power Transformers

4.3.1 Failure rate and failure rate reduction estimation based on Markov model

Referring to the Markov model in Fig 4.8, we assume that we have at our disposal a set of condition vectors $\underline{c}(t)=[\underline{c}_1(t),\underline{c}_2(t),\ldots,\underline{c}_K(t)]$ for K similar components taken over an extended period of time $t=0,1,\ldots,T$, where each vector $\underline{c}_k(t)$ provides M different measurements $c_{k1}(t)$, $c_{k2}(t),\ldots c_{kM}(t)$, on component k characterizing its condition at time t. Each of the J states of the Markov model represents a deterioration level. The particular representation of Fig. 4.7 shows $J=4$ deterioration levels, and deterioration level j can be reached only from deterioration level j-1. However, the model is flexible so that any number of deterioration levels can be represented, and, if data indicates that transitions occur between non-consecutive states (e.g., state 1 to state 3), the model can accommodate. The main features of this approach are described in what follows.

(a) Deterioration function: The deterioration function, denoted by $g(\underline{c}_k)$, may be an analytical expression if one is available or it may be a set of rules encoded as a program, consisting of a nested set of if-then statements that returns a scalar assessment value. For the model of Fig. 4.7, the assessment value would be a deterioration level 1, 2, 3, or 4. This represents a flexible and practical way of connecting our approach to the wealth of existing knowledge and experience contained in the industry in regards to interpreting condition monitoring measurements. Often, such rules depend not only on the measurements $\underline{c}_k(t)$ but also on the rates of change in such measurements. For example, reference [67] provides a comprehensive compilation of such rules for transformers developed by industry experts that identifies different measurements for characterizing various transformer failure modes. Examples of the most common measurements (and some of the failure modes they detect) include dissolved gas analyses results on main tank oil (insulation deterioration, deterioration of cooling system, oil pump failure) and load tap changer oil (oil dielectric weakening), thermography testing (magnetic circuit overheating, bushing overheating), ultrasonic testing (oil pump failure), partial discharge testing (magnetic circuit overheating), winding and oil temperature (deterioration of cooling system).

(b) Transition intensities: The transition intensities between the various states of the model can be obtained from life-histories of multiple units of the same manufacturer and model. In the case of Fig. 4.7, a_{12}, a_{23}, and a_{34} are computed. Suppose we have a set of condition measurements $\underline{c}(t)=[\underline{c}_1(t),\underline{c}_2(t),\ldots,\underline{c}_K(t)]$ for K similar components taken over an extended period of time $t=0,1,\ldots,T$, where $\underline{c}_k(t)$ for component k represents all measurements taken that characterize the component's condition with respect to a particular failure mode. Each measurement vector $\underline{c}_k(t)$ is processed by the deterioration function to associate a deterioration level with component k at time t. Processing the data for $t=1,\ldots,T$ enables identification of the time each component spends in deterioration level j. The estimated time spent in state j is the mean of these durations. Reasonable estimates of the desired transition intensities are obtained by inverting these mean duration times. This same processing of historical data enables identification of change in state caused by maintenance.

(c) Failure probability: For a particular set of transition intensities, the transition probability matrix for the model shown in Fig. 4.7 is given by eq. (4.17).

$$P=\begin{bmatrix} 1-a_{12} & a_{12} & 0 & 0 \\ 0 & 1-a_{23} & a_{23} & 0 \\ 0 & 0 & 1-a_{34} & a_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.17}$$

The state probability vector gives the probability that a component is in any particular deterioration level at a given time, and is denoted by $p(hT)=[p_1(hT) \quad p_2(hT) \quad p_3(hT) \quad p_4(hT)]$, where $h=1,2,3,\ldots$, and T is the time step. If at time t=0, the component resides in deterioration level 1, then the initial state probability vector is $\underline{p}(0)=[1 \quad 0 \quad 0 \quad 0]$. The probability of finding the component in any deterioration level at time hT is then given by

$$p(hT)=\underline{p}(0)*\underline{P}^h \tag{4.18}$$

Given that at time t_0, we know the component's deterioration level, this last equation provides the probability of residing in the failed state in any future time interval. We denote this failure probability for the k^{th} component as $p(k)$. This probability is a function of the time-dependent physical condition of the equipment $\underline{c}(t)$.

(d) Time to failure: The expected time to failure is captured by computing first passage times. First passage time is the expected value of the amount of time the process will take to transition from a given state j to another state i, under the assumption that the process begins in state j. From this computation, then, we may estimate the remaining life of the component. We utilize the method introduced [68] and to calculate the first passage time to failure as:

$$T_f = p(0) \times T \times (I - P_r(T))^{-1} \tag{4.19}$$

where T_f is the vector of time to failure from different states, and ***Pr(T)*** is a partition of the transition matrix $\underline{\boldsymbol{P}}$ corresponding to non-failure states [69]. The life extension Δt_k is obtained by calculating difference of time to failure of the states before and after maintenance.

(e) Failure rate reduction estimation: The level of each benefit from maintenance, with respect to a particular failure mode for a specific component, is associated with where on the hazard curve the component lies when the maintenance is performed. If the maintenance is performed during the deterioration period, e.g., at time t_f in Fig. 4.7, the benefit comes mainly from the decrease of failure rate, which results in a decrease in failure probability Δp, but for maintenance performed during the constant failure rate period, e.g., at time t_d, the benefit comes mainly from the life extension Δt because of delay of the deterioration period (t_d in Fig. 4.7). Good estimates of Δp and Δt resulting from a maintenance task may be obtained by statistically characterizing the failure mode deterioration level before and after the maintenance using condition assessment tools [70]. For a 4-level model in Fig 4.8, if a particular maintenance task results in renewing a component to deterioration level 1, for example, then, if the component is in deterioration level 3, the probability reduction for maintenance task *m, Dp(m,k),* is given by the last element of the 1×4 row vector resulting from the calculation:

$$[1 \quad 0 \quad 0 \quad 0]\underline{P} - [0 \quad 0 \quad 1 \quad 0]\underline{P} = [1 \quad 0 \quad -1 \quad 0]\underline{P} \tag{4.20}$$

Although the discussion of this section has focused on equipment-driven maintenance, the approach is also applicable to failures caused by tree-contact and associated tree-trimming maintenance. Here the condition vectors (measurements) $\underline{c}_k(t)$ for this failure mode consist of clearance between vegetation and power lines. The distance is evaluated with the vegetation growth model in [71]. Decreasing clearance intervals are assigned as discrete condition levels to conform to the model of Fig. 4.8, and transition rates between intervals computed from the condition data. The failed state is defined based on FERC requirements on distance between conductors and vegetation [72].

4.3.2 Hidden Markov Models

The above procedure assumes that the deterioration function provides perfect identification of the state. However, it might not always be true in condition monitoring. This is largely due to the complicated nature of component deterioration processes. For many failure modes, such as insulation deterioration, we cannot monitor the dielectric strength of the insulation material directly but must use some by-product of the deterioration process as an indicator of the degradation, such as DGA data. This will bring some uncertainties of state identification due to the incomplete understanding or information about the deterioration process. To account for uncertainty in state identification, we investigated the applicability of the hidden Markov model (HMM).

While the component is in a particular state, we characterize the probability that a particular measurement can be generated using a probability distribution. It is only the outcome, and not the state that is visible to an external observer, and therefore states are "hidden." This method is described in the following section. The following is a simple example of hidden Markov model [73]. As in Fig 4.8, we have two states of atmospheric pressure: 'low' and 'high'. We suppose the transitions back and forth between the two states form a Markov process and the transition probabilities are *P('High'|'Low')=0.7* , *P('Low'|'High')=0.2* respectively. The atmosphere usually cannot be observed or felt by people without special devices, but it is closely related to the humidity of the air. The humidity of air tends to be high for low pressure and low (or dry) for high pressure, and vise versa. So here we have two observations: 'rain' and 'dry', as shown in Fig. 4.8. However, there are some uncertainties of the relationship between the humidity and the pressure of air. The observation probabilities are: *P('Rain'|'Low')=0.6* , *P('Dry'|'Low')=0.4* , *P('Rain'|'High')=0.4* , *P('Dry'|'High')=0.3* .

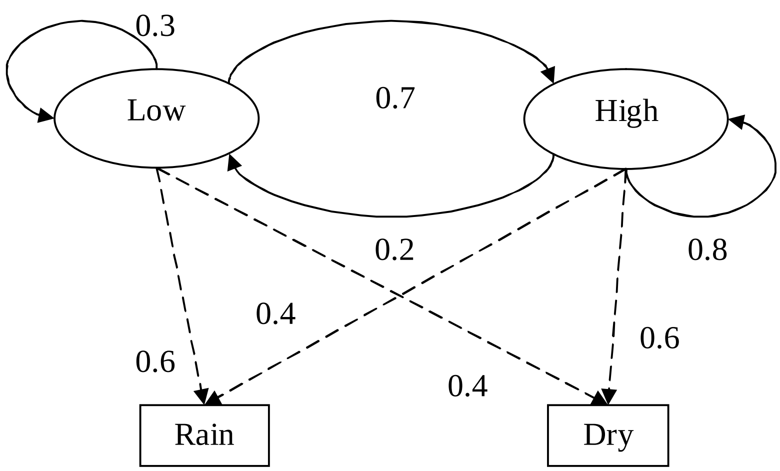

Fig. 4.8: Example of Hidden Markov Model

So this forms the hidden Markov model, with states of atmospheric pressure (hidden states) and the observation of weather (observation or visual states). HMM is a statistical method that uses probability measures to model sequential data represented by sequence of observation vectors [74]. It is a composition of two stochastic processes, a hidden Markov chain, which accounts for real status of the deterioration, and an observable process, which accounts for observation we get from monitoring and tests. While the component is in a particular state, we characterize the probability that a particular measurement can be generated according to a particular probability distribution. It is only the outcome, and not the state that is visible to an external observer, and therefore states are "hidden". The objective of hidden Markov model is to determine the HMM parameters (transition rate, observation probabilities and initial probabilities), given observation sequences and general structure of HMM (number of hidden and visual states).

4.3.2.1 Introduction of Hidden Markov model

Initially introduced and studied in the late 1960s and early 1970s, the basic theory of hidden Markov chain was published in a series of papers by Baum and his colleagues [75, 76, 77, 78, 79] and was widely used in speech recognition in the last twenty years of last century. The advantage of hidden Markov model (HMM) is that it can successfully represent the relationship between observations and the realities. It is a discrete-time, discrete-space dynamical system governed by a Markov chain. We have a sequence of observations, which are determined by the underlying (hidden) Markov process. In a particular state an outcome or observation can be generated, according to the associated probability distribution. It is only the outcome, not the state visible to an external observer and therefore states are 'hidden' to the outside; hence the name Hidden Markov Model. The initial application of HMM is to use this model for training to understand the underlying speech pattern with the heard language. Today, most commercial speech processing software for speech recognition, speaker identification, and speaker verification are based on HMM. HMM is also used in industries for failure pattern reorganization and condition monitoring using current data [80] and acoustic vibration data [81]. We will use Hidden Markov model to investigate the failure rate corresponding to the deterioration of oil in transformer, using dissolved gas analysis (DGA) data.

Articulation of the algorithm used to develop an HMM requires definition of the HMM model $q = \{A, B, p\}$ in terms of the three sets of probabilities comprising it, as follows. Assume that we have at our disposal a dataset of identified states (deterioration levels) and corresponding observations (test results). Suppose we have N states of the component deterioration level and M observations. Here observations are the test results, as interpreted by the deterioration function $g(c(t))$, which identifies the insulation status of transformer. The set of state transition probabilities between the states, to be determined by the HMM algorithm, are denoted as A={aij} and defined by

$$a_{ij} = p\{q_{t+1} = j \mid q_t = i\}, \;\; 1 \le i, j \le N \tag{4.21}$$

where q_t denotes the current state. The probability of obtaining an observation under a specific state, also to be determined by the HMM algorithm, is denoted as $B=\{bj(k)\}$ and defined by

$$b_j(k) = p\{o_t = v_k \mid q_t = j\}, \;\; 1 \le j \le N, \;\; 1 \le k \le M \tag{4.22}$$

Because the a_{ij} and the b_j are probabilities, they must add to 1, i.e., $\sum_{j=1}^{N} a_{ij} = 1 \quad 1 \le i \le N$ and

$$\sum_{k=1}^{M} b_j(k) = 1 \quad 1 \le j \le N.$$

The initial state distribution is determined by the latest observation, an input to the HMM algorithm, denoted by $p = \{p_i\}$, and defined by $p = p\{q_1 = i\} \quad 1 \le i \le N$. The parameter set $q = \{A, B, p\}$ is what is estimated according to the method introduced in the next section.

4.3.2.2 Parameter estimation

Estimating the transition matrix $A=\{a_{ij}\}$ is a learning problem: how to adjust the HMM parameters so that the given set of observations is represented by the model in the best way for the intended application. The most widely used method is the maximum likelihood estimation (MLE), which is to find the model which describes the observation sequence best, considering all unseen, possible state sequences. The training process is to get the optimal parameter $q = \{A, B, p\}$ to maximize the likelihood of observation $L_{tot} = p(O | q)$. First specifying the total number of states for the model and then by estimating the parameters of an appropriate probability density for each state achieve this. As for the state transition matrix *A*, this information can only be obtained by using a prior experimental knowledge of the deterioration. In general, the observation can be raw data or some function or transformation of the data.

There have been well-developed methods of doing this, like Baum-Welch Algorithm (also known as forward-backward algorithm) [82]. This method is used to train the model to fit the test data in the sense of MLE. Then we obtain the transition probabilities in each state and the probability of getting an observation each state. The basics of the Baum-Welch algorithm are captured in the following three-step procedure:

1. Transform the objective function $p(O | q)$ into a new function $F(\theta, \theta')$ that reflects the difference between the initial model θ and the updated model θ'.
2. Maximize the function $F(\theta, \theta')$ over θ' to improve θ in the sense of increasing the likelihood $p(O | q)$.
3. Continue by replacing θ with θ' and repeating the two steps above until some stopping criteria is met.

The following paragraphs provide a detailed illustration of the algorithm:

Baum-Welch algorithm:

Suppose we have a series of observations $O=\{o_1,o_2,..o_T\}$, which might the gas (or fluid) result from every testing instance. The o_i can be a vector or a combined index indicating the general test result. Also we have classified the deterioration procedure of the component into different states from 1 to *N*. Then we have a set of state transition probabilities $A=\{a_{ij}\}$

$$a_{ij} = p\{q_{t+1} = j \mid q_t = i\}, \ 1 \le i, j \le N \tag{4.23}$$

where q_t denotes the current state.

We also have probability of obtaining an observation under specific state, contained in the vector $B=\{b_j(k)\}$ where

$$b_j(k) = p\{o_t = v_k \mid q_t = j\}, \ 1 \le j \le N, \ 1 \le k \le M \tag{4.24}$$

Since A and B contain probabilities, $\sum_{j=1}^{N} a_{ij} = 1 \;\; 1 \le i \le N$ and $\sum_{k=1}^{M} b_j(k) = 1 \;\; 1 \le j \le N$.
The initial state distribution is denoted $p = \{p_i\}$, where $p_i = p\{q_1 = i\} \;\; 1 \le i \le N$.

The parameter set $\{A, B, p\}$ here are values that need to be estimated; the algorithm is initiated by assuming initial values for them. They are then updated during the training process. In the hidden Markov training, two auxiliary variables are defined: forward variable and backward variable.

1) Forward variable: The forward variable is defined as the probability of the partial observation sequence $o_1, o_2, ..o_t$, when it terminates at the state i.

$$a_t(i) = p(o_1, o_2, o_3, ..., o_t, q_t = i \mid q) \tag{4.25}$$

Then we can derive

$$a_{t+1}(j) = b_j(o_{t+1}) \sum_{i=1}^{N} a_t(i) a_{ij} \qquad 1 \le j \le N, \qquad 1 \le t \le T-1 \tag{4.26}$$

where $a_1(j) = p_j b_j(o_1) \qquad 1 \le j \le N$ (4.27)

So the required probability is given by

$$p(O \mid q) = \sum_{i=1}^{N} a_T(i) \tag{4.28}$$

2) Backward variable: The backward variable is the probability of the partial observation sequence $o_{t+1}, o_{t+2}, ..o_T$, given that the current state is i.

$$b_t(i) = p(o_{t+1}, o_{t+2}, o_{t+3}, ..., o_T \mid q_t = i, q) \tag{4.29}$$

There is a recursive relationship:

$$b_t(i) = \sum_{j=1}^{N} b_{t+1}(j) a_{ij} b_j(o_{t+1}) \qquad 1 \le i \le N, \qquad 1 \le t \le T-1 \tag{4.30}$$

where $b_T(i) = 1, \qquad 1 \le i \le N$ (4.31)

We can see that

$$a_t(i) b_t(i) = p\{O, q_t = i \mid q\} \qquad 1 \le i \le N \qquad 1 \le t \le T \tag{4.32}$$

There are two additional variables needed in the calculation:

3) Probability of being in state *i* at time=*t* and in state *j* at time=*t+1*.

$$e_t(i,j) = p\{q_t = i, q_{t+1} = j \mid O, q\} \tag{4.33}$$

It can be derived as:

$$\begin{aligned} e_t(i,j) &= \frac{p(o_1,\dots,o_t,q_t = i \mid l) * p(o_{t+1},\dots,o_T,q_{t+1} = j \mid q_t = i, q)}{p\{O \mid q\}} \\ &= \frac{a_t(i)a_{ij}b_{t+1}(j)b_j(o_{t+1})}{\sum_{i=1}^{N}\sum_{j=1}^{N} a_t(i)a_{ij}b_{t+1}(j)b_j(o_{t+1})} \end{aligned} \tag{4.34}$$

4) Posteriori probability, which is the probability of being in state *i* at time *t*, given the observation sequence and the model.

$$g_t(i) = p\{q_t = i \mid O, q\} \tag{4.35}$$

It is derived that

$$g_t(i) = \frac{p(O, q_t = i \mid q)}{p\{O \mid q\}} = \frac{a_t(i)b_1(i)}{\sum_{i=1}^{N} a_t(i)b_1(i)} = \sum_{j=1}^{N} e_t(i,j), \quad 1 \le i \le N, 1 \le t \le M \tag{4.36}$$

With the assumed starting model $q = \{A, B, p\}$, the training starts in the following way:

1) Use (4.26) and (4.30) to calculate the serial variable 'a's and 'b's.

2) Using (4.34) and (4.36) to update the HMM parameters:

$$\bar{p}_i = g_1(i), \ \ 1 \le i \le N \tag{4.37}$$

$$\bar{a}_{ij} = \frac{\sum_{t=1}^{T-1} e_t(i,j)}{\sum_{t=1}^{T-1} g_t(i)} \quad 1 \le i \le N, \qquad 1 \le j \le N \tag{4.38}$$

$$\bar{b}_j(k) = \frac{\sum_{\substack{t=1 \\ O_i = v_k}}^{T} g_t(j)}{\sum_{t=1}^{T} g_t(j)} \quad 1 \le i \le N, \qquad 1 \le j \le N \tag{4.39}$$

3) Update the HMM model parameters with (4.37)-(4.39).

It has been proven [78] that after each iteration described above, either the re-estimated parameter set $q' = \{A', B', p'\}$ is more likely than original set $q = \{A, B, p\}$ in the sense that $p(O \mid q') > p(O \mid q)$ or we have reached a stationary point of the likelihood function at which $q' = q$.

The Baum-Welch learning process updates the parameters of the HMM to maximize the quantity $p\{O \mid l\}$. But first, we need initial values for the model $q = \{A, B, p\}$. Initial values for parameters of A can be obtained using the method of [65], or a distribution of A can just be assumed. Initial values for parameters of B are obtained by assuming they obey a normal distribution. The mean value and variance of the distribution can be either assumed or based on pre-studied distribution of measurement with different component conditions, if available. The initial values of parameters in p are, (0,…,1,…0) where the only non-zero element corresponds to the state indicated by the most recent observation. All of the initial value of parameter set $q = \{A, B, p\}$ will be updated during the HMM training and will not affect the final result of parameter estimation.

4.3.2.3 Incomplete data and local maximization

For failure rate estimation based on condition data, the observations might be incomplete, which means there are some periods t that the observation data are not available. However, the HMM model requires an observation for each period t (i.e., the observation data must be continuous). This requirement might be satisfied for the case when the observations are obtained from online monitoring data but for data colleted from manual testing, it is likely that the data will have gaps. In such cases of incomplete data, if unobserved data dominates (which means the periods without observation is much more numerous than those with observations), , this might cause error in the HMM model training because the preset initial value will determine the stochastic process., since there is no observation in most periods t to adjust the parameter set $l = \{A, B, p\}$ in the training. So we must eliminate the effects of unobserved initials. The solution is to set the observation probability in each state to 1 or 1/N at time t when there is no observation, which is:

$$b_j(k) = p\{o_t = v_k \mid q_t = j\} = 1/N, \;\; 1 \le j \le N, \;\; 1 \le k \le M, t \in \{unobserved \;\; period\} \tag{4.40}$$

This means that at time t when there is no observation, the conditional probabilities that a specific observation will be generated are equal for every state. So only the observed data will take effect in the parameter estimation.

4.3.3 Application of Hidden Markov model in failure rate estimation of transformers

The observation sequences for HMMs are completely general and can consist of any combination of data features. That means it can be applied to simulate the deterioration process represented by any condition monitoring data, or their combination. In this report, we provide the applications of HMM in failure rate estimation based on DGA data and also based on a scoring system, which is a combination of health data on insulation material.

4.3.3.1 Estimation based on DGA data

Dissolved Gas-in-Oil Analysis (DGA) has been widely used throughout industry as the primary diagnostic tool for transformer maintenance. The detection of certain gases generated in an oil-filled transformer in service is frequently the first available indication of a malfunction that may eventually lead to failure if not corrected. Arcing, corona discharge, low-energy sparking, severe overloading, pump motor failure, and overheating in the insulation system are some of the possible mechanisms. One event or the combination of some of them, as simultaneous events, can result in decomposition of the insulating materials and the formation of various combustible and noncombustible gases.

One acceptable method for monitoring the deterioration of transformer insulating material involves calculating the total volume of gas evolved. The total volume of evolved gas is an indicator of the magnitude of incipient faults. Detailed evaluation information on concentrations for separate gases as well as the total concentration of all combustible gases is provided in [81], as shown in Table 4.1. Here conditions 1, 2, 3, 4 correspond to the deterioration levels 1, 2, 3, 4, respectively, in our Markov model.

TABLE 4.1: DETERMINE TRANSFORMER CONDITION BASED ON DGA (IEEE STD. C57.104-1991)

Status	Dissolved Key Gas Concentration Limits (ppm)							
	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG[4]
Condition 1	<100	<120	<35	<50	<65	<350	<2500	<720
Condition 2	101-700	121-400	36-50	51-100	66-100	351-570	2500-4000	721-1920
Condition 3	701-1800	401-1000	51-80	101-200	101-150	571-1400	4001-10000	1921-4630
Condition 4	>1800	>1000	>80	>200	>150	>1400	>10000	>4630

4.3.3.1.1. Parameter estimation

Table 4.2 gives the DGA data of one transformer between two oil filtering maintenance tasks, which is the main maintenance task for addressing the oil deterioration failure mode. So we use all records taken between two maintenance tasks to simulate the deterioration process. The transition rates for the Markov model are given in Table 4.3.

[4] TDCG: Total dissolved combustible gas. The TDCG is the value of summation of total combustible gases. It does not include CO_2, which is not combustible.

TABLE 4.2: DGA TEST DATA FOR TRANSFORMER

SAMPLE DATE	H2	C2H4	C2H2	CH4	C2H6	CO	TDCG
15-Sep-95	3	9	0	19	4	539	574
18-Sep-96	0	13	0	20	9	467	509
09-May-97	0	9	0	30	3	578	620
27-Aug-98	26	22	0	54	10	942	1054
12-Apr-99	21	28	0	60	6	731	846
10-Sep-02	305	691	0	648	192	657	2493
15-Oct-02	569	1703	7	1364	451	552	4646
22-Oct-02	573	1965	6	1637	520	643	5344
28-Oct-02	557	2002	7	1616	535	599	5316
10-Dec-02	1	22	0	7	6	5	41

TABLE 4.3: ESTIMATED TRANSITION INTENSITIES FOR MARKOV MODEL

Transition Rate	1	2	3	4
$a_{i,i}$	0.9917	0.9936	0.9891	1.0000
$a_{i,i+1}$	0.0083	0.0064	0.0109	0.0000

To validate the HMM performance, we compare the observation with the HMM results. In Table 4.4, *Si* is the status of the components with observation data, interpreted with the IEEE standards, and *Se* is the forecasted states predicted by the HMM, which is chosen as the state with the maximum probability of residing at that time t from the HMM training. We observe from the results that they match very well, indicating that the HMM can be used to simulate the deterioration process effectively.

TABLE 4.4: COMPARISON OF OBSERVATION AND FORECAST.

Time (week)	1	54	87	155	187	366	371	372	372
Si	1	1	1	2	2	3	4	4	4
Se	1	1	1	2	2	3	4	4	4

The desired probability is the instantaneous probability of the component to fail during the period of $[hT, (h+1)T]$ given the condition that it survives to time hT, which is expressed by (4.41)

$$\Pr(hT < x \le (h+1)T \mid x > hT) = \frac{P((h+1)T) - P(hT)}{1 - P(hT)} \tag{4.41}$$

where $P(hT)$ is the failure probability calculated in (4.20). Calculated instantaneous failure probability vs. time is shown in Fig 4.9.

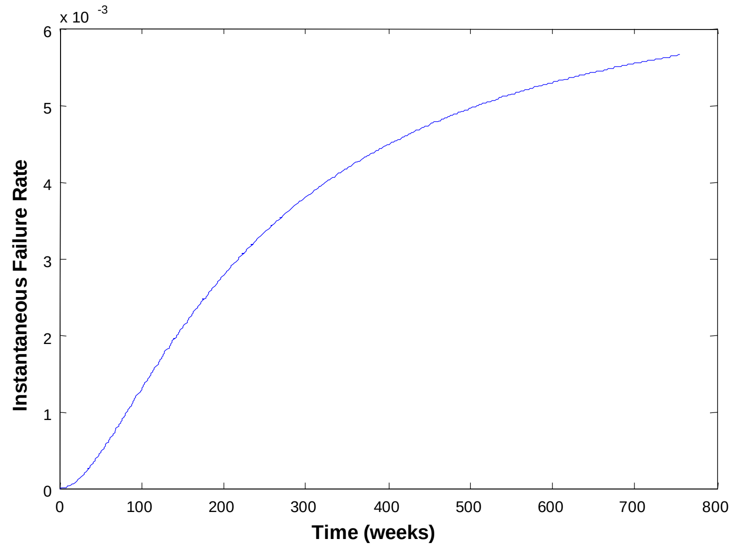

Fig. 4.9: Failure rate of transformer oil deterioration

Also we can use the results to calculate the change of failure probability after the maintenance for this particular transformer. The last record in Table 4.2 shows the maintenance (an oil change) was performed 377 weeks after the first record, which is the time of the previous maintenance. From Fig. 4.9, we observe that the failure probability at 377 weeks is about 4E-3, and exact calculation yields Pr(377)=0.004354. We also checked the DGA records just after the maintenance, and they indicated the oil was of course in very good condition, so that the computed failure probability was almost 0. Thus we can calculate Δp, the change of failure probability after maintenance, to be 0.004354.

We can also calculate the expected time to failure with the results from HMM. It is captured by computing first passage times, which is the expected value of the amount of time it will take to transit from a given state j to another state i, under the assumption that the process begins in state j. Letting state j be the current state and state i be the failed state, the first passage time, (4.19) provides an estimate of the component's remaining life. Table 4.5 gives the results for components in each state, the average time to next state and the estimate time to failure.

TABLE 4.5: FIRST PASSAGE TIME FOR EACH STATE

State	1	2	3
Time to next state (weeks)	120.5	155.4	91.9
Time to failure (weeks)	367.8	247.3	91.9

The time between states, per observations as given in Table 4.4 may differ significantly from the expected time between states per calculation as given in Table 4.5. For example, referring to Table 4.4, the difference between the observation at time 366 and time 371 might suggest that a state transition from state 3 to state 4 has occurred in only 371-366=5 weeks. Yet Table 4.5 indicates the expected time to transition between state 3 and state 4 is 91.9 weeks, clearly much larger. The reason for this is that the observations of Table 4.4 are not necessarily at the time the deterioration process first enters the indicated state. Returning to my example, the process could have entered state 3 well before week 366, perhaps at week 281, in which case, if the process enters state 4 precisely at week 371, the time to transition from state 3 to state 4 would have been exactly 91 weeks, and in fact, Table 4.5 tells us that if we considered a large number of such processes, 91 weeks would be the average of state 3 to 4 transition times.

4.3.3.1.2. Parameter distribution estimation on a group of data

To estimate from historical data all of the transition intensities for a given transformer's HMM, as in Table 4.3, it is necessary that the historical data contain oil samples spanning the entire range of possible conditions (or states). This may not be the case, particularly for newer transformers; in addition, it may be that a particular transformer's historical data does span the range of possible conditions, but the data for one or more states is very limited, e.g., some states may have only one or two recordings. These all-too-familiar situations of ***limited data*** are common, and we feel it essential to address this very practical issue. Our approach is to develop probability models for the transition rates using a pool of similar transformers, and then to use these probability models to estimate transition intensities for a particular transformer when the historical data for that transformer does not allow it otherwise.

We have used a pool of DGA testing data obtained for all transformers at a medium-sized utility company, and, for each transformer, computed the transition rates only between states for which data existed. The results are given in Table 4.6, with mean and standard deviation for each transition intensity given at the bottom of the table. We have also used (4.23) to calculate the first passage time between different states, and these calculations are provided in Table 4.7.

TABLE 4.6: TRANSITION RATE OF DIFFERENT STATES FOR TRANSFORMER INSULATION DETERIORATION

ID	a_{12}	a_{23}	a_{34}
1	0.0102	0.0036	0.0058
2	0.0101	0.0064	0.0088
3	0.0060		
4	0.0087		
5	0.0078		
6	0.0099	0.0082	0.0605
7	0.0117		
8		0.0074	
9	0.0136		
10	0.0111		
11	0.0080		
12	0.0108		
13	0.0067	0.0075	
14		0.0129	0.0359
15	0.0100		
16	0.0144		
17	0.0082	0.0061	0.0222
18	0.0098		
19	0.0042	0.0069	0.0648
20	0.0064		
21	0.0082	0.0055	0.0061
22		0.0045	0.0130
23	0.0116		
24	0.0082	0.0053	0.0066
25	0.0147		
26	0.0052		
27	0.0043		
28	0.0088		
29		0.0052	0.0047
30	0.0112	0.0062	0.0156
31	0.0192		
32	0.0127		
33		0.0052	
34	0.0133		
35	0.0078		
36	0.0179		
37	0.0196	0.0108	0.0163
38	0.0024		
39	0.0087		
40	0.0053		
41	0.0071	0.0062	0.0066
42		0.0051	0.0062
43	0.0075	0.0043	
44		0.0059	
45	0.0039	0.0051	0.0081
46	0.0080		
47	0.0101		

Table 4.6 (continued)

48	0.0055	0.0070	
49	0.0054		
50	0.0138	0.0054	
51	0.0047		
52	0.0034	0.0109	
53	0.0123		
54		0.0067	
55			0.0060
56	0.0082	0.0088	0.0082
57	0.0057	0.0130	
58	0.0043	0.0118	0.0119
59	0.0079		
60	0.0099		
61	0.0134		
62	0.0085		
63	0.0117		
64	0.0120		
65		0.0064	
66	0.0121		
67			0.0086
68	0.0092		
69		0.0069	
70	0.0083	0.0064	0.0109
Number	56	28	18

TABLE 4.7: FIRST PASSAGE TIME BETWEEN DIFFERENT STATES

ID	T_{12} *(week)*	T_{23} *(week)*	T_{34} *(week)*
1	98.25	281.23	172.87
2	98.52	155.28	113.70
3	166.67		
4	114.94		
5	128.21		
6	101.01	121.95	16.53
7	85.47		
8		135.14	
9	73.53		
10	90.09		
11	125.00		
12	92.59		
13	149.25	133.33	
14		77.52	27.86
15	100.00		
16	69.44		
17	121.95	164.10	45.05
18	102.04		
19	238.10	144.93	15.43
20	156.25		
21	121.25	181.39	163.13
22		222.22	76.92
23	86.21		
24	122.26	188.90	151.81
25	68.03		
26	192.31		
27	232.56		
28	113.64		
29		192.85	213.26
30	89.32	160.69	64.26
31	52.08		
32	78.74		
33		192.31	
34	75.19		
35	128.21		
36	55.87		
37	51.02	92.59	61.35
38	416.67		
39	114.94		
40	188.68		
41	140.85	162.27	151.68
42		196.26	162.02
43	132.65	233.06	
44		169.49	
45	256.41	196.15	123.26
46	125.00		
47	99.01		
48	181.82	142.86	

Table 4.7 (continued)

49	185.19		
50	72.46	185.19	
51	212.77		
52	294.12	91.74	
53	81.30		
54		149.25	
55			166.67
56	122.57	113.92	121.25
57	175.44	76.92	
58	232.56	84.75	84.03
59	126.58		
60	101.01		
61	74.63		
62	117.65		
63	85.47		
64	83.33		
65		156.25	
66	82.64		
67			116.28
68	108.70		
69		144.93	
70	120.50	155.40	91.90

Although the deterioration paths for transformers differ, due to different design, cumulative loading through-faults, and environments, a general view of the condition or estimation of the failure distribution can be useful. We have developed probability plots to find the most appropriate distribution and corresponding model parameters to fit the data (transition intensities between states). From the chosen distributions, the transition intensities can be estimated based on MLE.

Figures 4.10 – 4.15 are probability plots of first passage times between different states (which are the inverse of the corresponding transition intensities a_{12}, a_{23}, *and* a_{34}). The distributions we have tested are: Normal, Lognormal, Weibull, Exponential, Logistic and Loglogistic distribution.

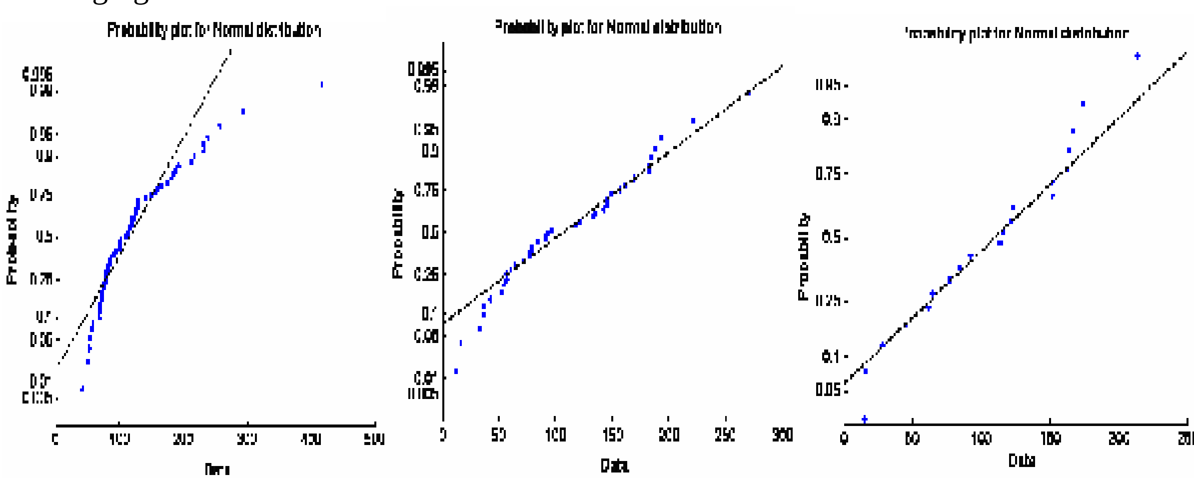

Fig. 4.10: Normal probability plot for transition rates between different states.

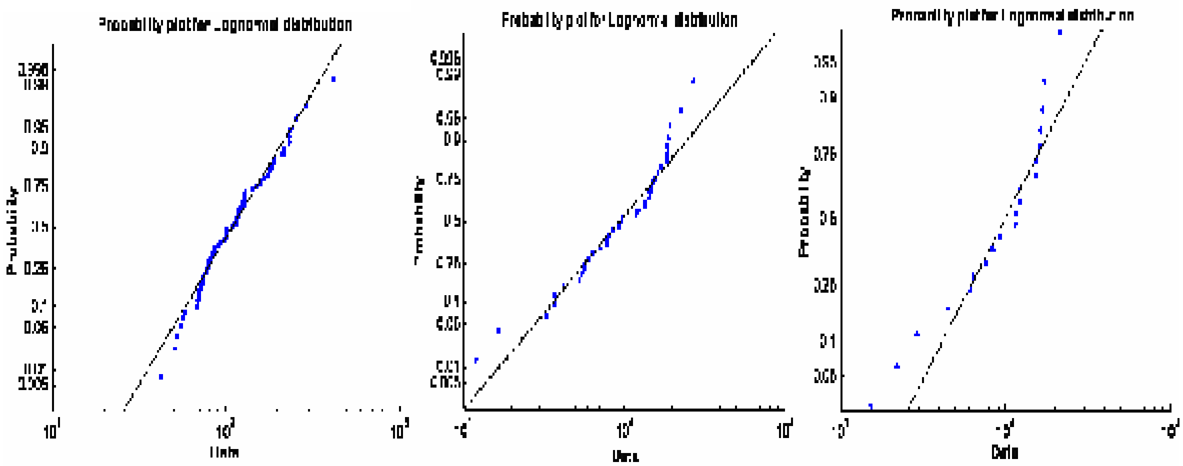

Fig. 4.11: Lognormal probability plot for transition rates between different states.

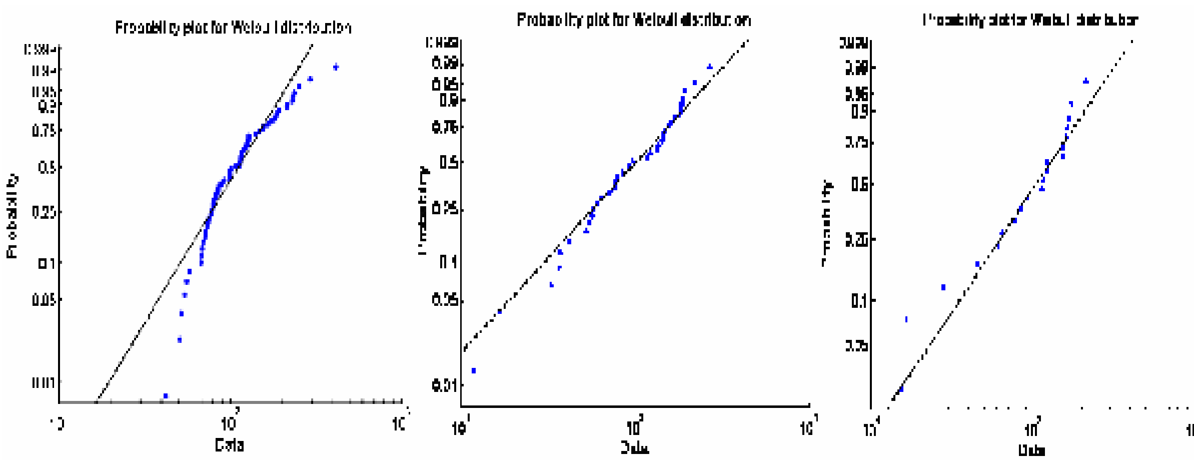

Fig. 4.12: Weibull probability plot for transition rates between different states.

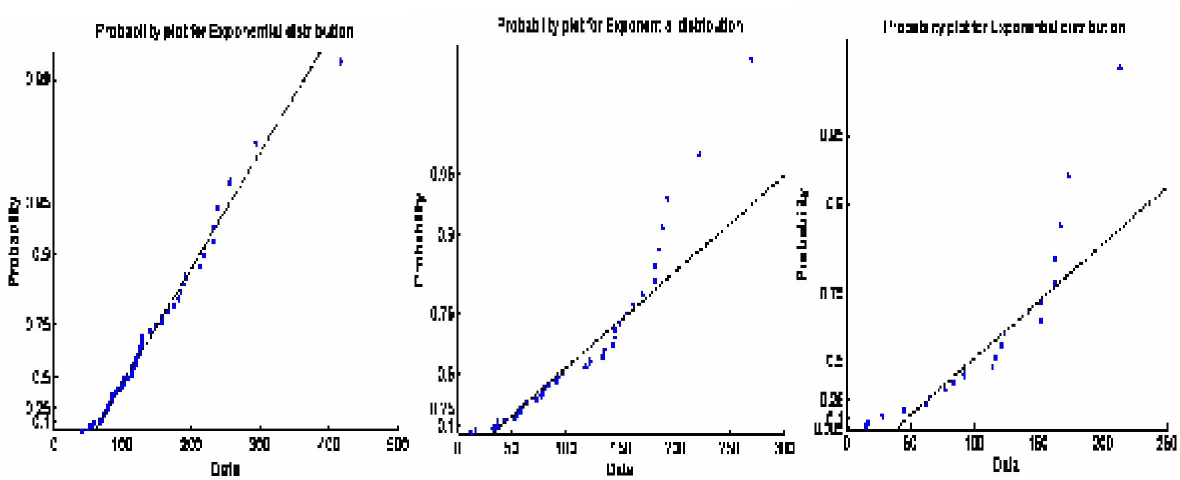

Fig. 4.13: Exponential probability plot for transition rates between different states.

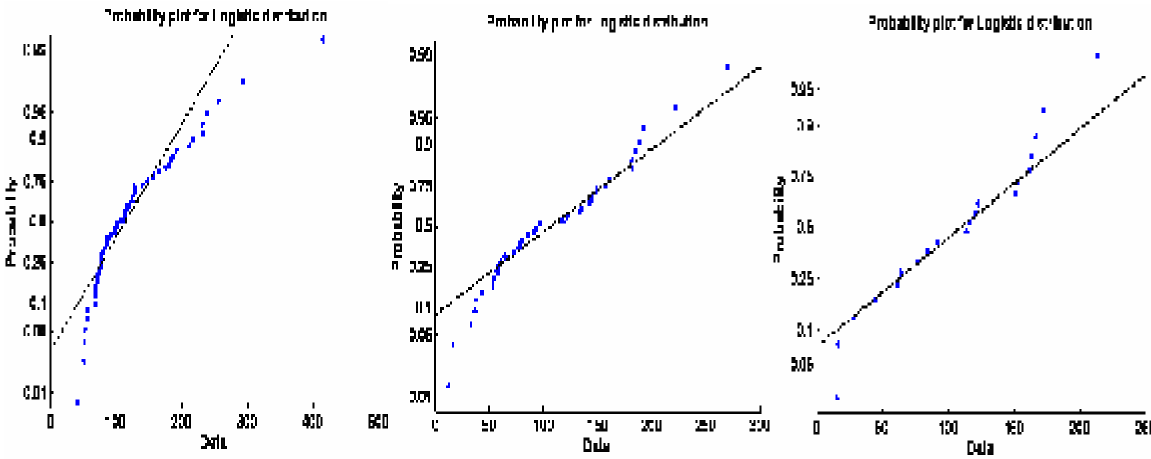

Fig. 4.14: Logistic probability plot for transition rates between different states.

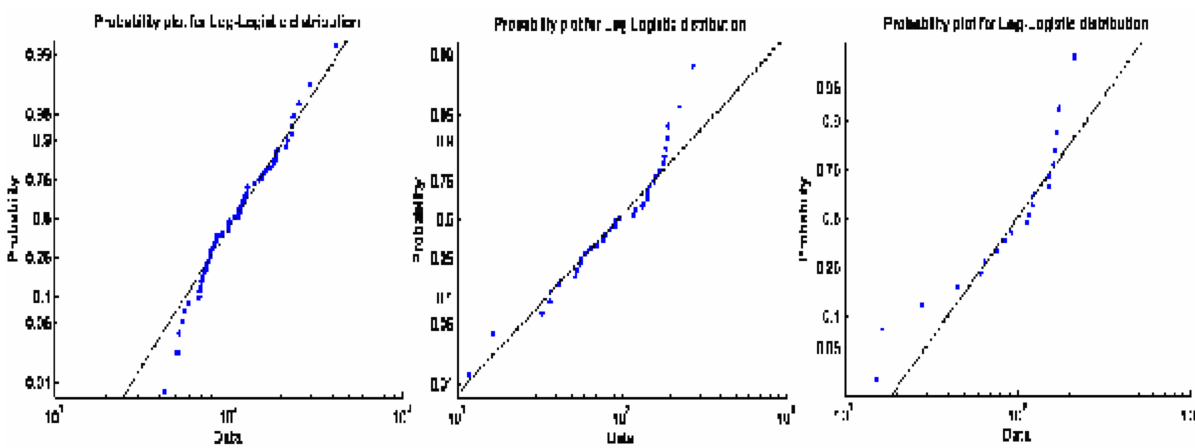

Fig. 4.15: Log-logistic probability plot for transition rates between different states.

Comparison of the plots in Fig. 4.11 to those of Figs. 12-15 suggests that the log normal distribution provides the best fit to the data. This finding is consistent with experience in modeling of other degradation processes [56].

$$Log(x) \sim Normal(m, s)$$

Also, with statistical tools, we can estimate the parameter of the lognormal distribution to describe the first passage time between different states, as in Table 4.8.The parameter estimates ($\hat{m}, \hat{s}$) are based on maximum likelihood estimation [56] and the 95% upper and lower confidential intervals were achieved with:

$$CI = \exp(\hat{m} \pm Z_{1-a/2} \times \hat{s} / \sqrt{n}) \qquad (4.42)$$

where $Z_{1-a/2}$ is the quantile of normal distribution with $a = 0.05$ and n is the samples size.

TABLE 4.8: MEAN VALUE AND CONFIDENCE INTERVAL OF FIRST PASSAGE TIME

Firs Passage Time (weeks)	T_{12}	T_{23}	T_{34}	Time to failure
Mean	117.87	145.97	82.01	345.85
Lower limit of 95% Confidence Interval	105.88	135.37	67.69	308.94
Upper limit of 95% Confidence Interval	131.22	157.40	99.36	387.98

So we can get the results from Table 3.8, that for the sample of transformers, their mean time to failure (assuming no maintenance) is 345.86 weeks (or 6.65 years) and the 95% confidence interval is [308.94,387.98] weeks (or [5.94,7.46] years).

This result corresponds to transformer oil insulation failure. This failure mode can develop quickly if the unit is older and not well maintained, compared to other failure modes such as mechanical failures. That is why utility companies need to inspect the oil quality every few months and perform proper maintenance (oil filtering, replacement) every several years.

4.3.3.2 Estimation based on score system (health index)

In the previous sections of this chapter, we assumed that insulation deterioration may be appropriately characterized using only DGA. Although DGA is arguably one of the best, if not the best indicator of insulation deterioration, it is not a perfect indicator, nor is it the other indicator. In fact, practitioners typically make use of a number of indicators, recognizing that each one gives a somewhat different view of the same problem, and that the best view is obtained from combining the information that is obtained from all of them. A standard method of combining this information is via a scoring system. In this section, we will make use of such a scoring system describe some testing towards that end that we have performed.

Some research has been done on obtaining such a relative condition or health index for a failure mode. For example, [83] proposes a concept of health indices and developed rules of health indices, and [84] presents a method to map equipment inspection data to a normalized condition score and suggests a formula to convert this score into failure probability. However, these approaches attempt to characterize the general condition of the equipment rather than a specific failure mode.

Our scoring system for insulation deterioration, based on various inspection date, is similar to that described in [83]. Suppose we have ***n*** inspection indicators ($r_1, r_2, \ldots, r_n$) for a transformer, each of which describes some information about the insulation deterioration. We assume that each measurement may be normalized to the range of [1, 4] corresponding to the 4 deterioration levels of the Markov model of Fig. 4.7.

Each inspection item result r_i is assigned a weight w_i based on its relative importance to overall equipment condition. These weights are typically determined by the combined opinion of equipment manufactures and field service personnel; they can be modified based on the particular experience of each utility company. The condition of the insulation is characterized by its condition score, as given in (4.24), calculated by taking the weighed average of inspection item results.

$$\text{Condition Score}=\sum_{i=1}^{n} w_i r_i \div \sum_{i=1}^{n} w_i \tag{4.43}$$

A condition score of 1 corresponds to the best condition; a condition score of 2 and 3 indicate some deterioration has occurred to the insulation material; a condition score of 4 indicates the equipment is in an emergency condition and needs to be removed from service. Table 4.9 gives an inspection form for power transformers. Table 4.10 illustrates a normalization for the criteria ‘age.’ Table 4.11 gives the inspection items and the information they carry for transformer insulation deterioration conditional assessment. Table 4.12 summarizes the condition scores for a single transformer (18 in Table 4.6) taken over a period of time from 1994 to 2000.

TABLE 4.9: INSPECTION FORM FOR POWER TRANSFORMER

Criterion		Weight	Score
History	Age (Years of operation)	8	
	Loading History	3	
	Inspection/maintenance	3	
	Faults History	2	
Condition	Solid insulation (Cellulose)	2	
	Gas in oil analysis	5	
	Gas in oil analysis (trend)	4	
	PD test	1	
	Water in oil	2	
	Acid in oil	2	
Total		32	
Condition score (weighted average)			

TABLE 4.10: NORMALIZATION FOR CRITERION ‘AGE’

Age (years)	*Score*
<1	*1.00*
1-20	*1+Age*0.015*
20-29	*1.3+(Age-20)*0.09*
29-32	*2.1+(Age-29)*0.15*
32-35	*2.5+(Age-32)*0.18*
35-39	*3.0+(Age-35)*0.20*
>=40	*4.00*

TABLE 4.11: INSPECTION TIMES AND CONDITION INFORMATION REFLECTED BY INSPECTION

Criterion	Condition information reflected by the inspection
Age	All parts including insulation material deteriorate under high thermal and electromagnetic stress. High failure probability occurs for aged transformer.
Loading history	Higher temperature due to heavy load significantly reduces the life of cellose.
Inspection/ Maintenance History	Equipments with routine inspection and proper maintenance can stay in service for a long time. Well-maintained facility can maximally mitigate most ‘hidden’ faults that might cause potential failures.
Fault History	When a transformer is subjected to a through fault, some damage may occur. Gases can increase; vibration and sonic values also increase due to forces associated with the fault potentially causing looseness in the core supports/windings.
Solid insulation	Use CO, CO2/CO ratio & CO increase trend as indicator of cellulose condition
DGA analysis	Mineral oil decomposes by breaking carbon-hydrogen & carbon-carbon bonds. Combustible gases form in the neighborhood of faults.
DGA analysis (trend)	A rapid increase of a specific gas indicates severe problem in the power transformer
Partial discharge test	Partial discharge occurring within insulation produces acoustic pulse, detectable at the tank wall.
Water in oil	By-product of oxidation of the cellulose. Significantly reduces dielectric strength of paper.
Acid in oil	Acids are produced as a result of oxidation of the oil. And the (H+) in acid speeds up oxidation.

TABLE 4.12: INSPECTION RESULTS AND WEIGHTED AVERAGE SCORE FOR TRANSFORMER 18

Date	Age	Loading History	Ins/Maint History	Fault History	Solid Insulation	DGA analysis	DGA trend	PD test	Water in oil	Acid in oil	Weighted Average Score
5/12/1994	2.75	1.15	1.0	1.0	1.0	1.0	1.0	1.0	3.0	1.0	1.58
6/16/1995	2.95	1.15	1.0	1.0	1.0	1.0	1.0	1.0	4.0	1.0	1.69
4/17/1996	3.06	1.15	1.0	1.0	1.0	2.0	1.0	1.0	2.0	1.0	1.75
10/8/1997	3.36	1.15	1.0	1.0	1.0	3.0	1.0	1.0	1.0	1.0	1.92
10/2/1998	3.56	1.15	1.0	1.0	1.0	4.0	1.0	1.0	3.0	1.0	2.25
5/23/2000	3.88	1.15	1.0	1.0	1.0	4.0	1.0	1.0	1.0	1.0	2.20
6/16/2000	3.90	1.15	1.0	1.0	1.0	4.0	1.0	1.0	1.0	1.0	2.21
7/6/2000	3.91	1.15	1.0	1.0	1.0	4.0	1.0	1.0	1.0	1.0	2.21
8/30/2000	3.94	1.15	1.0	1.0	1.0	4.0	1.0	1.0	1.0	1.0	2.22
11/15/2000	3.98	1.15	1.0	1.0	1.0	4.0	1.0	1.0	1.0	1.0	2.23

TABLE 4.13: MARKOV MODEL LEVEL CRITERION BASED ON WEIGHTED AVERAGE SCORE

State	Score	Mean	Variance
1	1-1.70	1.35	0.14
2	1.7-2.0	1.85	0.18
3	2.0-2.2	2.10	0.21
4	>2.2	2.50	0.25

We use the condition scores of Table 4.12, mapped to states via Table 4.13, in developing the HMM model. Resulting transition rates and first passage times between different states are shown in Table 4.14, and the corresponding failure rate is shown in Fig. 4.16.

TABLE 4.14: TRANSITION RATE AND FIRST PASSAGE TIME BASED ON SCORE RANKING SYSTEM

Transition Rate	1	2	3	4
$a_{i,i}$	0.9878	0.9890	0.9841	1
$a_{i,i+1}$	0.0122	0.0110	0.0159	0
$T_{i,i+1}$	81.98	91.21	63.07	N/A

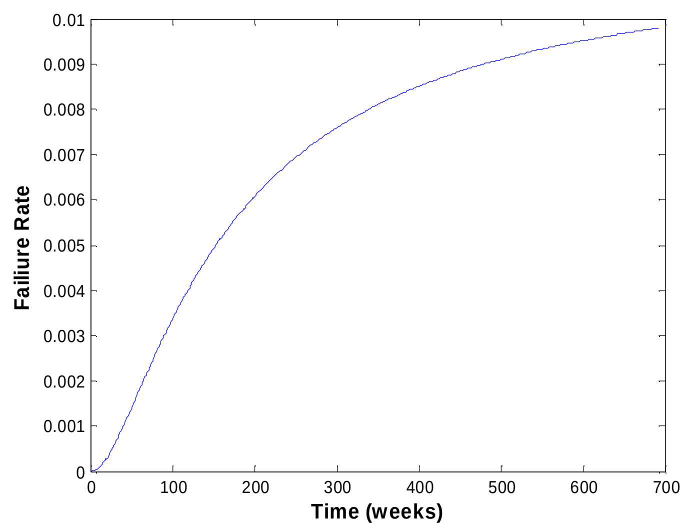

Fig. 4.16: Failure rate of insulation deterioration based on score ranking system

The scoring system method is attractive because it reflects more complete information about equipment condition; in addition, it builds on what many industry engineers already do. However, successful application of this scoring system needs relatively complete records of the component's conditions and rich experiences in adjusting the weighting factors from the field engineers.

4.4 Failure Rate Estimation of Circuit Breakers

This section starts with brief discussion about standard failure rate information of circuit breakers. Bayesian approach in estimation of failure rate is discussed followed by application of the approach to circuit breaker based on control circuit data. The method is still under development.

4.4.1 Standard failure rate information of circuit breakers

Various organizations have collected and published reliability data on electrical equipments. IEEE power system reliability subcommittee provided a comprehensive summary in standard 493-1997 of the published reliability data and listed the publications in the references as well [85]. The data are divided into two parts, consisting of data collected between 1976 and 1989 and that collected prior to 1976, covering a time period of 35 years. Statistical data like failure rate and downtime to repair or replace are provided to describe the failure characteristics of different equipments. The reliability data for circuit breaker is shown in table 4.15.

Since these reports cover a wide range of equipments, most reliability data for circuit breaker do not reach the detail of failure mode or sub-component of circuit breaker. Only a general classification is available on the circuit breaker type and rated voltage as the example provided in the above table.

TABLE 4.15: FAILURE RATES AND DOWNTIME PER FAILURE FOR CIRCUIT BREAKER

Subclass	Failure rate (failures per unit-year)	Actual hours of downtime per failure	
		Industry average	Median plant average
Fixed (including molded case)	0.0052	5.8	4.0
0-600V — All size	0.0042	4.7	4.0
0-600A	0.0035	2.2	1.0
Above 600 A	0.0096	9.6	8.0
Above 600 V	0.0176	10.6	3.8
Metal-clad draw-out type — All	0.0030	129.0	7.6
0-600 V — All sizes	0.0027	147.0	4.0
0-600 A	0.0023	3.2	1.0
Above 600 A	0.0030	232.0	5.0
Above 600 V	0.0036	109.0	168.0

Two exceptions are the data published by CIGRE 13.06 Working Group and the IEEE standard 500-1984 [86], [87]. CIGRE conducted two worldwide reliability surveys on circuit breaker reliability, and provided final reports on the data. The first enquiry covered the high voltage circuit breakers placed in service after 1964 with a service voltage of 63 KV and above. The second enquiry limited to single pressure SF6 gas circuit breakers placed in service after 1 January 1978 and with a rated voltage of 63 KV and above. Major and minor failure rates are provided for different characteristics, which can be fit into failure modes, and for important subassemblies of circuit breaker (Table 4.16).

TABLE 4.16: MF RATE BY CHARACTERISTIC FOR THE FIRST AND SECOND CIGRE ENQUIRY

CHARACTERISTIC	SECOND ENQUIRY		FIRST ENQUIRY	
	MF Rate	No Of Answers (% Of Total)	MF Rate	No Of Answers (% Of Total)
Does not close on command	0.164	116 (24.6%)	0.33	(33.7%)
Does not open on command	0.055	39 (8.3%)	0.14	(14.1%)
Closes without command	0.007	5 (1.0%)	0.02	(1.7%)
Opens without command	0.047	33 (7.0%)	0.05	(5.2%)
Does not make the current	0.011	8 (1.7%)	0.02	(1.6%)
Does not break the current	0.020	14 (2.9%)	0.02	(1.9%)
Fails to carry the current	0.010	7 (1.5%)	0.02	(2.5%)
Breakdown to earth	0.021	15 (3.2%)	0.03	(2.6%)
Breakdown between poles	0.010	7 (1.5%)	0.00	(0.5%)
Breakdown across open pole (internal)	0.024	17 (3.6%)	0.04	(4.0%)
Breakdown across open pole (external)	0.010	7 (1.5%)	0.01	(1.5%)
Locking in open or closed position	0.190	134 (28.5%)	—	—
Others	0.098	69 (14.6%)	0.31	(31.0%)
Total number of answers received		471		773

IEEE STD 500-1984 contains extensive reliability data for use in the design of nuclear power generating stations. The Chapter 3 of the standard lists the reliability data for a wide classification of circuit breakers and for different failure mode of each classification. References [85], [86] and [87] are three good sources for building the baseline of the reliability data for circuit breakers. If more detailed data of specific category are needed, readers are recommended to look for data from the following organizations.

- The Edison Electric Institute (EEI)
- The Institute of Electrical and Electronics Engineers (IEEE)
- The North American Electric Reliability Council (NERC)
- International Council on Large Electric Systems (CIGRE)
- The Institute of Nuclear Power Operations (INPO)
- Canadian Electric Association (CEA)
- Offshore Reliability Data (OREDA)

4.4.2 Bayesian updating

A Bayesian approach was developed in [88] for estimating the failure rate of power transformers. Because power transformer failures tend to be relatively rare events, empirical data for parameter estimation (e.g., the hazard function or the transition rates in Markov model) are generally spare. Thus, Bayesian method becomes a natural means to incorporate a wide variety of forms of information in the estimation process.

In the Bayesian framework, the uncertainties in the parameters due to lack of knowledge are expressed via probability distributions. This includes unknown distribution parameters. The Bayesian approach treats the unknown parameter, e.g., α or β in the Weibull characterization of the hazard function, or the transition rates in Markov model, as a random variable. Suppose t is an unknown parameter in our probability model. We first define a distribution, $P(t)$, which generally aim to be as uninformative as possible. $P(t)$ is the prior distribution which represents uncertainty about t based on prior knowledge, e.g. historical information. Then, the posterior distribution of t, given some observations of transformer condition monitoring data, is given by Bayes' Rule:

$$P(t|data) = \frac{P(data|t)P(t)}{P(data)} \tag{4.25}$$

Here $P(data) = \int P(data|t)P(t)dt$. Suppose the obtained condition monitoring information is represented by the following four attributes: x_1, x_2, x_3, x_4, which may represent the DGA results, temperature, and other information. Then the conditional distribution $P(data|t)$ takes the form of $P(x_1, x_2, x_3, x_4|t)$. By the product rule of probability, the conditional distribution can be factored as:

$$\begin{aligned} P(x_1, x_2, x_3 x_4|t) &= P_{X_4}(x_4|x_1, x_2, x_3, t) \times P_{X_3}(x_3|x_1, x_2, t) \\ &\times P_{X_2}(x_2|x_1, t) \times P_{X_1}(x_1|t) \end{aligned} \tag{4.26}$$

If x_1, x_2, x_3, x_4 are independently distributed, Eq. (4.26) can also be written as:

$$P(x_1, x_2, x_3, x_4|t) = P(x_1|t)P(x_2|t)P(x_3|t)P(x_4|t) \tag{4.27}$$

The resulting posterior distribution in (4.25) is a conditional distribution, conditional upon observing equipment-monitoring data. Thus, by using the above Bayesian approach, we can continuously update the equipment failure probability model based on available equipment condition monitoring information. A Bayesian framework of updating equipment hazard function is illustrated in Fig. 4.17.

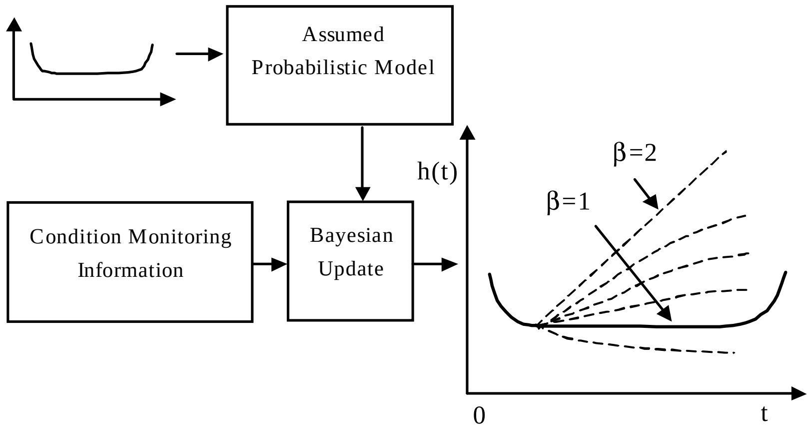

Fig. 4.17: Bayesian Analysis of Equipment Failure Rate

Reference [88] provides a Bayesian example for estimating transformer failure rate by updating the hazard function. By using the above Bayesian approach, we can continuously update the transformer failure distribution based on available equipment condition monitoring information. The approach can be applied to estimate failure rate of breaker, based on its control circuit data. The difficulty of this approach lies in the need of establishing the relationship (conditional distributions) between the monitoring data and the equipment's failure probability.

4.4.3 Application of Bayesian approach in failure rate estimation of circuit breakers

4.4.3.1 Background of breaker control circuit data

Various control circuit signals that can be monitored are mentioned in chapter 3. These signals contain information that can be used to evaluate the condition of different sub-assemblies of CB. For example, delayed transition of phase current indicates a slow operation; the excessive noise during the contact transition indicates a dirty auxiliary contact; the excessive voltage drop of DC voltage indicates a battery problem, etc [89]. In summary, two major categories of information can be identified from the control circuit signals. The first is the sequence (or coordination) of the transition times of different signals; the second are the abnormalities of each individual signal unrelated to time.

To extract relevant information from the signals, features reflecting the waveform abnormalities are defined, and signal parameters describing the features quantitatively are specified. Signal parameters are classified into two groups: a.) Events designated with T1~T10 describing the ten features, and b.) Waveform distortion parameters used for describing noise (NOI), ripple (RIP), voltage drop (DIP), etc [90]. An event refers to a signal transition or an unusual change in the waveform profile. A maximum of ten events have been identified and listed in table 4.17. Not all of these events will take place in a CB operation. For example, events related to X and Y coil will only appear in a close operation for certain types of CB. The first seven events are expected to show up in every data record as indicated in Fig. 4.18 [91].

TABLE 4.17: WAVEFORM ABNORMALITIES AND SIGNAL PARAMETERS [91]

EVENT #	EVENT DECRIPTION	SIGNAL
1	Trip or close operation is initiated (Trip or close	T1
2	Coil current picks up	T2
3	Coil current dips after saturation	T3
4	Coil current drops off	T4
5	B contact breaks or makes (a change of status	T5
6	A contact breaks or makes	T6
7	Phase currents makes or breaks	T7
8	X coil current picks up	T8
9	X coil current drops off	T9
10	Y coil current picks up	T10

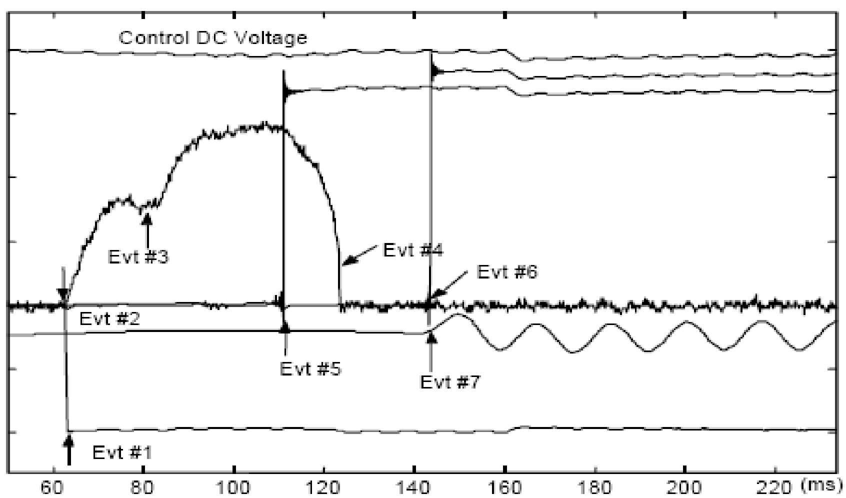

Fig. 4.18: Event features for a CB closing operation

Take the Trip Coil current as an example. A normal Trip Coil (TC) current makes a gradual transition to a nonzero value immediately after the Trip Initiate is activated. TC current continues to increase at a steady rate until it reaches a small dip before leveling off at the top of the waveform as shown in Fig. 4.19. The dip corresponds to "the point where the trip coil has released the trip linkage to allow the CB mechanism to operate" [89]. Then, the TC current may rise slightly or remain flat at its maximum value until it starts dropping down. The TC current signal should be fairly smooth except for the dip at the point T3. For a Trip Coil current signal, five parameters illustrated in Fig. 4.19 are selected to represent its features [92]. The Trip Coil current signals exhibit several different types of abnormalities. One type of abnormality found in the coil current is a delayed transition to a nonzero value. If the pick up of Trip Coil current is delayed, it will be represented by the parameter T2. Other parameters are defined in a similar way to characterize certain features in the signal.

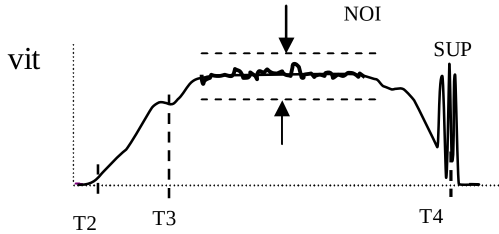

Fig. 4.19: Trip current waveform and parameters

4.4.3.2 Failure rate estimation model based on combination of Bayesian approach and Markov model

Signal processing and expert system module are designed to extract features from wave forms and evaluate the overall performance automatically [92]. Control circuit signals recorded over a period of time are analyzed with the signal processing module and a history of each parameter (T1-T10) is developed. As an example, timings of event 5 recorded during closing operation on a similar group of circuit breakers are given in table 4.18.

TABLE 4.18: TIMINGS OF EVENT 5 RECORDED ON SIMILAR GROUP OF BREAKERS

Manufacturer and Breaker type:: Westinghouse, R3			
Device Identifier	Parameter T5 of event 5 (seconds)	Device Identifier	parameter T5 of event 5 (seconds)
20B0	0.067188	20B0	0.059722
15A0	0.062153	19A0	0.057465
17A0	0.057292	21A0	0.048785
19A0	0.04566	10B0	0.061806
02B0	0.069444	09A0	0.059549
02B0	0.065799	11A0	0.062847
01A0	0.059375	13B0	0.041667
03A0	0.055556	12A0	0.057292
07A0	0.072222	14A0	0.059722
10B0	0.061979	14A0	0.059549
10B0	0.061979	13B0	0.059028
09A0	0.065972	13B0	0.061111
11A0	0.063715	12A0	0.065451
13B0	0.072743	21A0	0.069444
13B0	0.063021	19A0	0.059549
12A0	0.064931	17A0	0.060938
14A0	0.064583	15A0	0.082465
20B0	0.064236	11A0	0.055035

Next step is to fit a distribution for the parameter T5 using the recorded data. Probability plots are used to see the underlying distribution of the parameter. Fig. 4.20 shows the probability plot for Weibull distribution.

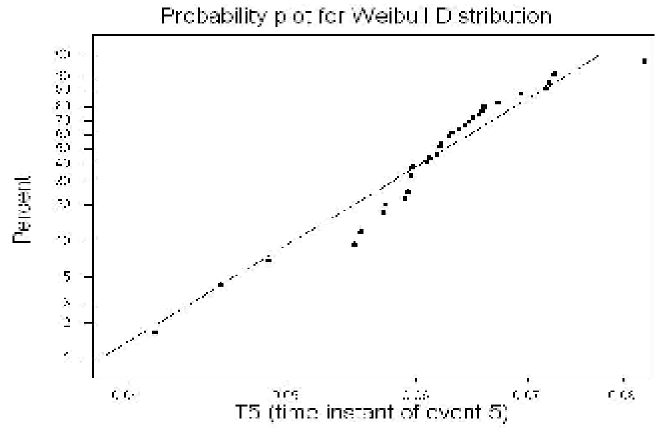

Fig. 4.20: Weibull probability plot for the parameter T5

Assume that the underlying distribution is Weibull. Then, the probability density function is defined as:

$$f(t\,|\,a,b)=\frac{b}{a}\left(\frac{t}{a}\right)^{b-1} e^{-\left(\frac{t}{a}\right)^{b}}, \qquad t \geq 0 \tag{4.28}$$

where *a and b* are called scale and shape parameters. Now, a model is to be developed which takes the probability distributions of all parameters (T1-T10) and determines the condition of circuit breaker. Then, Markov model approach can be used to compute transition rates between the states, and failure probabilities. We are exploring the ways to relate these individual signals to the breaker health. More research needs to be done in this area. An outline of the proposed model is shown in Fig. 4.21. We are proposing this method as an approach for future investigation.

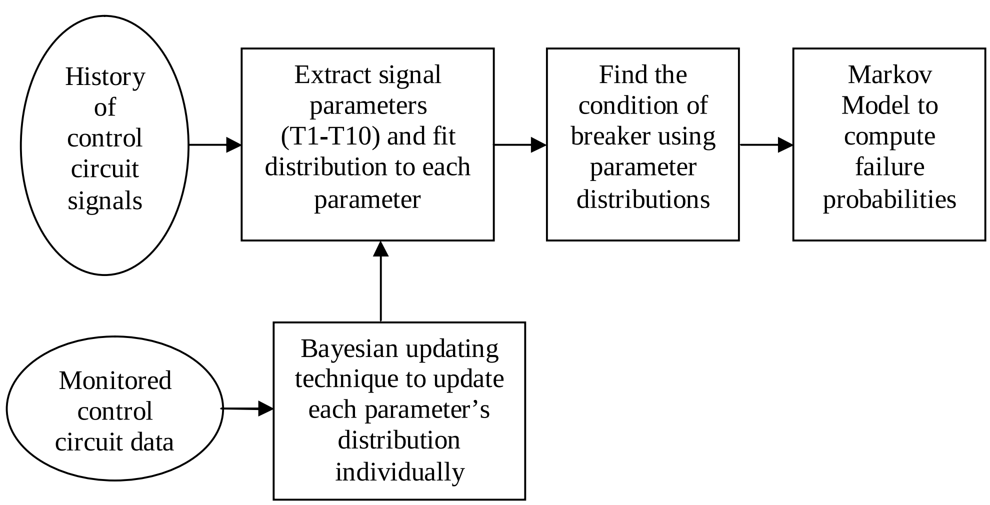

Fig. 4.21: Failure rate model based on breaker control circuit data

The procedure to update the distribution of each parameter (T1-T10), using Bayesian updating technique, is summarized below.

Step 1: Develop a history of one control circuit parameter, for example T5, as shown in Table 4.16

Step 2: Fit a probability distribution for the data. In this case, assume that the underlying distribution is Weibull, just for the purpose of illustration. The parameters of the Weibull distribution are a and b, which can be denoted by a vector, $q = (a, b)$

Step 3: Assume a prior distribution for q to be $p(q)$.

Step 4: Construct a likelihood function, $L(t_5|q) = \frac{b}{a}\left(\frac{t_5}{a}\right)^{b-1} e^{-\left(\frac{t_5}{a}\right)^b}$

Step 5: The posterior distribution for q is, $p(q|t_5) = \frac{L(t_5|q)p(q)}{\int L(t_5|q)p(q)dq}$

Step 6: Follow the above steps (step 1 to step 5) for all other control circuit parameters. Now we have posterior distributions of all parameters, $p(q_i)$, i = 1,2,…..10 corresponding to T1-T10.

Step 7: Find the condition of the breaker using these posterior distributions.

Step 8: Use Markov model to find failure probabilities.

We are currently working on various possibilities to relate these posterior distributions to the health of the breaker.

4.4.4 Failure rate reduction estimation

Quantizing the effect of maintenance is a challenging task for reliability engineers. It is not easy to see the effect of maintenance, especially with equipment like circuit breaker which rarely operates. This model permits to see the effect of maintenance in terms of reduction in failure rate. First, the failure rate will be estimated using history of control circuit data. Now, breaker will be operated and control circuit signals will be recorded after maintenance. The new data set is used to update the individual parameter distributions using the Bayesian updating technique, which was explained in section 4.4. Basically, the distribution parameters *a and b* (for the case of Weibull distribution) of each signal parameter (T1-T10) will be updated using Bayesian theorem. Once all the individual parameter distributions are updated, breaker failure rate will be estimated again. The difference in probabilities at particular time instant will be the direct result of maintenance.

4.5 Conclusions

Failure rate estimation for transformer and circuit breaker is very useful in asset management based on reliability centered maintenance, since it characterizes the state of each piece of equipment to be maintained in a way that formal decision algorithms can utilize. Different methods of failure rates estimation are illustrated and compared in this chapter. A new method of Hidden Markov Model (HMM) is introduced and case studies are performed on DGA data and health scores. Circuit breaker failure rate estimation model based on combination of Bayesian approach and Markov model is introduced.

5. Mid-Term Maintenance Scheduling

5.1 Introduction to Asset Management

Asset management is the process of actively allocating fixed economic resources in order to optimize the capture of revenue and maximize overall profitability. It utilizes a wide range of management decisions such as capacity allocation, asset purchase/lease decisions and pricing. It has become one of the most powerful levers in determining relative profitability in many business and most types of service provision [93].

In the electric power industry, asset management has become one of the most challenging problems today. It is concerned with the investment, operation, maintenance, replacement, and ultimate disposal of the equipment used to deliver electric power, including generation, transmission, and distribution facilities. Its increasing importance in recent years has occurred largely because the decreased availability of capital has inhibited investment in new facilities, and therefore companies in many cases have continued to maintain and operate increasingly aged equipment. As a result, companies find that maintenance needs often exceed available financial and human (labor) resources so that the problem to be solved is not what are the minimum resources needed to achieve a particular reliability level, but rather, what is the maximum reliability level that can be achieved with a limited amount of resources.

Asset management decision problems have the following characteristics:

1. There are strong interdependencies between physical performance of individual assets, physical performance of the overall system, and economic system performance;
2. Resources are limited;
3. There exist important uncertainties in individual component performance, system loading conditions, and available resources;
4. There may exist multiple objectives, e.g., system performance and economic efficiency.

These four characteristics are coupled and involve resource allocation with the objective to minimize cost and risk. The industry has made and continues to make major strides in developing solutions. However, there has been significantly less progress in data management, information processing and associated algorithms, risk assessment methods, and decision-making paradigms, especially in process coordination. The goal in this work is to develop strategies in asset management of transmission systems, especially in maintenance selection and scheduling, which can coordinate these solutions effectively and systematically and develop corresponding methods and algorithms.

For vertically integrated utility companies, maintenance practices receive a significantly larger percentage of resources for generation than for transmission and distribution (T&D) because the generation equipment represents a much larger percentage of the total capital investment in facilities. However, for today's companies that own and/or operate transmission and/or distribution circuits but little or no generation, the T&D assets represent almost all of their capital investment. The total replacement value of the lines alone (excluding land) has been conservatively estimated at over $100 billion dollars [94] and at least triples when including transformers and circuit breakers. As a result, maintenance of the aging T&D facilities is a high priority, and the percentage of resources allocated is high relative to the vertically integrated company. It is largely this fact that has motivated the high industry-wide interest in T&D asset management as well as the work reported herein. This work focuses entirely on transmission maintenance, although the concepts are applicable to distribution maintenance as well.

5.1.1 Current maintenance scheduling methods

The purpose of maintenance is to extend the component's lifetime or at least the mean time to the next failure. Maintenance approaches may be divided into two basic classes, corrective maintenance and preventive maintenance [95]. In corrective maintenance (CM), also known as run-to-failure, a piece of equipment is not maintained until it fails. This approach is appropriate when the cost of failure is not significant, which is obviously not suitable for most transmission system equipment. In preventive maintenance (PM), on the other hand, the maintenance is performed in order to avoid a failure. Preventive maintenance strategies may be further divided into several different types: time based maintenance, condition based maintenance, and reliability centered maintenance (RCM) [96]. Time based maintenance is usually a conservative (and costly) approach, whereby inspections and maintenance are performed at fixed time intervals, often, but not necessarily, based on manufacturer's specifications [97]. Condition based maintenance triggers a maintenance from information characterizing the equipment condition, since condition monitoring may identify incipient failures [98]. Relative to time based maintenance, condition based maintenance typically extends the interval between successive maintenances and therefore typically incurs less cost, although it requires a significant amount of infrastructure investment (e.g., sensors, diagnostic technology, communication channels, data repositories, processing software) to measure, communicate, store, and utilize the necessary information characterizing the state of the equipment. Reliability centered maintenance, on the other hand, utilizes condition monitoring information together with an analysis of needs and priorities and generally results in a prioritization of maintenance tasks based on some index or indices that reflect equipment condition and the equipment importance. Figure 5.1 gives the overview of the classification of different maintenance strategies [99]. From this figure, we can see that the reliability centered maintenance accounts for both importance and condition of the facilities.

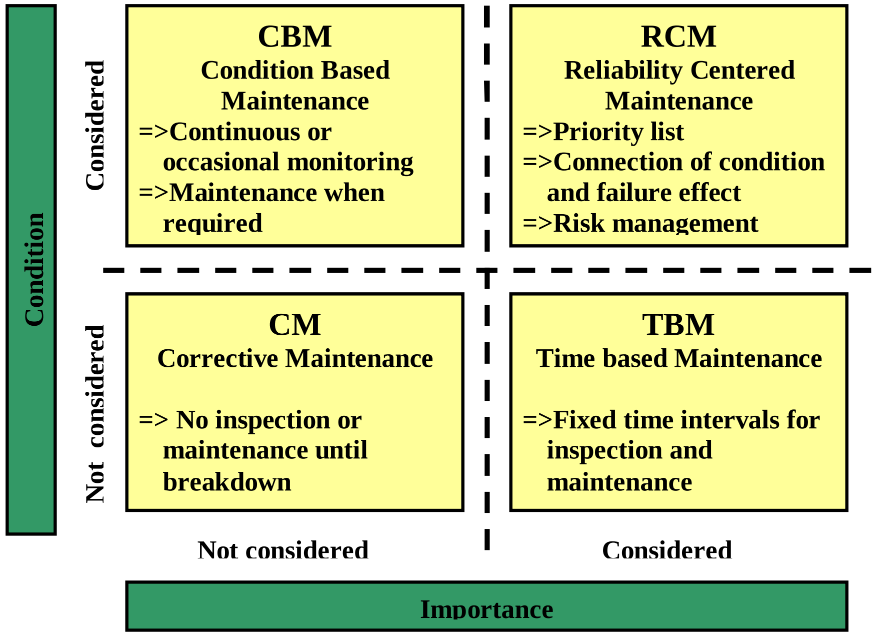

Fig. 5.1: Classification of maintenance

Reliability centered maintenance is an on-going process which determines the maintenance practices to provide the required reliability at the minimum cost. It can help reduce the cost of maintenance significantly. In this work, RCM has the following attributes:

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

RCM is a strategy for examining assets in a systematic manner to establish priorities with the final objective to maintain reliable performance of each component with cost effective maintenances. The concept of RCM was first developed in the commercial sector to optimize the maintenance procedure in the airline industry. The result was a report entitled "Reliability-Centered Maintenance", which became the foundation for modern day RCM processes [100]. Today, a number of processes called RCM are applied in nearly every major sector of industry, such as gas pipelines [101], mass traffic system [102], and telecommunications [103]. The underlying principle in RCM is that maintenance scheduling should be related to the failure likelihood so that a piece of equipment is maintained when its failure probability increases significantly. In electric power systems, different reliability centered maintenance strategies have been studied and applied in with different objective functions and optimization methods. Many methods utilize heuristic indices to represent the priority of the maintenance tasks, such as using a benefit-cost ratio [104], health index (probability of system being in 'healthy' state) [105], expected energy not supplied [106], and some weighted combinations of statistics of component performance [107]. Other methods use objectives like minimizing the cost of maintenance and operation, while satisfying system reliability constraints [108]. Shahidehpour [109] developed a method of describing objectives and constraints of the maintenance scheduling in the restructured power system. He also categorized the maintenance activities into different time scales (mid-term and short-term). W. Li in BC Hydro [106] uses Monte-Carlo simulation method and linear programming optimization model to perform the reliability evaluation of the transmission system with planned outage, and then schedules the maintenance with regard to the system operation constraints.

Comparing to the current RCM strategies, the work described in this chapter utilizes risk assessment instead of heuristic indices and instantaneous failure rate estimation instead of constant failure rate. In addition, a novel optimization method and resource reallocation solution is developed to implement a systematic maintenance solution which enables the asset manager to allocate resources strategically and economically.

5.1.2 Maintenance scheduling in different time horizons

Transmission maintenance scheduling is an optimization problem with complex constraints. The schedule may span over several time periods and may impact the reliability of the system. It can be divided into long-term, mid-term and short-term maintenance scheduling methods, each of which is unique due to the objective and available data. Maintenance strategies for different time scales should be incorporated. Maintenance scheduling strategies with different time scale and their scheduling constraints and methods are introduced as follows:

1. <u>Long-term transmission maintenance scheduling</u>: Long term maintenance scheduling is based on individual component performance and the objective is to maximize the residual life of equipments while minimizing the cost of maintenance and inspection plus the cost of repair and replacement. The typical result of such analysis is recommended maintenance/inspection interval (usually in the units of years) for components. The impact on the network is normally not considered.

2. <u>Mid-term transmission maintenance scheduling</u>: In mid-term transmission maintenance asset management, the scheduling is based on the forecast of network and loading condition for a period of time (usually one year), with limited resources to be allocated in the maintenance period. The period is divided into intervals (e.g., weeks) and a maintenance scheduling strategy for the intervals is derived to satisfy all scheduling constraints and maximize the system reliability level with the condition of load variations. The key point here is that in a budget cycle, allocation of available

economic resources for performing maintenance on a large number of facilities can be done strategically, as a function of risk (associated with the cost of network security problems and component damage) so as to minimize risk of wide-area bulk transmission system failures.

3. Short-term Transmission Maintenance Scheduling: Both bilateral and nodal priced electricity markets are heavily impacted by transmission outages, and reliability criteria cannot be violated. Identifying precise day and time for maintenance tasks that require transmission equipment outage requires a significant amount of human attention, using power flow programs together with generation schedules, and forecasted loadings, during the few days or even hours preceding the task [109].

So we can see that maintenance scheduling with different time scales should be coordinated. Long term maintenance scheduling gives the recommended maintenance interval for every component. Mid-term scheduling give the allocation of maintenance resources to optimize the system reliability and short-term scheduling decides the best time for performing the maintenance to maximize the revenues, with the constraint of contracts and transactions. Figure 5.2 depicts the incorporation of maintenance schedules for different time scales. In this chapter, we will focus on the mid-term maintenance scheduling of transmission equipment.

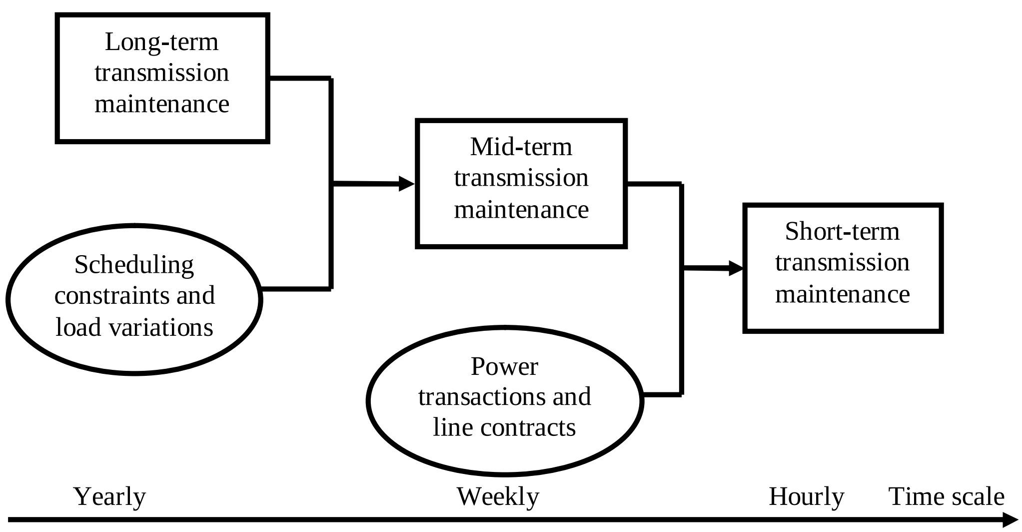

Fig. 5.2: Transmission maintenance incorporation for different time scales

5.1.3 Structure of mid-term maintenance scheduling

The risk-based maintenance approach has three steps: 1) mid-term simulation with risk-based security assessment performed at each hour, 2) risk reduction calculation, and 3) optimal selection and scheduling. These steps are illustrated in Fig. 5.3, and taken as a whole are referred to as the Integrated Maintenance Scheduler (IMS). Here, the long-term sequential simulator, when integrated with hourly risk-based security assessment capability, provides year-long hourly risk variation for each contingency of interest. The risk-based security assessment performs a contingency analysis for each hour using power-flow analysis for overload, cascading overload, and low voltage, and continuation power flow for voltage instability analysis.

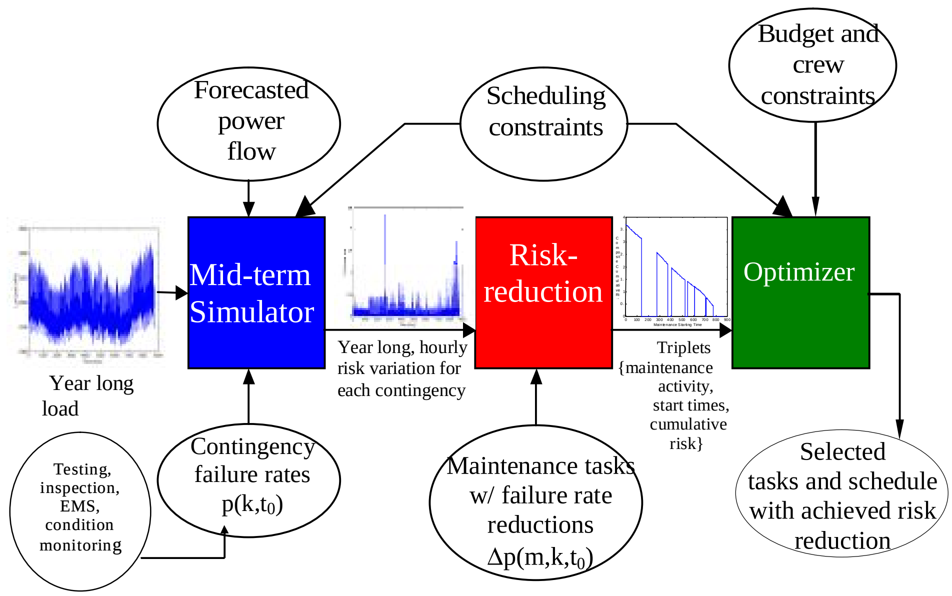

Fig. 5.3: Integrated Maintenance Scheduler (IMS)

The year-long hourly risk variation, when combined with a set of proposed maintenance activities and corresponding contingency probability reductions, yields cumulative-over-time risk reduction associated with each maintenance activity and associated possible start times. This cumulative risk-reduction captures, cumulatively over the next year (or more), the extent that failure of the component will adversely affect the system or other components in the system. Then, step 3) is an optimization whereby we select a number of task-time options subject to the constraints on feasible-times, total cost, and labor, with the objective to maximize the cumulative-over-time risk reduction.

5.2 Risk Assessment of an Electrical System

The deterministic method, where all contingencies in a designated category, or list, must satisfy some performance criterion, has been the primary means of performing power system security assessment for a long time. However, it does not yield a quantitative evaluation of security level which can be used within the objective function of a mathematical program. As a result, we have used the risk-based security analysis on transmission maintenance scheduling [110] in the process developed to optimize maintenance resources.

5.2.1 Computation of risk

The risk index is an expectation of severity, computed by summing over all possible outcomes the product of the outcome probability and its severity (or consequence), as in

Fig. 5.4. By assigning severity values to each contingency, the risk can be computed as the sum over all terminal states of their product of probability and severity, given by eq. 5.1:

$$\mathrm{Risk}(\mathrm{Sev} \mid X_t) = \sum_i \Pr(E_i)\mathrm{Sev}(E_i \mid X_t) \tag{5.1}$$

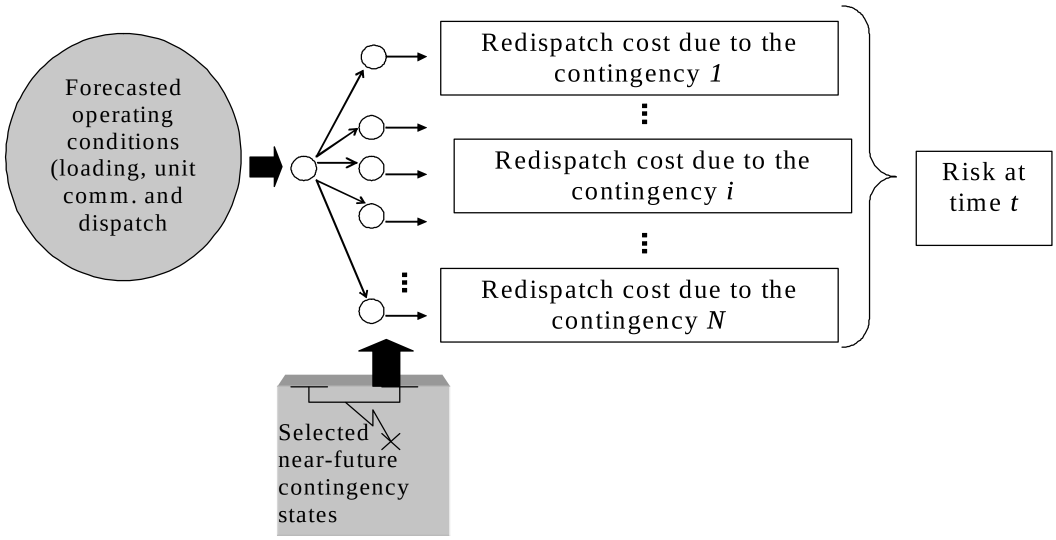

Fig. 5.4: Illustration of risk calculation for a given operating condition

Here:

- X_t is the forecasted operating condition at time t, generally specified in terms of loading. It is the expected value of the loading condition at time t.
- E_i is the i^{th} contingency. $Pr(E_i)$ is the probability for the i^{th} contingency. Here, we assume the existence of a contingency list.
- $Sev(E_i|X_{t,f})$ quantifies the severity, or consequence, of the i^{th} contingency E_i occurring under system operating condition at time t. It represents the severity associated with problems caused by the contingency. It can be very versatile according to the concern of the utility company. It can be represented with indices associated with network security problems such as overload, low voltage, voltage cascading, and cascading overloads. Our approach for evaluating this function is based on post-contingency power flow analysis for redispatch cost due to the contingency. We further describe the severity functions in the next section.

5.2.2 Modeling of severity

Severity provides a quantitative evaluation of what would happen to the power system in the specified condition in terms of severity, impact, consequence, or cost. CIGRE Task Force 38.02.21 [111] identified it as a challenging problem in probabilistic security assessment. One measure that is widely thought appropriate is loss of load. We have consistently resisted using such a measure because it is only an indicator and not indicative of what would really happen, yet it requires significant additional modeling and computation. To make the point, consider a line loaded to 105% of its emergency thermal rating. It is unlikely that an operator would interrupt load to off-load this line. Most likely, the operator will try to re-dispatch one or more generators to reduce the loading on the line. In many cases, an operator may even do nothing if the overload duration is relatively short. But a load-interruption based consequence measure would apply some criteria/algorithm to identify the load interruption necessary to reduce the line loading to 100%, in spite of the fact that load interruption would not occur. Although evaluation of the consequence in this way may be useful, it is not worth the additional computation if other approximations can be found that are easier and faster to compute.

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

$$\mathrm{Sev}(\mathrm{E}_i, \mathrm{X}_{t,j}) = \mathrm{Sev}_{\mathrm{system}}(\mathrm{E}_i, \mathrm{X}_{t,j}) + \mathrm{Sev}_{\mathrm{component}}(\mathrm{E}_i, \mathrm{X}_{t,j}) \tag{5.2}$$

5.3 Risk-Based Long-Term Simulation

Cumulative risk assessment performs sequential, hourly simulation over a long-term, e.g., 1 year, and it evaluates the security levels in terms of quantitative indices, reflecting risk of overload, cascading overload, low voltage, and voltage instability. The risk index for a single contingency is an expectation of severity, computed as the product of contingency k probability $p(k)$ with contingency severity $sev(k|m,t)$, where m indicates the m^{th} maintenance task and thus the network configuration in terms of network topology and unit commitment, and t indicates the hour and thus the operating conditions in terms of loading and dispatch. The risk is given by $R(k,m,t)= p(k)sev(k|m,t))$. A reference "base case" network configuration (with no maintenance task) is denoted with $m=0$. The severity function $sev(k|m,t)$ comprises two parts: system related severity function $sev_{sys}(k|m,t)$ and component damage severity function $sev_{comp}(k|m,t)$. The system related severity function $sev_{sys}(k|m,t)$ captures the contingency severity in terms of redispatch cost due to the contingency, while $sev_{comp}(k|m,t)$ describes severity related to component damage and repair cost.

The contingency risk associated with any given network configuration and operating condition is computed by summing over the all N contingencies:

$$R(m,t) = \sum_{k=1}^{N} p(k)\left[sev_{sys}(k \mid m,t) + sev_{comp}(k \mid m,t)\right] \tag{5.3}$$

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

The long-term cumulative risk simulator performs a full N-contingency security assessment for each hour in the year, and associated risk indices are computed per eq. (5.3). A contingency list is developed to reflect outages that may occur as a result of transmission equipments failures such as transformer and tap changer failure, tree contact and circuit breaker's failure to open. Given a contingency set, the simulator develops the power flow case and then, for each contingency, performs an optimal power flow to calculate the extra redispatch cost needed to avoid system overload, as severity of the contingency. The sequential approach used in our simulator evaluates a trajectory of operating conditions over time. The key features that drive the design are: (1) ***Hourly assessment***: In making a one-year risk computation, some components may see highest risk during off-peak or partial-peak conditions, when weak network topologies, weak unit commitment patterns, or unforeseen flow patterns are more likely to occur. (2) ***Sequential simulation***: Load-cycles, weather conditions, unit shut-down and start-up times, and maintenance strategies are examples of chronologically dependent constraints that affect system reliability.

5.3.1 System severity

Redispatch is a common operation when a contingency brings some threat to the system security, and we believe the cost of redispatch is an evaluation of the most direct consequence of the contingency. When a minor contingency occurs, if it does not bring much security concern to the system, usually a redispatch is not necessary. Redispatch is needed if a reliability criterion is violated, such as line overloads. Then the severity can be evaluated with the cost due to the redispatch.

Since branch failure due to overloading is a relatively slow process, a system operator usually has the time needed to perform redispatch so that the power flow of related line is adjusted to its nominal limit. In order to simulate the action of system operator, we use a linear program to model what a system operator will do to minimize the cost of redispatch. The system severity of the contingency can be defined as difference of extra cost of the redispatch due to the contingency:

$$Sev(E_i \mid X_t) := Cost(E_i \mid X_t) - Cost(0 \mid X_t) \tag{5.4}$$

where $Cost(E_i \mid X_t)$ and $Cost(0 \mid X_t)$ is the cost of energy production under contingency E_i and normal condition of the system respectively.

The minimization of redispatch cost is achieved by utilizing a DC OPF (Optimal Power Flow) and the objective function is:

$$Min : Cost = \sum_{m=\{1,\ldots,N_g\}} Cost(PG_m) \tag{5.5}$$

where the $Cost(PG_m)$ is the cost function of generator m. N_g is the number of the generator. The cost curve is represented as multiple segments linear cost functions, as shown in Fig. 5.5.

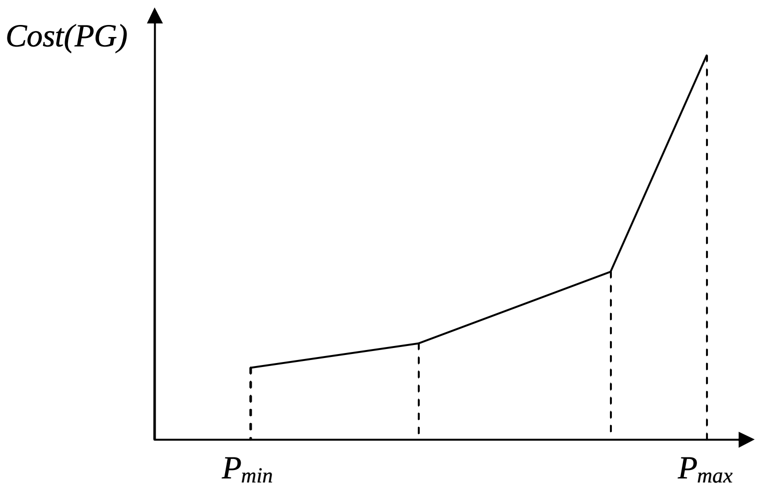

Fig. 5.5: Piecewise linear cost functions

Table 5.1 gives an example of the incremental cost of a machine with the increase of the output. One generator represented by a piecewise linear cost function is segmentized with an incremental cost associated with each segment. So the total cost of the machine is represented by:

$$Cost(PG_m) = \sum_{i=1}^{N_m} a_i P_m(i) \tag{5.6}$$

where N_m is the total number of the segments in Fig. 5.5, and α_i is the incremental cost for each segment. $P_m(i)$ is the output of generator m in the segment i, with its maximum as the length of the segment. Due to convexity, where incremental cost increases with the increase of output, as in Table 5.1, the optimal programming will guarantee that for each generator output $P_m(j)=0, (j>i)$ before $P_m(i)$ reaches its maximum.

TABLE 5.1: EXAMPLE OF INCREMENTAL COST OF MACHINE WITH THE INCREASE OF THE OUTPUT

(MW)	Incremental cost ($)
79	25.575
155	25.575
174	25.8323
194	26.6848
212	28.1325
230	30.1754
249	33.1297

The vector of generator output is represented as

$$PG = (P_1(1), \mathbf{L}, P_1(N_1), P_2(1), \mathbf{L}, P_{N_g}(N_{Ng}))^T \tag{5.7}$$

where $N_G = \sum_{m=1}^{N_g} N_m$ is the total cost function segments for all the generators in the system, and $P_m(i)$ is the output of each segment accordingly.

The objective function in (5.5) is subject to the following constraints:

$P_m(i)^{\max} \geq P_m(i) \geq 0, \quad m \in (1,\ldots,N_G)$	Each generator segment generates between 0 and $P_m(i)^{\max}$
$g_i PB_i^{\max} \geq PB_i \geq -g_i PB_i^{\max}, \quad i \in (1,\ldots,N_B)$	The power flow in each branch (line or transformer) is limited by its rating;
$B^T \times q = P^{inject} = (PG - PD)$	DC power flow equations;
$(D_B \times A) \times q - PB = 0$	Branch flow equations;

where

N_G is the total number of segments in the cost function of generators;

N_B is the total number of branches ;

PG_m is the real power generation of generator m;

$PG_m^{\max}$ and $PG_m^{\min}$ are the maximum and minimum real power generation of generator m respectively;

PB_i is the real power flow in branch i;

$PB_i^{\max}$ is the short term rating (MVA) of i;

g_i is the constant factor to account for the power factor of the power flow in branch i and $1 \geq g_i \geq 0$;

B^T is the $N \times N$ B - matrix used in DC power flow and N is the number of buses;

A is the $N_B \times N$ adjacacy (or incidence) matrix;

D is the $N_B \times N_B$ diagonal matrix where the i^{th} diagonal element is the admittance of the i^{th} branch ;

q is the $N \times 1$ vector representing the voltage angles in radius at each bus; and

P^{inject} is the $N \times 1$ vector representing the net power injection for each bus, and its element P_i^{inject} can be calculated by $P_i^{inject} = PG_i - PD_i$

In order to solve the above linear programming problem, we need to standardize the above inequalities and equalities so that it can be solved with standard LP methods in most commercial software. The objective function and the constraints are specified in the following standard format:

Objective:

$$\max f^T \cdot x \tag{5.8}$$

Constraints:

$$A_{eq} \cdot x = b_{eq} \tag{5.9}$$

$$lb \le x \le ub \tag{5.10}$$

We define

$$PG = \begin{pmatrix} PG_1 \\ PG_2 \\ \vdots \\ PG_{N_G} \end{pmatrix}_{(N_g \times 1)} ; \quad PB = \begin{pmatrix} PB_1 \\ PB_2 \\ \vdots \\ PB_{N_B} \end{pmatrix}_{(N_B \times 1)} ; \quad q = \begin{pmatrix} q_1 \\ q_2 \\ \vdots \\ q_N \end{pmatrix}_{(N \times 1)} \tag{5.11}$$

$$PG^{\max} = \begin{pmatrix} PG_1^{\max} \\ PG_2^{\max} \\ \vdots \\ PG_{N_G}^{\max} \end{pmatrix}_{(N_g \times 1)} ; \quad PB^{\max} = \begin{pmatrix} g_1 PB_1^{\max} \\ g_2 PB_2^{\max} \\ \vdots \\ g_{N_B} PB_{N_B}^{\max} \end{pmatrix}_{(N_B \times 1)} ; \quad q^{\max} = \begin{pmatrix} p \\ p \\ \vdots \\ p \end{pmatrix}_{(N \times 1)} \tag{5.12}$$

$$PG^{\min} = \begin{pmatrix} PG_1^{\min} \\ PG_2^{\min} \\ \vdots \\ PG_{N_G}^{\min} \end{pmatrix}_{(N_g \times 1)} ; \quad PB^{\min} = \begin{pmatrix} -g_1 PB_1^{\min} \\ -g_2 PB_2^{\min} \\ \vdots \\ -g_{N_B} PB_{N_B}^{\min} \end{pmatrix}_{(N_B \times 1)} ; \quad q^{\min} = \begin{pmatrix} -p \\ -p \\ \vdots \\ -p \end{pmatrix}_{(N \times 1)} \tag{5.13}$$

$$x = (PG^T \quad PB^T \quad q^T) \tag{5.14}$$

$$f_i = \begin{cases} a_m^T & \text{when } i \in [1, N_G] \\ 0 & \text{when } i \notin [1, N_G] \end{cases} \tag{5.15}$$

where a_m is the coefficient of the linear piecewise cost function corresponding to PG_m

$$A_{eq} = \begin{pmatrix} 0 & I_{N_B \times N_B} & -D_{N_B \times N_B} \times A_{N_B \times N} \\ I_{N \times N_G} & 0 & -B^T{}_{N \times N} \end{pmatrix}_{(N_B + N) \times (N_G + N_B + N)} \tag{5.16}$$

where the submatrix *A*, *D* and *B* inside A_{eq} are what we have defined at the beginning of this section, and I is the identity matrix.

$$B_{eq} = \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}_{(N_B+N)\times 1} \tag{5.17}$$

$$ub = \begin{pmatrix} PG^{\max} \\ PB^{\max} \\ q^{\max} \end{pmatrix} \tag{5.18}$$

$$lb = \begin{pmatrix} PG^{\min} \\ -PB^{\max} \\ q^{\min} \end{pmatrix} \tag{5.19}$$

After solving the LP to obtain a feasible solution for x, we get the minimum cost of the economic dispatch of the system, based on the network condition which is characterized by the matrices A,D,B and loading conditions PD. Then we can calculate the risk of the system with (5.4).

5.3.2 Component severity function

The system severity function described above represents the system consequence in terms of operational corrective actions such as redispatch cost necessary to relieve the reliability violations following an outage of a circuit. The representation is reasonable under the following assumptions:

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

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

(a) transformer failure can potentially involve significant physical damage

(b) transformer outage time may vary significantly as a function of

   i. the extent of the damage,

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

We make two modifications to the severity function to account for these issues. First, to account for transformer damage, we provide a non-zero value of component severity function $Sev_{component}$ in eq. (5.2). Assuming, conservatively, that any transformer failure requires its replacement, the component severity function, which represents the cost of purchasing a new transformer of the same MVA rating, is given by eq. (5.20):

$$Sev_{component}(E_i \mid X_t) = C \times MVA_{rated} \tag{5.20}$$

where MVA_{rated} is the MVA rating of the transformer and C is a constant that can be obtained based on eq. (5.21):

$$C = \frac{\text{replacement cost of a 100 MVA xfmr}}{100} \tag{5.21}$$

where obviously the replacement cost of a 100 MVA transformer must be estimated. We have used the estimates of replacement cost as $1,000,000. These estimates yield C=$10,000/MVA.

Second, to account for variation in transformer outage duration, based on the availability of spares, we require input data for each transformer indicating whether there is no spare available, an available off-site spare, or an available on-site spare. Because outage duration affects the system consequences, the information on spares is utilized to scale the system severity functions according to Table 5.2.

TABLE 5.2: SYSTEM SEVERITY SCALING FACTORS

Availability of spares	System severity scaling factor
No spare	10
Off-site spare	5
On-site spare	2

The implications of the scaling factors in Table 5.2 are that the redispatch costs for transformer outages with

- no spare will be 10 times that of replacement cost of a transfomer
- off-site spare will be 5 times that of replacement cost of a transformer
- on-site spare will be 2 times that of replacement cost of a transformer

and these factors should be adjusted based on field engineer’s suggestion for each individual transformer.

5.3.3 Components modeled in the simulation

Different types of equipments and the consequences of their failures should be modeled in the simulation. In our simulation, we have modeled several failure modes of the components in transmission system, as listed in Table 5.3.

TABLE 4.3: FAILURE MODES AND CORRESPONDING MAINTENANCE ACTIVITIES

Contingency	Failure modes	Maintenance activity	Frequency
Transmission line outage	Tree contact	Tree trimming	1 per year
	Line or equipment failure	Insulator cleaning, replacement and hardware tightening/replacement near the tower position.	1 per year
Transformer outage	Core problem, mechanical failure and general ageing	Transformer major maintenance (complete analysis including parts replacement, complete off-line testing and corresponding maintenance and oil change.)	1 per 6 years
	Oil deterioration	Transformer minor maintenance: (annually test and oil filtering makeup including some minor maintenance and oil analysis and filtering).	1 per year
Circuit Breaker Failure	Mechanical failure, excessive wear and maladjustments	Circuit breaker inspection and maintenance (visual inspection and operation test, repair and replacement of the cracked mechanical parts and polish the contact surface, lubrication)	100 operations

Most transmission maintenance practices perform a package of maintenance activities at the same time instead of performing a maintenance corresponding to each failure mode at a different time. This is because many inspection or maintenance activities may require the component to be removed out of service, or even opened or disassembled. So scheduling the inspection and maintenance activities at the same time may reduce the frequency of the outage and the cost of maintenance.

For transmission lines, tree contact and insulator failure are the two most common failure modes. For transformers, mechanical failure and insulation oil deterioration are the two most common failure modes. For circuit breakers, the failure which is caused by mechanical excessive wear and maladjustments is a major failure mode and could cause the failure of protection action. In the work reported in this chapter, for the circuit breaker, we only consider the failure mode of “failure to open.” Because this failure delays clearing of a faulted condition, it can result in high cost of repair, damage to other components, and instability of the system.

In the developed simulator, the failure of transmission lines and transformers are treated similarly (just a circuit outage), but the failure of circuit breakers requires identification of all components in the protection groups delineated by the circuit breaker. A method using switch-breaker topology data to identify the contingency resulting from a faulted condition followed by circuit breaker failure is given [112]. In the simulator developed in this project, an assumption was made that for each faulted circuit breaker, all of its neighboring circuit breakers function well and open to isolate the faulted protection groups. Based on this assumption, we have developed an automatic search routine within our simulator to obtain the system configuration following a faulted condition of post contingency.

5.3.4 Speed enhancement

The sequential simulator performs contingency-based risk assessment for each hour in the year. If there are N contingencies, 8760 x N different risk assessments must be performed. This is computationally intensive, so decreasing the computation time is an important concern. The most important speed enhancement we have used here is to avoid redundant assessments for similar operating conditions.

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

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

$$abs\left(\frac{P_{gki}-P_{gkj}}{P_{gki}}\right)< e \text{ and } abs\left(\frac{P_{gki}-P_{gkj}}{P_{gkj}}\right)< e \tag{5.22}$$

$$abs\left(\frac{P_{lki}-P_{lkj}}{P_{lki}}\right)< e \text{ and } abs\left(\frac{P_{lki}-P_{lkj}}{P_{lkj}}\right)< e \tag{5.23}$$

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

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

   a. Calculate the load flow of the next hour;

   b. Identify the branch with the lowest load flow;

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

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

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

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

5.4 Quantification of Maintenance Benefits-Risk Reduction Calculation

We have developed a table [113] matching maintenance tasks to the failure modes that they affect, based on literature review together with resources obtained from industry contacts, where a maintenance task is, with respect to a particular component (line, transformer, circuit breaker), a task that changes the state of the component. On the other hand, a monitoring activity such as inspection, testing or sampling is a task that provides information useful in assessing the component state. The change in component state resulting from a maintenance task should result in either failure probability reduction or extended life or both.

The hazard function is used to illustrate these benefits. A hazard function for a typical transmission equipment failure mode is shown in Fig. 4.6. This curve can be divided into two periods: 1) almost constant failure rate period and 2) deterioration period with increasing failure rate. The level of each benefit from maintenance, with respect to a particular failure mode for a specific component, is associated with where on the hazard curve the component lies when the maintenance is performed. If the maintenance is performed during the deterioration period, e.g., at time t_f in Fig. 4.6, the benefit comes mainly from the decrease of failure rate, which results in a decrease in failure probability Δp, but for maintenance performed during the constant failure rate period, e.g., at time t_d, the benefit comes mainly from the life extension Δt because of delay of the deterioration period (t_d in Fig. 4.7).

Good estimates of Δp and Δt resulting from a maintenance task may be obtained by statistically characterizing the failure mode deterioration level before and after the maintenance using condition assessment tools in chapter 3. The effect of maintenance m on component k completed at time t is expressed through its risk reductions due to failure rate reduction and life extension, as:

$$\boldsymbol{CRR(m,k,t) = CRR_1(m,k,t) + CRR_2(m,k,t) + C(m,k,t)} \tag{5.24}$$

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

5.4.1 Risk reduction due to failure rate decreases

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

$$\begin{aligned}\Delta CR(m,t_f) &= \Delta CR_{during}(m,t_f) + \Delta CR_{after}(m,t_f) \\ &= \int_{t_f - T_d}^{t_f} (R(0,t) - R_{during}(m,t))dt + \int_{t_f}^{8760} (R(0,t) - R_{after}(m,t))dt\end{aligned} \tag{5.25}$$

where T_d is the duration of the maintenance activity, ***R(0,t)*** is the risk variation over time with no maintenance, and ***R(m,t)*** is the risk variation over time with maintenance. The first integral in (5.25) is the risk reduction during the maintenance period, always non-positive indicating that risk may increase during the maintenance period. The second integral in (5.25) is the risk reduction after completion of the maintenance activity, always positive due to the decrease in failure probability. In each integral, ***R(0,t)*** is obtained from the long-term simulator. If, during the maintenance period, no component is outaged, then $DCR_{during}=0$. However, if the maintenance task requires removal of component ***k*** (a generator, line, transformer, circuit breaker), then $\Delta CR_{during}<0$ because of changes in operating conditions, e.g., voltages, flows, etc., which change the severity of ***all*** contingencies except contingency ***k*** (contingency ***k*** cannot occur due to the fact that the corresponding component is on maintenance outage). Therefore, the risk "reduction" during maintenance task ***m*** is:

$$\begin{aligned}\Delta CR_{during}(m,t_f) &= \int_{t_f - T_d}^{t_f} [R(0,t) - R(m,t)]dt = \int_{t_f - T_d}^{t_f} [\sum_{c=0}^{N} p(c)sev(c \mid 0,t) - \sum_{c=0, c\neq k}^{N} p(c)sev(c \mid m,t)]dt \\ &= \int_{t_f - T_d}^{t_f} [p(k)sev(k \mid 0,t) + \sum_{c=0, c\neq k}^{N} p(c)\big(sev(c \mid 0,t) - sev(c \mid m,t)\big)]dt\end{aligned} \tag{5.26}$$

Now consider the second integral in (5.25), the risk reduction after the maintenance activity. Here, the maintenance activity ***m*** reduces contingency ***k*** probability by *Dp(m,k)* but does not affect the contingency ***k*** severity. We assume that maintenance activity ***m*** affects only contingency ***k*** probability and no others. The risk reduction after maintenance activity ***m*** is

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

$$
\begin{aligned}
&= \int_{t_f}^{8760} \{[\,p(k)sev(k\,|\,0,t) + \sum_{\substack{c=0\\c\neq k}}^{N} p(c)sev(c\,|\,0,t)] \\
&-[(p(k)-\Delta p(m,k))sev(k\,|\,0,t) + \sum_{\substack{c=0\\c\neq k}}^{N} p(c)sev(c\,|\,m,t)]\}dt
\end{aligned}
\tag{5.27}
$$

where we have pulled from each summation the risk associated with contingency ***k***, since contingency ***k*** is the only one having a probability affected by the maintenance activity. After t_f, component ***k*** is back in service, and the operating conditions are unchanged relative to the case of no maintenance; therefore ***sev(c|0,t)=sev(c|m,t) " c=1,…,N***, and the two summations within the integral of (5.27) are equal so that:

$$
\begin{aligned}
\Delta CR_{after}(m,t_f) &= \int_{t_f}^{8760} \{p(k)sev(k\,|\,0,t) - (\,p(k)-\Delta p(m,k))sev(k\,|\,0,t)\}dt \\
&= \int_{t_f}^{8760} \{\Delta p(m,k))sev(k\,|\,0,t)\}dt
\end{aligned}
\tag{5.28}
$$

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

$$
\Delta CR_{after}(m,t_f) = \int_{t_f}^{8760} \Delta p(m,k)\left\{\frac{R(0,k,t)}{p(k)}\right\}dt = \frac{\Delta p(m,k)}{p(k)}\int_{t_f}^{8760} R(0,k,t)dt \tag{5.29}
$$

Substituting (5.27) and (5.29) into (5.25), and replacing ***p(k)sev(k|0,t)*** in (5.26) by ***R(0,k,t)***, results in the following expression for the total risk reduction associated with maintenance activity ***m*** completed at time t_f:

$$
\begin{aligned}
&\Delta CR(m,t_f) \\
&= \int_{t_f-T_d}^{t_f} [R(0,k,t) + \sum_{c=0,c\neq k}^{N} p(c)\big(sev(c\,|\,0,t) - sev(c\,|\,m,t)\big)]dt + \frac{\Delta p(m,k)}{p(k)}\int_{t_f}^{8760} R(0,k,t)dt
\end{aligned}
\tag{5.30}
$$

There are three main terms in the risk reduction expression of equation (5.30). The first term inside the first integral represents the reduction in risk, relative to the base case, because of maintenance outage of component ***k*** means that contingency ***k*** can no longer occur. The second term inside the first integral, the summation, represents the change in risk (usually a risk *increase*) from all remaining contingencies due to the change in operating conditions caused by the maintenance outage of component ***k***. The third term, the second integral, represents the risk reduction after the maintenance period from the maintenance-induced probability reduction of contingency ***k***.

We see that in order to obtain the change in cumulative risk due to a maintenance activity, we need to evaluate the two integrals. The first integral requires ***p(c)*** for all contingencies ***c=0,N*** (which we assume to be available), the severity of all contingencies associated with the base case configuration ***(0,t)***, and the severity of all contingencies occurring under the weakened configuration ***(m,t)***. The contingency severities associated with the base case configuration come from one run of the simulator, but the contingency severities associated with configuration ***(m,t)*** would require rerunning the simulator for every weakened condition, i.e., for every maintenance activity ***m***, and would be excessively computational. Thus we evaluate the first integral using approximate methods. For example, one might evaluate the severities associated with configuration ***(m,t)*** under the assumption that severity is linear, superposition holds, and the severity of removing two lines is the sum of the severity of removing each line alone. Alternatively, one might assume that maintenance task ***m***, which requires removal of component ***k***, causes no change in severity so that *sev(c|0,t)=sev(c|m,t)*, and the summation in the first integral of (5.30) is 0. This might be true as a result of, for example, operator initiated system adjustments during the maintenance period. We accept this assumption for this project. Under this assumption, the total risk reduction associated with maintenance task ***m*** completed at time t_f is

$$\Delta CR(m,t_f)=\int_{t_f-T_d}^{t_f}R(0,k,t)dt+\frac{\Delta p(m,k)}{p(k)}\int_{t_f}^{8760}R(0,k,t)dt \tag{5.31}$$

Thus, we need ***R(0,k,t)***, the risk variation for each contingency affected by a maintenance task under the base case network configuration, which is information obtained from a simulator run. In (5.31), the first term indicates the risk reduction accrued during the maintenance period because contingency ***k*** cannot occur and in general will be quite small. If one assumes that maintenance outages cause no severity increase, then it is reasonable to also neglect the first term in (5.30), which is:

$$CRR_1(m,t_f)=\frac{\Delta p(m,k)}{p(k)}\int_{t_f}^{8760}R(0,k,t)dt \tag{5.32}$$

where ***R(0,k,t)*** is the risk variation for each contingency under the system base case configuration, information obtained from a simulator run (these contingencies include only those having probability affected by a maintenance task), *Dp(m,k)* is the failure probability reduction due to the maintenance task ***m***, and ***p(k)*** is the failure probability of contingency ***k***.

5.4.2 Risk reduction due to life extension

The risk reduction due to the life extension *Δt*, i.e., due to the delay of deterioration is:

$$CRR_2(m,k,t)=RC(k)\times(1+r)^{-(MTTF-t)}\left[1-(1+r)^{-\Delta t_k}\right] \tag{5.33}$$

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

5.4.3 Risk variation caused by maintenance

When a maintenance task requires the component to be temporarily removed from service, there may be need for redispatch to avoid security violations. By including this redispatch cost *C* in (5.24), we provide the means of assessing tradeoffs between maintenance schedules at critical times requiring high redispatch costs and the risk-reduction obtained from them via CRR_1 and CRR_2.

Most of the components in the transmission system have non-zero values of all three terms in the (5.24). The exception is tap changer, since its failure usually does not cause an immediate outage, so that there is no security risk. Therefore its CRR_1=0 and the benefit of maintenance is credited to the life extension, reflected in the term CRR_2.

5.5 Optimization

5.5.1 Objective function and constraints

As indicated in Fig. 5.3, first we run the simulator to compute risk as a function of time for each hour over a long-term such as a year and then, for the example of this paper, we use (1) to compute risk reduction associated with each proposed maintenance task. This step results in triplets comprised of: {maintenance task, completion time, risk reduction}. These triplets serve as the input to the optimizer.

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

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

$$Ia(k,m,t) = \sum_{j=t-d(k,m)+1}^{t} Is(k,m,j), \forall (k,m,t) \tag{5.34}$$

Equation (5.34) indicates that determination of whether the m^{th} task for component *k* is active at time *t* is accomplished by searching the selection function over the duration of the task until *t*. Also, *cost(k,m)* is the cost of the m^{th} task for component *k*, and *CRR(k,m,t)* is its cumulative risk reduction if the task begins at time *t*. Let *Inf(k,m)* be the set of periods for which task *m* for component *k* cannot be performed and are therefore infeasible. Each {component, task} combination *(k,m)* is tagged with a budget category *B(k,m)=b*. For example, *b Î 1, 2, 3, 4,* where 1=transformer maintenance, 2=tree-trimming, 3=insulator cleaning, and 4=circuit breaker maintenance. *Crew(k,m)* is the required number of crews for m^{th} task for component *k*. *TotCrew(b,t)* is the number of labors available for maintenance category *b* at time *t*.

We have developed two forms for the resulting optimization problem. Problem 1 is constrained by a cost budget; this problem conforms to the situation where the scheduler is paying for the maintenance. Problem 2 is constrained by only feasible schedules submitted by equipment owners. This problem conforms to the case where the ISO schedules for multiple equipment owners who pay for their own maintenance. We present only problem 1 here as problem 2 can be solved as a special case of problem 1.

$$Max\,(\sum_{k=1}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} CRR\,(k,m,t)\times Is(k,m,t)) \tag{5.35}$$

subject to:

$$\sum_{m=1}^{L_m}\sum_{t=1}^{T} Is(k,m,t) \le 1,\ \ k=1,\mathbf{L},N \tag{5.36}$$

$$Ia\,(k,m,t) = 0, \forall\ t \in\ Inf\ \ (k,m), \forall\ (k,m) \tag{5.37}$$

$$\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m} Ia\,(k,m,t) * Crew(k,m) < TotCrew(b,t), \forall t, b=1,...4 \tag{5.38}$$

$$\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} cost(k,m) * Is(k,m,t) < TotCost(b), b=1,...,4 \tag{5.39}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m} Ia(k,m,t) * SEV(k,m,t) \le SEV_{\max}(t), \forall t \tag{5.40}$$

$$Is(k,m,t) \in \{0,1\}, \forall (k,m,t) \tag{5.41}$$

In this optimization problem, the objective (5.35) is to maximize total cumulative risk reduction. Constraint (5.36) restricts each component to be maintained at most once. Constraint (5.37) enables user-specified infeasible periods for task *(k, m)*. In our work, a DC-flow program is used to detect maintenance outages causing overloads at time *t* and this task will be identified as infeasible at time *t* with constraint (5.37). And after the maintenance scheduling, an AC-flow is run to check voltage violation. If any maintenance activity causes a voltage related problem during the maintenance period, the maintenance is marked as infeasible at that time with constraint (5.37), and the optimization is rerun. Constraint (5.38) stipulates the number of maintenance tasks ongoing during any period is limited by crew constraints. Constraint (5.39) represents budget constraints for each budget category. Constraint (5.40) ensures maintenance outage from task *(k,m)* resulting in a security concern of *SEV(k,m,t)* with respect to low voltage and voltage instability, due to outage of component *k* at time *t* does not exceed the maximum allowable threshold for time *t*, which will be explained in detail in the next section.

5.5.2 Security impact due to maintenance scheduling

Many maintenance activities will require the maintained components to be removed out of service. Such planned outage may increase the stress of the system during the maintenance interval, even if some corresponding redispatch are scheduled together with the maintenance to reduce the stress. To account for the security concern here, we have defined severity functions with respect to low voltage and voltage instability. The definition and simulation techniques were introduced in a previous PSERC report [110] about maintenance scheduling for transmission system. The principle here that is implemented here is reflected by eq. (5.40), which is as follows: for any time *t*, the summation of the severity of low voltage and voltage instability, due to the scheduled maintenance activities, should not exceed a preset threshold, *SEVmax(t)*, the maximum allowable severity for time *t.*

Although this approach does not guarantee that the bus voltage at each node is within the acceptable range, it does provide a systematic constraint to inhibit a maintenance task or a combination of maintenance tasks to be scheduled during stressed conditions. Stricter constraints on feasible times for each maintenance task, if desired, can be implemented with constraint (5.37).

5.5.3 Relaxed linear programming with dynamic programming

To solve this optimization problem is to determine *Is(k,m,t)*, which then determines *Ia(k,m,t)*. The optimization problem is integer, with multiple constraints and high dimension and therefore is challenging to solve. We have tested three different solution methods: heuristic, branch and bound, and relaxed linear programming with dynamic programming/heuristic (RLP-DPH). The first two of these are described in [98]. In comparing these methods, we found that RLP-DPH provides the best compromise between optimality and computational efficiency, resulting in near-optimal solutions with computation time reduced by an order of magnitude. This approach first solves a relaxed linear program (RLP) to obtain Lagrange multipliers on budget (5.39) and risk (5.40) constraints, and then a new objective function is developed, comprised of the original objective together with weighted cost and weighted risk, where the weights are Lagrange multipliers obtained from the RLP. It then solves knapsack problems [114] over the labor constraints (5.38) one period at a time, where a period is taken to be one week. The procedure follows.

A. Relaxed LP to get dual variables: Solve an RLP that includes all of the constraints (5.36)-(5.41) in order to get approximations on budget and risk constraint Lagrange multipliers m_1-m_4 and λ_t, $t=1,\ldots T$, respectively. This LP is "relaxed" in that variables are allowed to be non-integer. The solution to the linear program is not a solution to the original integer programming problem since the decision variables are not integer. However, the solution does provide reasonable estimates of the Lagrange multipliers. These estimates are used to form a Lagrangian function comprised of the original objective less the weighted constraint functions, where the weights are the Lagrange multiplier estimates. The advantage of doing this is that the resulting problem is in the form of a "knapsack" problem, a class of problems for which solution procedures are readily available. The knapsack problem is solved over the labor constraints (5.38) for the first period (e.g., first week) to identify the maintenance tasks to be performed in that week. Then we re-solve the RLP with the week-1 variables known, to get updated Lagrange multipliers on the budget and risk constraints, and then a knapsack problem for the second period (e.g., second week) is solved. The process is repeated until all periods are solved.

B. Solving knapsack problems: Moving risk and budget constraints to the objective function, the new objective function is a weighted sum of cumulative risk reduction, cost, and period risk, with the various Lagrange multipliers quantifying trade-offs between them. The problem of maximizing this objective subject to labor constraints (5.38) is a classical knapsack problem, stated as follows:

$$\begin{aligned}&\max F(Is(k,m,t))\\&=\sum_{k=1}^{N}\sum_{m=1}^{L_m}\Delta CR(k,m,t)\times Is(k,m,t)-\sum_{b=1}^{4}m_b\left\{\sum_{\substack{k=1\\(k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T}cost(k,m)*Is(k,m,t)-TotCost(b)\right\}\\&-\sum_{t}^{t+T_{\max}}l_t\left\{\sum_{k=1}^{N}\sum_{m=1}^{L_m}\Delta R(k,m,t)*Is(k,m,t)-\Delta R\max(t)\right\}\end{aligned} \tag{5.42}$$

subject to

$$\sum_{\substack{m=1\\(m,n):B(m,n)=b}}^{M}\sum_{n=1}^{M_m} Ia(m,n,t)*Crew(m,n)\leq Crew(b,t),\forall t,b=1,\ldots,4 \tag{5.43}$$

There is a knapsack problem for each period, and they are solved in chronological sequence. Some qualifying remarks follow. (a) The risk reduction is only for the given period *t*, so the first term of the objective function does not sum over the time intervals. (b) The Lagrange multipliers on the budget constraints are found for the yearly budget, so the second term of the objective function does sum over the time intervals. (c) There is a Lagrange multiplier on maximum risk for each period, but in solving for a single period, if we require that no task has duration exceeding a single period, we need only include the constraint corresponding to period *t*. However, some tasks may have durations exceeding one period (i.e., greater than 1 week). In this case, we must include the risk constraints for the current period *t* up to *t+Tmax*, where *Tmax* is the longest duration for any task. Therefore, the third term in the objective function must sum over period *t* to *t+Tmax*. (d) Available hours for any period must be reduced by ongoing tasks that begin in earlier periods. (e) Infeasible periods from constraint (5.37) are enforced using negative objective function coefficients.

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

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

5.5.4 Discussion of optimality of the algorithm

The RLP-DPH utilized the Lagrange multipliers from relaxed linear programming to set up the new objective function to solve the integer problem. This may bring some loss of optimality since the multipliers are only 'approximates' of multipliers in integer programming. Usually Lagrange relaxation method is used to search the Lagrange multipliers for the integer solutions, but it is more complex and convergence is a concern. This section addresses loss of optimality and compares between our method and Lagrange relaxation.

In our project, the goal of the optimization is to identify the selection and schedule of maintenance activities that maximizes system reliability, subject to the various constraints. The formulation of the problem is listed as (5.35)-(5.41)

Constraint (5.41) indicates that determination of whether the m^{th} task for component k is active at time t is accomplished by searching the selection function over the duration of the task until t. This variable brings some difficulties in optimization because it is difficult to apply common solution procedure available to integer programming to model this constraint. To simplify the discussion of algorithm, the constraint (5.37) is relaxed, without loss of generality, and the problem is converted to the mixed integer programming as follows:

$$Max \ \left(\sum_{k=1}^{N} \sum_{m=1}^{L_m} \sum_{t=1}^{T} a_{k,m,t} * x_{k,m,t}\right) \tag{5.44}$$

subject to:

$$\sum_{m=1}^{L_m} \sum_{t=1}^{T} x_{k,m,t} \leq 1, \ k = 1, \ldots, N \tag{5.45}$$

$$\sum_{k=1}^{N} \sum_{m=1}^{L_m} b_{k,m} * x_{k,m,t} < B(t), \forall t \tag{5.46}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} c_{k,m,t} * x_{k,m,t} < C \tag{5.47}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m} d_{k,m,t} * x_{k,m,t} \le D(t), \forall t \tag{5.48}$$

$$x_{k,m,t} \in \{0,1\}, \forall (k,m,t) \tag{5.49}$$

From this formulation, we see it is a mixed integer programming. It is a NP-hard problem, which means that no known algorithm solves it in polynomial time for all instances of the problem. It is similar with knapsack problem but more complex because of the multiple constraints. Branch and bound or dynamic programming has been used to solve the knapsack problem, but both of them have very bad worse-case complexities (exponential for branch and bound and pseudo-polynomial for dynamic programming). Therefore, it is unlikely that either of these methods can be used in practice [115].

To solve the integer program, the effective way is to find the lowest upper bound or highest lower bound for the solution space, and find the best feasible solution in the space. So relaxation techniques are popular here. The most commonly used method is linear programming relaxation (LP) and Lagrange relaxation (LR). LP relieves the need of integer variables and solves the optimization problem in real number space. The results are not integer because of the relaxation and therefore not a solution to the problem of interest, but there is useful information provided. In contrast, LR searches the best multipliers in the integer space and finds the exact optimal answer, but the searching in integer space brings convergence problems. So we combine the two methods to overcome the shortcoming of both, via use of linear programming relaxation with Lagrange multipliers. Since it is known that LR method solves to optimality for integer programming, what we need to do now is to show that the result from our method is similar to the result from LR.

To this end, we discuss the solution of (5.44-5.49) in two cases:

A1) Change the constraint (5.45) as $\sum_{n=1}^{L_m}\sum_{t=1}^{T} x_{k,m,t} = 1,\ k = 1, \mathbf{L}, N$, which means all of the maintenance tasks will be scheduled. So this is a problem of scheduling without the problem of selecting the maintenance activities (they are all selected).

A2) Keep (5.45), which means not all of the maintenance tasks will be scheduled, as our problem.

Under the condition of A1), [115] has proved that the duality gaps for LR and for LP relaxations are exactly the same, or that they provide the same upper bounds for the maximization problem. For our problem, we can convert the problem by relaxing the constraint (5.46)-(5.48):

LR1:

$$\min_{a,b,c \ge 0} \left\{ \begin{array}{l} Max\left(\sum_{k=1}^{N}\sum_{m=1}^{L_m}\left(\sum_{t=1}^{T}(a_{k,m,t} - a_t b_{k,m,t} - b_t c_{k,m,t} - c_t d_{k,m,t})\right) \times x_{k,m,t} + \sum_{t=1}^{T}[a_t B(t) + b_t C + c_t D(t)]\right), \\ s.t. \sum_{m=1}^{L_m}\sum_{t=1}^{T} x_{k,m,t} = 1,\ \forall k \quad and \quad x_{k,m,t} \in \{0,1\} \end{array} \right\} \tag{5.50}$$

For given Lagrange multipliers, the solutions to the max part of LR1 is to set for each k all $x_{k,m,t} = 0$ except for the variable corresponding to $(m,t)_k = \arg\max(a_{k,m,t} - a_t b_{k,m,t} - b_t c_{k,m,t} - c_t d_{k,m,t})$, which is set to one. And if we were to solve the LP relaxation of the max part in LR1, there should be N constraints in it. By linear programming we know that an optimal solution to a linear program is a basic feasible solution. The number of positive valued variables in a basic feasible solution is at most the number of constraints in LP. Hence there may be at most N positives $x_{k,m,t}$'s for the problem under consideration. But at least one $x_{k,m,t}$ must be positive for each k in order to satisfy each constraint. And so an easy counting argument tells us that exactly N $x_{k,m,t}$ will be 1 and the rest will be zero in the LP relaxed programming. Since this solution is integral, it means that integrality constraints in max part of LR1 could have been dropped without loss of optimality. After this, we solve the LR1 (actually it becomes a linear relaxation problem with Lagrange multipliers without the integer constraint) with linear programming but get the same duality gap as Lagrange relaxation.

However, under the condition of A2, the constraint (5.45) means there need not be exactly N positive $x_{k,m,t}$. Hence the requirements of integer cannot be dropped without potential loss of optimality. However, the Lagrange multipliers reflect the benefit of objective function with respect to the violation of constraints, at the optimal point. Since all of our constraints and objective function are linear function and the variables are constrained in the range of [0,1]. The Lagrange multipliers from sub-gradient method should not be very far from the real value of the multipliers at the integer solution point. And by doing this, we convert the problem into the following formulation in LR2:

LR2:

$$\min_{a,b,c,l\geq 0}\left\{\begin{array}{l} Max\left(\sum_{k=1}^{N}\sum_{m=1}^{L_m}\left(\sum_{t=1}^{T}(a_{k,m,t} - a_t b_{k,m,t} - b_t c_{k,m,t} - c_t d_{k,m,t} - l_k)\times x_{k,m,t} + \sum_{t=1}^{T}[a_t B(t) + b_t C + c_t D(t)] + \sum_{k=1}^{N} l_k\right),\right. \\ s.t \quad x_{k,m,t} \in \{0,1\} \end{array}\right\} \tag{5.51}$$

It should be noted here that the complexity of an LR comes both from solving exactly the relaxed problem and searching for the best multipliers. In doing LR2, we need to search a much higher dimensional spaces (*N+ dimension of LR1*). This complexity is not likely to be less than that of LR1 without integer constraint, which in turn, guarantees a duality gap (error) no better than LP relaxation.

So the conclusion here is:

1) Lagrange relaxation is an exact solution method in integer programming. It searches the best multipliers in the integer space and can find the exact optimal answer, but the searching in integer space brings a lot of problems of convergence.

2) For scheduling problem only, the linear programming relaxation provides good results, which is optimal since we can prove that it provides the same result as Lagrange relaxation while LR can provide exact solution to the optimization.

3) For scheduling and selection problem, the linear programming provides the sub optimal solution, since the requirements of integer cannot be dropped. But we can

say with confidence that the linear relaxation with Lagrange multipliers should not provide a worse result as Lagrange relaxation with the same calculation burden, because the complexity of the linear programming is smaller and searching directions are much less.

To show the performance of our program, we have tested the result with some other mixed linear programming methods in commercial software and obtained satisfying results. The comparison will be illustrated in Section 5.6.7.

5.6 Results

We have illustrated our procedure, using a model of an actual utility system but with hypothetical maintenance activities. The system has 36 generators, 566 buses, 561 transmission lines and 115 transformers. The power flow model also includes switchable shunt capacitors and reactors to ensure an appropriate voltage profile as loading changes. In addition, the data characterizing 1-year projected hour-by-hour operating conditions was obtained. This data included the following:

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

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

The hour-by-hour 1-year loading trajectory, obtained from the EMS-history file and shown in Fig.5-6, was used as the next year's expected loading trajectory.

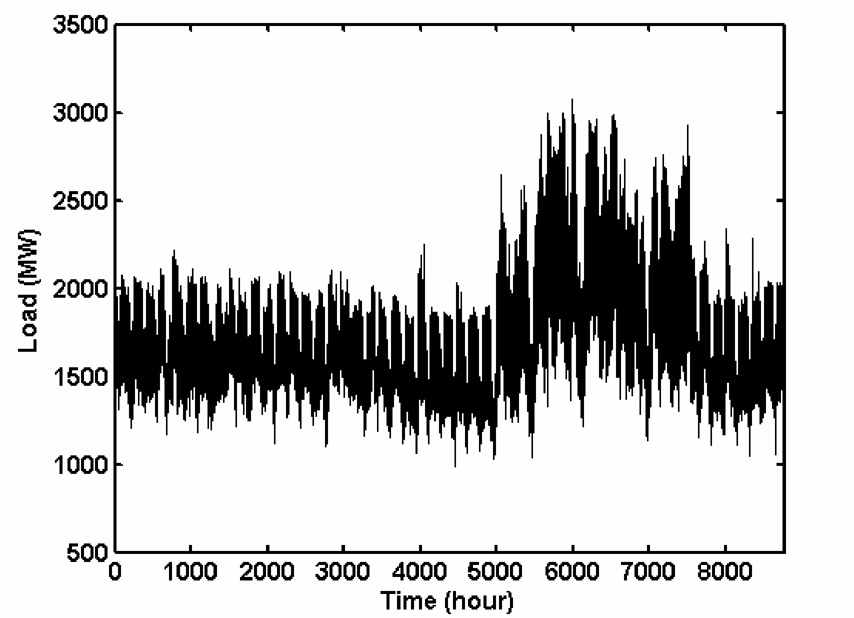

Fig. 4.6: One year loading trajectory of testing system

The time t=0 corresponds to October 1. The yearly peak load is 3077 MW occurring at the end of July. The minimum load is 955 MW occurring at the end of September.

5.6.1 Description of contingencies and maintenance activities

Contingency analysis must be done for any component that we are considering to maintain. Thus, we do not consider contingencies involving generator outages, assuming that scheduling for generator unit maintenance is done a-priori and serves as an input to our procedure as indicated in the previous section. (The maintenance scheduling method applied here could, in principle, be applied to generator units as well, or, to both generator units and transmission components simultaneously. However, generator maintenance, or, power plant maintenance, is a much more complicated subject because of the large number of failure modes and corresponding maintenance activities). Therefore, the contingency list includes only branch outages (lines and transformers). In addition, we have limited the contingency list to lines and transformers that have potential to result in system security violations during the year, assumed for purposes of our study to include lines or transformers interconnected at 69 kV or above.

The previously stated assumption does not imply that equipment at lower voltage levels (e.g., sub-transmission and distribution equipment) should not be maintained but rather that the failure consequence for equipment at lower voltages is different than the failure consequence for equipment at higher voltages. Whereas we measure failure consequence of high voltage equipment in terms of redispatch cost, we measure failure consequence of lower voltage equipment in terms of repair cost and load interruption. Given this change, we think the approach proposed in this project would also apply to the selection and scheduling of distribution equipment maintenance tasks as well, and another PSERC-project (T-24) is ongoing to this end.

For transmission lines, tree contact and insulator failure are the two most common failure modes. For transformers, mechanical failure and insulation oil deterioration are the two most common failure modes. For circuit breakers, the failure of operation put the system under very high threat of instability and component damages. We limit the maintenance tasks scheduled in our illustration to those affecting these failure modes. This means that there are 170 contingencies to assess; 89 line outages, 46 transformer outages and 35 circuit breaker failures. The failure modes and corresponding maintenance activities are listed in Table 5.3.

5.6.2 Failure rate determination and the effect of maintenance

With the method we introduced in Chapter 4, we can estimate the failure rate of components in transmission system, based on condition monitoring data and statistical analysis. For failure modes that we are lack of data or the condition monitoring is unavailable, we can use typical failure-rate data based on certain assumptions for the equipment in our system. Individual companies may be able to provide equipment-specific failure rates which, if available, could be used in place of the typical data described below.

1) Transformers:

a. Failure modes of oil deterioration

For failure modes of oil deterioration, we can use the method in Chapter 4 to estimate the failure rate and failure rate reduction, based on the condition monitoring data. For example, based on the sample transformer result in Chapter 4, and we assume that the transformer is in the 377 weeks after its previous maintenance (oil filtering). With the Markov model and the parameter we get form the simulation, we can calculate the failure rate of this transformer during the whole year, with the failure mode of oil deterioration.

$$p(hT) = \underline{p}(0) * \underline{P}^h \tag{5.52}$$

For the maintenance of oil refinement (oil filtering and oil replacement), the records after maintenance always shows that the oil is in very good condition, we can assume that the maintenance renew the oil and the failure probability returns to 0. Thus we can calculate Δp, the change of failure probability after maintenance, as $\Delta p = p(hT)$.

b. Failure modes of core problem, mechanical failure and general ageing:

Reference [116] provides a typical MTTF for power transformers of 25 years. We assume in the work reported in this chapter that:

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

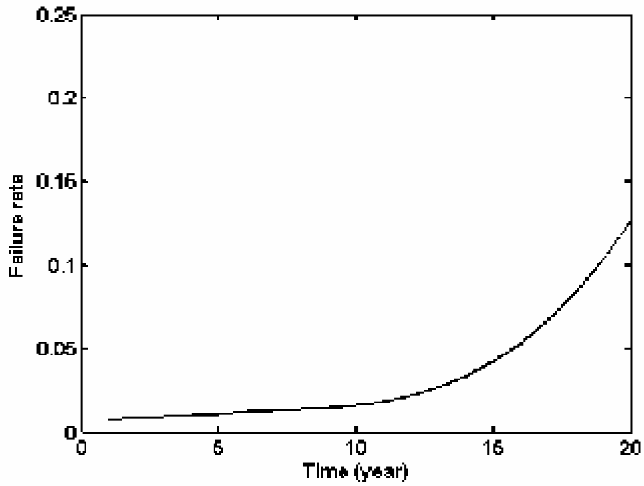

Fig. 5.7: Failure rate (cumulative hazard function) assumed for transformers

Based on the above assumptions, then, we see, for example, that if a 16 year-old transformer is not maintained in the current year, the failure rate increases from 5.4% to 6.8%, but if major maintenance is performed, the failure rate returns to that of the 10 year age of 1.66%. Since both major and minor maintenance return an 11-year-old transformer to the 10 year level, it makes sense to perform minor maintenance to the 11-year old transformer, reducing the failure rate from the 11-year-old level of 2.5% to the 10-year-old level of 1.66%. The core issues here are the ability to estimate failure rates specific to each piece of equipment at any particular time, and the ability to identify the effect of maintenance on failure rate. Both of these issues relate to the use of condition date (testing, sampling, inspecting, and monitoring). These issues are being pursued in depth in another PSERC-funded project.

2) Transmission lines

Typical transmission line failure rate data is 1 outage/100km/year for 345kV and 161 kV lines [117]. From [118], the typical failure rate of tree contact is p=0.05 outages/100miles/year or 0.03125 outages/100km/year. We assume that after tree trimming, the failure rate drops to zero so that the maintenance induced probability reduction is $\Delta p=p$. The failure rate of tree contact also changes during the year and can be expected to increase linearly, since according to the high voltage test (U50), the disruptive voltage with 50% of discharge probability increases linearly with decreasing distance if the distance is less than 2 meters. Otherwise it is nearly constant. We make the assumption that all tree-contact-related failure rates are 1 outage/100km/year at the beginning of year, and if the tree trimming is not scheduled, the failure rate increases linearly to 1.03125 occ/100km/year. In the middle of the year, the failure rate will be determined by the linear function. Transmission line device failure is also related to the line length and voltage level. For 161KV, the typical failure rate is set to be p=0.26 occurrences/100miles/year. For 345KV, the typical failure rate is set to be p=0.20 occurrences/100miles/year.

3) Circuit Breakers

One major failure mode of circuit breaker is it fails to operate when a fault occurs in its protection region. So this is a higher order contingency and its failure rate should be achieved with the information of system configuration and topology data, together with probability analysis. Suppose for a circuit breaker with failure rate P_c, there are N components within its protection region and each with failure rate P_i . And failure of each component requires the operation of trip of circuit breaker. We assume that the failures of all components are independent. So the rate of failure of this two order contingency is:

$$P = P_c \times \sum_{i=1}^{N} P_i \tag{5.53}$$

The failure rate of circuit breaker can be achieved from failure reports and test. Typical failure rate data for circuit breaker is 0.009-0.015 faults/year, depending on the voltage levels of the circuit breaker [119][120].

5.6.3 Maintenance activities

Five categories of maintenance are considered. We desire to identify the maintenance tasks and their schedule that results in the largest risk decrease for the specified contingencies. We consider performing tree-trimming for every line, insulator cleaning for every line, and minor and major maintenance for every transformer, where each task may be done at any time of the year. Table 5.4 summarizes the possible tasks and their attributes, together with the corresponding contingencies. In Table 5.4, ***type*** indicates the category of maintenance tasks (1-Tree trimming; 2-Transmission line insulator maintenance; 3-Transformer minor maintenance; 4-Transformer major maintenance; 5-Circuit breaker maintenance). ***Hour*** is the total labor hours required for the maintenance task. *Cost* is and *Duration* are the budget and time interval required to perform the maintenance task. For each maintenance, *Hour=Crew* Duration*, where "*Crew*" is the number of persons in the crew required to perform the task. The column of contingency gives the bus numbers terminating the line or transformer identified for the contingency.

TABLE 5.4: PROPOSED TRANSMISSION COMPONENT MAINTENANCE TASKS

ID	Name	Type	Hour	Cost	Duration	Contingency	ID	Name	Type	Hour	Cost	Duration	Contingency
1	Trim1	1	120	1000	40	11 12	131	Trans42	2	96	1960	48	172 175
2	Trim2	1	48	400	16	11 13	132	Trans43	2	192	2920	96	172 323
3	Trim3	1	192	1600	64	13 19	133	Trans44	2	72	1720	36	174 175
4	Trim4	1	192	1600	64	14 16	134	Trans45	2	48	1480	24	177 351
5	Trim5	1	192	1600	64	14 52	135	Trans46	2	96	1960	48	179 181
6	Trim6	1	264	2200	88	16 17	136	Trans47	2	96	1960	48	181 351
7	Trim7	1	240	2000	80	17 18	137	Trans48	2	72	1720	36	183 196
8	Trim8	1	240	2000	80	17 19	138	Trans49	2	192	2920	96	184 187
9	Trim9	1	168	1400	56	18 85	139	Trans50	2	96	1960	48	184 193
10	Trim10	1	144	1200	48	19 85	140	Trans51	2	120	2200	60	185 200
11	Trim11	1	96	800	32	21 30	141	Trans52	2	96	1960	48	186 189
12	Trim12	1	264	2200	88	21 31	142	Trans53	2	48	1480	24	186 205
13	Trim13	1	96	800	32	22 33	143	Trans54	2	72	1720	36	186 212
14	Trim14	1	48	400	16	23 39	144	Trans55	2	120	2200	60	187 188
15	Trim15	1	48	400	16	24 26	145	Trans56	2	216	3160	108	188 204
16	Trim16	1	120	1000	40	25 41	146	Trans57	2	168	2680	84	189 207
17	Trim17	1	120	1000	40	27 28	147	Trans58	2	72	1720	36	190 197
18	Trim18	1	72	600	24	27 41	148	Trans59	2	186	4840	93	191 229
19	Trim19	1	96	800	32	28 29	149	Trans60	2	240	3400	120	191 539
20	Trim20	1	168	1400	56	29 44	150	Trans61	2	96	1960	48	193 204
21	Trim21	1	132	3600	44	29 253	151	Trans62	2	96	1960	48	195 203
22	Trim22	1	132	2800	44	31 88	152	Trans63	2	72	1720	36	196 205
23	Trim23	1	72	600	24	88 99	153	Trans64	2	72	1720	36	199 203
24	Trim24	1	120	1000	40	103 59	154	Trans65	2	48	1480	24	200 203
25	Trim25	1	168	1400	56	103 161	155	Trans66	2	327	6280	164	207 210
26	Trim26	1	180	3000	60	112 115	156	Trans67	2	264	3640	132	210 225
27	Trim27	1	144	1200	48	118 161	157	Trans68	2	186	4840	93	225 232
28	Trim28	1	144	1200	48	135 143	158	Trans69	2	72	1720	36	232 555
29	Trim29	1	96	800	32	135 374	159	Trans70	2	48	1480	24	350 455
30	Trim30	1	48	400	16	139 374	160	Trans71	2	120	2200	60	360 361
31	Trim31	1	120	1000	40	141 143	161	Trans72	2	144	2440	72	372 434
32	Trim32	1	180	4000	60	141 148	162	Trans73	2	72	1720	36	377 378
33	Trim33	1	72	600	24	141 391	163	Trans74	2	120	2200	60	384 385
34	Trim34	1	120	1000	40	153 154	164	Trans75	2	264	3640	132	393 402
35	Trim35	1	228	3400	76	154 156	165	Trans76	2	240	3400	120	395 400
36	Trim36	1	264	2200	88	156 159	166	Trans77	2	96	1960	48	396 426
37	Trim37	1	96	800	32	159 161	167	Trans78	2	144	2440	72	427 430
38	Trim38	1	144	1200	48	161 163	168	Trans79	2	96	1960	48	447 448
39	Trim39	1	96	800	32	166 167	169	Trans80	2	228	6280	114	453 454
40	Trim40	1	216	2600	72	166 323	170	Trans81	2	216	4120	108	459 528
41	Trim41	1	228	4400	76	168 175	171	Trans82	2	96	1960	48	463 481
42	Trim42	1	96	800	32	172 175	172	Trans83	2	192	2920	96	467 491
43	Trim43	1	192	1600	64	172 323	173	Trans84	2	72	1720	36	475 483
44	Trim44	1	72	600	24	174 175	174	Trans85	2	48	1480	24	476 491
45	Trim45	1	48	400	16	177 351	175	Trans86	2	96	1960	48	478 487
46	Trim46	1	96	800	32	179 181	176	Trans87	2	96	1960	48	482 512

Table 5.4 (continued)

47	Trim47	1	96	800	32	181 351	177	Trans88	2	72	1720	36	497 515
48	Trim48	1	72	600	24	183 196	178	Trans89	2	192	2920	96	500 507
49	Trim49	1	192	1600	64	184 187	179	Xrmi1	3	240	2625	120	21 71
50	Trim50	1	96	800	32	184 193	180	Xrmi2	3	240	2625	120	21 72
51	Trim51	1	120	1000	40	185 200	181	Xrmi3	3	240	2100	120	73 24
52	Trim52	1	96	800	32	186 189	182	Xrmi4	3	240	2247	120	79 29
53	Trim53	1	48	400	16	186 205	183	Xrmi5	3	240	2352	120	88 94
54	Trim54	1	72	600	24	186 212	184	Xrmi6	3	240	1764	120	112 113
55	Trim55	1	120	1000	40	187 188	185	Xrmi7	3	240	1764	120	119 118
56	Trim56	1	216	1800	72	188 204	186	Xrmi8	3	240	1764	120	129 167
57	Trim57	1	168	1400	56	189 207	187	Xrmi9	3	240	1743	120	408 136
58	Trim58	1	72	600	24	190 197	188	Xrmi10	3	240	3150	120	138 137
59	Trim59	1	186	3200	62	191 229	189	Xrmi11	3	240	3150	120	139 140
60	Trim60	1	240	2000	80	191 539	190	Xrmi12	3	240	3150	120	141 142
61	Trim61	1	96	800	32	193 204	191	Xrmi13	3	240	2100	120	534 173
62	Trim62	1	96	800	32	195 203	192	Xrmi14	3	240	1890	120	497 207
63	Trim63	1	72	600	24	196 205	193	Xrmi15	3	240	1890	120	211 212
64	Trim64	1	72	600	24	199 203	194	Xrmi16	3	240	1890	120	233 232
65	Trim65	1	48	400	16	200 203	195	Xrmi17	3	240	2625	120	232 562
66	Trim66	1	327	4400	109	207 210	196	Xrmi18	3	240	1890	120	235 234
67	Trim67	1	264	2200	88	210 225	197	Xrmi19	3	240	2650	120	323 324
68	Trim68	1	186	3200	62	225 232	198	Xrmi20	3	240	2925	120	336 337
69	Trim69	1	72	600	24	232 555	199	Xrmi21	3	240	2200	120	353 352
70	Trim70	1	48	400	16	350 455	200	Xrmi22	3	240	2267	120	392 393
71	Trim71	1	96	800	32	360 361	201	Xrmi23	3	240	2372	120	422 421
72	Trim72	1	48	400	16	372 434	202	Xrmi24	3	240	1768	120	449 410
73	Trim73	1	192	1600	64	377 378	203	Xrmi25	3	240	1768	120	477 523
74	Trim74	1	264	2200	48	384 385	204	Xrmi26	3	240	2625	120	517 518
75	Trim75	1	192	1600	64	393 402	205	Xrmj1	4	480	20000	120	21 11
76	Trim76	1	264	2200	88	395 400	206	Xrmj2	4	480	20000	120	22 12
77	Trim77	1	240	2000	80	396 426	207	Xrmj3	4	480	20000	120	27 14
78	Trim78	1	240	2000	80	427 430	208	Xrmj4	4	480	5000	120	27 76
79	Trim79	1	168	1400	56	447 448	209	Xrmj5	4	480	5000	120	79 29
80	Trim80	1	144	1200	48	453 454	210	Xrmj6	4	480	12000	120	89 86
81	Trim81	1	96	800	32	459 528	211	Xrmj7	4	480	4480	120	88 94
82	Trim82	1	264	2200	88	463 481	212	Xrmj8	4	480	12000	120	135 134
83	Trim83	1	96	800	32	467 491	213	Xrmj9	4	480	12000	120	135 134
84	Trim84	1	48	400	16	475 483	214	Xrmj10	4	480	3720	120	149 148
85	Trim85	1	96	800	32	476 491	215	Xrmj11	4	480	3320	120	155 154
86	Trim86	1	120	1000	40	478 487	216	Xrmj12	4	480	3360	120	161 162
87	Trim87	1	120	1000	40	482 512	217	Xrmj13	4	480	3320	120	163 164
88	Trim88	1	72	600	24	497 515	218	Xrmj14	4	480	3320	120	168 169
89	Trim89	1	96	800	32	500 507	219	Xrmj15	4	480	4000	120	179 180
90	Trans1	2	120	2200	60	11 12	220	Xrmj16	4	480	3600	120	464 186
91	Trans2	2	48	1480	24	11 13	221	Xrmj17	4	480	3600	120	192 190
92	Trans3	2	192	2920	96	13 19	222	Xrmj18	4	480	3600	120	224 191
93	Trans4	2	192	2920	96	14 16	223	Xrmj19	4	480	6000	120	203 206
94	Trans5	2	192	2920	96	14 52	224	Xrmj20	4	480	6000	120	203 206

Table 5.4 (continued)

95	Trans6	2	264	3640	132	16	17	225	CB1	5	300	3100	80	8 273
96	Trans7	2	240	3400	120	17	18	226	CB2	5	300	3500	80	19 85
97	Trans8	2	240	3400	120	17	19	227	CB3	5	300	2958	80	122 297
98	Trans9	2	168	2680	84	18	85	228	CB4	5	300	4056	80	122 447
99	Trans10	2	144	2440	72	19	85	229	CB5	5	300	3800	80	188 517
100	Trans11	2	96	1960	48	21	30	230	CB6	5	300	5200	80	199 212
101	Trans12	2	264	3640	132	21	31	231	CB7	5	300	2958	80	224 191
102	Trans13	2	96	1960	48	22	33	232	CB8	5	300	3986	80	497 207
103	Trans14	2	48	1480	24	23	39	233	CB9	5	300	3500	80	211 212
104	Trans15	2	48	1480	24	24	26	234	CB10	5	300	3678	80	211 212
105	Trans16	2	120	2200	60	25	41	235	CB11	5	300	3678	80	228 229
106	Trans17	2	120	2200	60	27	28	236	CB12	5	300	3200	80	230 231
107	Trans18	2	72	1720	36	27	41	237	CB13	5	300	2758	80	232 231
108	Trans19	2	96	1960	48	28	29	238	CB14	5	300	3052	80	235 234
109	Trans20	2	168	2680	84	29	44	239	CB15	5	300	3654	80	353 352
110	Trans21	2	132	5320	66	29	253	240	CB16	5	300	4200	80	191 539
111	Trans22	2	132	4360	66	31	88	241	CB17	5	300	2968	80	192 488
112	Trans23	2	72	1720	36	88	99	242	CB18	5	300	2688	80	192 509
113	Trans24	2	120	2200	60	103	159	243	CB19	5	300	2688	80	193 218
114	Trans25	2	168	2680	84	103	161	244	CB20	5	300	2678	80	207 210
115	Trans26	2	180	4600	90	112	115	245	CB21	5	300	3100	80	209 462
116	Trans27	2	144	2440	72	118	161	246	CB22	5	300	3500	80	210 225
117	Trans28	2	144	2440	72	135	143	247	CB23	5	300	1958	80	211 213
118	Trans29	2	96	1960	48	135	374	248	CB24	5	300	2056	80	211 487
119	Trans30	2	48	1480	24	139	374	249	CB25	5	300	3660	80	213 469
120	Trans31	2	120	2200	60	141	143	250	CB26	5	300	3200	80	220 221
121	Trans32	2	180	5800	90	141	148	251	CB27	5	300	2958	80	225 232
122	Trans33	2	72	1720	36	141	391	252	CB28	5	300	3986	80	226 278
123	Trans34	2	120	2200	60	153	154	253	CB29	5	300	3500	80	228 554
124	Trans35	2	228	5080	114	154	156	254	CB30	5	300	3678	80	232 539
125	Trans36	2	264	3640	132	156	159	255	CB31	5	300	3100	80	232 555
126	Trans37	2	96	1960	48	159	161	256	CB32	5	300	3500	80	233 235
127	Trans38	2	144	2440	72	161	163	257	CB33	5	300	2958	80	233 558
128	Trans39	2	96	1960	48	166	167	258	CB34	5	300	3688	80	234 555
129	Trans40	2	216	4120	108	166	323	259	CB35	5	300	4800	80	235 540
130	Trans41	2	228	6280	114	168	175							

5.6.4 Description of results

Using the previously described system data, we illustrate the process of risk-based transmission component maintenance scheduling. For the contingencies identified in Table 5.4 we perform risk assessment over one year. The composite risk variation through the year (the sum of risk over all contingencies) is shown in Fig. 5.8.

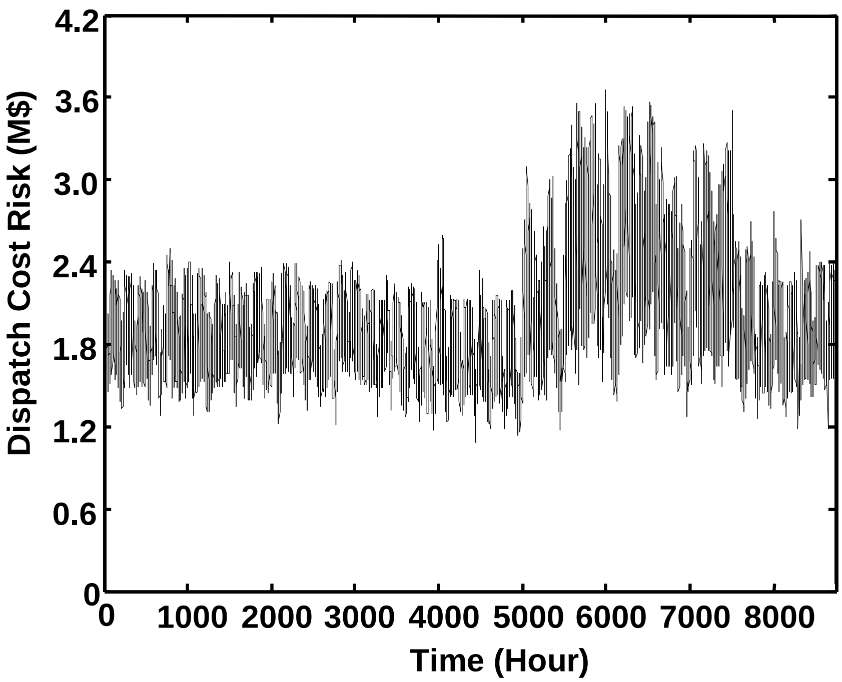

Fig. 5.8 Composite system risk

Figure 5.8 provides a global sense of how the system risk varies through the year. However, optimization of the maintenance is based entirely on contingency-specific risk variation. We list contingency-specific risk variation in Table 5.5, and we identify the highest risk contingencies for the specified problem-type at three different load levels (peak, minimum, and average). Table 5.3 lists the highest-risk contingencies at the three different load levels. Figures 5.9 and 5.10 are the yearly risk curves for the two contingencies, 66 and 21, which have the highest risk and 10th highest risk at peak load.

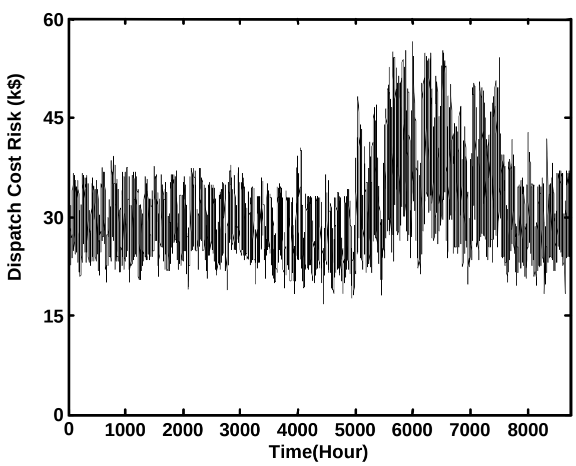

Fig. 5.9: Yearly risks of contingency 66

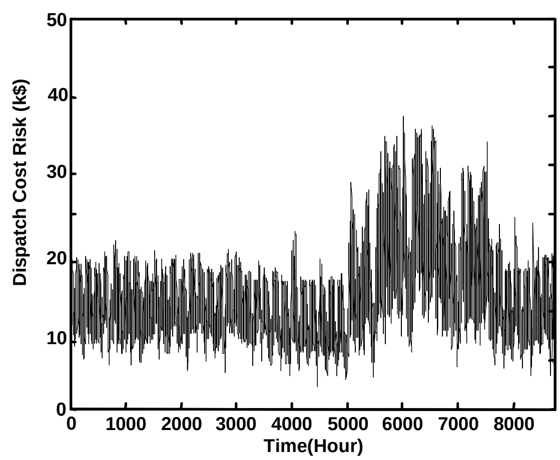

Fig. 5.10: Yearly risks of contingency 21

TABLE 4.5: HIGHEST-RISK CONTINGENCIES FOR OVERLOAD RISK AT DIFFERENT LOAD LEVELS

System peak load, P=3073MW, hour=5993			
Order	Contingency ID	Risk	Category
1	66	188.70	161KV Transmission tree contact
2	174	184.78	161KV Transmission line failure
3	41	184.76	161KV Transmission tree contact
4	149	170.99	69KV Transmission line failure
5	257	151.49	69 KV Circuit breaker failure
6	140	151.17	161KV Transmission line failure
7	248	145.35	69KV Circuit breaker failure
8	32	137.77	69KV Transmission tree contact
9	129	137.49	69KV Transmission line failure
10	21	123.18	69KV Transmission tree contact
System minimum load, P=987MW, hour=4445			
Order	Contingency	Risk	Category
1	66	56.06	161KV Transmission tree contact
2	174	54.90	161KV Transmission line failure
3	149	50.80	69KV Transmission line failure
4	41	50.79	161KV Transmission tree contact
5	257	45.00	69 KV Circuit breaker failure
6	140	44.91	161KV Transmission line failure
7	32	43.18	69KV Transmission tree contact
8	248	40.94	69KV Circuit breaker failure
9	129	40.85	69KV Transmission line failure
10	237	36.60	69KV Circuit breaker failure
System average load, P=1693MW, hour=33			
Order	Contingency	Risk	Category
1	66	98.42	161KV Transmission tree contact
2	174	96.38	161KV Transmission line failure
3	149	89.18	69KV Transmission line failure
4	41	89.16	161KV Transmission tree contact
5	257	79.00	69 KV Circuit breaker failure
6	140	78.85	161KV Transmission line failure
7	32	75.81	69KV Transmission tree contact
8	248	71.86	69KV Circuit breaker failure
9	129	71.71	69KV Transmission line failure
10	21	64.24	69KV Transmission tree contact

5.6.5 Risk reduction with maintenance

Based on cumulative risk assessment, risk reduction curves *CRR(k,m,t)* for component *k*, task *m*, completed at time *t*, based on eq. (5.33) are computed for each maintenance task. Figures 5-11 and 5-12 show the risk reduction curves for maintenance Trim66 and Trim21 (one such curve exists for each component *k*, task *m* combination). We see it is non-increasing, indicating that the earlier the maintenance is scheduled, the larger will be the risk reduction. However, not all the maintenance start times indicated in

Figs. 5-11 and 5-12 are feasible because some of them incur very high risk due to maintenance-outage. This constraint is represented in the optimization model.

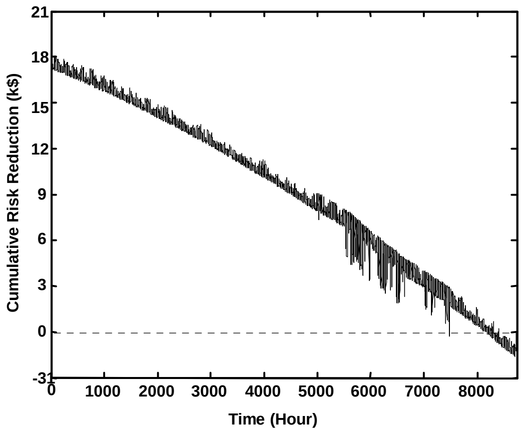

Fig. 5.11: Risk reduction of contingency 66

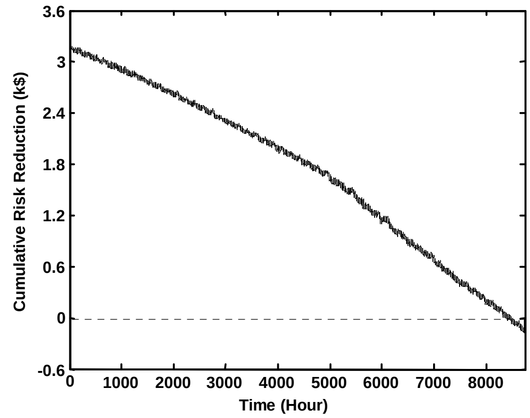

Fig. 5.12: Risk reduction of contingency 21

From Figs. 5.11 and 5.12, we observe that at the end of the year, the cumulative risk reduction falls below zero. This is because in (5.33), there is a non-positive item which is due to redispatch cost during the maintenance outage. Since at the end of the year the cumulative risk reduction is very small, the redispatch cost required by the outage might exceed the cumulative risk reduction obtained from maintenance.

5.6.6 Maximum risk reduction with budget and labor constraints

The labor and budget constraints are summarized in Table 5.6. These constraints, combined with the risk-reduction curves for each contingency and corresponding maintenance task, constitute the input to our optimization problem. The column titled "Total Cost" indicates the cost of all desired maintenance tasks under each of the four categories if they were performed. Comparison of "total cost" to the budget constraint for each category indicates there are more tasks than the budget will allow.

As described in section 5.5.3, this problem is solved using a novel relaxed linear programming/dynamic programming algorithm. Although we use only five maintenance types in this illustration, it is easy to use our algorithm for any number of maintenance types. We may also easily accept different types of categorization; for example, it may be of interest to provide budget and labor constraints by geographical regions.

The maintenance task selection and schedule computed by the optimization program is shown in Table 5.7, where the schedule is given by weekly periods. Because the total budget is less than the cost needed to perform all of the desired maintenance tasks, there are some maintenance tasks left unscheduled based on their lower level or risk reduction. The total cumulative risk reduction over the year is 598.97k$. This means that the above maintenance schedule can be expected (on average if this scenario was experienced many times) to result in a decrease of 598.97k$ of operation cost over the next year.

TABLE 4.6: CONSTRAINTS FOR MAINTENANCE SCHEDULING

Maintenance type	Maintenance description	Labor constraint (labor hour of employees)	Budget constraint ($)	Total Cost ($)
1	Tree_Trimming	400	80000	121000
2	Transmission_line_maintenance	480	125000	235640
3	Transformer_minor_maintenance	320	32000	59294
4	Transformer_major_maintenance	480	150000	154320
5	Circuit_breaker_maintenance	400	100000	117942

Table 5.7 indicates that maintenance tasks are scheduled early in the year, insofar as crew and risk constraints allow, so as to reduce the risk of the most risky components as soon as possible, reducing those risks for the remainder of the year, which in turn tends to maximize the risk reduction achieved, in conformance with the objective. Scheduling maintenance at the end of a chosen time period (in this case, a year), may still occur if the optimizer is run on a rolling basis, say, monthly, using the current year's remaining resources, with each run having objective of scheduling over an entire year's duration.

From the results we can see the effect of resource constraints on maintenance scheduling. For tree trimming, transmission line maintenance and transformer minor maintenance, the dominating constraint is budget. Almost all of the budgets in those categories were consumed before the end of the year, thus leaving some periods of no activity although crews were available. For transformer major maintenance and circuit breaker maintenance, the dominating constraint should be the labor constraint, so not all maintenance can be scheduled during the period of year although they have enough funds available. There are a few weeks at the end where no maintenance is scheduled, this is because at end of the year a task would probably incur a cost without a risk-reduction in the budget year, as indicated in Figs 5.11 and 5.12. So different constraints may have different effects on maintenance selection and scheduling, so their effects on optimization results should be analyzed.

TABLE 5.7: TRANSMISSION MAINTENANCE SCHEDULE

Periods	Tree trimming	Transmission line maintenance	XFMR minor maintenance	XFMR major maintenance	Circuit breaker maintenance
1	Trim32 Trim68	Trans32 Trans61 Trans68	Xrmi2	Xrmj12	CB11
2	Trim32 Trim68	Trans32 Trans61 Trans68	Xrmi2	Xrmj12	CB11
3	Trim2 Trim6 Trim58	Trans32 Trans39 Trans68	Xrmi2	Xrmj12	CB8
4	Trim1 Trim6	Trans1 Trans6 Trans39	Xrmi4	Xrmj16	CB8
5	Trim6 Trim45 Trim54	Trans1 Trans6 Trans52	Xrmi4	Xrmj16	CB31
6	Trim12 Trim30 Trim63	Trans2 Trans6 Trans52 Trans58	Xrmi4	Xrmj16	CB31
7	Trim12 Trim37	Trans6 Trans89	Xrmi11	Xrmj8	CB14
8	Trim12 Trim61	Trans12 Trans89	Xrmi11	Xrmj8	CB14
9	Trim20 Trim35	Trans12 Trans89	Xrmi11	Xrmj8	CB12
10	Trim20 Trim35	Trans12 Trans40	Xrmi10	Xrmj13	CB12
11	Trim27 Trim40	Trans12 Trans40	Xrmi10	Xrmj13	CB13
12	Trim27 Trim40	Trans35 Trans40	Xrmi10	Xrmj13	CB13
13	Trim33 Trim67 Trim70	Trans35 Trans60	Xrmi15	Xrmj11	CB35
14	Trim67 Trim89	Trans35 Trans60	Xrmi15	Xrmj11	CB35

TABLE 5.7: TRANSMISSION MAINTENANCE SCHEDULE (CONTINUED)

15	Trim52 Trim67	Trans41 Trans60	Xrmi15	Xrmj11	CB2
16	Trim28 Trim60	Trans41 Trans45 Trans83	Xrmi16	Xrmj15	CB2
17	Trim28 Trim60	Trans30 Trans41 Trans83	Xrmi16	Xrmj15	CB7
18	Trim41 Trim79	Trans67 Trans83	Xrmi16	Xrmj15	CB7
19	Trim41 Trim79	Trans37 Trans42 Trans67	Xrmi7	Xrmj17	CB34
20	Trim4 Trim59	Trans37 Trans42 Trans67	Xrmi7	Xrmj17	CB34
21	Trim4 Trim59	Trans20 Trans70 Trans67	Xrmi7	Xrmj17	CB9
22	Trim39 Trim42 Trim62 Trim65 Trim72	Trans4 Trans20 Trans31	Xrmi23	Xrmj7	CB9
23	Trim15 Trim31 Trim51 Trim84 Trim85	Trans4 Trams20 Trans31	Xrmi23	Xrmj7	CB25
24	Trim44 Trim64 Trim80 Trim83	Trans4 Trans27 Trans28	Xrmi23	Xrmj7	CB25
25	Trim56 Trim80	Trans27 Trans28 Trans62 Trans79	Xrmi24	Xrmj10	CB32
26	Trim47 Trim56 Trim69	Trans51 Trans54 Trans62 Trans79 Trans86	Xrmi24	Xrmj10	CB32
27	Trim5 Trim46 Trim50	Trans51 Trans59 Trans63 Trans86	Xrmi24	Xrmj10	CB22
28	Trim5 Trim14 Trim38	Trans44 Trans47 Trans59 Trans65 Trans69	Xrmi13	Xrmj5	CB22
29	Trim 38 Trim86 Trim87	Trans14 Trans15 Trans47 Trans59 Trans87	Xrmi13	Xrmj5	CB15
30	Trim73 Trim75	Trans16 Trans46 Trans64 Trans84 Trans87	Xrmi13	Xrmj5	CB15
31	Trim73 Trim75	Trans16 Trans33 Trans46 Trans50 Trans88	Xrmi6	Xrmj20	CB1
32	Trim9 Trim10 Trim88	Trans50 Trans56 Trans73 Trans85	Xrmi6	Xrmj20	CB1
33	Trim9 Trim10 Trim48	Trans56	Xrmi6	Xrmj20	CB6
34	Trim34 Trim49	Trans56	Xrmi21	Xrmj14	CB6
35	Trim13 Trim49		Xrmi21	Xrmj14	CB29
36	Trim57		Xrmi21	Xrmj14	CB29
37	Trim57		Xrmi26	Xrmj4	CB3
38			Xrmi26	Xrmj4	CB3
39			Xrmi26	Xrmj4	CB20
40			Xrmi9	Xrmj6	CB20
41			Xrmi9	Xrmj6	CB28
42			Xrmi9	Xrmj6	CB28
43				Xrmj3	CB27
44				Xrmj3	CB27
45				Xrmj3	CB19
46				Xrmj18	CB19
47				Xrmj18	
48				Xrmj18	
49					
50					
51					
52					
# scheduled	62	51	14	16	23
Total cost	75800	126120	31288	96320	79602

5.6.7 Optimality of solutions

To assess the performance of our RLP-DPH algorithm, we have compared it to commercial mixed linear program solvers. Because of the size of our problem, the solver should have the ability to deal with large size integer programming. We tested two commercial solvers. One is a function in the Matlab 7.0 optimization toolbox, called *bintprog.* It uses the branch and bound (B&B) method and effectively solves small integer programming problems. However, it is limited in solving high dimensional problems. When the number of maintenance tasks exceeds 5 (so that the number of variables exceeds 5 tasks*52 weeks=206), program run-time is unacceptably large, and we were not able to use it in solving realistic versions of our problem.

The second solver we tested was from CPLEX. CPLEX provides large-scale mathematical programming software and services for resource optimization. It has linear, mixed-integer and quadratic programming solvers and is known for good performance -- particularly on high-dimensional problems. The integer programming solver is also based on the B&B method. In this method, a series of LP sub-problems is solved and a tree of sub-problems is built; each sub-problem is node of the tree. The root node is the LP relaxation of the original MIP problem. The sub-problems can result in an all-integer solution, an infeasible problem, or another fractional solution. If the solution is fractional, the process is repeated.

We have tested the performance of both the Matlab and the CPLEX programs on different instances of our problem, where the different instances are distinguished by different resource allocation as indicated in Table 5.8. The comparison of results from our program and CPLEX is given in Table 5.9. Conclusions are as follows:

1) CPLEX solves to optimality if given enough time, but because of the large tree it must build and search, it is computationally and memory intensive. In many cases, the memory is exceeded before optimality is reached. But CPLEX always identifies the best feasible solution and a bound on the objective. Usually the gap (difference between the bound and the value of the objective for the identified best feasible solution) is less than 1%).

2) CPLEX uses excessive time in searching since it uses B&B method, which is a partial enumeration method. Usually it consumes more than 6 hours of computing until the memory is exhausted (on a 1.6 MHz machine with 1 GB memory).

3) Compared to the optimal solution of CPLEX, our RLP-DPH algorithm provides suboptimal, but good results, at a ***much*** lower computational cost. As indicated in Table 5.9, the RLP-DPH solution is within 4.5% of the CPLEX solution, but computation is less by more than 2 orders of magnitude.

TABLE 5.8: CASES WITH DIFFERENT RESOURCE ALLOCATION

Case	Maintenance category									
	1. Tree trimming		2. Trans. Line maintainence		3. Transformer minor maint.		4. Transformer major maint.		5. Circuit Breaker maintenance	
	Budget	Crew	Budget	Crew	Budget	Crew	Budget	Crew	Budget	Crew
A	80000	400	125000	480	32000	320	150000	480	100000	400
B	225000	640	75000	320	75000	240	75000	480	75000	320
C	75000	320	225000	640	75000	240	75000	480	75000	320
D	75000	320	75000	320	225000	560	75000	480	75000	320
E	75000	320	75000	320	75000	240	225000	800	75000	320
F	75000	320	75000	320	75000	240	75000	480	225000	640

TABLE 5.9: COMPARISON OF RESULTS BETWEEN RLP-DPH AND CPLEX

	RLP-DPH		CPLEX					
Case	CRR(k$)	Time (sec)	CRR(k$)	Time (sec)	Upper-Limit (k$)	Gap	Error*	Gap*
A	598.97	134	623.35	35687	625.28	0.31%	3.91%	4.20%
B	593.50	132	610.72	31568	616.16	0.89%	2.82%	3.67%
C	599.77	144	626.34	35698	628.78	0.39%	4.24%	4.61%
D	580.73	152	601.84	34658	607.44	0.93%	3.51%	4.39%
E	576.99	150	598.87	38759	603.30	0.74%	3.65%	4.35%
F	590.28	148	613.69	36764	614.63	0.15%	3.82%	3.96%

Error*: The difference between solutions, in terms of objective, of RLP-DPH and CPLEX.
Gap*: The difference between solution of RLP-DPH and the upper-bound on the objective, as obtained from CPLEX.

5.6.8 Optimization results with different resource allocations

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

Since we have five categories of maintenance activities, suppose we have four proposed budget and labor allocations (case B to F) as listed in Table 5.8. In each case, we emphasize one type of maintenance and assign two more times of the budget than the other category and about 1/3 of the total labor hours to it. The total financial resource is $525,000 and there are altogether 200000 labor hours (about 100 crews). The results are shown in figure 5.13-5.17.

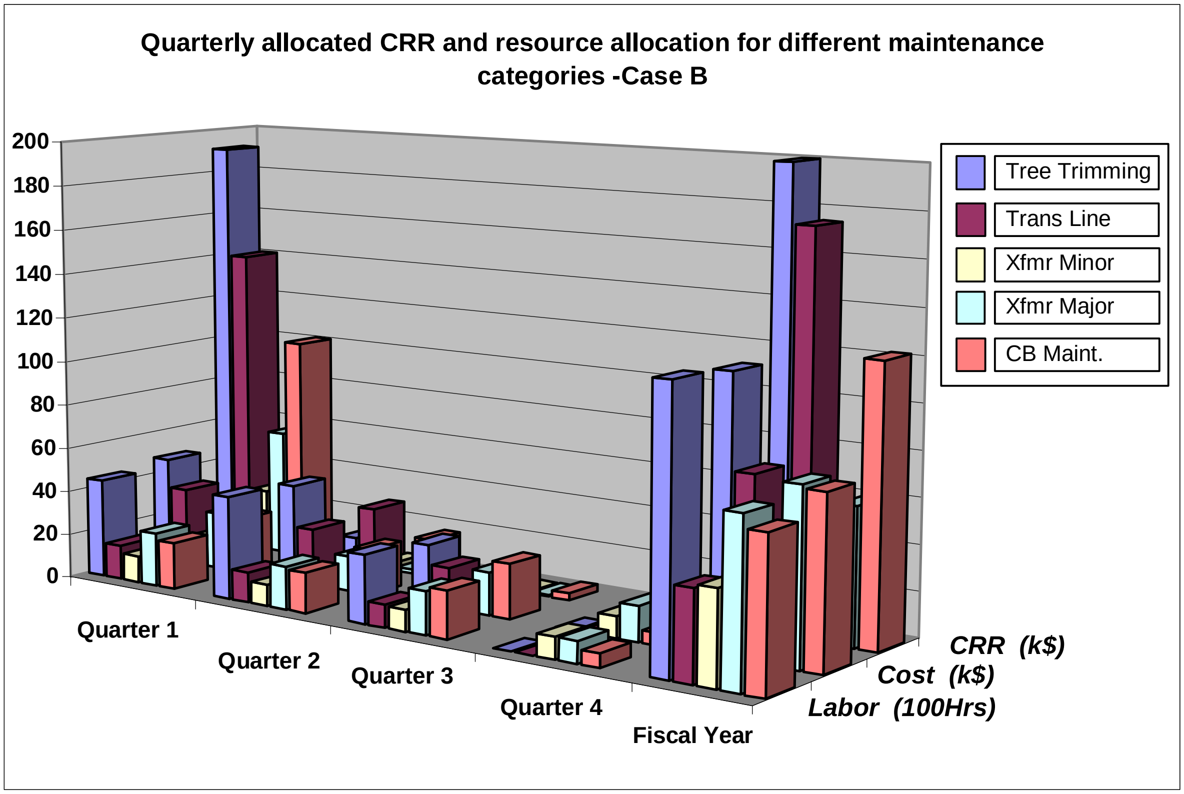

Fig. 5.13: Quarterly allocated CRR and resource allocation for case B

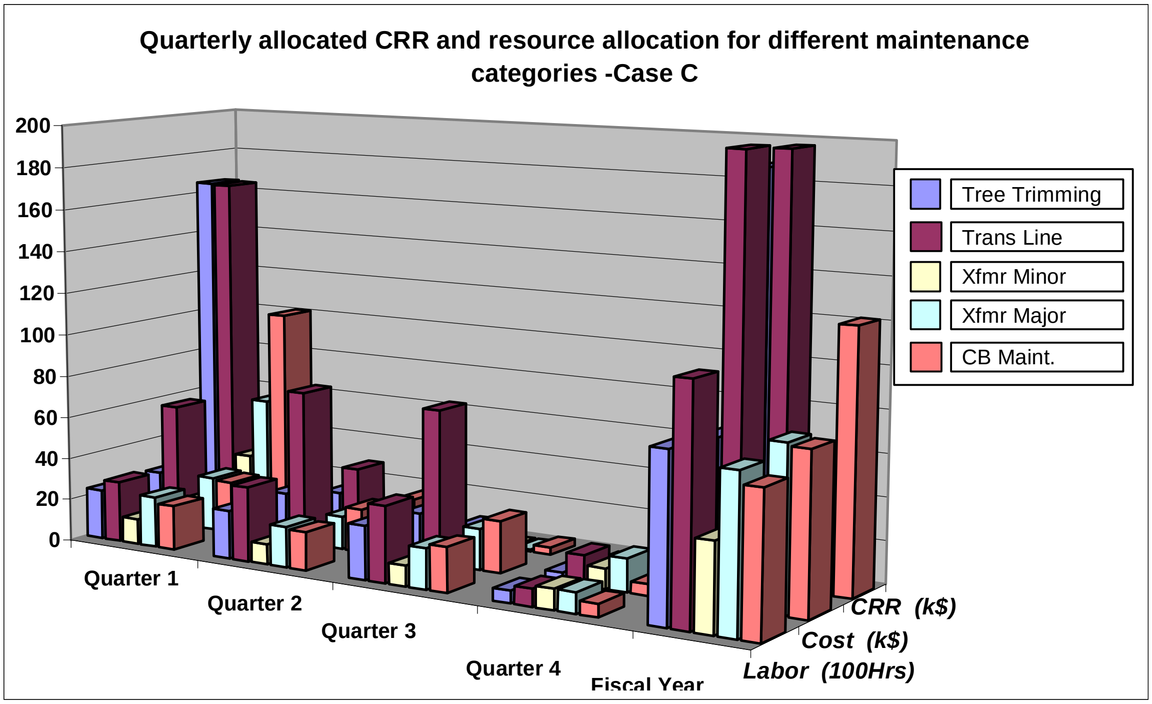

Fig. 5.14: Quarterly allocated CRR and resource allocation for case C

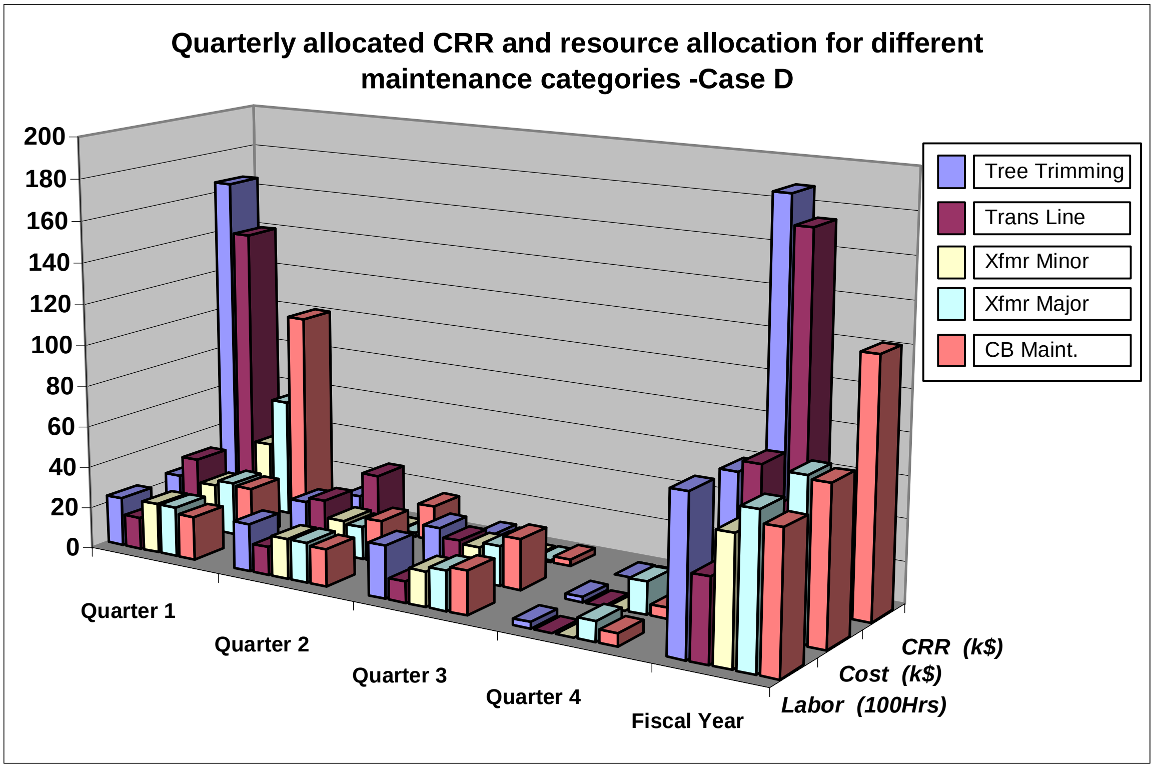

Fig. 5.15: Quarterly allocated CRR and resource allocation for case D

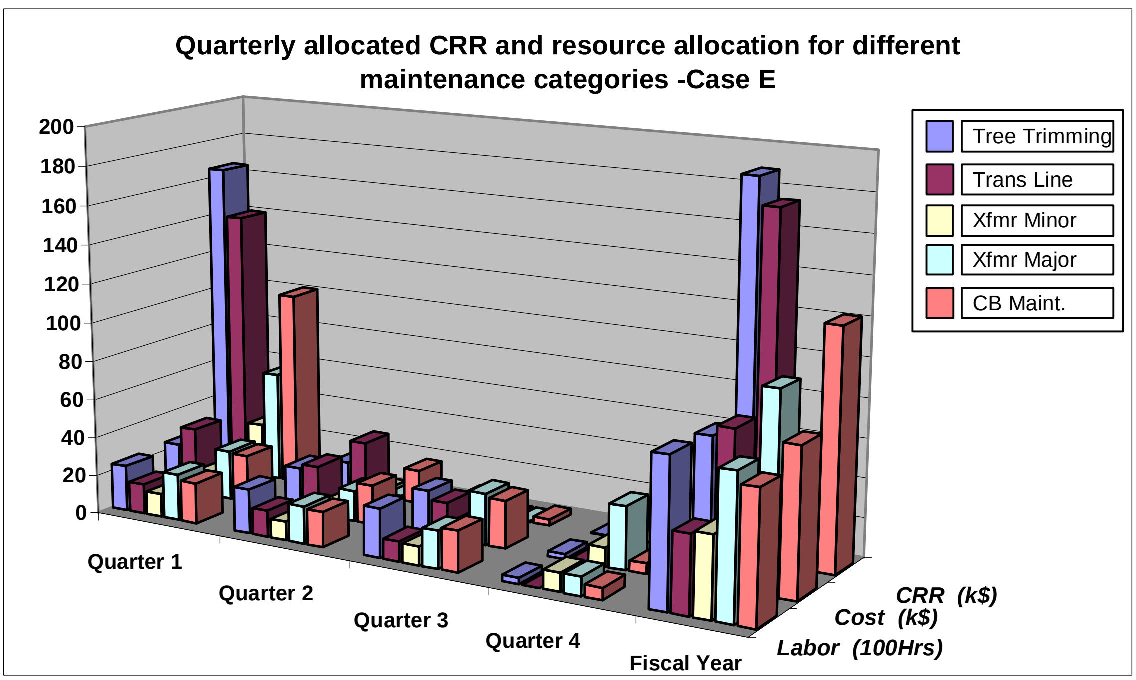

Fig. 5.16: Quarterly allocated CRR and resource allocation for case E

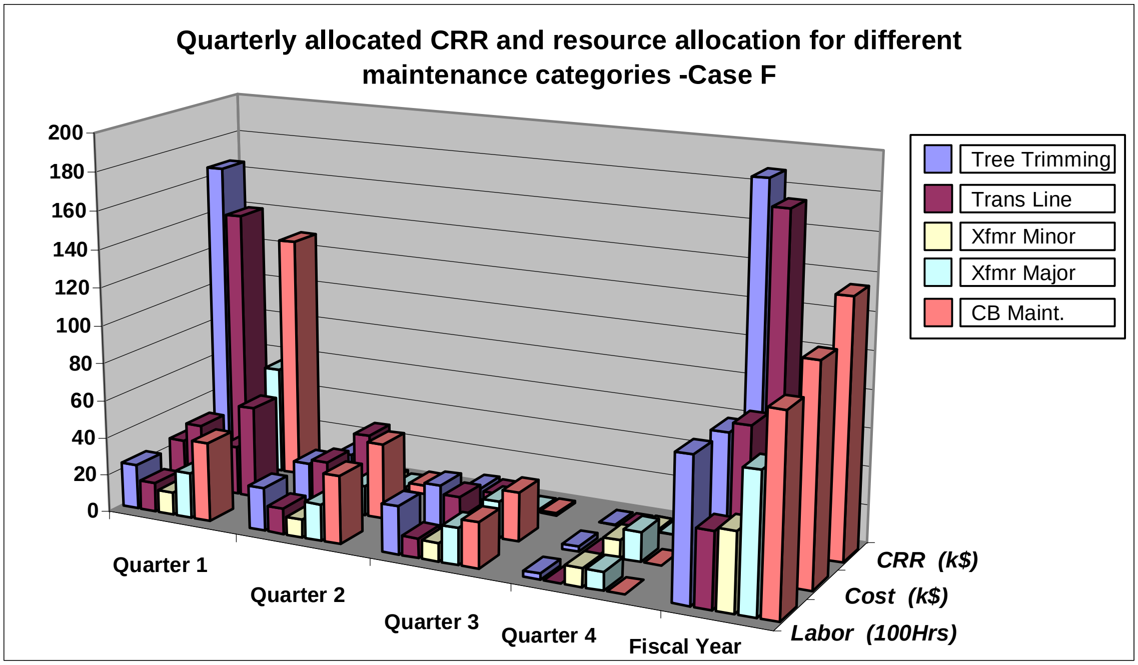

Fig. 5.17: Quarterly allocated CRR and resource allocation for case F

Table 5.10 lists the quarterly performance (CRR, CRR/labor and CRR/cost) of general maintenance scheduling for each allocation case and yearly performance for each category. CRR/labor is in unit of $/Hour and it represents the labor efficiency in achieving the benefit of maintenance. CRR/cost is the benefit/cost ratio and it represents the economic efficiency of the maintenance scheduling.

TABLE 5.10 QUARTERLY PERFORMANCE OF MAINTENANCE ACTIVITIES

	Case	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Categories					Total
						1	2	3	4	5	
CRR (k$)	B	517.74	62.26	13.13	0.39	204.79	174.42	32.31	60.16	121.84	593.51
	C	516.19	66.12	16.63	0.84	188.47	197.00	32.31	60.16	121.84	599.78
	D	497.85	63.44	19.11	0.35	188.36	174.42	35.98	60.16	121.84	580.74
	E	491.98	65.22	19.28	0.53	188.36	174.42	32.31	60.16	121.84	577.09
	F	520.07	52.56	17.27	0.39	188.36	174.42	32.31	60.16	135.04	590.28
CRR/ Hour ($/Hour)	B	44.319	5.843	1.453	0.155	16.926	44.518	7.919	8.356	18.461	17.510
	C	47.166	6.308	1.502	0.215	24.388	18.241	7.919	8.356	18.461	16.474
	D	46.097	6.839	2.070	0.187	25.236	44.518	5.997	8.356	18.461	18.625
	E	51.248	7.843	2.265	0.187	25.236	44.518	7.919	8.344	18.461	19.719
	F	44.450	5.196	1.959	0.175	25.236	44.518	7.919	8.356	13.239	17.963
CRR/ Cost	B	3.565	0.548	0.135	0.013	1.724	2.238	0.826	0.788	1.631	1.534
	C	3.525	0.472	0.113	0.017	2.513	0.902	0.826	0.788	1.631	1.241
	D	3.768	0.624	0.188	0.015	2.587	2.238	0.631	0.788	1.631	1.619
	E	4.025	0.706	0.192	0.011	2.587	2.238	0.826	0.602	1.631	1.584
	F	3.555	0.471	0.182	0.014	2.587	2.238	0.826	0.788	1.182	1.552

From Figs. 5.13-5.17 and Table 5.10, we draw the following conclusions:

1. Effect of number of tasks and hours per task: For each case, we observe that categories 1 and 2 (tree trimming and transmission line maintenance) consume more resources and thus produce more benefit than other categories. This is because they have significantly more proposed maintenance tasks (89) than transformer minor maintenance (26), transformer major maintenance (20) and circuit breakers (35). Also they require less labor hours and this permits several tasks to be scheduled at the same week as early as possible, as shown in Table 5.7.
2. Effect of increased resources when category is not labor constrained: For most categories, an increase in allocated resources results in an increase in cumulative risk reduction (see Fig. 5.13-5.17), but the efficiency (CRR/Hour, CRR/Cost) of the category drops, as shown in Table 5.10. This is reasonable because the optimal algorithm chooses the most efficient tasks first. When more resources are available, less efficient tasks will then be chosen.
3. Effect of increased resources when category is labor-constrained: Category 4 (transformer major maintenance) does not show an increase with CRR when more resources are allocated to it. This is because this category is much more labor constrained. We observe in Table 5.7 that the tasks of this category will be scheduled until the end of the year. Our reallocation of labor resources is not enough to allow multiple tasks scheduled during the same week. Therefore, category 4's result was not affected by our resource reallocation from case B to F.
4. Effect of finite time interval of simulation: In each of the cases, as illustrated in Figs. 5.13-5.17, the CRR decreases dramatically from the first quarter to the last quarter of the year. This is because the objective function (CRR) is cumulative over a year, and thus: (a) The optimization algorithm will choose those tasks producing the largest cumulative risk reduction to be scheduled as early as possible; (b) The tasks scheduled during later quarters are do not benefit from risk reduction during earlier time periods. The fact that the approach does not account for risk reduction incurred after the end of the simulation time interval would only affect the selection and timing if the system conditions during successive years are significantly different than those in the simulated year. If one wanted to account for this, a rolling execution of the procedure could be implemented where the next 12 months could be simulated each quarter, or each month.
5. Resource re-allocation: From Table 5.10 we can see that generally, category 2 (transmission line maintenance) has the highest labor efficiency (CRR/Hours), and category 1 and 2 (tree trimming and transmission line maintenance) have the highest cost efficiency (CRR/Cost). This is because these two maintenance activities generally cause more failure probability reduction than those in other categories, together with less resource consumption. This indication provides direction in resource re-allocation between different categories.
6. When we compare the 5 cases in Table 5.10, we can see that case C, in which the category 2 (transmission line maintenance) received more resource allocation, provides the highest output (599.78k$ of CRR). This is because it is the category with most efficient resource characteristic, as stated in 5. But it also has the lowest

benefit/resource ratios (CRR/Hours, CRR/Cost). This is because more available resource permits the program to have more less-efficient tasks to be scheduled. That is the say, by emphasizing category 2, we can schedule more tasks, but with lower benefit/cost ratio.

From above analysis, we can identify performance of each maintenance category in terms of cumulative risk reduction and in terms of efficiency in utilizing the resources. And we can obtain indications of how to reallocate resources so as to increase overall risk reduction. However, the analysis is rather ad-hoc and subjective. We extend our effort with a more accurate method in the next section.

5.6.9 Resource reallocation based on Lagrange Multipliers

From optimization results in Table 5.7 and analysis of section 5.6.8 we can see that the resource constraint has significant influence on the result of optimization. And it is very likely by shifting resources between categories, we may find desirable effects on the overall risk reduction achieved. In this section, we describe and illustrate a systematic method for identifying such reallocations.

In solving the relaxed (linear programming) version of (5.35), we can get Lagrange multipliers for different constraints. The Lagrange multipliers indicate the decrease in objective function for a per-unit increase in the right hand side of the corresponding constraint. So we can take them as good indicators for resource reallocations, although they are only multipliers for the relaxed linear programming and thus may have some error with respect to the multipliers for the integer solution.

An algorithm was designed to reallocate the resource according to value of Lagrange multipliers of constraints of budget and labor: Suppose we have N categories of maintenance activities $i=1\dots,N$, each with allocated resource C_i. Resources may reallocated from the categories with lower values of Lagrange multipliers to the category with the highest multiplier according to the following procedure.

1) Solve the relaxed linear programming (5.35)-(5.41) of the problem, and obtain the Lagrange multiplier λ_i for resource constraint of each category i. The category with the highest multiplier λ_{max} will be reallocated more resources from other categories. Set the total reallocated resource amount ΔC.

2) If there is a category with multiplier of 0, it means the category has excessive resources and all of the reallocated resource will come from that category.

3) If all of multipliers are less than zero (indicating increase in resources will decrease the objective in the negative direction, i.e., the CRR will increase), then the resource allocation is determined by the difference between these multipliers with the maximum Lagrange multipliers:

$$\Delta C_i = \frac{l_i - l_{\max}}{\sum_{j=1}^{N} (l_j - l_{\max})} \times \Delta C \tag{5.54}$$

For the labor constraints, since they are weekly constraints, there is also a lower limit of the resource (a minimum resource allocation) allocated to each category, so that the labor availability in each week is enough to perform one maintenance activity. This is especially important for transformer maintenance, which might need more people for each mission. When the lower limit is reached, then the labor in that category is fixed at the lower limit and is no longer adjusted.

4) Modify the constraints with allocated resources and go back to 1). Iteration stops when the optimal result is reached.

Table 5.11 shows different resource allocation among maintenance categories for cases A1-A6. In each case, the allocation is made so that one type of maintenance is favored over the others. And the resources of money and labor are adjusted simultaneously. In Table 5.12, the Lagrange multipliers for every category, and for each case, are listed. Form the results we can se that A5 provides highest outcome and the iteration should stop there. More detail adjustment might be performed by reducing the step length but this will require longer computation time.

TABLE 5.11: RESOURCE ALLOCATION AMONG MAINTENANCE CATEGORIES

Case	Maintenance category									
	1. Tree trimming		2. Trans. Line maintenance		3. Transformer minor maint.		4. Transformer major maint.		5. Circuit Breaker maintenance	
	Budget	Crew	Budget	Crew	Budget	Crew	Budget	Crew	Budget	Crew
A1	80000	480	125000	560	32000	560	120000	600	90000	480
A2	80000	456	165000	760	32000	469	80000	531	90000	464
A3	78192	450	185000	743	27090	343	72450	480	84268	664
A4	76980	500	205000	793	20565	276	63140	480	81315	631
A5	91980	516	201584	813	18767	240	56154	480	78515	631
A6	94980	511	201266	833	18635	240	53770	480	78347	615

TABLE 5.12: REALLOCATION OF RESOURCES BASED ON LAGRANGE MULTIPLIERS

Case		Case A1	Case A2	Case A3	Case A4	Case A5	Case A6
Lagrange multipliers on budget constraint	1	-16.50	-16.44	-16.29	-19.47	-13.45	-12.99
	2	-27.18	-21.16	-18.52	-11.60	-12.20	-12.19
	3	-8.75	-8.33	-6.52	-15.33	-12.93	-12.84
	4	0	-1.43	-1.40	-3.38	-4.06	-6.913
	5	-7.46	-6.18	-13.09	-13.02	-12.79	-12.76
Lagrange multipliers on labor constraint	1	-44.91	-47.23	-47.63	-41.04	-41.49	-42.31
	2	-57.34	-43.93	-47.88	-45.96	-44.36	-43.87
	3	-10.32	-11.58	-14.99	-14.74	-18.67	-18.69
	4	-21.85	-20.61	-31.27	-29.39	-28.32	-26.57
	5	-48.85	-48.80	-31.87	-33.89	-33.72	-33.04
CRR (k$)		569.38	614.82	624.77	626.29	631.53	627.41

From the results shown in Table 5.12 we can see that we get significant increase of CRR by reallocating the resources between different maintenance categories, from 569.38 to

631.53 (10.9% increase). By tracking the reallocation, with reference of Table 5.10 we can find the resource is flowing out of categories with lower benefit/cost ratios to those with higher benefit/cost ratios. For example, the labor resource is reallocated with the direction from category 3 (transformer minor maintenance), 4 (transformer major maintenance) to 1 (tree trimming), 2 (transmission line maintenance) and 5 (CB maintenance); and budget resource is flowing out of category 3, 4 and 5 to 1 and 2.

5.6.10 Effect of constraints on optimization results

We have investigated the effect of budget and labor reallocation between different categories, with fixed total available resources. It may also be of interest to identify a good total investment level over all of the categories. A basic principle to guide this kind of effort is to look to maximize benefit/resource ratios. To this end, we introduce indices reflecting different attributes of the solution:

1) *CRR*: Cumulative Risk Reduction. This is the value of the objective function and a high-level indicator of the solution quality. We identified it as 203.72 in the case A5 of section 5.6.10.

2) *CRR/Cost*: Ratio of CRR to total cost. This index indicates the risk reduction per unit dollar spent, where higher values indicate more desirable solutions.

3) *Cost/Budget (%)*: This index indicates, for each maintenance category, the percentage of the budget actually spent. Solutions that have values of this index significantly less than 100% indicate that the corresponding category may be over-budgeted.

4) *CRR/labor*: Ratio of CRR to total labor in hours. This index indicates the risk reduction per hour of human labor, where higher values indicate more desirable solutions.

5) *Labor/available labor (%)*: This index indicates, for each maintenance category, the percentage of the available labor actually utilized. Solutions that have values of this index significantly less than 100% indicate that the corresponding category may have an over-allocated number of assigned personnel.

6) *CRR/Total possible CRR (%)*: This index indicates the percentage of possible risk reduction that is actually achieved via the solution. The possible risk reduction can be computed in two ways. It can be computed assuming there are no labor constraints so that *all selected tasks* (given the budget constraint) could be scheduled in the *first* week. The index computed in this way provides a measure of additional benefit that could be achieved from additional labor under the given budget. Alternatively, it can be computed assuming there are no labor or budget constraints so that *all proposed tasks* could be scheduled in the *first* week. The index computed in this way provides a measure of additional benefit that could be achieved from additional budget and labor resources. We have elected to compute the index in the first way. For both ways, solutions that have values of this index much less than 1 stand to significantly benefit from additional financial and/or labor resources.

7) *Unscheduled number of tasks/Total number of tasks (%)*: This index indicates the percentage of tasks that could be completed with additional financial or labor

resources. Solutions that have values of this index close to 1 may stand to significantly benefit from additional financial and/or labor resources.

It is also possible to utilize the LaGrange multipliers (m_1-m_4 on the budget constraints and l_t, $t=1,\ldots T$ on the risk constraints) to obtain useful information about the solution. Specifically,

- m_1-m_4 gives the increase in cumulative risk reduction when the corresponding budget is increased by a dollar. Thus, the budget b with the highest m_b provides the largest benefit, in terms of risk reduction, if it were increased.
- l_t, $t=1,\ldots T$ give the increase in cumulative risk reduction when the corresponding week t risk is allowed to increase by 1 unit. The week t with the highest l_t provides the largest benefit, in terms of risk reduction, if we relieve security constraints so as to allow additional maintenance-related outages during that week.

We compute and plot these various indices for two scenarios based on the case A4, which has the best resource allocation. In Section 5.6.1, we fix the labor constraints for each maintenance type and vary the budget constraint. In Section 5.6.2, we fix the budget constraints for each maintenance type and vary the labor constraints.

Additionally, in Section 5.6.3, we illustrate how to use the optimizer for performing comparative analysis of different resource allocations among the defined categories, assuming that the total financial and labor resources are limited. The objectives of the studies summarized in the next three sections are to (a) validate the reasonableness of the models and algorithm, and (b) illustrate the potential of using the tool to perform analysis of different maintenance resource allocations.

5.6.10.1 Effect of budget variation on maintenance scheduling

To illustrate the effect of total budget on maintenance scheduling, a fixed number of crew members are assigned to each type of maintenance, as shown in Table 5.13, and the budget is varied from \$246k to \$648k. The results in terms of the various indices are summarized in Table 5.14.

TABLE 4.13: LABOR LEVEL FOR BUDGET VARIATION

Maintenance type	Maintenance description	Labor Hours
1	Tree_Trimming	516
2	Transmission_line_maintenance	813
3	Transformer_minor_maintenance	240
4	Transformer_major_maintenance	480
5	Circuit_breaker_maintenance	631

Table 5.14 indicates that in some cases, the cost/budget is a little above 100%. It is caused by a program feature that allows a maintenance task to be scheduled if the remaining budget is very close to the cost of next maintenance to be scheduled. Variations in indices with increasing budget are illustrated in Figs. 5-18 to 5-24. We make the following observations:

TABLE 4.14: INDICES CALCULATED FROM DIFFERENT BUDGET SETTINGS

Total Budget (k$)	CRR (k$)	CRR/ Cost	CRR/ labor	Cost/ Budget (%)	Labor/ Available labor (%)	CRR/ Possible CRR(%)	Unscheduled Maintenance (%)
246	587.85	2.59	34.65	92.48	37.98	94.78	73.70
268	615.94	2.38	31.38	96.36	41.83	93.77	65.62
291	617.15	2.30	25.25	92.39	45.19	93.70	65.17
313	627.63	2.00	26.77	100.4	50.00	93.01	53.48
335	628.65	1.92	25.13	97.82	54.33	92.89	50.78
358	631.32	1.80	23.59	98.06	57.21	92.73	46.30
380	633.83	1.65	21.65	101.33	62.50	92.46	38.65
402	630.39	1.57	20.43	100.16	68.75	91.92	36.86
425	632.06	1.49	19.57	100.11	71.63	91.72	32.81
447	631.53	1.40	18.36	100.66	75.96	91.35	30.12
469	630.94	1.39	18.13	96.59	76.44	91.40	29.66
492	632.62	1.28	16.70	100.56	84.13	91.07	21.58
514	632.43	1.26	16.58	97.67	85.58	91.06	22.92
536	632.25	1.22	16.07	96.45	87.98	90.92	20.67
559	632.03	1.21	15.71	93.26	91.35	90.92	19.33
581	632.31	1.19	15.39	91.46	93.27	90.89	17.53
603	632.59	1.18	15.20	88.85	93.75	90.83	16.18
626	633.11	1.14	14.65	88.38	96.64	90.62	12.58
648	633.18	1.14	14.54	85.73	98.08	90.59	11.69

1. CRR: Fig. 5.18 shows that as the budget increases, the cumulative risk reduction increases until a budget of about $400k after where the budget covers the cost of all the maintenance. Budget increases beyond that value are of no value.

2. CRR/budget and CRR/total labor: Figs. 5.19 and 5.20 indicate that as the budget increases, the CRR per dollar budgeted and CRR per hour of labor decreases, indicating that resource effectiveness in reducing risk tails off as resources increase. This is not surprising since our algorithm always selects the most effective maintenance tasks first, so as resources increase, the less effective maintenance tasks will be selected, resulting in the trend seen in Figs. 5.19 and 5.20. This does not necessarily imply that one should not utilize the greater resource levels. To this end, we comment that the decision to allocate a certain level of resources depends on the effectiveness of those resources in reducing risk, quantifiable by our program, but it also requires information regarding the effectiveness of those resources if expended elsewhere in the company.

3. Cost/budget: Fig. 5.21 indicates that as the budget increases, the maintenance cost approximately equal the budgeted dollars (so that the budget constraint is active) until the budget becomes very large (about $500k), and for larger budgets, the labor constraints become active and maintenance cost is almost constant. Fig. 5.21 also indicates that cost/budget ratio increases between $250k and $350k from about 93% to almost 100%, implying that lower budgets are not totally utilized whereas higher

budgets are. This apparent anomaly is a result of the lumpiness of maintenance projects, i.e., the lower budgets became "stuck" at 93% because any additional project would result in a budget limit violation, whereas the higher budgets got "stuck" at values much closer to 100%.

4. ***CRR/*<u>Total possible</u> *CRR***: Fig. 5.22 shows that as the budget increases, this index decreases, indicating that the rate of increase of CRR with budget is significantly less than the rate of increase of possible CRR with budget. The reason for this is that higher budgets allow more tasks to be selected, but because of labor constraints, most of these tasks must be scheduled in the latter part of the year. Tasks scheduled at the later part of the year do not provide much CRR but do provide significant amount of possible CRR.

5. <u>Labor hours/available labor hours</u>: Fig. 5.23 shows that as the budget increases, the labor hours used/available labor hours ratio increases. This is reasonable as long as labor constraints are not active, implying crews are more fully utilized as budget increases.

6. <u>Unscheduled maintenance</u>: Fig. 5.24 shows that the percentage of unscheduled maintenance tasks decreases as the budget increases.

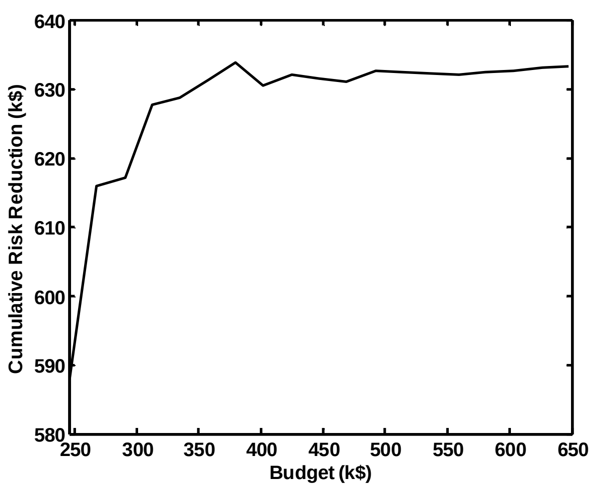

Fig. 5.18: Cumulative Risk Reduction

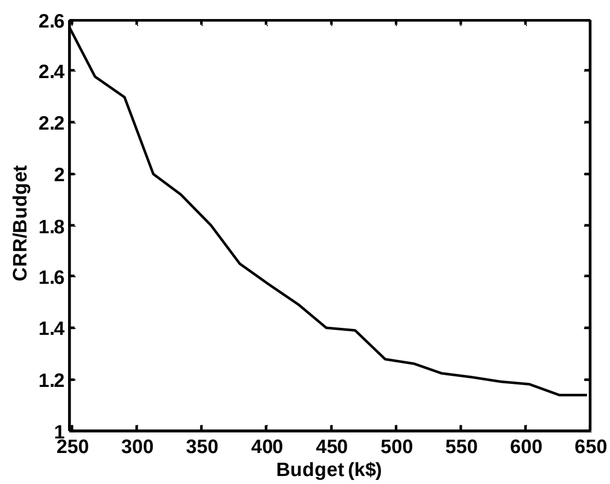

Fig. 5.19: CRR/Budget

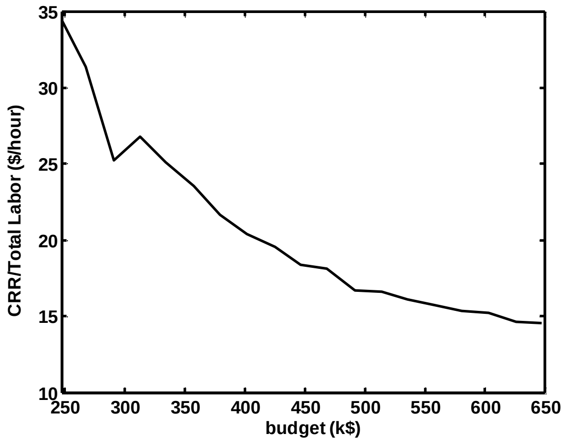

Fig. 5.20: CRR/Total labor

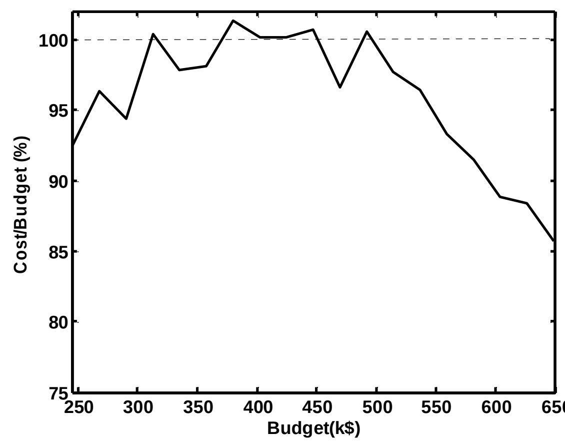

Fig. 5.21: Cost/Budget

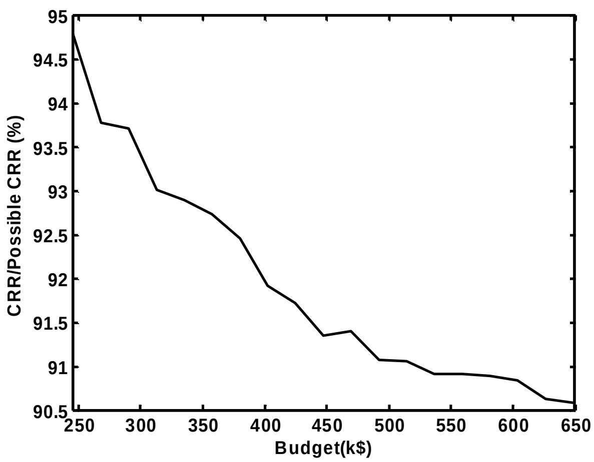

Fig. 5.22: CRR/Possible CRR

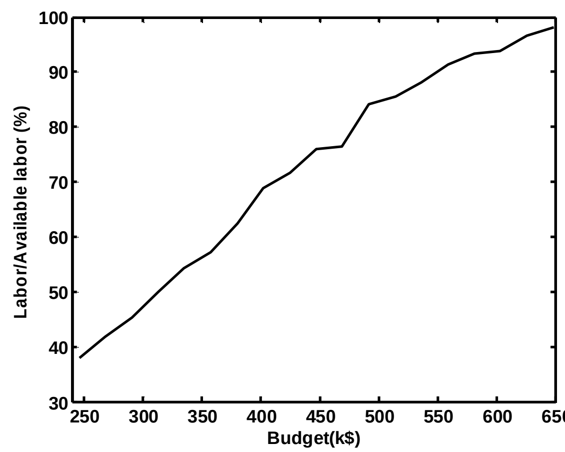

Fig. 5.23: Labor usage

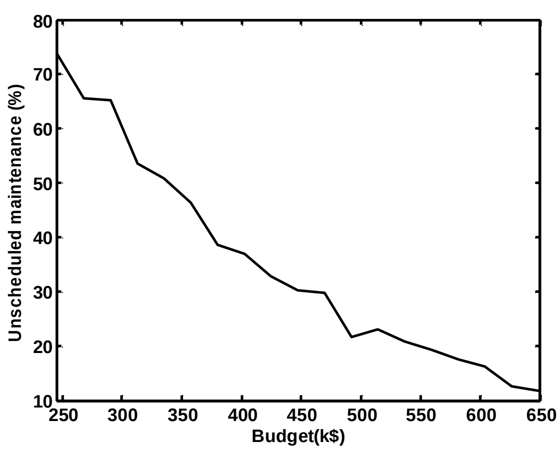

Fig. 5.24: Unscheduled maintenance

5.6.10.2 Effect of labor variation on maintenance scheduling

To illustrate the effect of labor on maintenance scheduling, fixed budgets are assigned to each type of maintenance, as shown in Table 5.15, and the labor hour varies from 1798 to 3886 hour per week, as indicated in Table 5.16. The results in terms of the various indices are summarized in Table 5.16.

TABLE 5.15: BUDGET LEVEL FOR LABOR VARIATION

Maintenance type	Maintenance description	Budget ($)
1	Tree_Trimming	94980
2	Transmission_line_maintenance	201266
3	Transformer_minor_maintenance	18635
4	Transformer_major_maintenance	53770
5	Circuit_breaker_maintenance	78347

TABLE 5.16: INDICES CALCULATED FROM DIFFERENT LABOR SETTINGS

Total labor hour per week	CRR (k$)	CRR/ Cost	CRR/ labor	Cost/ Budget (%)	Labor/ Available labor (%)	CRR/ Possible CRR (%)	Unscheduled Maintenance (%)
1798	568.39	1.53	19.76	83.08	78.08	86.60	42.47
1896	575.86	1.54	19.76	83.49	76.54	86.97	43.24
1994	585.75	1.51	19.41	86.82	76.15	87.18	39.77
2092	586.71	1.53	19.24	85.93	73.85	87.95	40.93
2190	601.99	1.54	19.89	87.34	71.54	89.02	40.93
2288	601.90	1.52	19.51	88.56	69.62	88.76	37.45
2386	607.48	1.54	19.70	88.00	68.08	90.12	37.45
2484	602.05	1.50	19.43	89.74	65.39	88.97	35.91
2582	612.90	1.50	19.63	91.21	64.62	90.31	33.98
2680	631.53	1.40	18.36	100.66	60.77	91.35	30.12
2814	630.85	1.45	18.86	97.35	60.00	91.62	28.96
2948	638.91	1.44	18.59	100.67	59.62	92.53	25.10
3082	640.89	1.44	18.84	99.86	55.77	92.71	24.32
3216	645.05	1.44	18.80	100.45	55.39	93.28	23.94
3350	640.71	1.43	18.68	100.05	53.46	92.67	24.32
3484	640.55	1.43	18.57	100.41	52.69	92.62	23.55
3618	639.78	1.43	18.69	100.26	51.15	92.50	23.55
3752	647.22	1.43	18.50	101.55	53.08	93.55	23.17
3886	644.89	1.32	18.25	98.26	41.54	95.04	21.11

Variations in indices with changing labor are illustrated in Figs. 5.25 - 5.31. We make the following observations:

1. CRR: Fig. 5.25 shows that CRR increases with increasing labor. With increasing budget, we observed a leveling off of CRR (see Fig. 5.19) when the budget was sufficient to perform all projects. Here, however, increasing labor resources make it

possible to continuously shift projects earlier in time, so that we do not observe the saturation of CRR.

2. CRR/budget and CRR/total labor: Figs. 5.26 and 5.27 show that as the labor increases, the CRR per dollar budgeted and CRR per hour of labor generally decrease, indicating that resource effectiveness in reducing risk increase as labor resources decrease. This effect is due to the same reason as 5.14 and 5.15 that the program always selects the most effective maintenance tasks first so as labors increase, the less effective maintenance tasks will be selected, resulting in the trend seen in Figs. 5.26 and 5.27.
3. Cost/budget: Fig. 5.28 indicates that as the labor increases, the percent of budget actually utilized continues to increase. This effect is very reasonable since the additional labor provides the ability to perform more maintenance tasks.
4. Labor hours/available labor hours: Fig. 5.29 shows that as the labor increases, the ratio of labor hours used/available labor hours decreases from 78% to 41%, indicating that labor efficiency is reduced with the increase of labor resources.
5. ***CRR/*****Total possible *CRR***: Fig. 5.30 shows that as the labor increases, this index increases, indicating that the rate of increase of CRR with budget is significantly higher than the rate of increase of possible CRR with budget. The reason for this is that with more labors, more tasks can be scheduled earlier. This will cause significant increase of CRR since it decreases with time.
6. Unscheduled maintenance: Fig. 5.31 shows that the percentage of unscheduled maintenance tasks decreases as the labor increases.

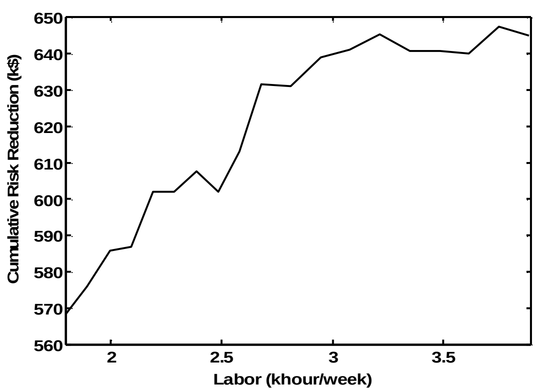

Fig. 5.25: Cumulative risk reduction

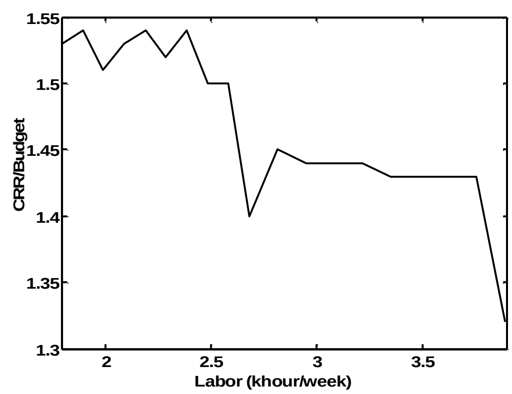

Fig. 5.26: CRR/Cost

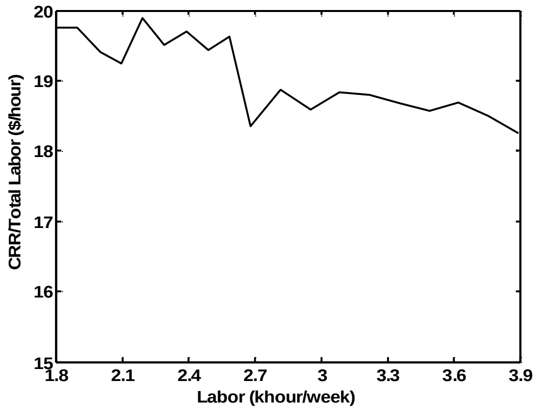

Fig. 5.27: CRR/Total Labor

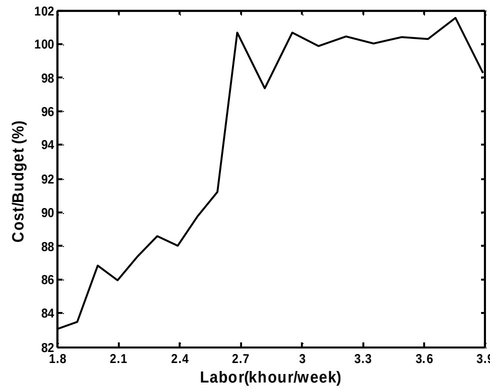

Fig. 5.28: Cost/Budget

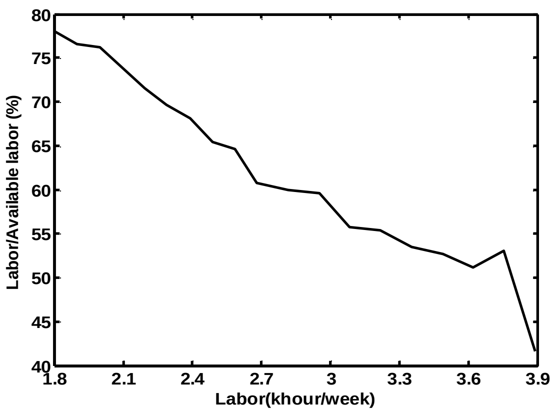

Fig. 5.29: Labor usage

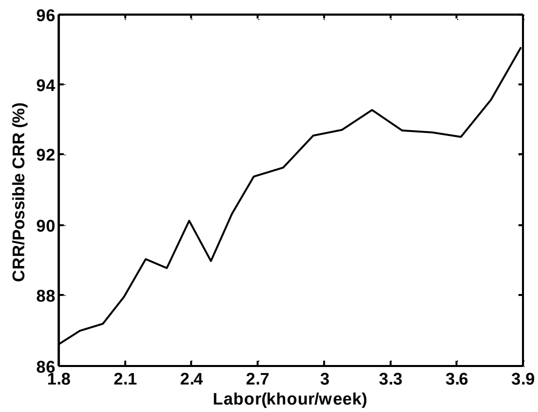

Fig. 5.30: CRR/Possible CRR

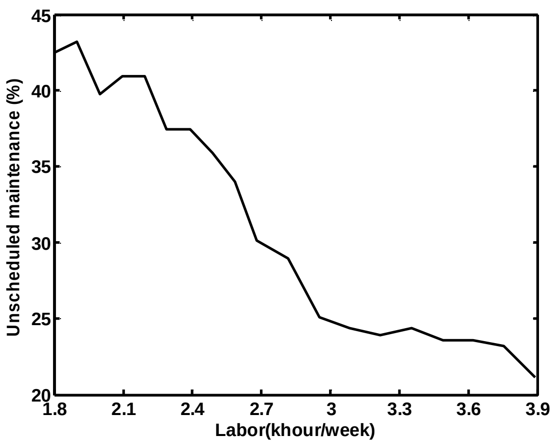

Fig. 5.31: Unscheduled maintenance

It is similar with the case of different budget. Some of the indices here are contradictive because they represent different part of interest of the budget makers. Balance among them is needed to make the best decision.

5.6.11 Decision making on resource scheduling and allocation

As indicated in the last section, the optimization algorithm we have developed not only provides the best selection and scheduling of current maintenance activities, with fixed resource allocations, it also provides useful information on planning budgets and scheduling labor resources, so that the maximum efficiency will be achieved. Fig. 5.32 provides another way to view the information to assist in this kind of decision-making. Here, the total budget varies from \$111k to \$961k, and the labor varies from 0.67k to 5.76k hours per week.

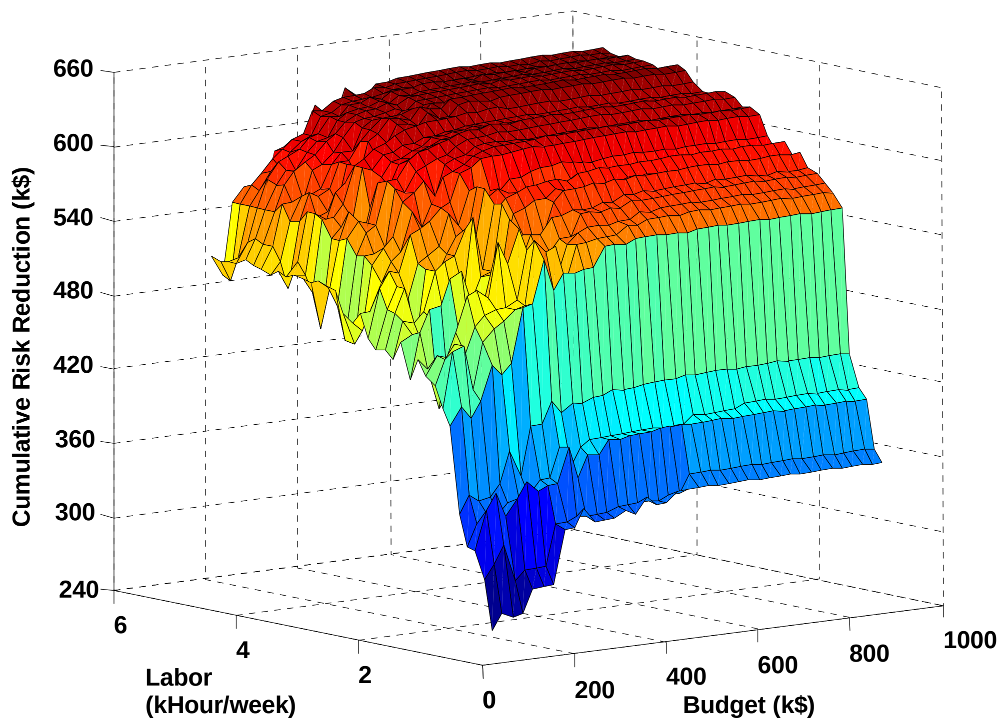

Fig. 5.32: CRR surface with different resource conditions

From Fig. 5.32 we observe objective function increase with the increase of the labor or budget constraint. There is some lumpiness of the surface due to the sub-optimal feature of our algorithm, a price that is paid for obtaining much faster computational speed. But it is the speed of the algorithm which enables development of the kind of information displayed by Fig. 5.32 where we observe so many combinations of resource conditions.

Figs. 5.33 and Fig. 5.34 provide alternative views into budget and labor efficiency. We observe that the best efficiency was achieved with lowest resource allocations. This is due to the nature our cumulative risk reduction – resource efficient maintenance tasks will generally be selected, and scheduled to achieve the maximum objective function. So while we make budget and labor planning for the next year, we need to consider both objective function and efficiency. Here we may need to calculate the total cost of the maintenance. For example, total cost of the maintenance can be calculated as the summation of the project cost and the wages of the labors. Suppose the hourly wage for each employee is W dollars/hour, and then the total cost of each resource scenarios can be calculated as:

$$TotalCost = BudgetUsed(\$) + LaborUsed(Hour) * W(\$/hour) \tag{5.55}$$

Here *BudgetUsed* is the total money spent in the budget after scheduling; *LaborUsed* is the actual usage of the labors after scheduling, then the efficiency of the maintenance scheduling is:

$$E = CRR / TotalCost \tag{5.56}$$

A common practice will be to choose the allocation with the highest budget and labor efficiency with specified objective function value. The procedure for doing this is:

1. Determine the required objective function value *CRR*' of maintenance scheduling.
2. Perform the maintenance scheduling with combination of different resource allocation within reasonable range, as in Fig. 5.32
3. For each combination, we calculate the total cost of the scheduling and the efficiency ratio with (5.55) and (5.56)
4. Choose the scheduling scenario with the highest efficiency ratio with required objective function *CRR>CRR'*.

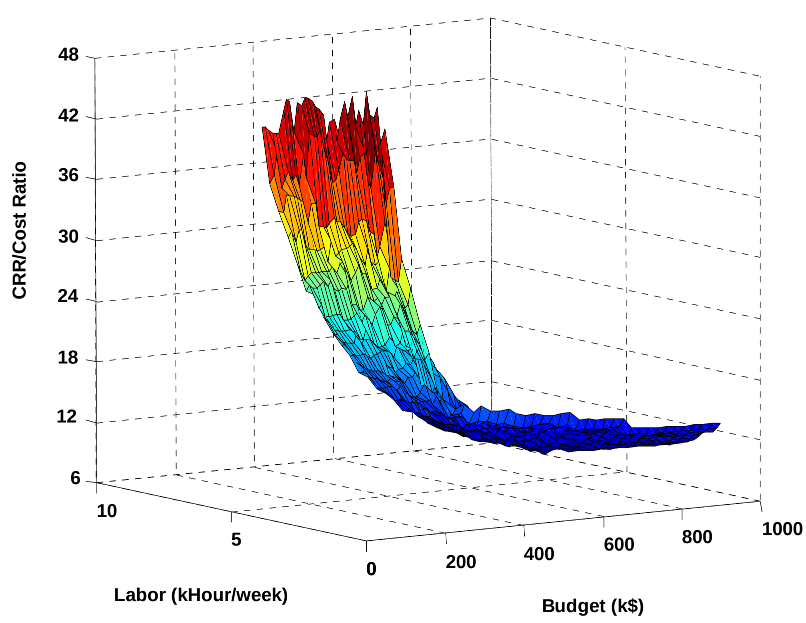

Fig. 5.33: CRR/Cost with different resource conditions

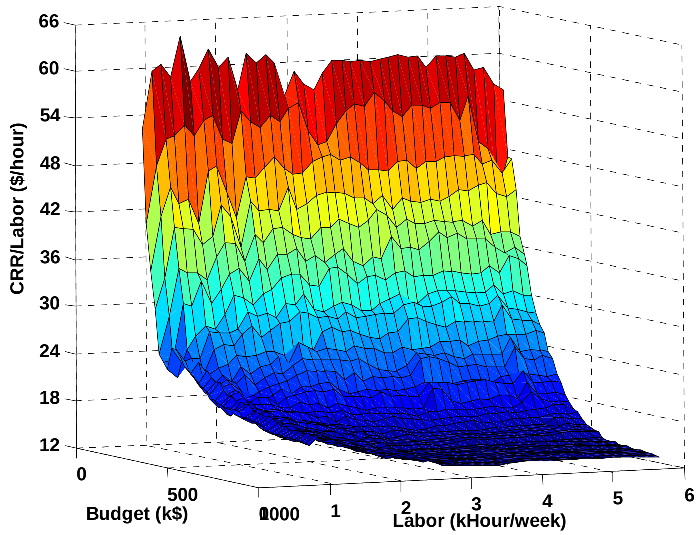

Fig. 5.34: CRR/Labor with different resource conditions

Suppose the hourly wage is set as 16$/hour, Fig 5.35 is the efficiency ratio of maintenance scheduling under different resource combinations. From Fig 5.35 we can see that maximum efficiency is achieved with the minimum resource allocation. However, we also need to meet the preset objective of our maintenance scheduling. Suppose we want to have a CRR>620k$, then we can use Fig 5.33 and Fig 5.34 to find the most efficient resource scheduling while satisfying CRR>620k$, which is *BudgetUsed* =227.85k$ and *LaborUsed*=16932Hours. Under such resource planning, the optimal CRR is 628.90k$U and efficiency ratio is 1.2609.

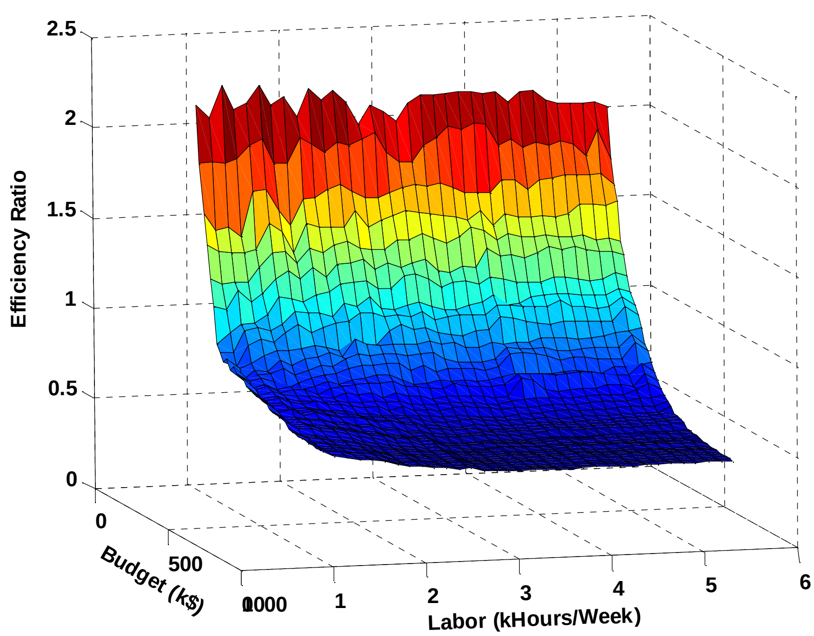

Fig. 5.35: Efficiency Ratio with different resource allocations

5.7 Conclusion

In this chapter, a risk model based on dispatch cost due to the failure of transmission system components is set up. Maintenance selection and scheduling is based on relaxed linear programming with knapsack solutions, which is very effective in solving industry size integer programming problems. A 566 bus system is used to test the effectiveness of the Integrated Maintenance Scheduler, and results are provided and analyzed. Results are in terms of task selection, task scheduling, and indices characterizing the quality of the solution. We conclude that the tool performs very well giving results that are consistent with expectations. The optimizer may also be used to provide insight into the effects on solution quality of different resource allocations. Such insight is useful in managerial decision-making associated with company budgeting processes.

6. Long-Term Maintenance Scheduling

6.1 Introduction

In chapter 5, we introduced the mid-term maintenance scheduling with time frame of one year, based on forecast of the system conditions during that period. We used a time frame of a year because that is typically the budget cycle, but equipment has no such cycle and they deteriorate continuously, but there is information about the future (beyond the 1 year period) which could influence our maintenance decision. This chapter addresses this issue through the development of long-term maintenance and its coordination with the mid-term maintenance scheduling.

Long term maintenance scheduling is based on individual component performance and the objective is to maximize the residual life of equipments. The output is just recommended maintenance/inspection interval (usually in the unit of year) for components and it does not consider the network constraints and load trajectory. This is because for the long-term time frame, it is difficult to get accurate forecast on network model and loading conditions. There are multiple constraints which will affect the result of maintenance scheduling such as budget, labor, feasible time and many other factors. Also, the utility companies must consider the load variation during the maintenance time period, in the reason of maintaining system reliability. This information will be used in mid-term transmission maintenance scheduling.

There is relatively little literature on quantifying the effect of maintenance on reliability in power systems. A transformer inspection and maintenance model is proposed utilizing the concept of device of stage. And the model is extended to circuit breakers. We are still going to use the concept of deterioration status as in Fig. 4.7. At each stage, inspection test is implemented to determine component condition in investigation process. Depending upon the maintenance action taken, the subsequent condition of the components will be determined.

The model parameters which are mean time in each stage, inspection rate of each stage, and probabilities of transition from one stage to others, have an effect on reliability and cost of maintenance. Note that inspection rate of each stage is the only parameter that can be varied to achieve high reliability with minimum cost. Therefore, this parameter is of the most concern in the analysis. The analysis covers two aspects: mean time to the first failure, and all associated costs (Failure cost, Maintenance cost, Inspection cost). Sensitivity analysis of inspection rate of each stage is implemented on the model using MATLAB. The simulation results from MATLAB are presented and examined.

Detailed analyses are corroborated with equivalent mathematical model to verify the simulation results, and, most importantly, to furnish an insight into the effect of maintenance. Two equivalent models; perfect maintenance and imperfect maintenance model, are introduced to simplify the transformer maintenance model for mathematical analysis. The equivalent models have three discrete stages representing the deterioration processes. Assume that maintenance is implemented at every inspection, maintenance and inspection rate of each stage is considered to be an equivalent repair rate. First passage time method and frequency balance technique are utilized to compute mean time to the first failure of a transformer and steady state probability of each stage correspondingly. All related costs are calculated from the steady state probabilities. The relationship between maintenance and cost is developed. A criterion of implementing maintenance is suggested by comparing the failure and maintenance cost. In addition, inspection model has been constructed for inspection cost analysis. The analysis suggests the inspection is introduced only to determine the stage of device.

6.2 Component Analysis for Long-Term Maintenance Scheduling

6.2.1 Physical transformer analysis for long-term maintenance scheduling

6.2.1.1 Failure mode, maintenance in long-term transformer maintenance scheduling

The failure mode and corresponding inspection, maintenance activities for long-term maintenance scheduling is the same as described in chapter 2. To simplify the problem, we only put our study in two major deterioration processes: 1) Deterioration process of cellulose in the winding and 2) Deterioration process of the insulation oil. These two processes happen concurrently and dependently. Water produced in the deterioration process of the paper increases the ageing rate of the oil and vice versa. Both processes are accelerated by high temperature, moisture and oxygen so we combine them to be an insulation failure mode, which happens as a result of deterioration process. It can happen either in winding or oil; for example, loss of too much moisture of paper insulation in winding, dielectric breakdown, or partial discharge [121]. And the corresponding maintenance activities are:

1. *Oil filtering to reduce moisture and dirt particles*

Most of the moisture comes from the degradation process of paper, which is used in the winding for wrapping around conductors and spacers; therefore, maintenance action would require a complete dismantling of this device. Moreover, the cost of this action represents a replacement by a new transformer.

During the deterioration process of insulating paper, water and fiber are produced in the oil; thus, the effective action would be drying and filtering the oil [122]. The drying method consists of filtering oil at high temperature. This on-line maintenance action will not only reduce moisture but also remove fiber and dirt particles, which are possible sources for partial discharge or electrical breakdown in the oil, as illustrated in Fig. 6.1.

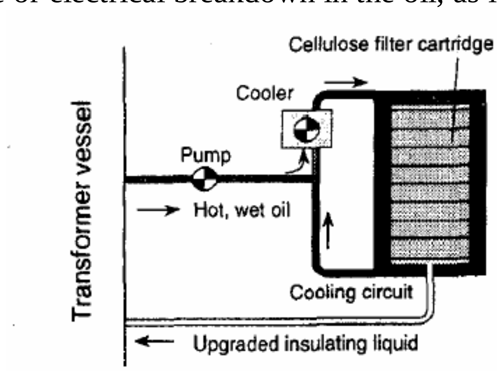

Fig. 6.1: Oil Filtering Process

2. *Oil Replacement*

This maintenance action will be done off-line when properties of oil; i.e., dielectric breakdown voltage, sludge, resistivity, etc. are in a more adverse condition.

6.2.1.2 Transformer inspection tests

The same as described in chapter 2, the monitoring/inspection techniques of transformer insulation materials are:

1. *Routine fluid sampling test*

A sample is taken from oil and run through the following analysis. The test includes dielectric strength, resistivity, acidity, fiber count: small (<2 mm), medium (2-5 mm) and large (>5 mm) [123], moisture content

2. *Dissolved gas analysis*

This analysis measures gases that are produced by the ageing process (H_2, C_2H_2, C_2H_4, CH_4, CO).

3. *Furfural analysis*

This analysis measures FFA which can determine the age of the paper insulation. Fig. 6.2 [124] is plotted between DP and FFA during paper ageing.

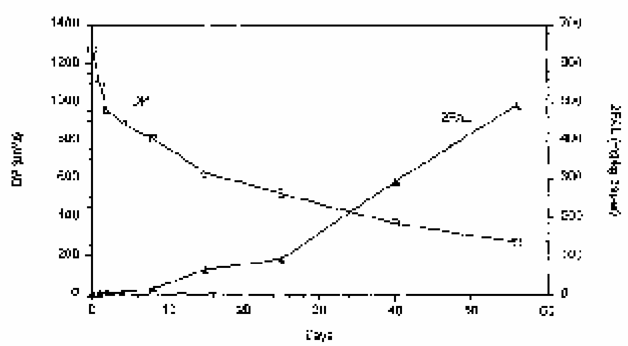

Fig. 6.2: Relationships between DP and FFA

Partial discharge monitoring

This measurement helps to predict and prevent breakdown of transformer [125]. Many types of equipment have been developed for this test, for example, radio interference and acoustic emission. The cost varies according to accuracy of results and sophistication of tools used.

4. *Temperature measurement*

This will provide information on ageing of oil and paper since high temperature has a major impact on this process.

6.2.2 Physical circuit breaker analysis for long-term maintenance scheduling

6.2.2.1 Failure mode, maintenance in long-term circuit breaker maintenance scheduling

Failure modes and corresponding inspection, maintenance activities for long-term maintenance scheduling is the same as described in chapter 3. In this work, we consider the following deterioration processes for circuit breakers: 1) Deterioration process of operating mechanism 2) Deterioration process of contacts and 3) Deterioration process of oil (for oil circuit breakers). Moisture and corrosion of metal parts are some of the reasons that are responsible for deterioration process of operating mechanism. Oxidation of contacts results in formation of a thin oxide film over the contact surfaces. At higher temperatures these oxide materials will begin to soften and might result in a plastic deformation. Finally, contact erosion takes place due to the vaporization of electrodes during the current interruption process [43]. These conditions may result in binding of contacts. Arc byproducts combine with moisture and oxygen in the oil and reduce the dielectric strength of the oil. Accumulation of these products contributes to the deterioration of oil [49]. If prolonged, this condition causes arcing in the insulation gradually developing into an internal fault. The corresponding maintenance activities that are considered in the model are:

A. Basic maintenance

1) Operating mechanism

- Clean and lubricate operating mechanism and apply suitable grease for the wearing surfaces of cams, rollers, bearings etc.
- Adjust breaker-operating mechanism as described in the manufacturer's instruction book
- Make sure all bolts, nuts, washers, cotter pins etc. are properly tightened
- After servicing the circuit breaker, verify whether the contacts can move to the fully opened and fully closed positions or not

2) Contacts

- Check the alignment and condition of the contacts and make adjustments according to the manufacturer's instruction book
- Check if the contact wear and travel time meet specifications

3) Insulating medium and arc extinction

- Check for leaks and remove any water content. Check for governor and compressor for required pressure
- Recondition oil by filtering

B. Replacement

This includes the replacement of various components.

- Arc chute and nozzle parts if damaged
- Governors and compressors if worn or malfunctioning
- Contacts if badly worn or burned

- Oil if dielectric strength drops below an allowable limit and if any arc products are found in the oil

6.2.2.2 Circuit breaker inspection tests

As described in chapter 3, the monitoring/inspection techniques for circuit breaker are:

A. Operating mechanism

1) Breaker timing test

Breaker timing test provides dynamic information about the operating mechanism, which include mechanical links and interrupter contacts. The test typically monitors the contact travel, speed, wipe and bounce during the entire cycle of opening and closing operation. A transducer is mechanically attached to the moving part of the mechanism, which measures the displacement of contacts with respect to travel time, and electrically connected to a timing set. These results are compared to the last test and to the manufacturers' recommendations [43].

2) Vibration analysis

Mechanical malfunctions, excessive contact wears, maladjustments, other irregularities and failures can be detected through vibration patterns [44]. Accelerometers mounted usually on the arcing chamber and operating mechanism, are used to record the vibrations. The recorded vibration patterns are converted into time/frequency patterns using signal-processing techniques. The time-axes of reference frequency pattern and test frequency pattern are aligned to indicate any changes in the condition of the operating mechanism. The presence of an abnormal event in the test signature will change the frequency, and the time at which this event occurs.

3) Control circuit monitoring

Portable test sets are generally used to monitor the control circuit. The circuit breaker is forced into operation and the control circuit signals are recorded [31]. The following are the typical control circuit signals that can be monitored in practice [47].

- Trip coil current
- Close coil current
- DC Supply voltage
- A, B auxiliary contacts
- X & Y Coils
- Trip initiation
- Close initiation

B. Contacts

1) Breaker contact resistance test

Breaker contact resistance test is used to monitor the condition of breaker contact wear and deterioration. A DC current, usually 10 or 100 amps is applied to the contacts. The voltage across the contacts is measured and the resistance can be calculated using Ohm's Law. Resistances of about 200 micro-ohms are normal, although manufacturers routinely publish their own design limits. This value is trended over time to assess deterioration. Maximum limits can be obtained from manufacturers. More about this test can be easily found in the literature [45].

2) Contact temperature monitoring

Large changes in contact temperature may be due to broken contact fingers, excessive burning of the main contacts, material degradation, oxide formation, weak contact springs, improperly or not fully closed contacts etc. Optical sensors are used to measure the temperature of the contacts [43].

C. Inspection of oil

Oil sample can be taken and tested for its dielectric strength. The following are the inspections that can be done in practice [49].

- Color and visual inspection
- Interfacial tension (soluble contaminants measurement)
- Dissipation factor (measure of power lost as heat)

D. Partial discharge

Insulation failures of circuit breakers can be detected by Partial discharge monitoring. The test procedure and equipment for the partial discharge monitoring are discussed in detail in reference [9].Various methods are reported in literature so far but the cost varies according to the test procedures and accuracy of results.

6.3 Model Building Technique

The model is constructed based on the concept of representing the deterioration process by the device of stages [126, 127]. Three stages of deterioration process are introduced; D1 (initial), D2 (minor deterioration), and D3 (major deterioration), which is same as Fig. 4.8 except it does not contain the failure status. At each stage, inspection test is implemented to determine oil condition in investigation process. Depending upon the maintenance action taken, the subsequent condition of the transformer is determined. The concept of device of stages is introduced below.

6.3.1 Device-of-stages concept

Usefulness of maintenance inherently assumes that there is an underlying deterioration process and that the distribution representing the life time is non-exponential. The basic concept is that a non-exponential distribution can be represented by a combination of stages [127]. The reference [127] proposes many possible combinations of stages to represent various types of failure models. In this proposed research, a series combination of stages is selected. The model is shown in Fig. 6.3. Time spent in each stages is assumed to be exponentially distributed.

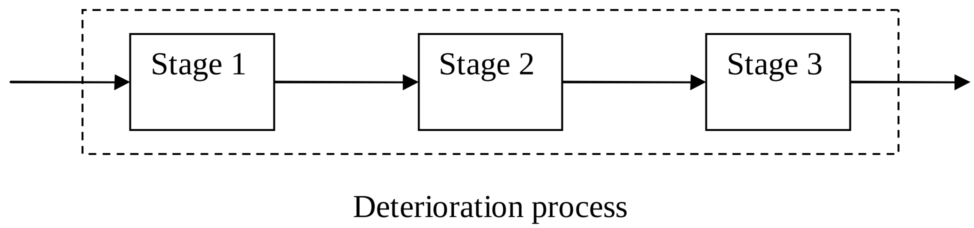

Fig. 6.3: A Series Combination of Stages

6.3.2 Classification of transformers by load priority

In long-term maintenance scheduling, we cannot use time-dependent risk to describe the relative importance of the components and the compact of their failures, since the system condition is uncertain in the long run. So we are going to classify the transformers based on the loads they serve. In power systems, transformers are used for different load types. Loss of load cost varies by load types. Customer damage function is an index used for determining importance of each load. From the least important to the most important, loads can be categorized into residential, agriculture, commercial, industrial, offices, governmental and institutional, and large users. The proposed transformer maintenance models are classified into three categories by load priority. Tests for each model vary in accuracy and their effect on resulting reliability.

1. *Model for Low Customer Damage loads*

Inspection test in this model is routine sampling test, which will give the least accuracy and effect on reliability. Maintenance cost is the cheapest among the three models.

2. *Model for Medium Customer Damage Loads*

Inspection result is more accurate and reliable than the first model since we use both routine test and DGA. Maintenance cost will also increase. Loss of this transformer type has considerable impact on the system. This model seems to be the most common in the industry.

3. *Model for High Customer Damage Loads*

This model should be used for transformers at an important load location such as industry or on high voltage grid. Loss of this transformer type costs a lot of money; thus, its reliability is of the most concern. Inspection tests are routine test, DGA, and PD. These tests are the most expensive especially PD analysis. Transformer that is suggested to use this model is power transformer since the cost of this transformer type is very high as well as the cost of a catastrophic failure.

6.4 Model Description and Parameters

6.4.1 Transformer model description and parameters

In this section, a model is proposed in Fig. 6.4. Based on this proposed model, model description and parameters are thoroughly explained.

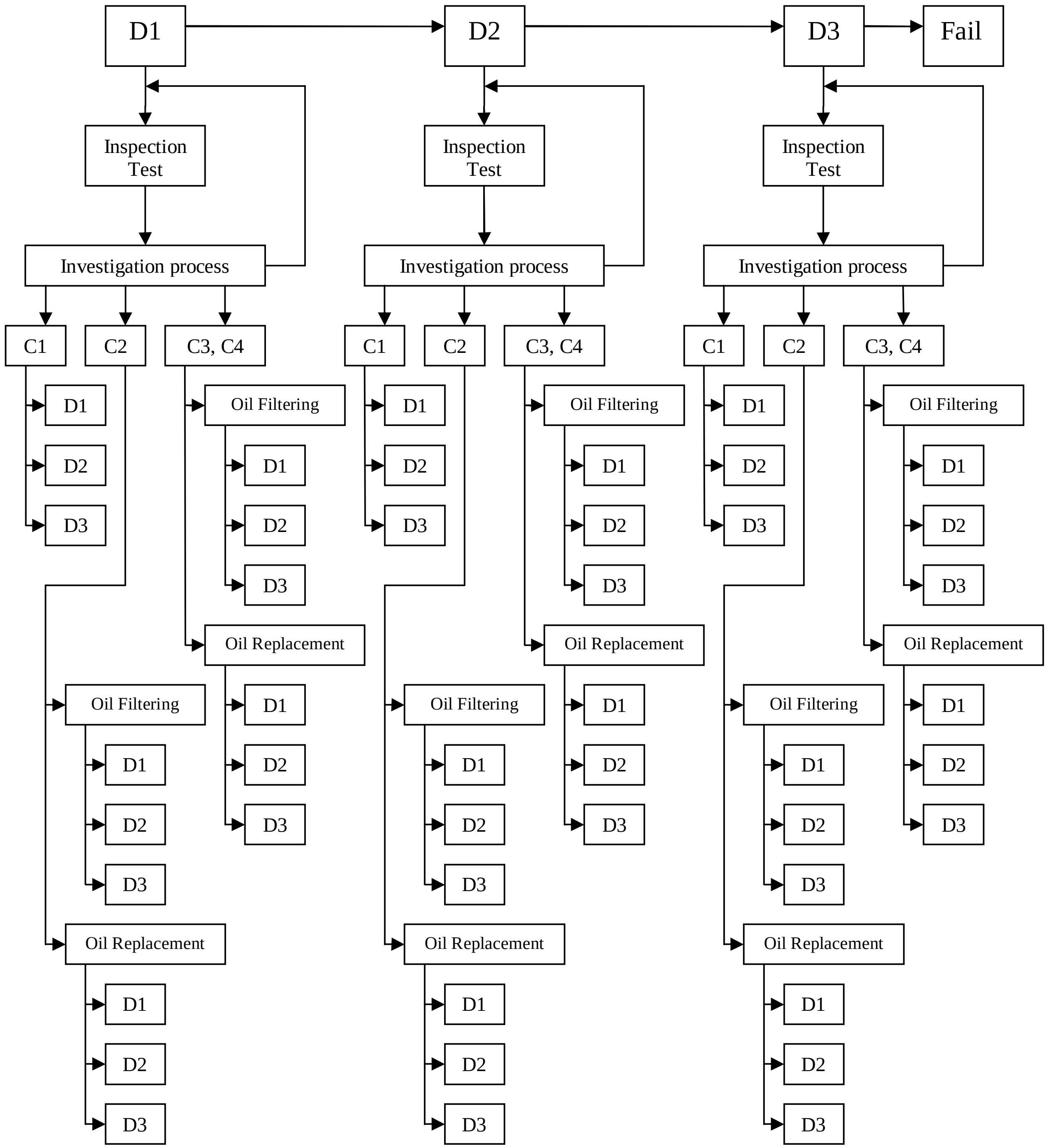

Fig. 6.4: Proposed Transformer Maintenance Model

6.4.1.1 Model description

In the proposed models in Fig. 6.4, the deterioration process is represented by three stages; D1, D2, and D3. D1 represents the good working stage while D2 and D3 represent minor deterioration and major deterioration stages respectively. This model is based on the concept of representing the deterioration process by the device of stages [127, 126, 128]. At each stage, inspection test is implemented to determine oil condition in the investigation process. Depending upon the maintenance action taken, the subsequent condition of the transformer is determined.

Inspection tests

Three types of inspection tests are introduced in the model in Fig. 6.4.

1. Routine Fluid Test

The inspection items listed below are relatively common in the industry for determining the oil condition [129].

- Color and Visual Appearance
- Dielectric breakdown voltage
- Neutralization number (acidity measurement)
- Interfacial tension (soluble contaminants measurement)
- Water content

Serviced-aged oils are classified into four conditions as follows [129].

1. Group 1: satisfactory
2. Group 2: require reconditioning for further use
3. Group 3: poor, should be reclaimed or disposed
4. Group 4: adverse condition, dispose only

The criteria used for oil classification is shown in tables 6.1 and 6.2. Table 6.1 [129] suggests test limits for group 1, Table 6.2 [129] suggests test limit for group 2 and 3.

TABLE 6.1: SUGGESTED LIMITS FOR IN-SERVICE OIL GROUP 1 BY VOLTAGE CLASS

Property	Limit		
Voltage Class	69 kV and below	69– 288 kV	345 kV and above
Dielectric breakdown voltage 60 Hz, 0.100 gap 1 min, kV, min	26	26	26
Dielectric breakdown voltage 0.040 gap, kV, min	23	26	26
Dielectric breakdown voltage 0.080 gap, kV, min	34	45	45
Neutralization number max, mg KOH/g	0.2	0.2	0.1
Interfacial tension, min, mN/m	24	26	30
Water max, ppm*	35	25	20

*Does not pertain to free breathing transformer or compartment

TABLE 6.2: SUGGESTED LIMITS FOR OIL TO BE RECONDITIONED OR RECLAIMED

Property	Group 2	Group 3
Neutralization number max, mg KOH/g	0.2	0.5
Interfacial tension, min, mN/m	24	16

2. Dissolved Gas Analysis

Four-level condition of dissolved gas in oil, and total dissolved combustible gas (TDCG) are as follows, which is also listed in Table 4.1[6].

1) Condition 1: Satisfactory
2) Condition 2: Prompt additional investigation
3) Condition 3: Indicates high level of decomposition. Prompt additional investigation
4) Condition 4: Excessive decomposition

3. Partial Discharge

The analysis of PD from acoustic emissions should be made according to the size of transformer. Large transformers are considered for further investigation if any internal partial discharges are detected. Smaller transformers, on the other hand, use PD count rate to examine the condition of transformer [125].

Investigation process

All the data from inspection tests are collected. This data will determine maintenance action and rate of the next inspection. If oil condition is high, the inspection rate for the same stage is increased. Maintenance action is chosen according to oil condition.

Maintenance action

To simplify the problem, we classify only 3 levels of maintenance action. Maintenance action is assigned corresponding to the oil condition. If oil condition is C1, nothing is done. If oil condition is C2, C3, or C4, two options are available and are assigned with different probabilities: oil filtering or oil replacement. For example, if the present stage is D2 with oil condition C2, the probability of oil filtering will be higher than oil replacement. On the other hand, if the present stage is D2 with oil condition C3 or C4, the probability of oil replacement will be higher. After maintenance, the device will have 3 options, going to stage D1, D2, or D3. The probability of transferring to other stages depends on the present stage and maintenance practice.

1. Do nothing

The probability that the system will be set back to the same stage is higher than transferring to the next states. Oil is in satisfactory condition.

2. Oil Filtering

After filtering, the probability of going back to the previous stage is relatively high.

3. *Oil Replacement*

After oil replacement, system stage is set back to the beginning (D1).

6.4.1.2 Model parameters

Parameters in transformer maintenance model are listed below.

1. *Mean time in each stage*

These parameters determine the transition rate of each stage in the deterioration process.

2. *Inspection rate of each stage*

This parameter can be treated as maintenance rate of each stage under the assumption that inspection, test and maintenance actions are implemented sequentially.

3. *Probabilities of transition from one stage to others*

These parameters are the probabilities of oil condition after the inspection process, probabilities of transferring from any oil condition to a given stage, probabilities of filtering or replacing the oil, and probabilities of transferring to each stage after maintenance. These probabilities can be treated as equivalent transition rates from one stage to others. The equivalent model is introduced to clarify this point later.

Notice that model parameters 1 and 3 can be approximated from historical data of oil condition of a physical transformer; thus, these parameters are assumed given. However, inspection rate of each stage can be varied to achieve high reliability with minimum cost. Therefore, this parameter is of the most concern in the analysis.

6.4.2 Circuit breaker model description and parameters

A probabilistic maintenance model for circuit breaker is proposed in Fig. 6.5. Based on this proposed model, model description and parameters are thoroughly explained.

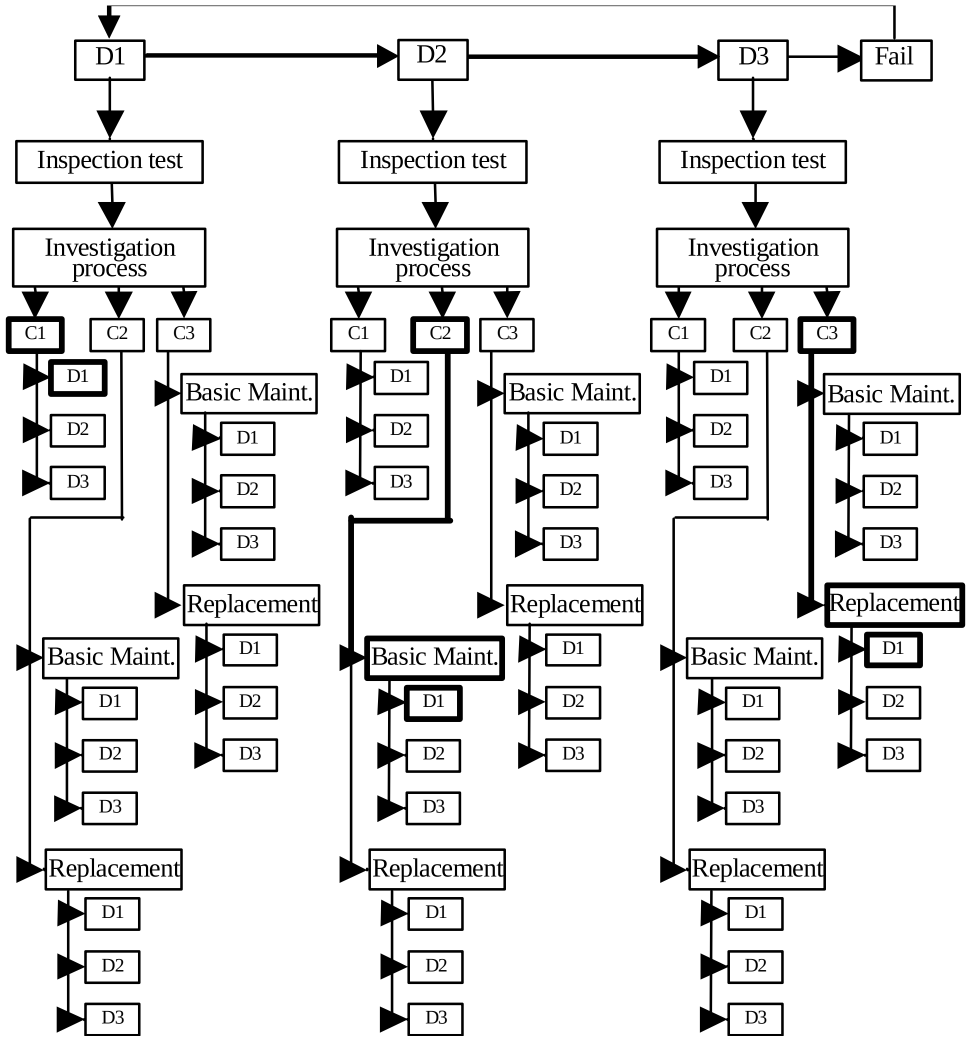

Fig. 6.5: Proposed Circuit Breaker Probabilistic Maintenance Model

6.4.2.1 Model description

Three deterioration stages, i.e., the initial stage (D1), minor (D2) and, major (D3) deterioration stages, followed by a failure stage are considered. Inspection test is implemented at each stage and the collected data is investigated to determine the condition of the breaker. In this model, three different levels of breaker condition are defined: C1- satisfactory and no maintenance is needed, C2- indication of abnormality or caution stage, needs further investigation or related maintenance and C3- Failure stage or poor condition, needs replacement. Further, the maintenance process is divided into three levels; (1) Do nothing, (2) Basic maintenance, and (3) Replacement. Once the suggested maintenance action is taken, the subsequent condition of the breaker is determined.

Inspection tests

The following inspection tests are considered in developing the proposed model. Air blast and oil circuit breakers are considered in this study.

1. Breaker timing test

Condition of the circuit breaker can be obtained by comparing the test curve with the reference curve. The following are some possible observations that can be made from such measurements [43].

- *Contact separation occurred sooner than before*: contact wear
- *Faster circuit breaker stroke*: kinetic energy of the mechanism is above its upper limit
- *No damping at the end of the operation*: shock absorber failure
- *Reduction in total travel distance*: binding or stalling of the mechanism or insufficient stored driving energy

The proposed criterion for assessment of the condition of operating mechanism is:

Condition 1: satisfactory, test results follow the reference curve

Condition 2: caution stage, test results deviate slightly and need more attention

Condition 3: excessive wear and need complete overhaul or replacement

2. Control circuit monitoring

The recorded control signals are analyzed to find any abnormalities in the breaker operation. Sluggish trip latch, defective close coil, defective auxiliary switch and defective battery are some abnormalities that can be detected from monitoring control circuit signals [47].

The proposed criterion for the condition of control circuit is:

Condition 1: within specification and will not require maintenance

Condition 2: caution stage, need more attention

Condition 3: final stage, need major replacement

3. Contact resistance measurement

The possible causes for abnormal increase in contact resistance are deposition of foreign material in contacts, loose contacts and loose bushing connections [45].

The proposed criterion for the condition of contacts is

Condition 1: satisfactory

Condition 2: caution stage; need more attention

Condition 3: excessive wear and need complete overhaul

4. Inspection of oil

Service-aged oils are classified into the following three conditions [49].

Condition 1: satisfactory

Condition 2: should be reconditioned for further use

Condition 3: poor condition; dispose

Suggested limits for oil in condition 1 are listed in table 6.3[49]. Criterion for recondition is excessive carbon in oil and reduced dielectric strength (dielectric strength drops below the accepted limit).

TABLE 6.3: SUGGESTED LIMITS FOR CONTINUED USE OF SERVICE-AGED CIRCUIT BREAKER INSULATING OIL

Test and method	Suggested limit
Dielectric strength kV minimum	25
Dielectric strength, kV minimum	
1 mm gap*	20
2 mm gap*	27
Dissipation factor (power factor), 25 ^{o}C, % maximum	1.0
Interfacial tension, mN/m minimum	25
Color , ASTM units, maximum	2.0

*Alternative measurements of 0.04 in and 0.08 in respectively for gaps

Investigation process

Information out of the inspection tests can be used to determine the condition of the device followed by the necessary maintenance action and rate of the next inspection.

Maintenance action

Following are the three maintenance levels introduced in this model. These maintenance actions are already discussed in section 6.3.

1. *Do nothing*

The breaker is in satisfactory condition and no maintenance is needed. The probability that the system is set back to same stage is relatively high.

2. *Basic maintenance*

This maintenance action increases the probability of going back to the previous stage.

3. *Replacement*

Replacement of damaged components brings the system back to its original stage i.e. beginning stage

6.4.2.2 Model parameters

Circuit breaker model parameters are same as those of transformer model parameters.

6.5 Sensitivity Analysis

In the following sections, sensitivity analysis of inspection rate of each stage is implemented on the model in Fig. 6.4 and Fig. 6.5 using MATLAB. Other model parameters are listed in appendix 6.1. The analysis covers two aspects: mean time to the first failure, and all associated costs (Failure cost, Maintenance cost, Inspection cost). The simulation results from MATLAB are presented and examined in each section.

6.5.1 Sensitivity analysis of transformer model

6.5.1.1 Sensitivity analysis of inspection rate on Mean Time to the First Failure (MTTFF)

Mean time to the first failure is the expected operating time before failure of the transformer starting from initial stage. This analysis will provide information of how the transformer operating time changes when the inspection rate of each stage changes.

Let i1 = inspection rate of D1 (per year)
i2 = inspection rate of D2 (per year)
i3 = inspection rate of D3 (per year)

The simulation results of the relationship of each inspection rate and MTTFF are shown in Fig. 6.5-6.7

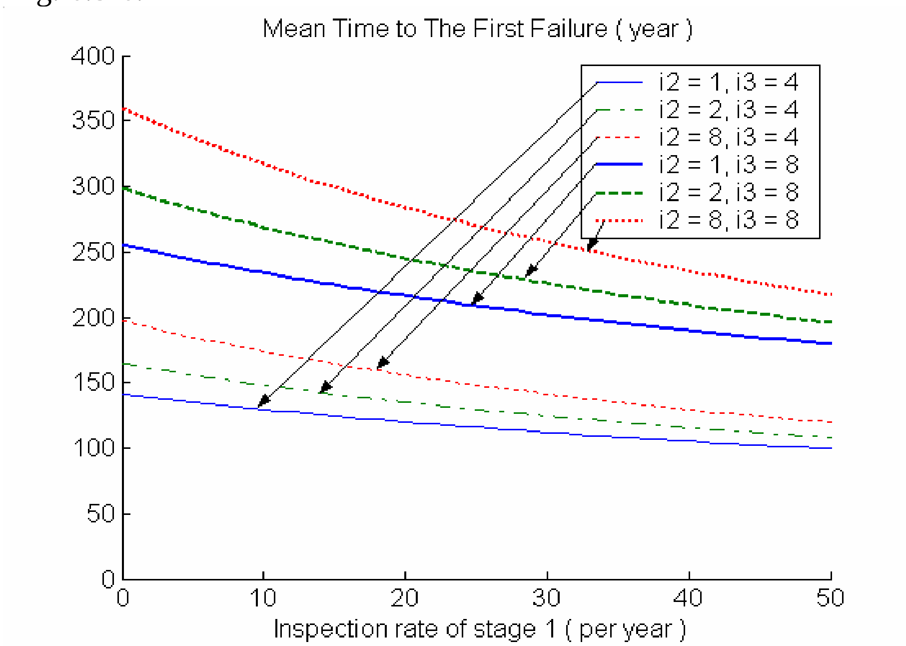

Fig. 6.6: Relationships between MTTFF and Inspection Rate of Stage 1

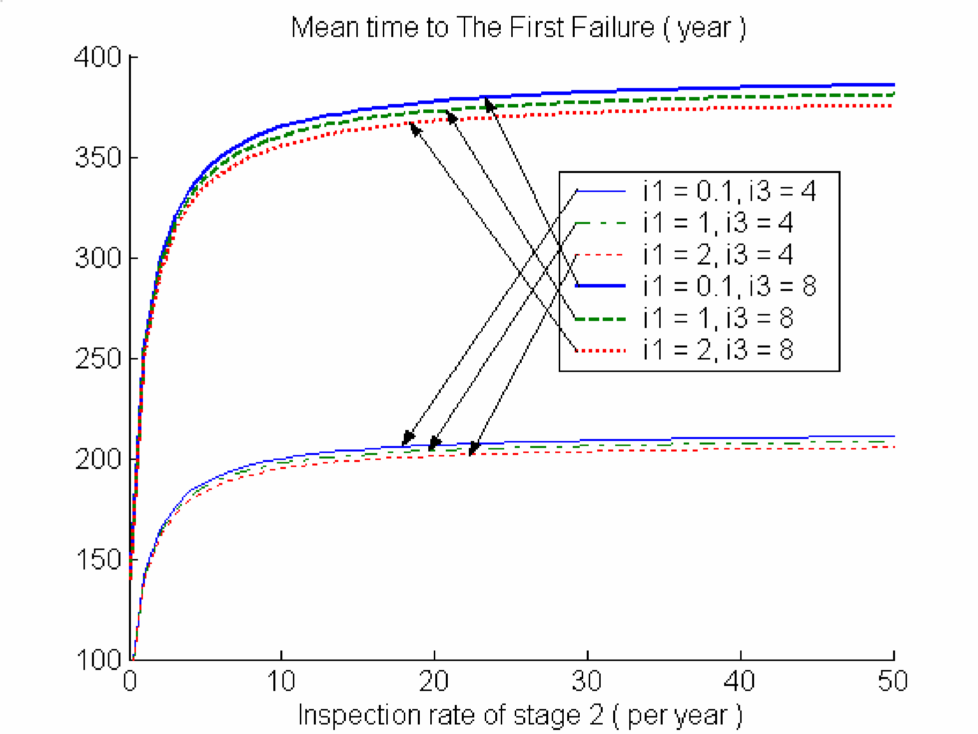

Fig. 6.7: Relationships between MTTFF and Inspection Rate of Stage 2

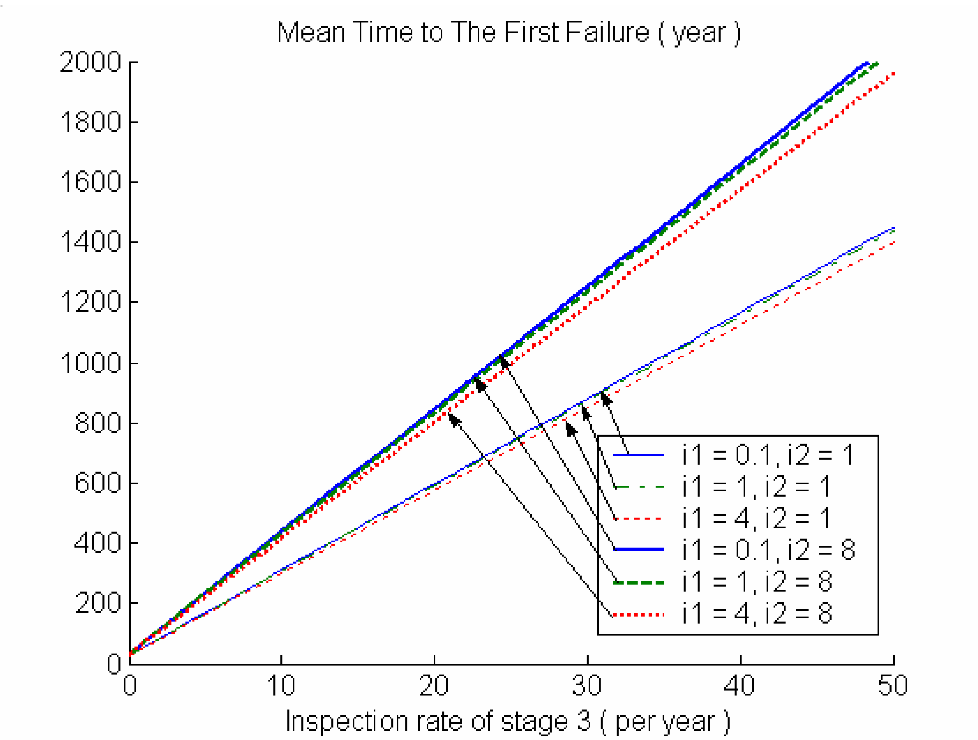

Fig. 6.8: Relationships between MTTFF and Inspection Rate of Stage 3

The following observations can be drawn from these simulation results.

1. In Fig. 6.6, MTTFF decreases with i1. This is caused by the assumption of exponential distribution of time spent in each stage. The exponential distribution implies constant failure rate. This is of particular significance in stage D1. This means that the inspections, which lead back to D1, will not improve the time to failure in D1; however, those leading to D2 and D3 will result in degradation. Thus, the effect of inspection will always be degradation. In other words, if we assume an exponential distribution for stage 1, then maintenance cannot be useful.

2. In Fig. 6.7, MTTFF increases at a decreasing rate with i2 and stays at some value.

3. In Fig. 6.8, MTTFF has a positive and linear relationship with i3.

Next, the model in Fig. 6.4 is modified by representing stage D1 by three sub-stages in order to relax the assumption of exponential distribution. Although each sub-stage is exponentially distributed, the overall D1 will have deterioration. The simulation results of relationship of each inspection rate and MTTFF are shown in Fig. 6.9-6.11

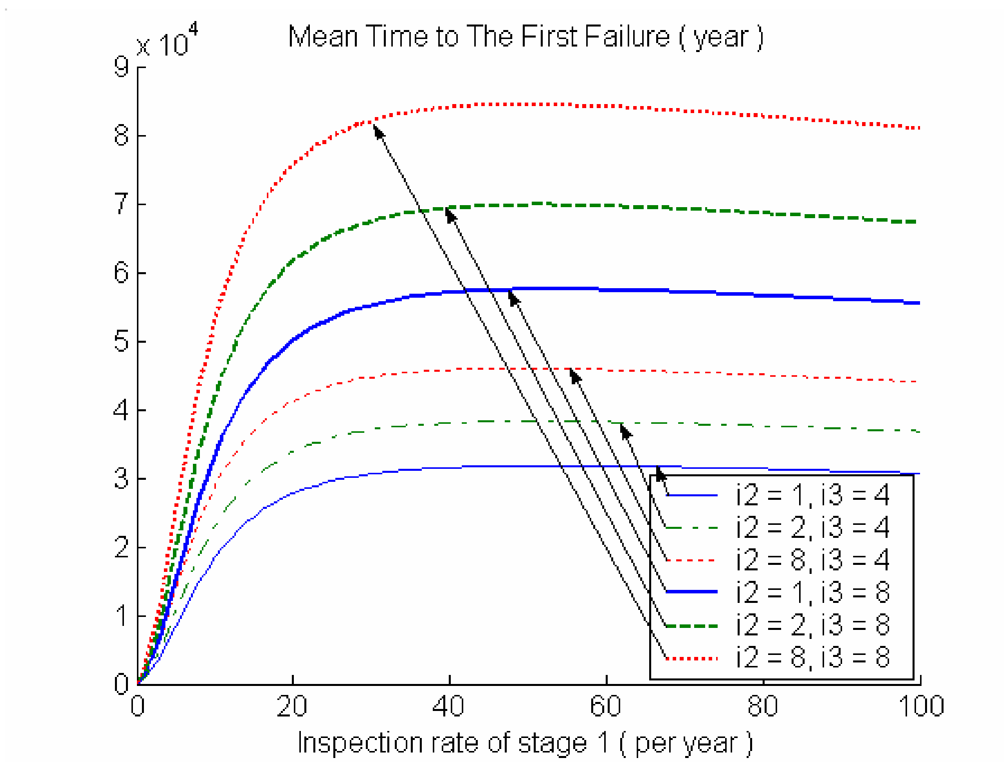

Fig. 6.9: Relationship between MTTFF and Inspection Rate of Stage 1 with Three Sub-stages representing D1

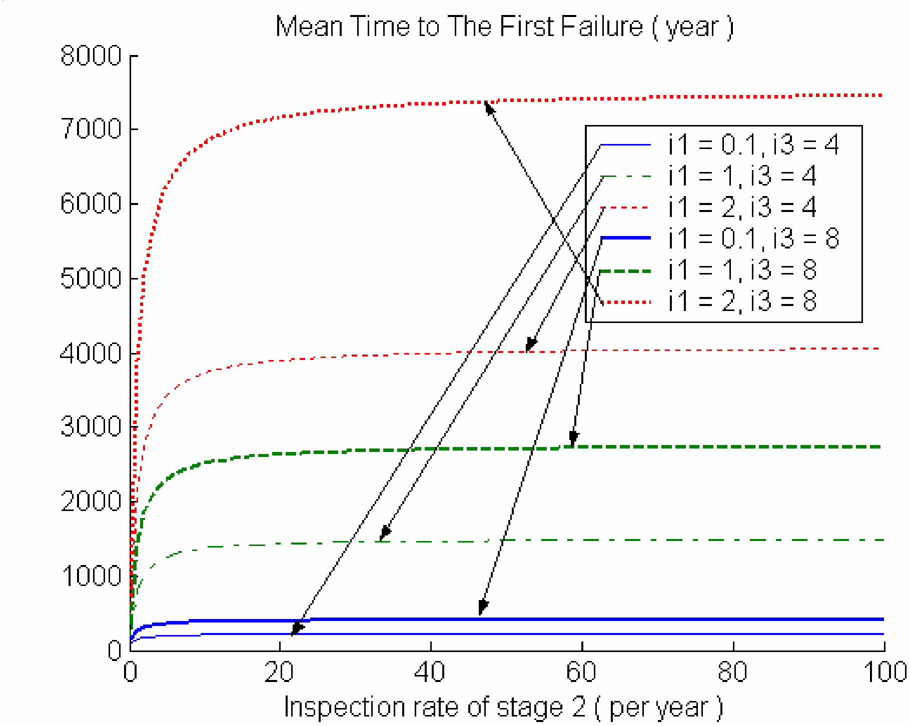

Fig. 6.10: Relationship between MTTFF and Inspection Rate of Stage 2 with Three Sub-stages representing D1

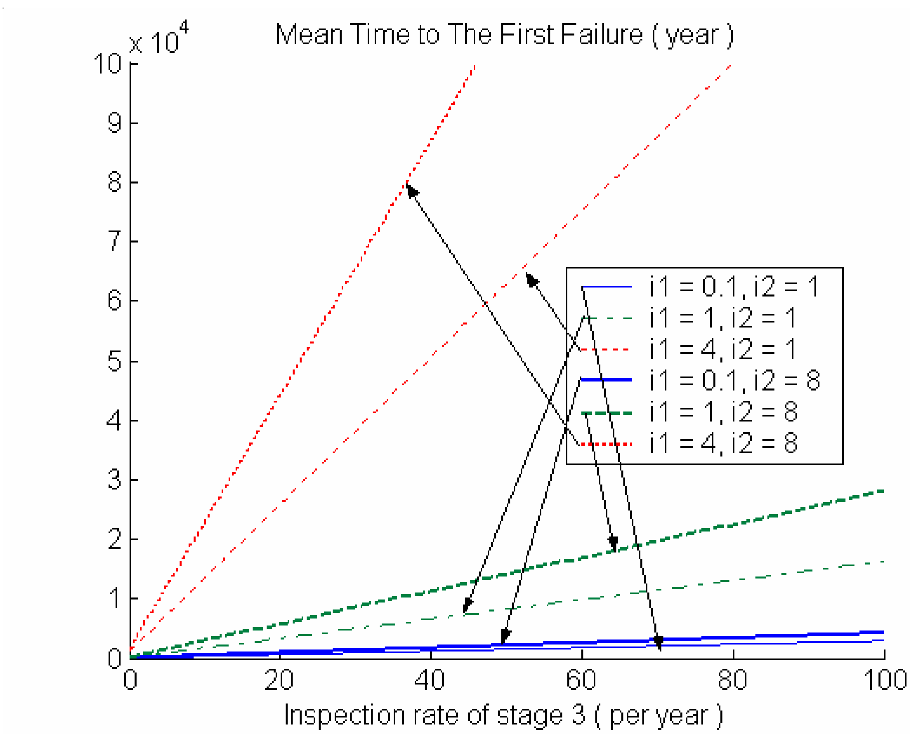

Fig. 6.11: Relationship between MTTFF and Inspection Rate of Stage 3 with Three Sub-stages representing D1

In Fig. 6.9, MTTFF increases rapidly when increasing i1and then slightly decreases at high i1. The simulation results in Fig 6.10 and 6.11 give the same observations as in Fig. 6.7 and 6.8.

The simulation results suggest that inspection rate of D1 helps extending MTTFF; however, too high inspection rate of D1 might reduce MTTFF. In addition, inspection rate of D2 beyond a certain value has a minimal impact on reliability. Fig. 6.11 indicates that transformer lifetime will be longer with improved inspection rate of D3.

6.5.1.2 Sensitivity analysis of inspection rate on all associated cost

Costs from maintenance practice in model in Fig. 6.4 are inspection cost, oil filtering cost, oil replacement cost, and failure cost. This analysis will provide information about the effect of inspection rate on all associated cost. We assume cost parameters in appendix 6.1. The simulation result of relationship between each inspection rate and all associated costs are shown in Fig. 6.12-6.23.

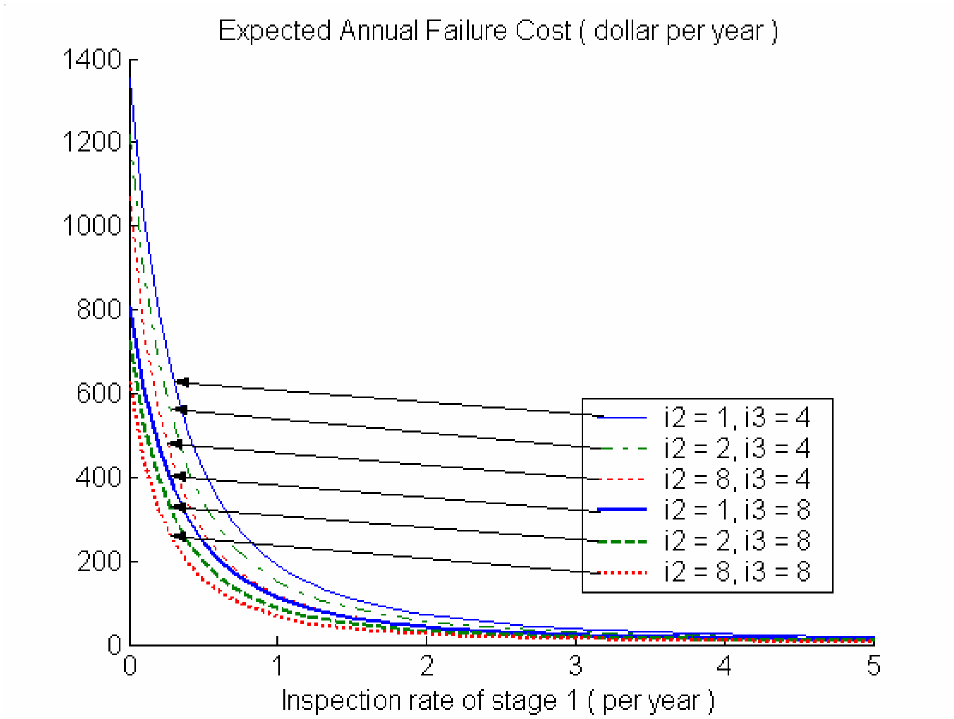

Fig. 6.12: Relationships between Expected Annual Failure Cost and Inspection Rate of Stage 1

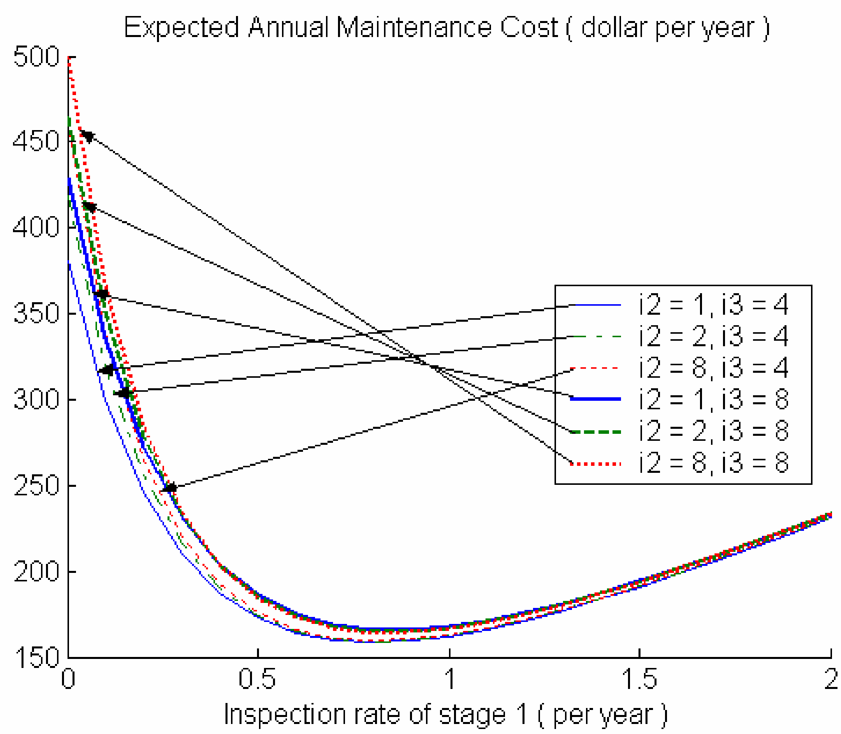

Fig. 6.13: Relationships between Expected Annual Maintenance Cost and Inspection Rate of Stage 1

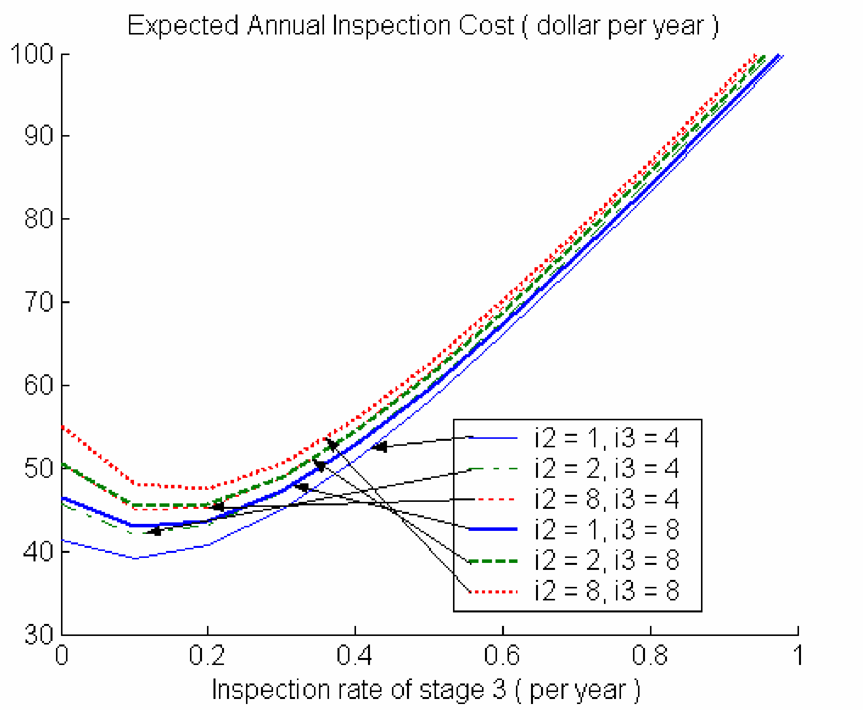

Fig. 6.14: Relationships between Expected Annual Inspection Cost and Inspection Rate of Stage 1

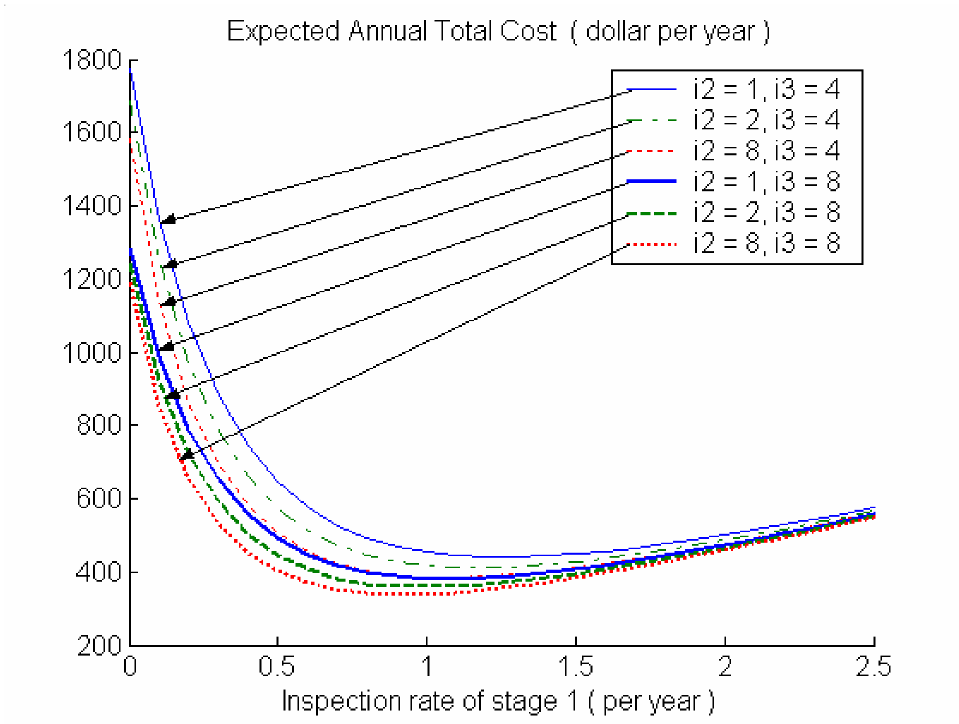

Fig. 6.15: Relationships between Expected Annual Total Cost and Inspection Rate of Stage 1

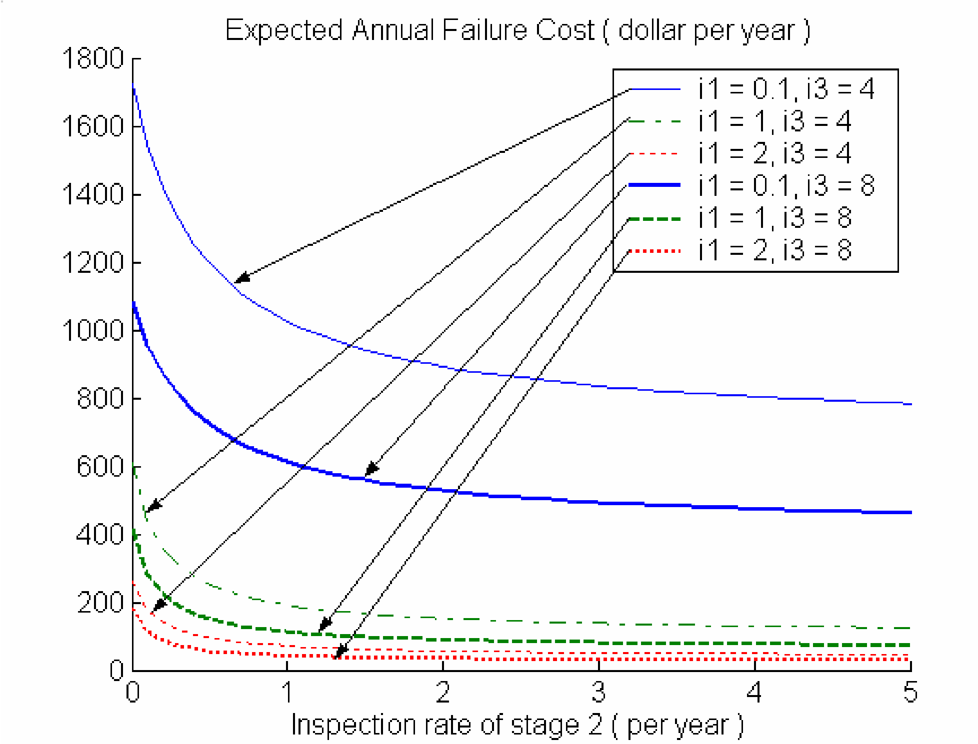

Fig. 6.16: Relationships between Expected Annual Failure Cost and Inspection Rate of Stage 2

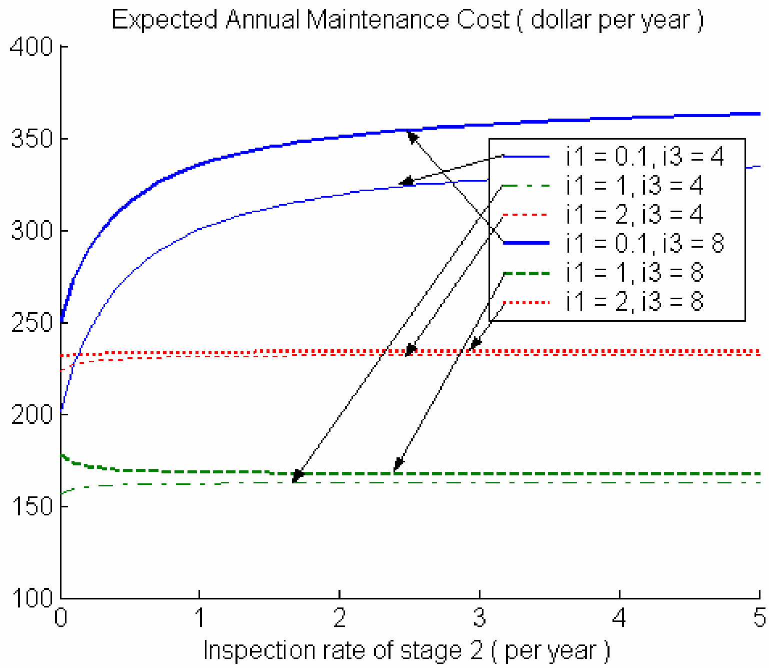

Fig. 6.17: Relationships between Expected Annual Maintenance Cost and Inspection Rate of Stage 2

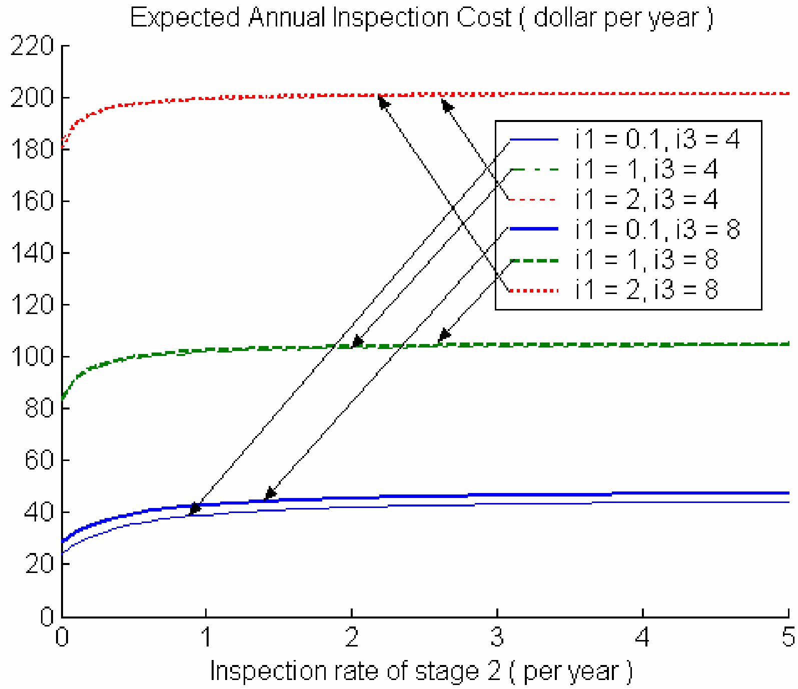

Fig. 6.18: Relationships between Expected Annual Inspection Cost and Inspection Rate of Stage 2

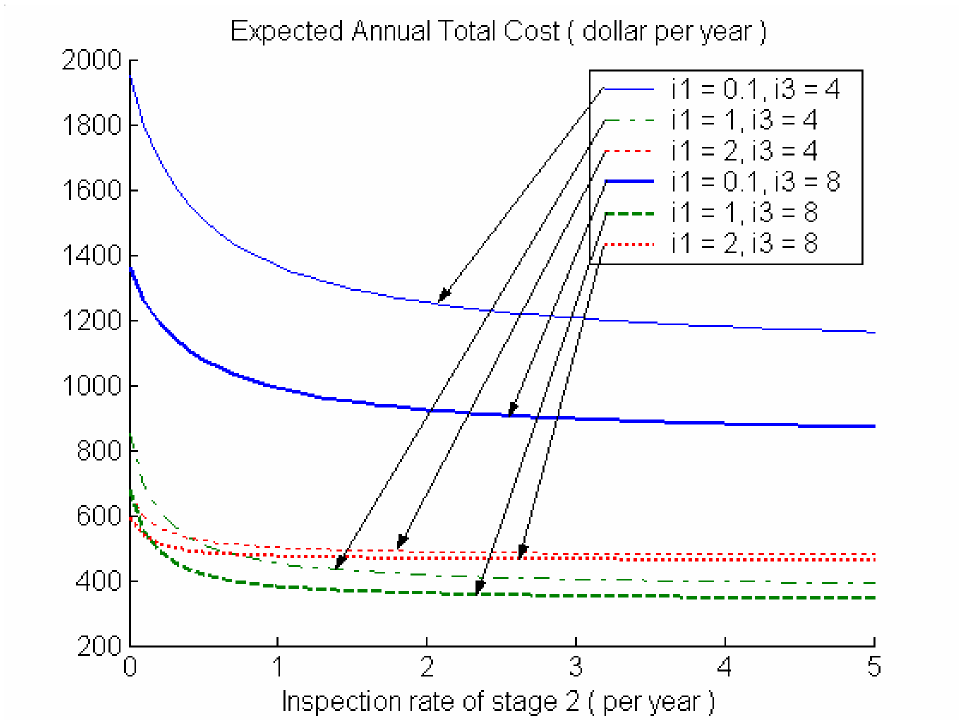

Fig. 6.19: Relationships between Expected Annual Total Cost and Inspection Rate of Stage 2

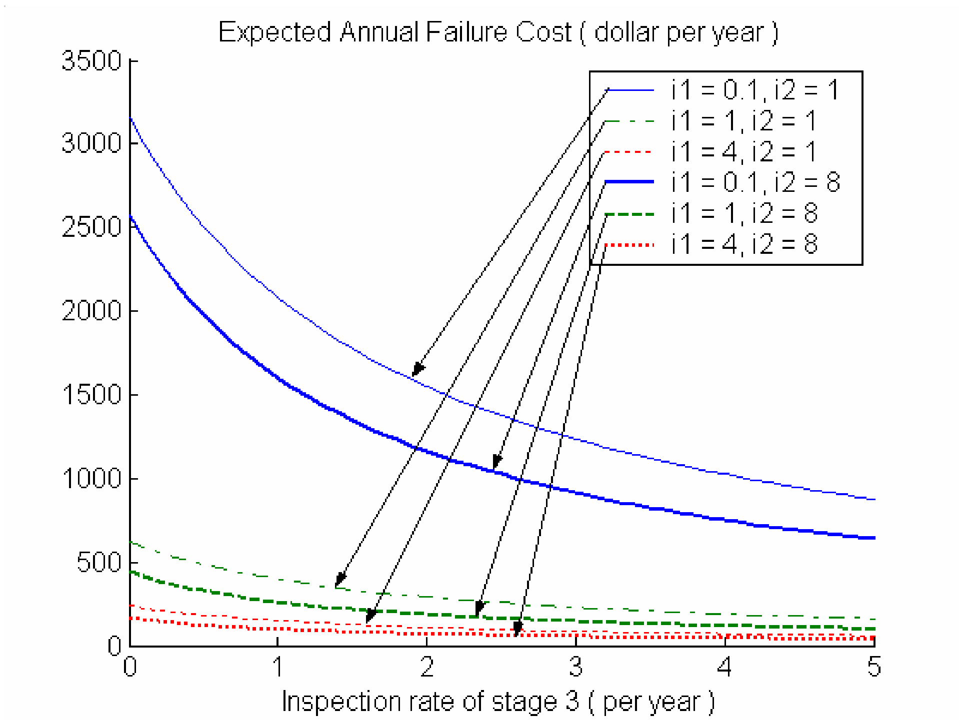

Fig. 6.20: Relationships between Expected Annual Failure Cost and Inspection Rate of Stage 3

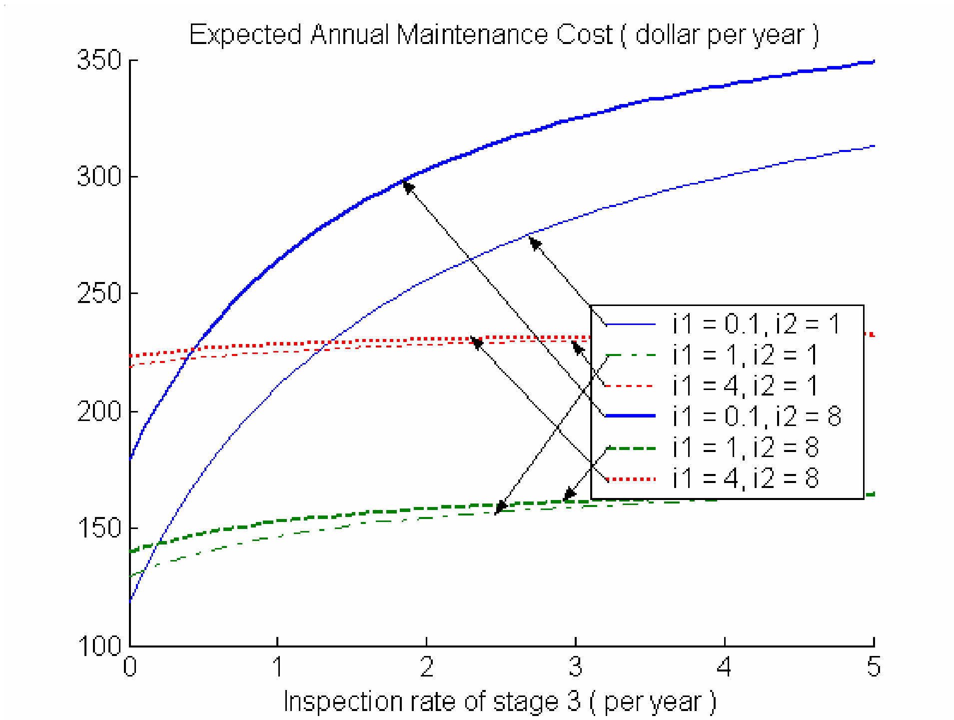

Fig. 6.21: Relationships between Expected Annual Maintenance Cost and Inspection Rate of Stage 3

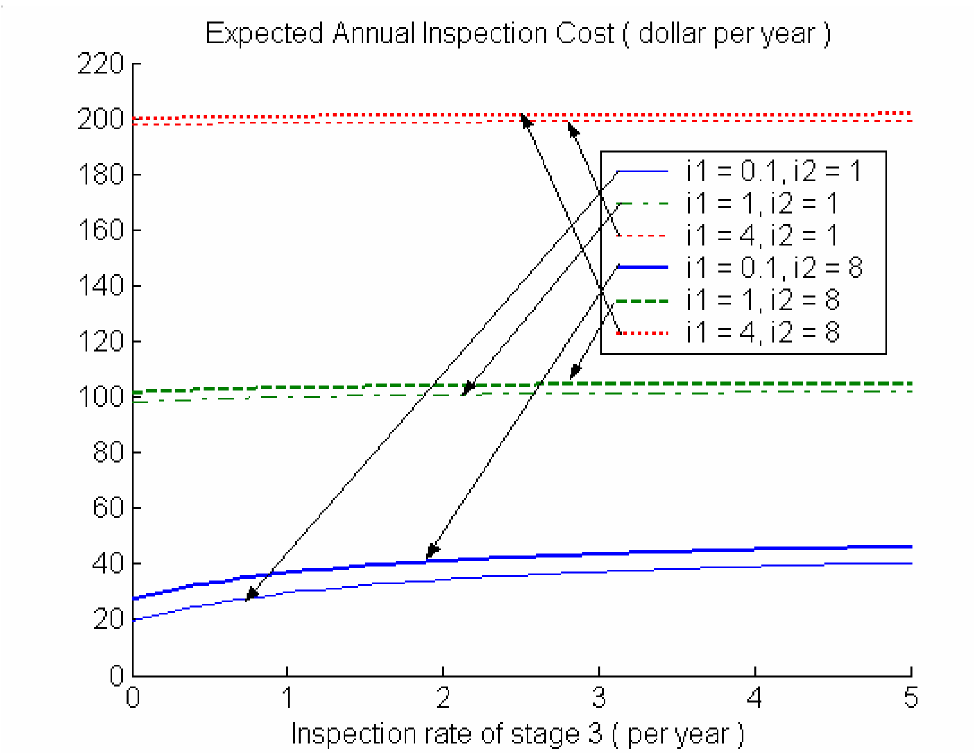

Fig. 6.22 Relationships between Expected Annual Inspection Cost and Inspection Rate of Stage 3

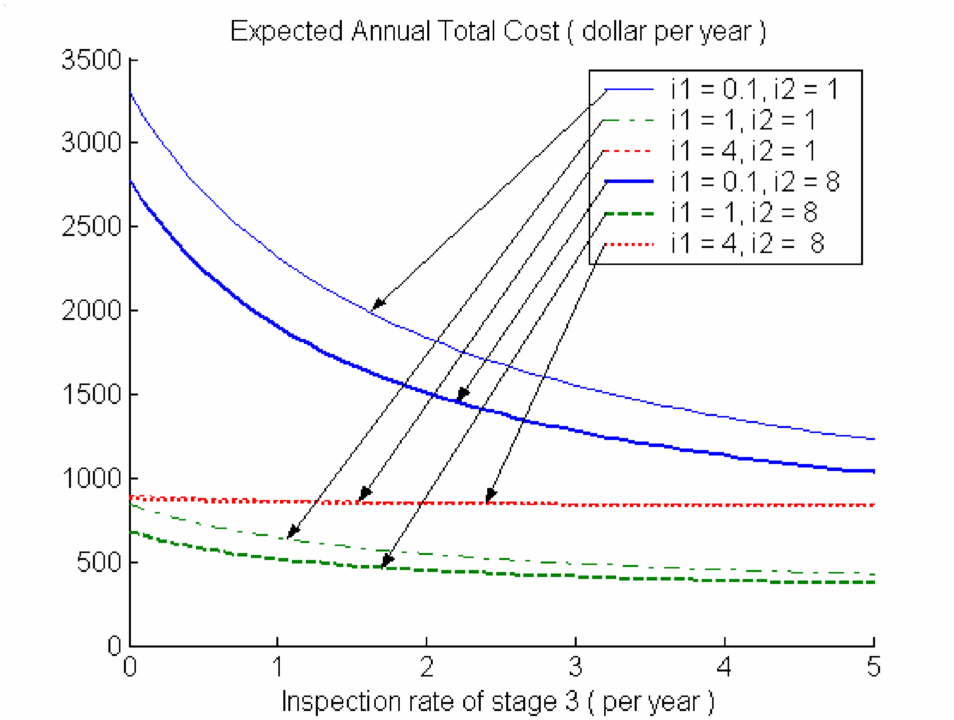

Fig. 6.23 Relationships between Expected Annual Total Cost and Inspection Rate of Stage 3

The following observations can be made from the simulation results.

1. In Fig. 6.12, 6.16 and 6.20 failure cost decreases exponentially as inspection rate of D1, D2 and D3 increases.
2. In Fig. 6.13 maintenance cost first decreases as inspection rate of D1 increases and then increase with inspection rate of D1. The optimal region of inspection rate of D1 that will minimize maintenance cost is 0.5-1 per year.
3. In Fig. 6.17 and 6.21, maintenance cost increases with inspection rate of D2 and D3 and stays at constant value at higher inspection rate of D2 and D3.
4. In Fig. 6.14, inspection cost increases linearly with inspection rate of D1.
5. In Fig. 6.18 and 6.22, inspection cost increases as inspection rate of D2 and D3 increases and remains constant at high inspection rate of D2 and D3.
6. In Fig. 6.15, the optimum region of inspection rate of D1 that will minimize total cost depends on inspection rate of D2 and D3. If the inspection rate of D2 and D3 are higher, the optimal value of inspection rate of D1 will be smaller. Failure cost dominates total cost at small inspection rate of D1 while maintenance cost dominates total cost at high inspection rate of D1.
7. In Fig. 6.19 and 6.23, the minimum total cost will occur at very high inspection rate of D2 and D3. Failure cost dominates total cost at small inspection rate of D2 and D3 while maintenance cost dominates total cost at high inspection rate of D2 and D3.

The simulation result suggests that cost effective maintenance occurs at small inspection rate of D1 and high inspection rate of D2 and D3. The sensitivity analysis of inspection rate on MTTFF and all associated costs are discussed in the previous section based on simulation results of model in Fig. 6.4. In the section 6.6, equivalent mathematical models are presented for simpler analysis. Equations derived from mathematical analysis will provide an explicit relationship of each inspection rate with MTTFF and costs.

6.5.2 Sensitivity analysis of circuit breaker model

6.5.2.1 Sensitivity analysis of inspection rate on Mean Time to the First Failure (MTTFF)

As explained in section 6.5.1.1, maintenance cannot be useful if we assume an exponential distribution for stage 1. In order to relax this assumption, stage D1 is represented by three sub-stages. Although, each sub-stage is exponentially distributed, overall D1 will have deterioration. Simulation results showing the relationship between MTTFF and inspection rate are shown in Fig. 6.24-6.26. The following observations can be made from these simulations results.

- MTTFF increases rapidly with increasing i1 and can be observed in Fig. 6.24.
- Fig. 6.25 shows the relationship between MTTFF and i2 keeping i1 and i3 fixed. MTTFF increases with i2 and stays at some value.
- Fig. 6.26 shows the variation of MTTFF with i3 keeping i1 and i2 constant. MTTFF has a positive and linear relation ship with i3.

Finally, simulation results suggest that the inspection rate of stage D1 helps in extending MTTFF. Inspection rate of stage D2 increases the MTTFF but has a minimal impact on reliability beyond a certain value. Further, circuit breaker lifetime will be improved with increase in inspection rare of stage D3.

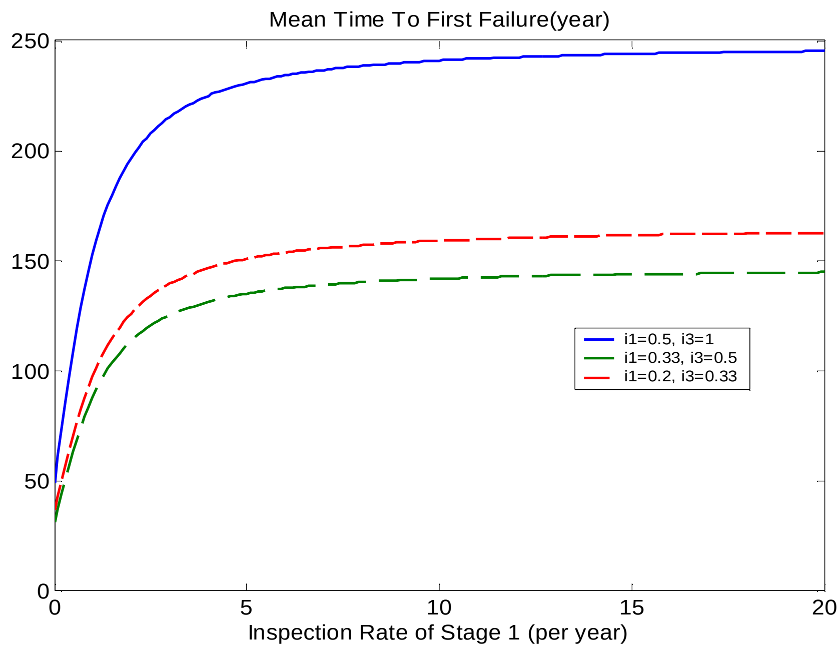

Fig. 6.24 Relationship between Mean Time to The First Failure and Inspection Rate of Stage 1 with Three Sub-stages representing D1

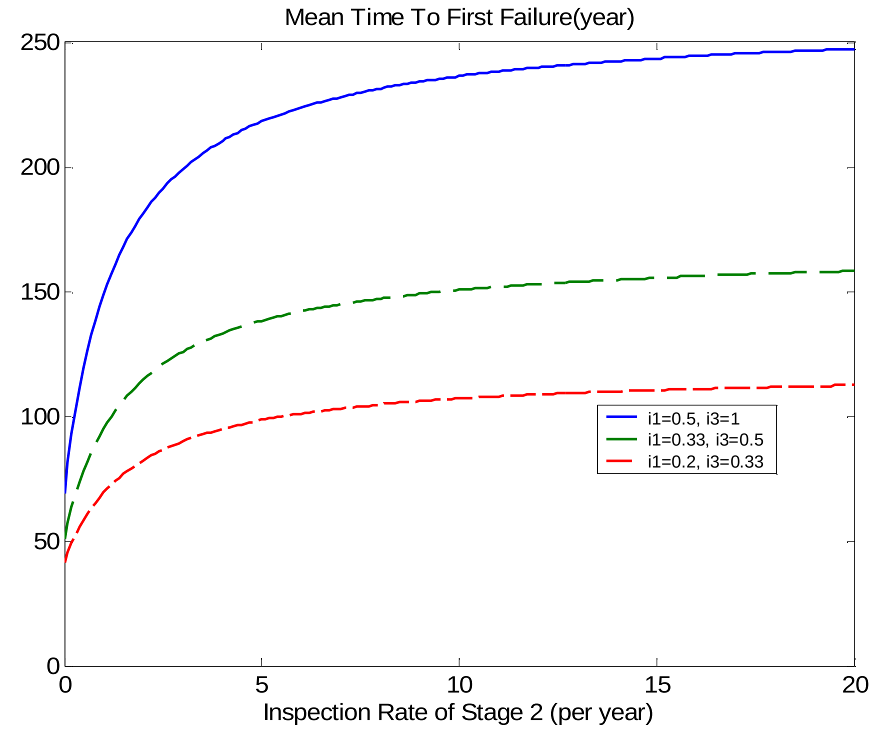

Fig. 6.25 Relationship between Mean Time to The First Failure and Inspection Rate of Stage 2 with Three Sub-stages representing D1

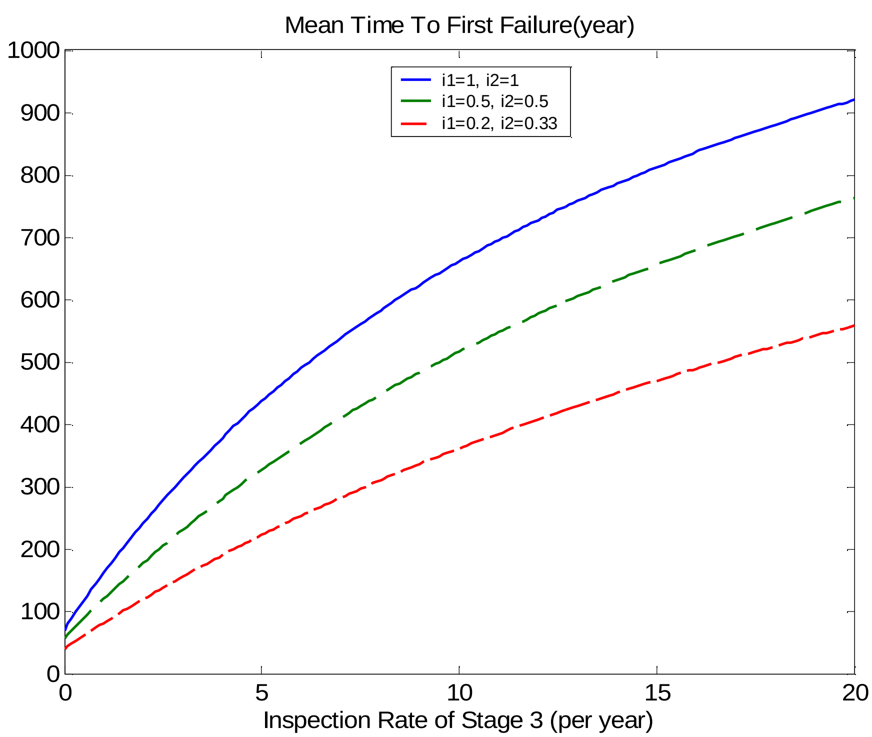

Fig. 6.26 Relationship between Mean Time to The First Failure and Inspection Rate of Stage 3 with Three Sub-stages representing D1

6.5.2.2 Sensitivity analysis of inspection rate on all associated cost

Costs associated in the maintenance model are inspection cost, basic maintenance cost, replacement cost and failure cost. Assumed cost parameters are listed in appendix. This analysis will give insight into all the associated costs. The simulation results, showing the relation between inspection rate and associated costs, are shown in Fig.6.27-6.38.

Fig.6.27-6.30 shows simulation results corresponding to change in inspection rate of D1. Following observations can be made out of the simulation results.

- Failure cost decreases exponentially and then increases as the inspection rate of D1 increases
- Maintenance cost first decreases as the inspection rate of D1 increases and then increases with inspection rate of D1.
- Inspection cost increases linearly with inspection rate of D1
- The optimal region of inspection rate of D1 that will minimize the total cost is 0.5-1 per year.
- Maintenance of the device at its stage D1 is not useful.

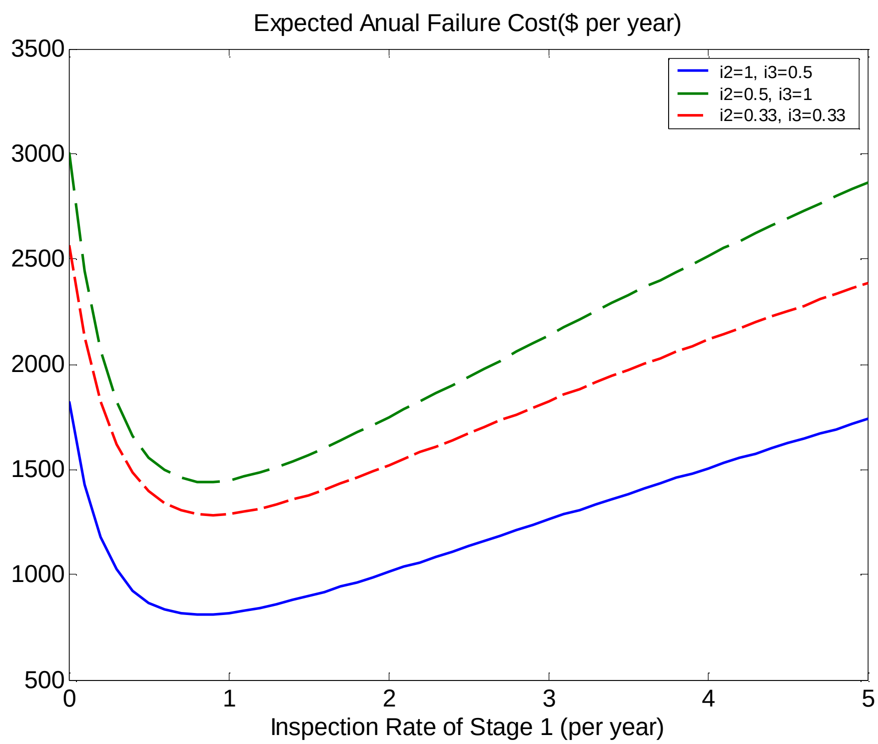

Fig.6.27: Relationships between Expected Annual Failure Cost and Inspection Rate of Stage 1

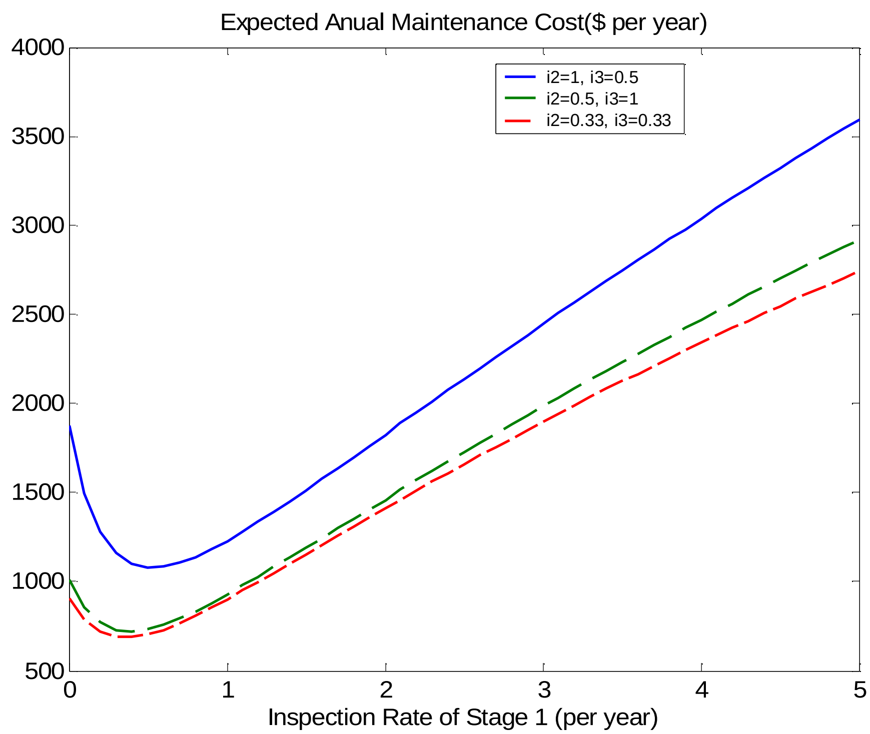

Fig.6.28: Relationships between Expected Annual Maintenance Cost and Inspection Rate of Stage 1

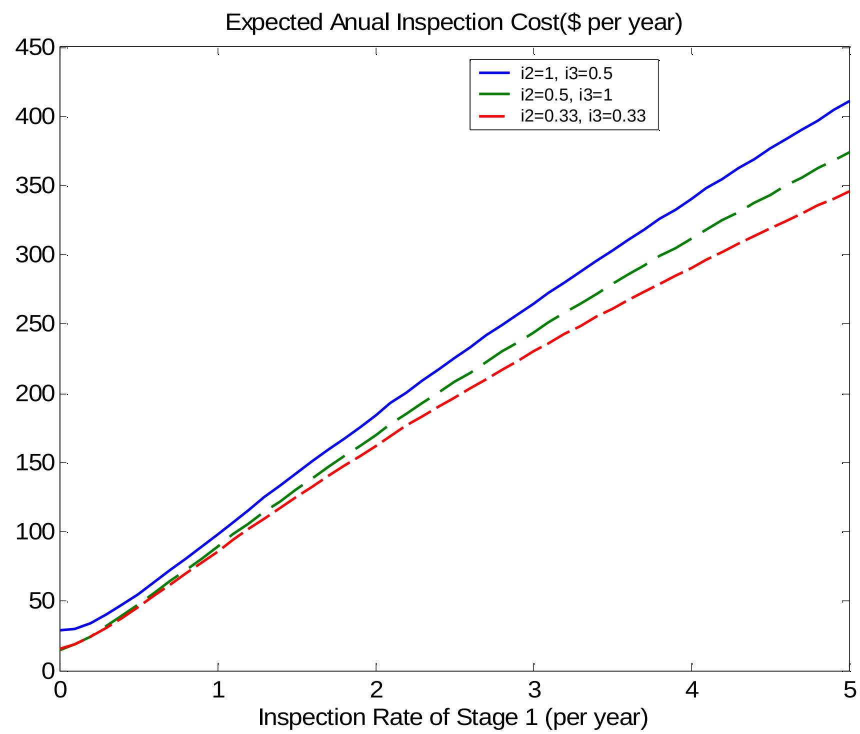

Fig.6.29: Relationships between Expected Annual Inspection Cost and Inspection Rate of Stage 1

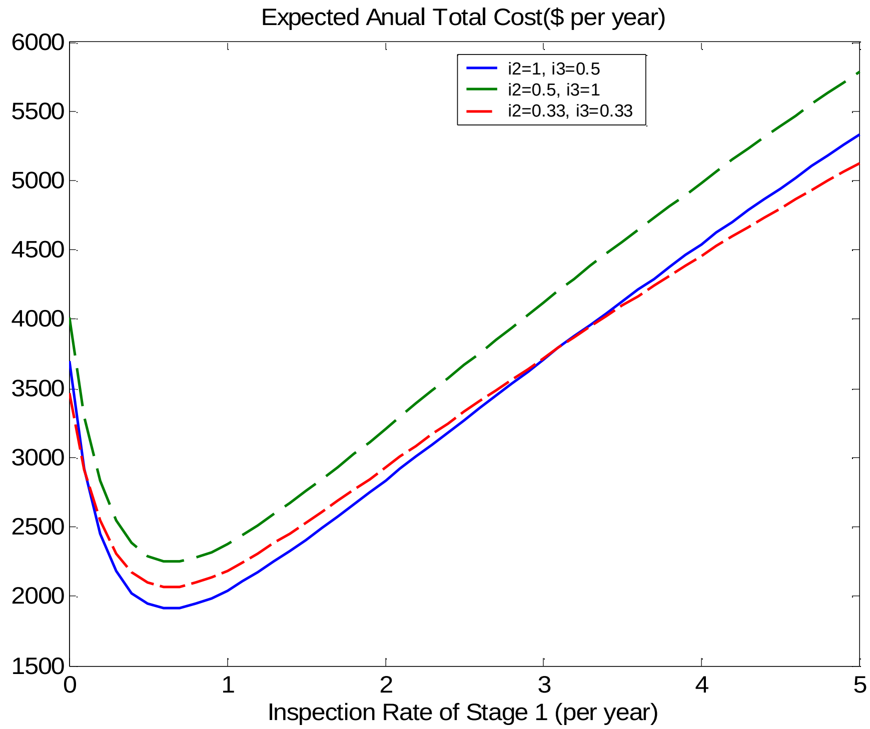

Fig.6.30: Relationships between Expected Annual Total Cost and Inspection Rate of Stage 1

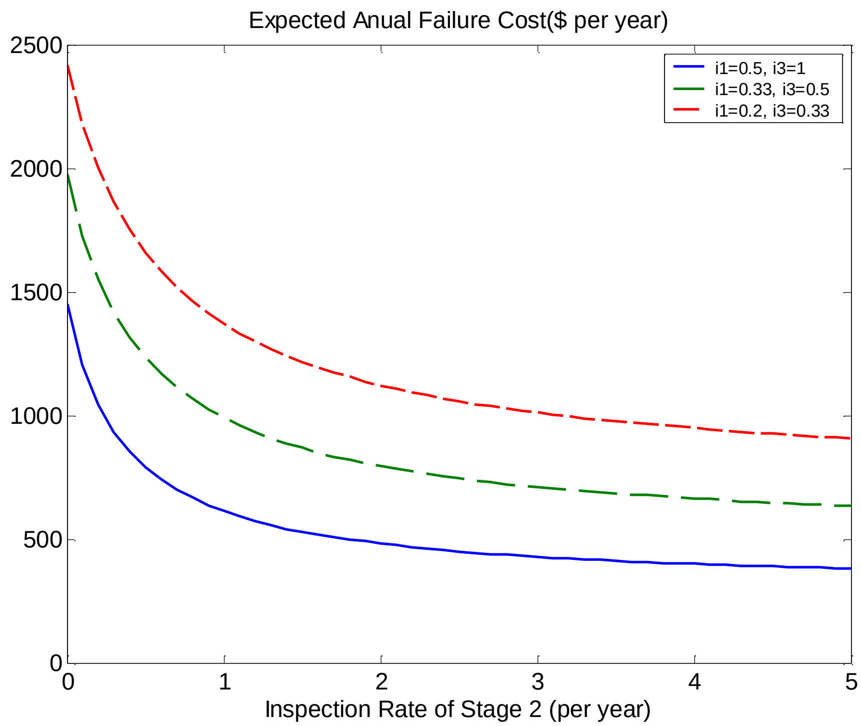

Fig.6.31: Relationships between Expected Annual Failure Cost and Inspection Rate of Stage 2

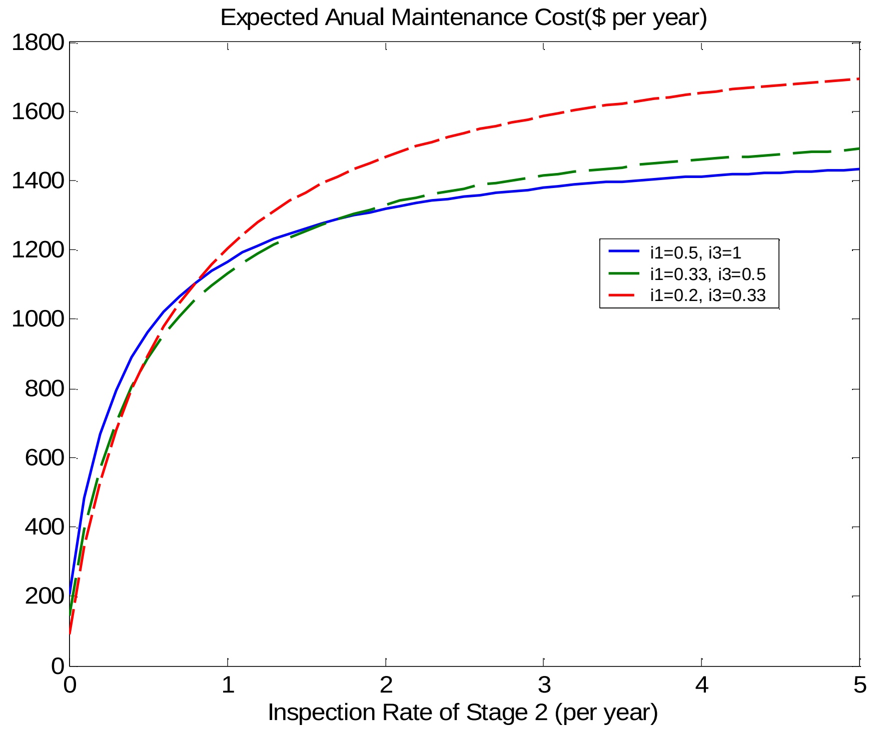

Fig.6.32: Relationships between Expected Annual Maintenance Cost and Inspection Rate of Stage 2

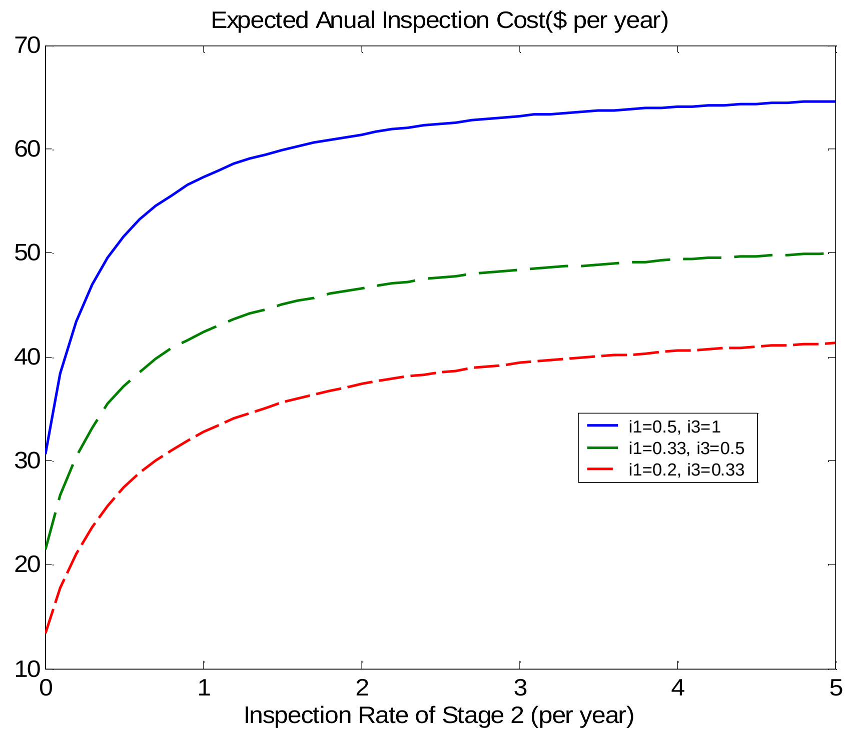

Fig.6.33: Relationships between Expected Annual Inspection Cost and Inspection Rate of Stage 2

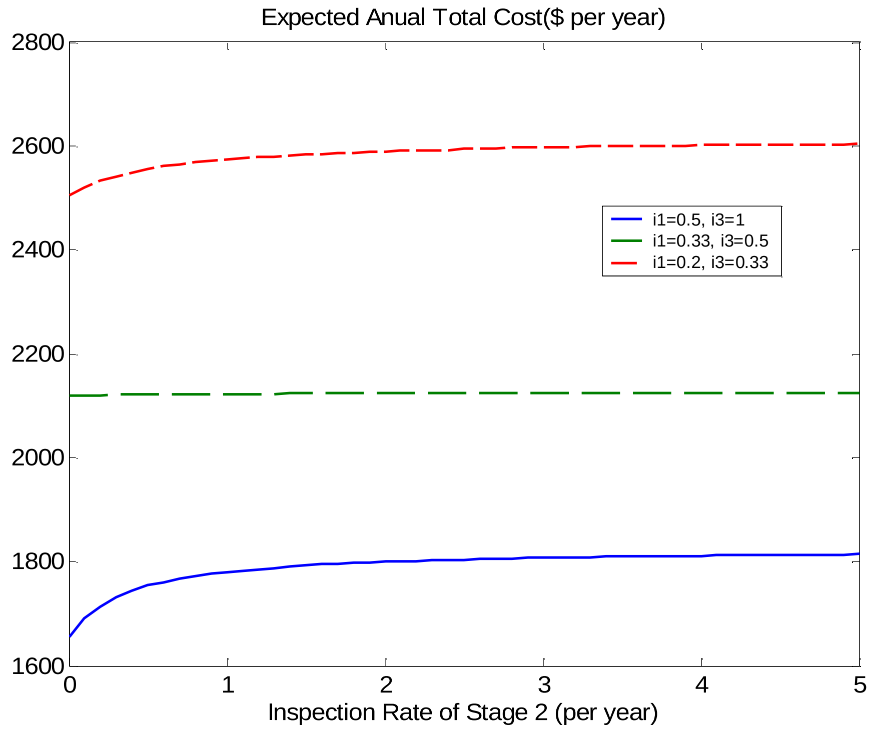

Fig.6.34: Relationships between Expected Annual Total Cost and Inspection Rate of Stage 2

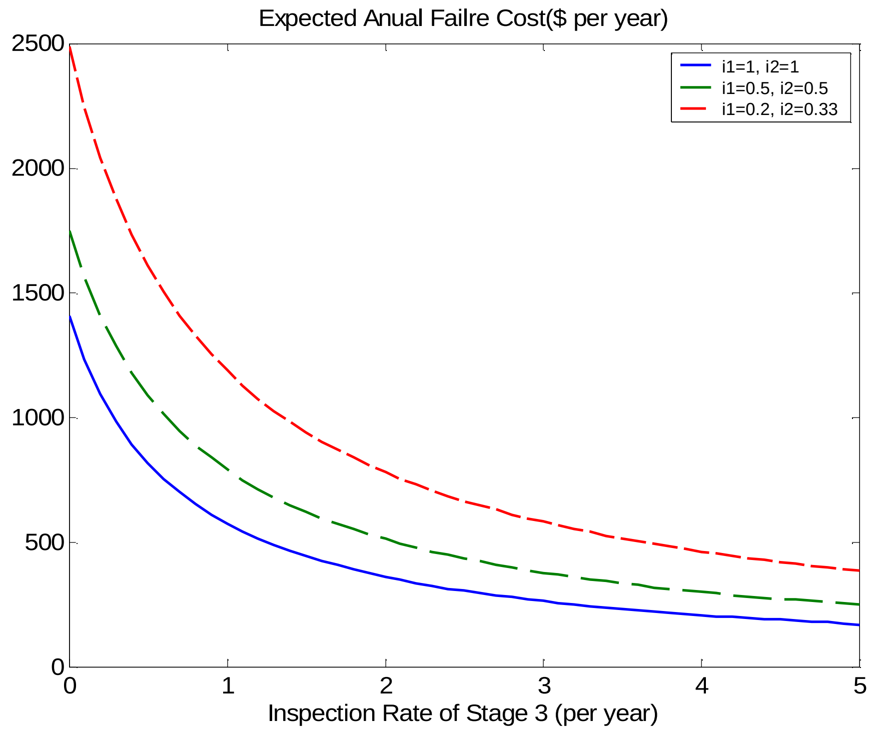

Fig.6.35: Relationships between Expected Annual Failure Cost and Inspection Rate of Stage 3

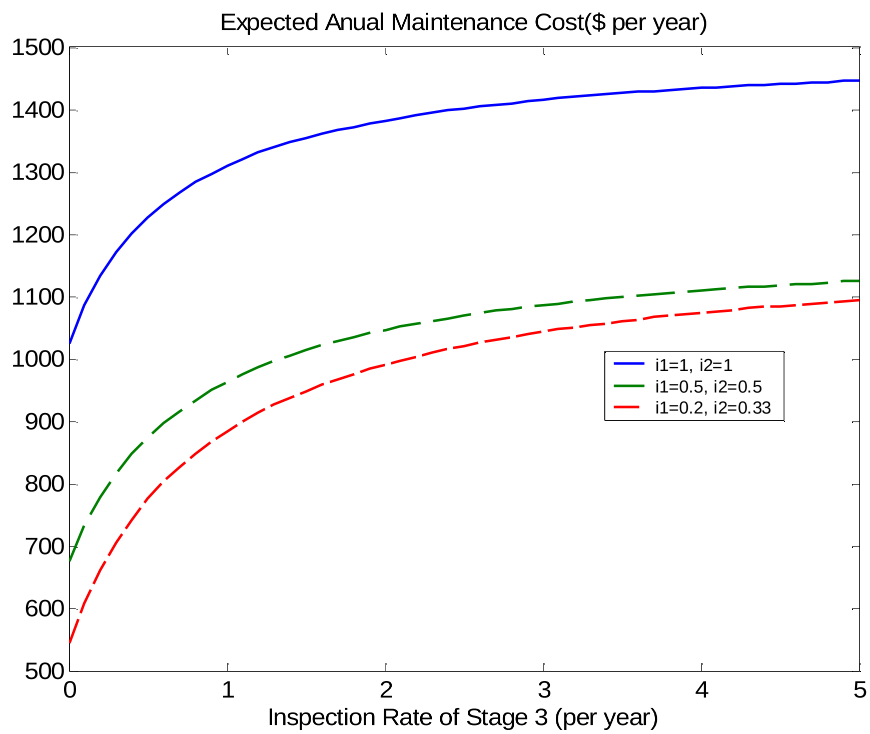

Fig.6.36: Relationships between Expected Annual Maintenance Cost and Inspection Rate of Stage 3

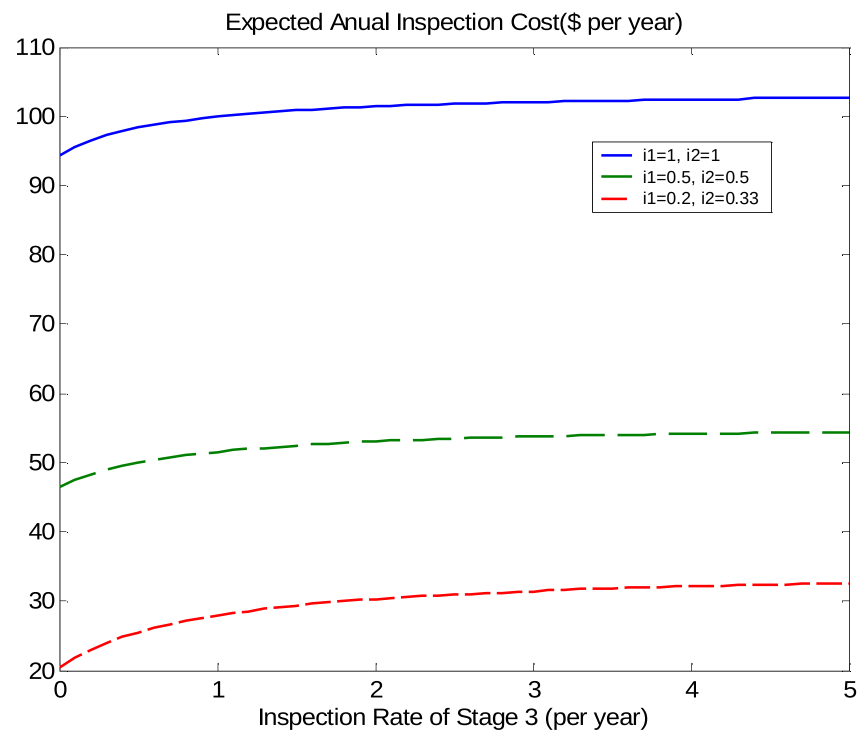

Fig.6.37: Relationships between Expected Annual Inspection Cost and Inspection Rate of Stage 3

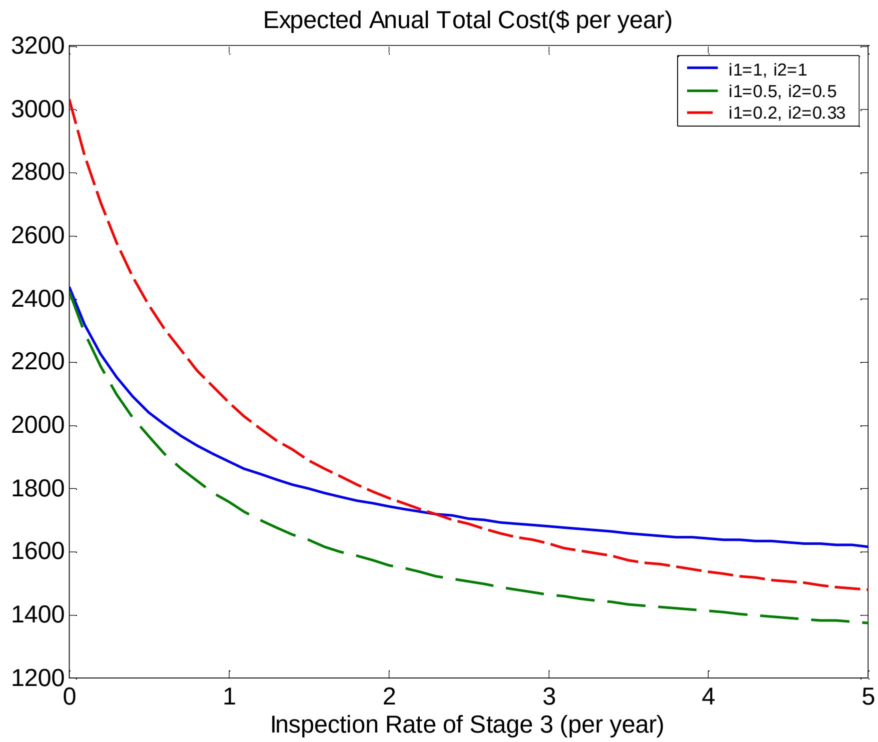

Fig.6.38: Relationships between Expected Annual Total Cost and Inspection Rate of Stage 1

Fig. 6.31-6.34 presents the relation between inspection rate of D2 and all associated costs. Following are the observations made from the simulation results.

- Failure cost decreases exponentially as the inspection rate of D2 increases
- Both Maintenance and inspection costs increases with increase in inspection rate of D2 and stays at constant value at higher inspection rate.
- Total cost is minimum at high inspection rate of D2

The effect of inspection rate of D3 on all associated costs is shown in Fig. 6.35-6.38. The following observations can be made from the simulation results.

- Failure cost decreases exponentially as the inspection rate of D3 increases
- Both Maintenance and inspection costs increases with increase in inspection rate of D3 and stays at constant value at higher inspection rate.
- Total cost is minimum at high inspection rate of D3

Finally, results suggest that small inspection rate of D1 and high inspection rate of D2 and D3 will lead to cost effective maintenance. The model helps in allocating the available sources towards maintenance of the device. The model finds its importance in long-term planning purposes.

6.6 Mathematical Equivalent Models and Analysis

Two equivalent models are introduced to simplify the maintenance models shown in Fig. 6.4 and 6.5. The equivalent models have 3 discrete stages representing the deterioration processes. Assume that maintenance is implemented at every inspection, maintenance and inspection rate of each stage is considered to be an equivalent repair rate.

Let D1: stage 1
D2: stage 2, minor deterioration
D3: stage 3, major deterioration
F: failure stage

y_1 = mean time in stage 1 (year)

y_2 = mean time in stage 2 (year)

y_3 = mean time in stage 3 (year)

m_{21} = repair rate from stage 2 to 1 (/year)

m_{32} = repair rate from stage 3 to 2 (/year)

m_{31} = repair rate from stage 3 to 1 (/year)

1. *Perfect maintenance equivalent model*

It is assumed that in the initial stage the component is in good working condition that needs no maintenance. Moreover, it is assumed that maintenance will always improve the device to the previous stage; therefore, repair rate of stage 2 will improve the device to stage 1 and repair rate of stage 3 will improve the device to stage 2. The model is shown in Fig. 6.39

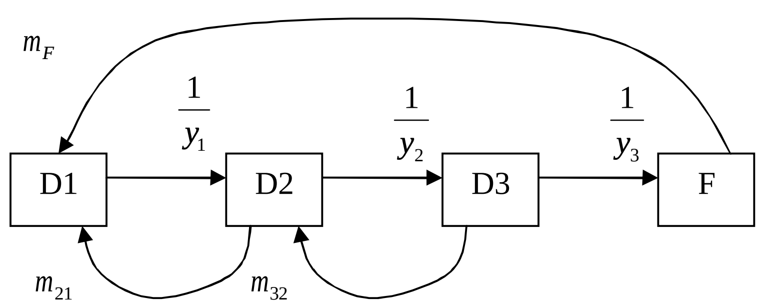

Fig. 6.39: Perfect Maintenance Equivalent Model

2. *Imperfect maintenance equivalent model*

This model is slightly different from the model in Fig. 6.40. Transition rate from stage 1 to 3 is introduced (l_{13}) to describe an imperfect inspection of stage 1. This model accounts for the probability that inspection of stage 1 might cause the system to transit to stage 3. Note that this model is an equivalent model for transformer and breaker maintenance models in Fig. 6.4 and 6.5 since it accounts for a transition of stage 1 to 3.

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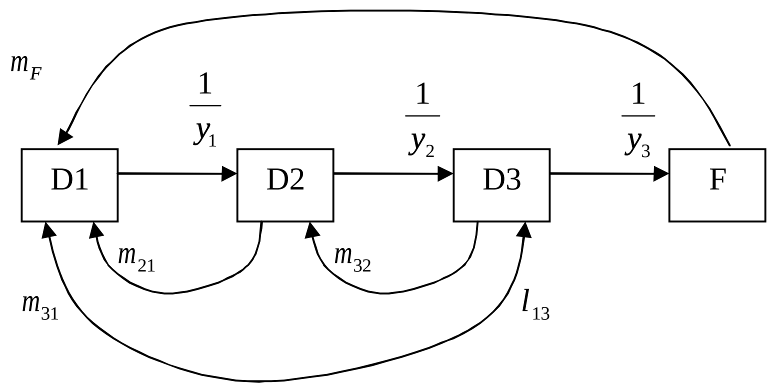

Fig. 6.40: Imperfect Maintenance Equivalent Model

The equivalent models will be employed in analyses in the next section, MTTFF and Cost analysis. The first passage time and steady state probability calculation will be used. The equations obtained from the analyses will be used to verify the simulation results from the previous analyses.

Mean Time to the First Failure Analysis

MTTFF equations are derived using the methodology of first passage time calculation [127]. These equations will explain the simulation results in Fig. 6.6-6.11 and Fig. 6.24-6.26. The analysis is based on equivalent math models, perfect maintenance model and imperfect maintenance model.

<u>Perfect Maintenance Model</u>

Transitional probability matrix for perfect maintenance model is written as (6.1).

$$T = \begin{bmatrix} 1-\frac{1}{y_1} & \frac{1}{y_1} & 0 & 0 \\ m_{21} & 1-\left(m_{21}+\frac{1}{y_2}\right) & \frac{1}{y_2} & 0 \\ 0 & m_{32} & 1-\left(m_{32}+\frac{1}{y_3}\right) & \frac{1}{y_3} \\ m_F & 0 & 0 & 1-m_F \end{bmatrix} \tag{6.1}$$

Truncated transitional probability matrix Q is constructed by deleting row 4 and column 4 which associated with the absorbing state [127].

$$Q_n = \begin{bmatrix} 1-\frac{1}{y_1} & \frac{1}{y_1} & 0 \\ m_{21} & 1-\left(m_{21}+\frac{1}{y_2}\right) & \frac{1}{y_2} \\ 0 & m_{32} & 1-\left(m_{32}+\frac{1}{y_3}\right) \end{bmatrix} \tag{6.2}$$

The expected number of time intervals matrix is calculated from $N = [I - Q_n]^{-1}$

$$N = \begin{bmatrix} \frac{1}{y_1} & -\frac{1}{y_1} & 0 \\ -m_{21} & m_{21}+\frac{1}{y_2} & -\frac{1}{y_2} \\ 0 & -m_{32} & m_{32}+\frac{1}{y_3} \end{bmatrix}^{-1} \tag{6.3}$$

$$\det(N) = \left\{\frac{1}{y_1}\cdot\left(m_{21}+\frac{1}{y_2}\right)\cdot\left(m_{32}+\frac{1}{y_3}\right)\right\} - \left\{\left(\frac{1}{y_1}\cdot\frac{-1}{y_2}\cdot(-m_{32})\right)+\left(\frac{-1}{y_1}\cdot(-m_{21})\cdot\left(m_{32}+\frac{1}{y_3}\right)\right)\right\} \tag{6.4}$$

$$\det(N) = \frac{m_{21}m_{32}}{y_1} + \frac{m_{21}}{y_1 y_3} + \frac{m_{32}}{y_1 y_2} + \frac{1}{y_1 y_2 y_3} - \left(\frac{m_{32}}{y_1 y_2} + \frac{m_{21}m_{32}}{y_1} + \frac{m_{21}}{y_1 y_3}\right) = \frac{1}{y_1 y_2 y_3} \tag{6.5}$$

$$N = y_1 y_2 y_3 \begin{bmatrix} \begin{vmatrix} m_{21}+\frac{1}{y_2} & -\frac{1}{y_2} \\ -m_{32} & m_{32}+\frac{1}{y_3} \end{vmatrix} & -\begin{vmatrix} -m_{21} & -\frac{1}{y_2} \\ 0 & m_{32}+\frac{1}{y_3} \end{vmatrix} & \begin{vmatrix} -m_{21} & m_{21}+\frac{1}{y_2} \\ 0 & -m_{32} \end{vmatrix} \\ -\begin{vmatrix} -\frac{1}{y_1} & 0 \\ -m_{32} & m_{32}+\frac{1}{y_3} \end{vmatrix} & \begin{vmatrix} \frac{1}{y_1} & 0 \\ 0 & m_{32}+\frac{1}{y_3} \end{vmatrix} & -\begin{vmatrix} \frac{1}{y_1} & -\frac{1}{y_1} \\ 0 & -m_{32} \end{vmatrix} \\ \begin{vmatrix} -\frac{1}{y_1} & 0 \\ m_{21}+\frac{1}{y_2} & -\frac{1}{y_2} \end{vmatrix} & -\begin{vmatrix} \frac{1}{y_1} & 0 \\ -m_{21} & -\frac{1}{y_2} \end{vmatrix} & \begin{vmatrix} \frac{1}{y_1} & -\frac{1}{y_1} \\ -m_{21} & m_{21}+\frac{1}{y_2} \end{vmatrix} \end{bmatrix}^T \tag{6.6}$$

$$N = y_1 y_2 y_3 \begin{bmatrix} m_{21}m_{32} + \dfrac{m_{21}}{y_3} + \dfrac{1}{y_2 y_3} & m_{21}m_{32} + \dfrac{m_{21}}{y_3} & m_{21}m_{32} \\ \dfrac{m_{32}}{y_1} + \dfrac{1}{y_1 y_3} & \dfrac{m_{32}}{y_1} + \dfrac{1}{y_1 y_3} & \dfrac{m_{32}}{y_1} \\ \dfrac{1}{y_1 y_2} & \dfrac{1}{y_1 y_2} & \dfrac{1}{y_1 y_2} \end{bmatrix}^T = [N(1) \quad N(2) \quad N(3)]^T \quad (6.7)$$

Mean time to the first failure starting with different stages is calculated in the following.

1. Entering from stage 1, MTTFF is the summation of matrix $N(1)$

$$MTTFF = y_1 + y_2 + y_3 + m_{21}y_1y_2 + m_{32}y_2y_3 + m_{21}m_{32}y_1y_2y_3 \quad (6.8)$$

2. Entering from stage 2, MTTFF is the summation of matrix $N(2)$

$$MTTFF = y_2 + y_3 + m_{21}y_1y_2 + m_{32}y_2y_3 + m_{21}m_{32}y_1y_2y_3 \quad (6.9)$$

3. Entering from stage 3, MTTFF is the summation of matrix $N(3)$

$$MTTFF = y_3 + m_{32}y_2y_3 + m_{21}m_{32}y_1y_2y_3 \quad (6.10)$$

Assume that the system starts at stage 1, then

$$MTTFF = y_1 + y_2 + y_3 + m_{21}y_1y_2 + m_{32}y_2y_3 + m_{21}m_{32}y_1y_2y_3 \quad (6.11)$$

Let T_0 = life time without maintenance

T_E = extended life time with maintenance

$l_{12} = \dfrac{1}{y_1}$ transition rate from D1 to D2

$l_{23} = \dfrac{1}{y_2}$ transition rate from D2 to D3

$l_{3f} = \dfrac{1}{y_3}$ transition rate from D3 to F

Then, $T_0 = y_1 + y_2 + y_3$ (6.12)

$$T_E = \frac{m_{21}}{l_{12}l_{23}} + \frac{m_{32}}{l_{23}l_{3f}} + \frac{m_{21}m_{32}}{l_{12}l_{23}l_{3f}} \quad (6.13)$$

$$MTTFF = T_0 + T_E \quad (6.14)$$

Notice that the extended time consists of the following terms;

1. The first term, $\frac{m_{21}}{l_{12} l_{23}}$, is the ratio between the maintenance rate from stage 2 to stage 1 and the failure rate from stage 1 to 2 and 2 to 3.

2. The second term, $\frac{m_{32}}{l_{23} l_{3f}}$, is the ratio between the maintenance rate from stage 3 to stage 2 and the failure rate from stage 2 to 3 and 3 to failure stage.

3. The third term, $\frac{m_{21} m_{32}}{l_{12} l_{23} l_{3f}}$, is the ratio between the two maintenance rates (from 2 to 1 and from 3 to 2) and the failure rate of all stages.

The extended time of perfect maintenance model is a summation of all possible combinations of ratios between maintenance rate of the current stage and failure rate of the current and previous stage. Since T_E can only be positive in this model, inspection and maintenance will always extend the equipment life time.

If the repair rate of each stage is very high relative to the transition rate of that stage to the previous stage ($m_{21} >> l_{12} l_{23}, m_{32} >> l_{23} l_{3f}$), the lifetime before failure of the device will be high.

<u>Imperfect Maintenance Model</u>

Transitional probability matrix for imperfect maintenance model is written as (6.15).

$$T = \begin{bmatrix} 1-\left(l_{13}+\frac{1}{y_1}\right) & \frac{1}{y_1} & l_{13} & 0 \\ m_{21} & 1-\left(m_{21}+\frac{1}{y_2}\right) & \frac{1}{y_2} & 0 \\ m_{31} & m_{32} & 1-\left(m_{31}+m_{32}+\frac{1}{y_3}\right) & \frac{1}{y_3} \\ m_F & 0 & 0 & 1-m_F \end{bmatrix} \tag{6.15}$$

Truncated transitional probability matrix Q is constructed by deleting row 4 and column 4 which associated with the absorbing state [127].

$$Q_n = \begin{bmatrix} 1-\left(l_{13}+\frac{1}{y_1}\right) & \frac{1}{y_1} & l_{13} \\ m_{21} & 1-\left(m_{21}+\frac{1}{y_2}\right) & \frac{1}{y_2} \\ m_{31} & m_{32} & 1-\left(m_{31}+m_{32}+\frac{1}{y_3}\right) \end{bmatrix} \tag{6.16}$$

The expected number of time intervals matrix is calculated from $N = \left[I - Q_n\right]^{-1}$

$$N = \begin{bmatrix} l_{13} + \dfrac{1}{y_1} & -\dfrac{1}{y_1} & -l_{13} \\ -m_{21} & m_{21} + \dfrac{1}{y_2} & -\dfrac{1}{y_2} \\ -m_{31} & -m_{32} & m_{31} + m_{32} + \dfrac{1}{y_3} \end{bmatrix}^{-1} \tag{6.17}$$

$$\begin{aligned} \det(N) = &\left\{\left(l_{13} + \frac{1}{y_1}\right)\cdot\left(m_{21} + \frac{1}{y_2}\right)\cdot\left(m_{31} + m_{32} + \frac{1}{y_3}\right) + \left(\frac{-1}{y_1}\right)\cdot\left(\frac{-1}{y_2}\right)\cdot(-m_{31}) + (-l_{13})\cdot(-m_{21})\cdot(-m_{32})\right\} \\ &- \left\{(-m_{31})\cdot\left(m_{21} + \frac{1}{y_2}\right)\cdot(-l_{13}) + \left(l_{13} + \frac{1}{y_1}\right)\cdot\left(\frac{-1}{y_2}\right)\cdot(-m_{32}) + \left(\frac{-1}{y_1}\right)\cdot(-m_{21})\cdot\left(m_{31} + m_{32} + \frac{1}{y_3}\right)\right\} \end{aligned} \tag{6.18}$$

$$\det(N) = \frac{1}{y_1 y_2 y_3} + \frac{l_{13}}{y_2 y_3} + \frac{l_{13} m_{21}}{y_3} \tag{6.19}$$

$$N = \frac{1}{\det(N)} \begin{bmatrix} \begin{vmatrix} m_{21} + \frac{1}{y_2} & -\frac{1}{y_2} \\ -m_{32} & m_{31} + m_{32} + \frac{1}{y_3} \end{vmatrix} & -\begin{vmatrix} -m_{21} & -\frac{1}{y_2} \\ -m_{31} & m_{31} + m_{32} + \frac{1}{y_3} \end{vmatrix} & \begin{vmatrix} -m_{21} & m_{21} + \frac{1}{y_2} \\ -m_{31} & -m_{32} \end{vmatrix} \\ -\begin{vmatrix} -\frac{1}{y_1} & -l_{13} \\ -m_{32} & m_{31} + m_{32} + \frac{1}{y_3} \end{vmatrix} & \begin{vmatrix} l_{13} + \frac{1}{y_1} & -l_{13} \\ -m_{31} & m_{31} + m_{32} + \frac{1}{y_3} \end{vmatrix} & -\begin{vmatrix} l_{13} + \frac{1}{y_1} & -\frac{1}{y_1} \\ -m_{31} & -m_{32} \end{vmatrix} \\ \begin{vmatrix} -\frac{1}{y_1} & -l_{13} \\ m_{21} + \frac{1}{y_2} & -\frac{1}{y_2} \end{vmatrix} & -\begin{vmatrix} l_{13} + \frac{1}{y_1} & -l_{13} \\ -m_{21} & -\frac{1}{y_2} \end{vmatrix} & \begin{vmatrix} l_{13} + \frac{1}{y_1} & -\frac{1}{y_1} \\ -m_{21} & m_{21} + \frac{1}{y_2} \end{vmatrix} \end{bmatrix}^T \tag{6.20}$$

$$\begin{aligned} N &= \frac{1}{\det(N)} \begin{bmatrix} \frac{1}{y_2 y_3} + m_{21}(m_{31} + m_{32}) + \frac{m_{21}}{y_3} + \frac{m_{31}}{y_2} & m_{21}(m_{31} + m_{32}) + \frac{m_{21}}{y_3} + \frac{m_{31}}{y_2} & m_{21}(m_{31} + m_{32}) + \frac{m_{31}}{y_2} \\ \frac{1}{y_1 y_3} + m_{32} l_{13} + \frac{m_{31}}{y_1} + \frac{m_{32}}{y_1} & \frac{1}{y_1 y_3} + m_{32} l_{13} + \frac{m_{31}}{y_1} + \frac{m_{32}}{y_1} + \frac{l_{13}}{y_3} & m_{32} l_{13} + \frac{m_{31}}{y_1} + \frac{m_{32}}{y_1} \\ \frac{1}{y_1 y_2} + \frac{l_{13}}{y_2} + m_{21} l_{13} & \frac{1}{y_1 y_2} + \frac{l_{13}}{y_2} + m_{21} l_{13} & \frac{1}{y_1 y_2} + \frac{l_{13}}{y_2} + m_{21} l_{13} \end{bmatrix}^T \\ &= \left[N(1) \quad N(2) \quad N(3)\right]^T \end{aligned} \tag{6.21}$$

Mean time to the first failure starting with different stages is calculated in the following.

1. Entering from stage 1, MTTFF is the summation of matrix $N(1)$

$$MTTFF = \frac{1}{\det(N)}\left(\frac{1}{y_2y_3}+\frac{1}{y_1y_3}+\frac{1}{y_1y_2}+m_{21}(m_{31}+m_{32})+\frac{m_{21}}{y_3}+\frac{m_{31}}{y_2}+m_{32}l_{13}+\frac{m_{31}}{y_1}+\frac{m_{32}}{y_1}+\frac{l_{13}}{y_2}+m_{21}l_{13}\right) \quad (6.22)$$

2. Entering from stage 2, MTTFF is the summation of matrix $N(2)$

$$MTTFF = \frac{1}{\det(N)}\left(\frac{1}{y_1y_3}+\frac{1}{y_1y_2}+m_{21}(m_{31}+m_{32})+\frac{m_{21}}{y_3}+\frac{m_{31}}{y_2}+m_{32}l_{13}+\frac{l_{13}}{y_3}+\frac{m_{31}}{y_1}+\frac{m_{32}}{y_1}+\frac{l_{13}}{y_2}+m_{21}l_{13}\right) \quad (6.23)$$

3. Entering from stage 3, MTTFF is the summation of matrix $N(3)$

$$MTTFF = \frac{1}{\det(N)}\left(\frac{1}{y_1y_2}+m_{21}(m_{31}+m_{32})+\frac{m_{31}}{y_2}+m_{32}l_{13}+\frac{m_{31}}{y_1}+\frac{m_{32}}{y_1}+\frac{l_{13}}{y_2}+m_{21}l_{13}\right) \quad (6.24)$$

Assume that the system starts at stage 1, then

$$MTTFF = \frac{1}{\det(N)}\left(\frac{1}{y_2y_3}+\frac{1}{y_1y_3}+\frac{1}{y_1y_2}+m_{21}(m_{31}+m_{32})+\frac{m_{21}}{y_3}+\frac{m_{31}}{y_2}+m_{32}l_{13}+\frac{m_{31}}{y_1}+\frac{m_{32}}{y_1}+\frac{l_{13}}{y_2}+m_{21}l_{13}\right) \quad (6.25)$$

From $\det(N)=\frac{1}{y_1y_2y_3}+\frac{l_{13}}{y_2y_3}+\frac{l_{13}m_{21}}{y_3}$; $\frac{1}{\det(N)}=\frac{y_1y_2y_3}{(1+l_{13}y_1+l_{13}m_{21}y_1y_2)}$ (6.26)

$$MTTFF = \frac{T_0+y_1y_2y_3\cdot(m_{21}m_{31}+m_{21}m_{32}+m_{21}l_{13}+m_{32}l_{13})+y_1y_2m_{21}+y_1y_3\cdot(l_{13}+m_{31})+y_2y_3\cdot(m_{31}+m_{32})}{(1+l_{13}y_1+l_{13}m_{21}y_1y_2)} \quad (6.27)$$

Let T_0 = life time without maintenance

T_E = extended life time with maintenance

$l_{12}=\frac{1}{y_1}$ transition rate from D1 to D2

$l_{23}=\frac{1}{y_2}$ transition rate from D2 to D3

$l_{3f}=\frac{1}{y_3}$ transition rate from D3 to F

Then, $$MTTFF = \frac{T_0+T_E}{1+\frac{l_{13}}{l_{12}}+\frac{l_{13}m_{21}}{l_{12}l_{23}}} \quad (6.28)$$

$$T_E = \frac{m_{21}m_{31}+m_{21}m_{32}+m_{21}l_{13}+m_{32}l_{13}}{l_{12}l_{23}l_{3f}}+\frac{m_{21}}{l_{12}l_{23}}+\frac{m_{31}}{l_{23}l_{3f}}+\frac{m_{31}}{l_{12}l_{3f}}+\frac{m_{32}}{l_{23}l_{3f}}+\frac{l_{13}}{l_{12}l_{3f}} \quad (6.29)$$

The relationships of inspection rate of each stage and MTTFF are listed in the following.

1. Inspection rate of stage 1

It is possible that inspection and maintenance will reduce MTTFF at very high inspection rate of stage 1 (recall that high inspection in stage 1 will increase l_{13}; thus, denominator may be large). This will increase the failure rate from stage 1 to 3; therefore, MTTFF may decrease. This conclusion is verified by the simulation result in Fig. 6.9

2. Inspection rate of stage 2

High inspection rate of stage 2 will increase the repair rate from stage 2 to 1 (m_{21}). Assuming that this repair rate is very high,

$$MTTFF \approx \frac{1 + y_3\left(m_{31} + m_{32} + l_{13}\right)}{l_{13}} \tag{6.30}$$

Then MTTFF will increase to a constant value. This is verified by the simulation result in Fig. 6.10 and Fig. 6.25.

3. Inspection rate of stage 3

High inspection rate of D3 will increase the repair rate from stage 3 to 2 (m_{32}) and also repair rate of stage 3 to 1 (m_{31}). These rates are linearly related to MTTFF; therefore, the lifetime will increase linearly with inspection rate of stage 3. This is verified by the simulation result in Fig. 6.11 and Fig. 6.26

Cost Analysis

Cost equations are derived using steady state probability calculation. The cost analyses include failure cost, maintenance cost, and total cost. Maintenance cost in this analysis includes inspection cost based on the assumption of the equivalent model that maintenance is implemented at every inspection. These equations will explain the simulation results in Fig. 6.12-6.23 and Fig. 6.27-6.38.

<u>Perfect Maintenance Model</u>

The matrix of transition rates and resulting steady state probability are derived in the following.

Transition rate matrix is

$$R=\begin{bmatrix} -\frac{1}{y_1} & m_{21} & 0 & m_F \\ \frac{1}{y_1} & -\left(m_{21}+\frac{1}{y_2}\right) & m_{32} & 0 \\ 0 & \frac{1}{y_2} & -\left(m_{32}+\frac{1}{y_3}\right) & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F \end{bmatrix} \tag{6.31}$$

Using frequency balance approach, steady state probability is calculated from

$$P=\begin{bmatrix} -\frac{1}{y_1} & m_{21} & 0 & m_F \\ 1 & 1 & 1 & 1 \\ 0 & \frac{1}{y_2} & -\left(m_{32}+\frac{1}{y_3}\right) & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F \end{bmatrix}^{-1} \cdot \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \tag{6.32}$$

$$\det(P)=\begin{vmatrix} -\frac{1}{y_1} & m_{21} & 0 & m_F \\ 1 & 1 & 1 & 1 \\ 0 & \frac{1}{y_2} & -\left(m_{32}+\frac{1}{y_3}\right) & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F \end{vmatrix} = \begin{vmatrix} -\frac{1}{y_1} & m_{21} & 0 & m_F \\ 0 & y_1 m_{21}+1 & 1 & y_1 m_F+1 \\ 0 & \frac{1}{y_2} & -\left(m_{32}+\frac{1}{y_3}\right) & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F \end{vmatrix} \tag{6.33}$$

$$\det(P)=-\frac{1}{y_1}\times\begin{vmatrix} y_1 m_{21}+1 & 1 & y_1 m_F+1 \\ \frac{1}{y_2} & -\left(m_{32}+\frac{1}{y_3}\right) & 0 \\ 0 & \frac{1}{y_3} & -m_F \end{vmatrix} \tag{6.34}$$

$$\begin{aligned} \det(P)&=-\frac{1}{y_1}\cdot\left[\left(y_1 m_{21}+1\right)\left(m_{32}+\frac{1}{y_3}\right)\left(m_F\right)+\left(y_1 m_F+1\right)\left(\frac{1}{y_2}\right)\left(\frac{1}{y_3}\right)-\left(-m_F\right)\left(\frac{1}{y_2}\right)\right] \\ &=-\frac{1}{y_1 y_2 y_3}-m_F\left(\frac{1}{y_1 y_2}+\frac{1}{y_2 y_3}+\frac{1}{y_1 y_3}+\frac{m_{21}}{y_3}+\frac{m_{32}}{y_1}+m_{21}m_{32}\right) \end{aligned} \tag{6.35}$$

From, $MTTFF = T_0 + m_{21}y_1y_2 + m_{32}y_2y_3 + m_{21}m_{32}y_1y_2y_3$

Then, $$\det(P) = -\frac{m_F}{y_1y_2y_3}\left(\frac{1}{m_F} + (T_0 + m_{21}y_1y_2 + m_{32}y_2y_3 + m_{21}m_{32}y_1y_2y_3)\right) = -\frac{m_F}{y_1y_2y_3}\left(\frac{1}{m_F} + MTTFF\right) \quad (6.36)$$

Let $T_R = \dfrac{1}{m_F}$: the repair time (year)

$$\det(P) = -\frac{m_F}{y_1y_2y_3}(T_R + MTTFF) \quad (6.37)$$

$$P = \frac{1}{\det(P)}\begin{bmatrix} -\begin{vmatrix} m_{21} & 0 & m_F \\ \frac{1}{y_2} & -\left(m_{32} + \frac{1}{y_3}\right) & 0 \\ 0 & \frac{1}{y_3} & -m_F \end{vmatrix} \\ \begin{vmatrix} -\frac{1}{y_1} & 0 & m_F \\ 0 & -\left(m_{32} + \frac{1}{y_3}\right) & 0 \\ 0 & \frac{1}{y_3} & -m_F \end{vmatrix} \\ -\begin{vmatrix} -\frac{1}{y_1} & m_{21} & m_F \\ 0 & \frac{1}{y_2} & 0 \\ 0 & 0 & -m_F \end{vmatrix} \\ \begin{vmatrix} -\frac{1}{y_1} & m_{21} & 0 \\ 0 & \frac{1}{y_2} & -\left(m_{32} + \frac{1}{y_3}\right) \\ 0 & 0 & \frac{1}{y_3} \end{vmatrix} \end{bmatrix} = \frac{-y_1y_2y_3}{m_F(T_R + MTTFF)}\begin{bmatrix} -m_F\left\{m_{21}\left(m_{32} + \frac{1}{y_3}\right) + \frac{1}{y_2y_3}\right\} \\ -\frac{m_F}{y_1}\left(m_{32} + \frac{1}{y_3}\right) \\ -\frac{m_F}{y_1y_2} \\ -\frac{1}{y_1y_2y_3} \end{bmatrix} \quad (6.38)$$

$$P = \frac{1}{(T_R + MTTFF)}\begin{bmatrix} y_1 + y_1y_2m_{21} + y_1y_2y_3m_{21}m_{32} \\ y_2 + y_2y_3m_{32} \\ y_3 \\ T_R \end{bmatrix} \quad (6.39)$$

Let FC = repair cost after failure (dollar/time)

MC = maintenance cost (dollar/time)

P(i) = steady state probability of stage i; i = 1,2, or 3

C_F = expected annual failure cost (dollar/year)

C_M = expected annual maintenance cost (dollar/year)

C_T = expected annual total cost (dollar/year)

T_R = repair time (year)

1. *Failure cost analysis*

The expected failure cost per year is

$C_F = FC \times$ frequency of failure (6.40)

$$C_F = FC \times P(3) \times \frac{1}{y_3} = \frac{FC}{T_R + MTTFF} \tag{6.41}$$

The failure cost is an average cost over lifetime in one cycle of the device. This indicates that as MTTFF increases, the annual failure cost will reduce and it can also reduce to zero.

Consider the case of very frequent maintenance, this cost will approach zero. On the other hand, without maintenance; this cost will be an average cost over a total life time (life time without maintenance plus repair time). This indicates that failure cost will be the highest without maintenance; therefore, maintenance helps reducing failure cost.

2. *Maintenance Cost Analysis*

The expected maintenance cost per year is

$C_M = MC \times$ frequency of maintenance (6.42)

$$C_M = MC \times \left(P(2) \cdot m_{21} + P(3) \cdot m_{32}\right) = \frac{MC\left(y_2 m_{21} + y_3 m_{32} + y_2 y_3 m_{21} m_{32}\right)}{T_R + MTTFF} \tag{6.43}$$

Maintenance cost depends on repair rate of stage 2 and 3. Without maintenance, this cost will obviously be zero. Consider the case of very frequent maintenance causing the device to stay in stage 1 longer, maintenance cost will be the highest and equal to an average cost over a lifetime in stage 1. Therefore, maintenance cost will increase from zero to some constant value.

3. *Total Cost Analysis*

The expected total cost is a summation of failure and maintenance cost. Clearly, without maintenance the total cost will be only a failure cost which is an average cost over a total lifetime. Consider very frequent maintenance, failure cost will be zero while maintenance cost will be the highest. Thus, total cost is dominated by failure cost at small inspection rate and is dominated by maintenance cost at high inspection rate.

Should we do the maintenance at all?

Since maintenance is introduced in order to reduce the total cost, it should be implemented only if the highest possible total cost without maintenance is less than the highest possible total cost with maintenance, i.e.,

$$C_F\left(m_{21}=0, m_{32}=0\right) < C_M\left(m_{21}\neq 0 \middle| m_{32}\neq 0\right) \tag{6.44}$$

$$C_F\left(m_{21}=0, m_{32}=0\right) = \frac{FC}{T_R+T_0} \tag{6.45}$$

$$C_M\left(m_{21}\neq 0 \middle| m_{32}\neq 0\right) = \begin{cases} C_M\left(m_{21}=0, m_{32}\to\infty\right) = \dfrac{MC}{y_2} \\ C_M\left(m_{21}\to\infty, m_{32}=0\right) = \dfrac{MC}{y_1} \\ C_M\left(m_{21}\to\infty, m_{32}\to\infty\right) = \dfrac{MC}{y_1} \end{cases} \tag{6.46}$$

Thus, the following inequality should be considered.

$$\frac{FC}{T_R+T_0} > \frac{MC}{y_1} \quad or \quad \frac{MC}{y_2} \tag{6.47}$$

Similarly,

$$\frac{FC}{MC} > \frac{T_R+T_0}{y_1} \quad or \quad \frac{T_R+T_0}{y_2} \tag{6.48}$$

The inequality tells that if the ratio of failure cost and maintenance cost is higher than a constant value, then the maintenance should be implemented. Intuitively, if the failure cost is not expensive, we would rather replace the device than maintain it.

Imperfect Maintenance Model

The matrix of transition rate and the resulting steady state probabilities are derived in the following.

Transition rate matrix is

$$R=\begin{bmatrix} -\left(\frac{1}{y_1}+l_{13}\right) & m_{21} & m_{31} & m_F \\ \frac{1}{y_1} & -\left(m_{21}+\frac{1}{y_2}\right) & m_{32} & 0 \\ l_{13} & \frac{1}{y_2} & -\left(m_{31}+m_{32}+\frac{1}{y_3}\right) & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F \end{bmatrix} \tag{6.49}$$

Using frequency balance approach, steady state probability is calculated from

$$P=\begin{bmatrix} 1 & 1 & 1 & 1 \\ \frac{1}{y_1} & -\left(m_{21}+\frac{1}{y_2}\right) & m_{32} & 0 \\ l_{13} & \frac{1}{y_2} & -\left(m_{31}+m_{32}+\frac{1}{y_3}\right) & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F \end{bmatrix}^{-1} \cdot \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{6.50}$$

$$\det(P)=\begin{vmatrix} 1 & 1 & 1 & 1 \\ 0 & -\left(m_{21}+\frac{1}{y_1}+\frac{1}{y_2}\right) & m_{32}-\frac{1}{y_1} & -\frac{1}{y_1} \\ 0 & \frac{1}{y_2}-l_{13} & -\left(m_{31}+m_{32}+l_{13}+\frac{1}{y_3}\right) & -l_{13} \\ 0 & 0 & \frac{1}{y_3} & -m_F \end{vmatrix} \tag{6.51}$$

$$\det(P)=\begin{vmatrix} -\left(m_{21}+\frac{1}{y_1}+\frac{1}{y_2}\right) & m_{32}-\frac{1}{y_1} & -\frac{1}{y_1} \\ \frac{1}{y_2}-l_{13} & -\left(m_{31}+m_{32}+l_{13}+\frac{1}{y_3}\right) & -l_{13} \\ 0 & \frac{1}{y_3} & -m_F \end{vmatrix} \tag{6.52}$$

$$\begin{aligned} \det(P)&=\left[-m_F\left(m_{21}+\frac{1}{y_1}+\frac{1}{y_2}\right)\left(m_{31}+m_{32}+l_{13}+\frac{1}{y_3}\right)-\frac{1}{y_1}\left(\frac{1}{y_2}-l_{13}\right)\left(\frac{1}{y_3}\right)\right] \\ &=-\left[\frac{l_{13}}{y_3}\left(m_{21}+\frac{1}{y_1}+\frac{1}{y_2}\right)-m_F\left(m_{32}-\frac{1}{y_1}\right)\left(\frac{1}{y_2}-l_{13}\right)\right] \end{aligned} \tag{6.53}$$

$$\det(P) = -\frac{m_F}{y_1 y_2 y_3}\left[\frac{1}{m_F}\left(1 + y_1 l_{13} + y_1 y_2 m_{21} l_{13}\right) + MTTFF\left(1 + y_1 l_{13} + y_1 y_2 m_{21} l_{13}\right)\right]$$
$$= -\frac{m_F}{y_1 y_2 y_3}\left(T_R + MTTFF\right)\left(1 + y_1 l_{13} + y_1 y_2 m_{21} l_{13}\right) \tag{6.54}$$

where $T_R = \dfrac{1}{m_F}$

$$MTTFF = \frac{T_0 + y_1 y_2 y_3 \cdot \left(m_{21} m_{31} + m_{21} m_{32} + m_{21} l_{13} + m_{32} l_{13}\right) + y_1 y_2 m_{21} + y_1 y_3 \cdot \left(l_{13} + m_{31}\right) + y_2 y_3 \cdot \left(m_{31} + m_{32}\right)}{\left(1 + l_{13} y_1 + l_{13} m_{21} y_1 y_2\right)} \tag{6.55}$$

Then, the steady state probability is

$$P = \frac{1}{\det(P)}\begin{bmatrix} \begin{vmatrix} -\left(m_{21} + \frac{1}{y_2}\right) & m_{32} & 0 \\ \frac{1}{y_2} & -\left(m_{31} + m_{32} + \frac{1}{y_3}\right) & 0 \\ 0 & \frac{1}{y_3} & -m_F \end{vmatrix} \\ -\begin{vmatrix} \frac{1}{y_1} & m_{32} & 0 \\ l_{13} & -\left(m_{31} + m_{32} + \frac{1}{y_3}\right) & 0 \\ 0 & \frac{1}{y_3} & -m_F \end{vmatrix} \\ \begin{vmatrix} \frac{1}{y_1} & -\left(m_{21} + \frac{1}{y_2}\right) & 0 \\ l_{13} & \frac{1}{y_2} & 0 \\ 0 & 0 & -m_F \end{vmatrix} \\ -\begin{vmatrix} \frac{1}{y_1} & -\left(m_{21} + \frac{1}{y_2}\right) & m_{32} \\ l_{13} & \frac{1}{y_2} & -\left(m_{31} + m_{32} + \frac{1}{y_3}\right) \\ 0 & 0 & \frac{1}{y_3} \end{vmatrix} \end{bmatrix} = \frac{1}{\det(P)}\begin{bmatrix} -m_F\left\{m_{21} m_{32} + m_{21} m_{31} + \frac{m_{21}}{y_3} + \frac{m_{31}}{y_2} + \frac{1}{y_2 y_3}\right\} \\ -m_F\left(\frac{m_{31}}{y_1} + \frac{m_{32}}{y_1} + \frac{1}{y_1 y_3} + l_{13} m_{32}\right) \\ -m_F\left(\frac{1}{y_1 y_2} + l_{13} m_{21} + \frac{l_{13}}{y_2}\right) \\ -\frac{1}{y_1 y_2 y_3} - \frac{l_{13}}{y_3}\left(m_{21} + \frac{1}{y_2}\right) \end{bmatrix} \tag{6.56}$$

$$P = \frac{1}{\left(T_R + MTTFF\right)}\begin{bmatrix} \dfrac{y_1 + y_1 y_2 m_{21} + y_1 y_3 m_{31} + y_1 y_2 y_3 m_{21} m_{31} + y_1 y_2 y_3 m_{21} m_{32}}{\left(1 + l_{13} y_1 + l_{13} m_{21} y_1 y_2\right)} \\ \dfrac{y_2 + y_2 y_3 m_{31} + y_2 y_3 m_{32} + y_1 y_2 y_3 l_{13} m_{32}}{\left(1 + l_{13} y_1 + l_{13} m_{21} y_1 y_2\right)} \\ y_3 \\ T_R \end{bmatrix} \tag{6.57}$$

1. *Failure Cost Analysis*

The expected failure cost per year is

C_F = FC × frequency of failure

$$C_F = FC \times P(3) \times \frac{1}{y_3} = \frac{FC}{T_R + MTTFF} \tag{6.58}$$

Without any maintenance, $C_F = \frac{FC}{T_R + T_0}$ is the highest possible value. If we assume that the failure rate from 1 to 3 is smaller than failure rate from 1 to 2 ($l_{13} << l_{12}$) and failure rate from 2 to 3 ($l_{13} << l_{23}$), then MTTFF will be higher and C_F will decrease as we increase repair rate of any stages (m_{12}, m_{31}, or m_{32}). On the other hand, if the failure rate from stage 1 to 3 is slightly larger (or slightly smaller) than the failure rate from stage 1 to 2 ($\frac{l_{12}}{l_{13}} \approx 1$), then MTTFF is possibly small. If MTTFF is small relative to T_R, then C_F will converge to $C_F = \frac{FC}{T_R}$.

Failure cost equation of this model is the same as that of perfect maintenance model; however, MTTFF equation is different. From MTTFF analysis, MTTFF will be greater than the lifetime without maintenance as long as the probability of transferring from stage 1 to 3 is not high which is usually true. Therefore, failure cost will reduce to a constant value as inspection rate of any stage increases. This conclusion is verified by simulation results in Fig. 6.12, 6.16, 6.20, 6.27, 6.31, and 6.35.

2. *Maintenance Cost Analysis*

The expected maintenance cost per year is

C_M = MC × frequency of maintenance

$$C_M = MC \times \left(P(1) \cdot l_{13} + P(2) \cdot m_{21} + P(3) \cdot (m_{31} + m_{32})\right) \tag{6.59}$$

If the probability of transferring from stage 1 to 3 is very small then the analysis is the same as in perfect maintenance model. Maintenance cost will increase from zero to some constant value when inspection rates of D2 and D3 increase. This is verified by simulation results in Fig. 6.17, 6.21, 6.32 and 6.36. However, when inspection rate of D1 increases (probability of transferring from stage 1 to 3 is higher), maintenance cost could increase to infinity. This is verified by the simulation result in Fig. 6.13 and 6.28. It might be the case that the device condition gets worse and worse with every inspection and maintenance.

3. *Total Cost Analysis*

Failure cost dominates total cost at small inspection rate while maintenance cost dominates total cost at high inspection rate. Total cost will be smallest at optimum region of inspection rate of stage 1 and high inspection rate of stage 2 and 3. This conclusion is verified by simulation results in Fig. 6.15, 6.19, 6.23, 6.30, 6.34 and 6.38.

Note that in this cost analysis, the inspection cost is accounted in the maintenance cost. However, if the inspection is used only to determine the stage of the device then the inspection cost need to be addressed in the model separately.

Inspection Model and Inspection Cost Analysis

An inspection stage is added to the perfect maintenance model. Note that the inspection stage has no transition rate to other stage under an assumption of perfect inspection that the device after inspection will stay in the same stage.

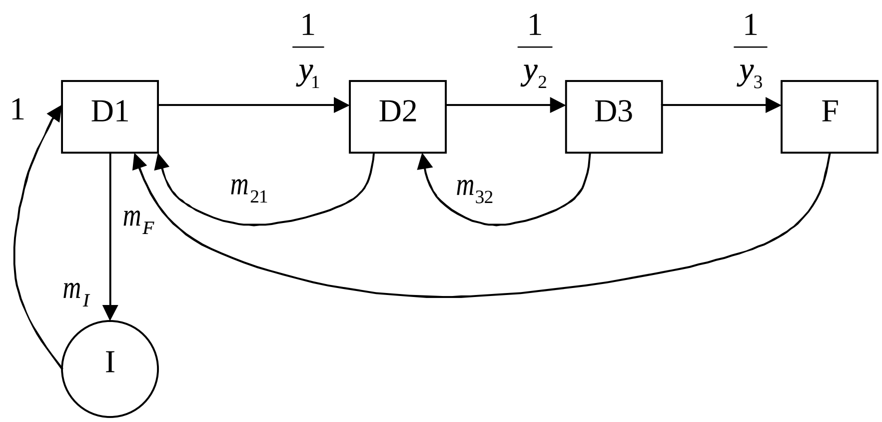

Fig. 6.41: Inspection Model

Transitional probability matrix and resulting steady state probability are derived in the following.

Mean time to the first failure

Transitional probability matrix for perfect maintenance model with inspection state is written as (6.60).

$$T = \begin{bmatrix} 1-\left(m_I + \frac{1}{y_1}\right) & \frac{1}{y_1} & 0 & 0 & m_I \\ m_{21} & 1-\left(m_{21} + \frac{1}{y_2}\right) & \frac{1}{y_2} & 0 & 0 \\ 0 & m_{32} & 1-\left(m_{32} + \frac{1}{y_3}\right) & \frac{1}{y_3} & 0 \\ m_F & 0 & 0 & 1-m_F & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{6.60}$$

Truncated transitional probability matrix Q is constructed by deleting row 4 and column 4 which associated with the absorbing state [127].

$$Q_n = \begin{bmatrix} 1-\left(m_I+\dfrac{1}{y_1}\right) & \dfrac{1}{y_1} & 0 & m_I \\ m_{21} & 1-\left(m_{21}+\dfrac{1}{y_2}\right) & \dfrac{1}{y_2} & 0 \\ 0 & m_{32} & 1-\left(m_{32}+\dfrac{1}{y_3}\right) & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \tag{6.61}$$

The expected number of time intervals matrix is calculated from $N=[I-Q_n]^{-1}$

$$N = \begin{bmatrix} m_I+\dfrac{1}{y_1} & -\dfrac{1}{y_1} & 0 & -m_I \\ -m_{21} & m_{21}+\dfrac{1}{y_2} & -\dfrac{1}{y_2} & 0 \\ 0 & -m_{32} & m_{32}+\dfrac{1}{y_3} & 0 \\ -1 & 0 & 0 & 1 \end{bmatrix}^{-1} \tag{6.62}$$

$$\det(N) = \begin{vmatrix} \dfrac{1+y_1m_I}{y_1} & -\dfrac{1}{y_1} & 0 & -m_I \\ -m_{21} & m_{21}+\dfrac{1}{y_2} & -\dfrac{1}{y_2} & 0 \\ 0 & -m_{32} & m_{32}+\dfrac{1}{y_3} & 0 \\ -1 & 0 & 0 & 1 \end{vmatrix} = \frac{1+y_1m_I}{y_1} \begin{vmatrix} m_{21}+\dfrac{1}{y_2}-\dfrac{m_{21}}{1+y_1m_I} & -\dfrac{1}{y_2} & -\dfrac{y_1m_Im_{21}}{1+y_1m_I} \\ -m_{32} & m_{32}+\dfrac{1}{y_3} & 0 \\ -\dfrac{1}{1+y_1m_I} & 0 & 1-\dfrac{y_1m_I}{1+y_1m_I} \end{vmatrix} \tag{6.63}$$

$$\det(N) = \frac{1}{y_1y_2y_3} \tag{6.64}$$

$$N(1) = y_1y_2y_3 \begin{bmatrix} \begin{vmatrix} m_{21}+\frac{1}{y_2} & -\frac{1}{y_2} & 0 \\ -m_{32} & m_{32}+\frac{1}{y_3} & 0 \\ 0 & 0 & 1 \end{vmatrix} \\ -\begin{vmatrix} -\frac{1}{y_1} & 0 & -m_I \\ -m_{32} & m_{32}+\frac{1}{y_3} & 0 \\ 0 & 0 & 1 \end{vmatrix} \\ \begin{vmatrix} -\frac{1}{y_1} & 0 & -m_I \\ m_{21}+\frac{1}{y_2} & -\frac{1}{y_2} & 0 \\ 0 & 0 & 1 \end{vmatrix} \\ -\begin{vmatrix} -\frac{1}{y_1} & 0 & -m_I \\ m_{21}+\frac{1}{y_2} & -\frac{1}{y_2} & 0 \\ -m_{32} & m_{32}+\frac{1}{y_3} & 0 \end{vmatrix} \end{bmatrix}^T = y_1y_2y_3 \begin{bmatrix} \frac{1}{y_2y_3}+\frac{m_{21}}{y_3}+m_{21}m_{32} \\ \frac{1}{y_1y_3}+\frac{m_{32}}{y_1} \\ \frac{1}{y_1y_2} \\ m_I\left(\frac{1}{y_2y_3}+\frac{m_{21}}{y_3}+m_{21}m_{32}\right) \end{bmatrix} \tag{6.65}$$

$$N(1) = \begin{bmatrix} y_1 + y_1y_2m_{21} + y_1y_2y_3m_{21}m_{32} \\ y_2 + y_2y_3m_{32} \\ y_3 \\ m_I(y_1 + y_1y_2m_{21} + y_1y_2y_3m_{21}m_{32}) \end{bmatrix}^T \tag{6.66}$$

Then, mean time to the first failure is the time spent in stage 1, 2 and 3;

$$MTTFF = y_1 + y_2 + y_3 + m_{21}y_1y_2 + m_{32}y_2y_3 + m_{21}m_{32}y_1y_2y_3 \tag{6.67}$$

Notice that the MTTFF equation is the same as that of the model without inspection. Moreover, the steady state probability equations are the same as those of perfect inspection model.

Intuitively, inspection by itself should not improve operating lifetime of the device since it is introduced only to determine the stage of the device. However, in this case the inspection has no transition rate to other stage because we assume perfect inspection that the device after inspected will stay in the same stage. Clearly, the inspection does not affect the failure and maintenance cost.

Inspection cost Analysis

The matrix of transition rate and the resulting steady state probabilities are derived in the following.

Transition rate matrix is

$$R=\begin{bmatrix} -\left(m_I+\frac{1}{y_1}\right) & m_{21} & 0 & m_F & 1 \\ \frac{1}{y_1} & -\left(m_{21}+\frac{1}{y_2}\right) & m_{32} & 0 & 0 \\ 0 & \frac{1}{y_2} & -\left(m_{32}+\frac{1}{y_3}\right) & 0 & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F & 0 \\ m_I & 0 & 0 & 0 & -1 \end{bmatrix} \tag{6.68}$$

Using frequency balance approach, steady state probability is calculated from

$$P=\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ \frac{1}{y_1} & -\left(m_{21}+\frac{1}{y_2}\right) & m_{32} & 0 & 0 \\ 0 & \frac{1}{y_2} & -\left(m_{32}+\frac{1}{y_3}\right) & 0 & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F & 0 \\ m_I & 0 & 0 & 0 & -1 \end{bmatrix}^{-1} \cdot \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{6.69}$$

$$\det(P)=\begin{vmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & -\left(m_{21}+\frac{1}{y_2}+\frac{1}{y_1}\right) & m_{32}-\frac{1}{y_1} & -\frac{1}{y_1} & -\frac{1}{y_1} \\ 0 & \frac{1}{y_2} & -\left(m_{32}+\frac{1}{y_3}\right) & 0 & 0 \\ 0 & 0 & \frac{1}{y_3} & -m_F & 0 \\ 0 & -m_I & -m_I & -m_I & -(1+m_I) \end{vmatrix} \tag{6.70}$$

$$\det(P)=\frac{m_F}{y_1y_2y_3}\left(y_1+y_2+y_3+y_1y_2m_{21}+y_2y_3m_{32}+y_1y_2y_3m_{21}m_{32}+m_I(y_1+y_1y_2m_{21}+y_1y_2y_3m_{21}m_{32})+\frac{1}{m_F}\right) \tag{6.71}$$

From, $MTTFF=T_0+m_{21}y_1y_2+m_{32}y_2y_3+m_{21}m_{32}y_1y_2y_3$

Let $T_I=m_I(y_1+m_{21}y_1y_2+m_{21}m_{32}y_1y_2y_3)$: time in inspection stage

$T_R=\frac{1}{m_F}$: the repair time (year)

Then, $\det(P) = \frac{m_F}{y_1 y_2 y_3}(T_R + T_I + MTTFF)$ (6.72)

$$P = \frac{y_1 y_2 y_3}{m_F(T_R + T_I + MTTFF)} \begin{bmatrix} m_F\left(\frac{1}{y_2 y_3} + \frac{m_{21}}{y_3} + m_{21}m_{32}\right) \\ m_F\left(\frac{1}{y_1 y_3} + \frac{m_{32}}{y_1}\right) \\ \frac{m_F}{y_1 y_2} \\ \frac{1}{y_1 y_2 y_3} \\ m_I m_F\left(\frac{1}{y_2 y_3} + \frac{m_{21}}{y_3} + m_{21}m_{32}\right) \end{bmatrix} = \begin{bmatrix} \frac{y_1 + y_1 y_2 m_{21} + y_1 y_2 y_3 m_{21} m_{32}}{T_R + T_I + MTTFF} \\ \frac{y_2 + y_2 y_3 m_{32}}{T_R + T_I + MTTFF} \\ \frac{y_3}{T_R + T_I + MTTFF} \\ \frac{T_R}{T_R + T_I + MTTFF} \\ \frac{m_I(y_1 + y_1 y_2 m_{21} + y_1 y_2 y_3 m_{21} m_{32})}{T_R + T_I + MTTFF} \end{bmatrix} \quad (6.73)$$

The conditional probabilities of stage 1, 2 and 3 given that the stages are in working stages (excluding time spent in inspection stage) are

Then, the steady stage probability for each stage is as follow:

$$P(1) = \frac{\frac{y_1 + y_1 y_2 m_{21} + y_1 y_2 y_3 m_{21} m_{32}}{T_R + T_I + MTTFF}}{1 - \frac{m_I(y_1 + y_1 y_2 m_{21} + y_1 y_2 y_3 m_{21} m_{32})}{T_R + T_I + MTTFF}} = \frac{y_1 + y_1 y_2 m_{21} + y_1 y_2 y_3 m_{21} m_{32}}{T_R + MTTFF} \quad (6.74)$$

$$P(2) = \frac{\frac{y_2 + y_2 y_3 m_{32}}{T_R + T_I + MTTFF}}{1 - \frac{m_I(y_1 + y_1 y_2 m_{21} + y_1 y_2 y_3 m_{21} m_{32})}{T_R + T_I + MTTFF}} = \frac{y_2 + y_2 y_3 m_{32}}{T_R + MTTFF} \quad (6.75)$$

$$P(3) = \frac{\frac{y_3}{T_R + T_I + MTTFF}}{1 - \frac{m_I(y_1 + y_1 y_2 m_{21} + y_1 y_2 y_3 m_{21} m_{32})}{T_R + T_I + MTTFF}} = \frac{y_3}{T_R + MTTFF} \quad (6.76)$$

Let IC = inspection cost (dollar/time)

C_I = expected inspection cost (dollar/year)

The expected annual inspection cost is

$$C_I = IC \times P(1) \times m_I \quad (6.77)$$

$$C_I = IC \times \frac{m_I(y_1 + y_1 y_2 m_{21} + y_1 y_2 y_3 m_{21} m_{32})}{T_R + MTTFF} \quad (6.78)$$

Inspection cost is a linear function of inspection rate and probability of being in stage 1; therefore, higher inspection rate and repair rate of going from any stage to stage 1 will increase the inspection cost.

What is the advantage of inspection?

Obviously, inspection increases the total cost. However, inspection is intended to determine the stage which is a crucial issue. Inspection is neither introduced to extend the device lifetime nor to reduce the cost. As long as the inspection does not cause the system to transit to higher stages, it should be implemented.

6.7 Integration to Mid-Term Maintenance Scheduling

Long-term maintenance scheduling is based on steady state probability and all parameters in the model are based on probability and transition rate. The effect of maintenance on component lifetime is quantified by expected values (expected maintenance cost, inspection cost, failure cost, and total cost) of maintenance rate. Therefore, the analysis requires historical data of the device in order to obtain probability of transferring from one stage to others. Thus, this analysis is suitable for a transformer or circuit breaker with long working history. The analysis itself provides important information of the range of cost-effective maintenance schedule in each stage of the device. In the absence of historical data, some of these values may need to be estimated from experience of the maintenance personnel.

However, long-term maintenance scheduling considers one device at a time and does not include operating condition of the system. Nevertheless, the long-term maintenance analysis can provide some crucial input parameters to compute risk reduction of a particular device for mid-term maintenance analysis. In mid-term maintenance scheduling, the risk reduction indices of each device are evaluated from reduction of failure probability with respect to maintenance activities. These indices can be estimated from sensitivity analysis of the long-term maintenance model. Since the maintenance level can be adjusted through the probability of transferring to oil filtering or oil replacement stage, the effect of these parameters can be quantified.

The long-term maintenance sensitivity analysis not only yields input parameters for mid-term maintenance scheduling analysis but also provides some overall perspective of effect of maintenance on a transformer and breaker. The equivalent mathematical model provides some insights into the effect of maintenance and inspection. In addition, the information obtained from this analysis can be applied to condition-based monitoring approach to attain the best maintenance strategy when the condition of a device is known from the monitoring data.

6.8 Conclusion

In this section, long-term maintenance scheduling of both transformers and circuit breakers is developed. Deterioration process of the two devices is studied and characterized. Transformer and breaker maintenance models for long-term analysis are proposed utilizing the concept of device of stages. The analyses are based on steady state probability and expected costs which are maintenance cost, inspection cost, and failure cost. The optimal maintenance schedule is determined from sensitivity analysis of expected total cost (summation of all expected costs) and inspection rate in each stage. Equivalent mathematical models for perfect maintenance and imperfect maintenance are corroborated to verify the simulation results. The simplified mathematical model provides some insight into the complexity of the proposed model. Long-term and mid-term maintenance scheduling are complementing one another in a way that one consider steady state maintenance property while another considers transient maintenance property.

6.9 Appendix

<u>Model Parameters</u>

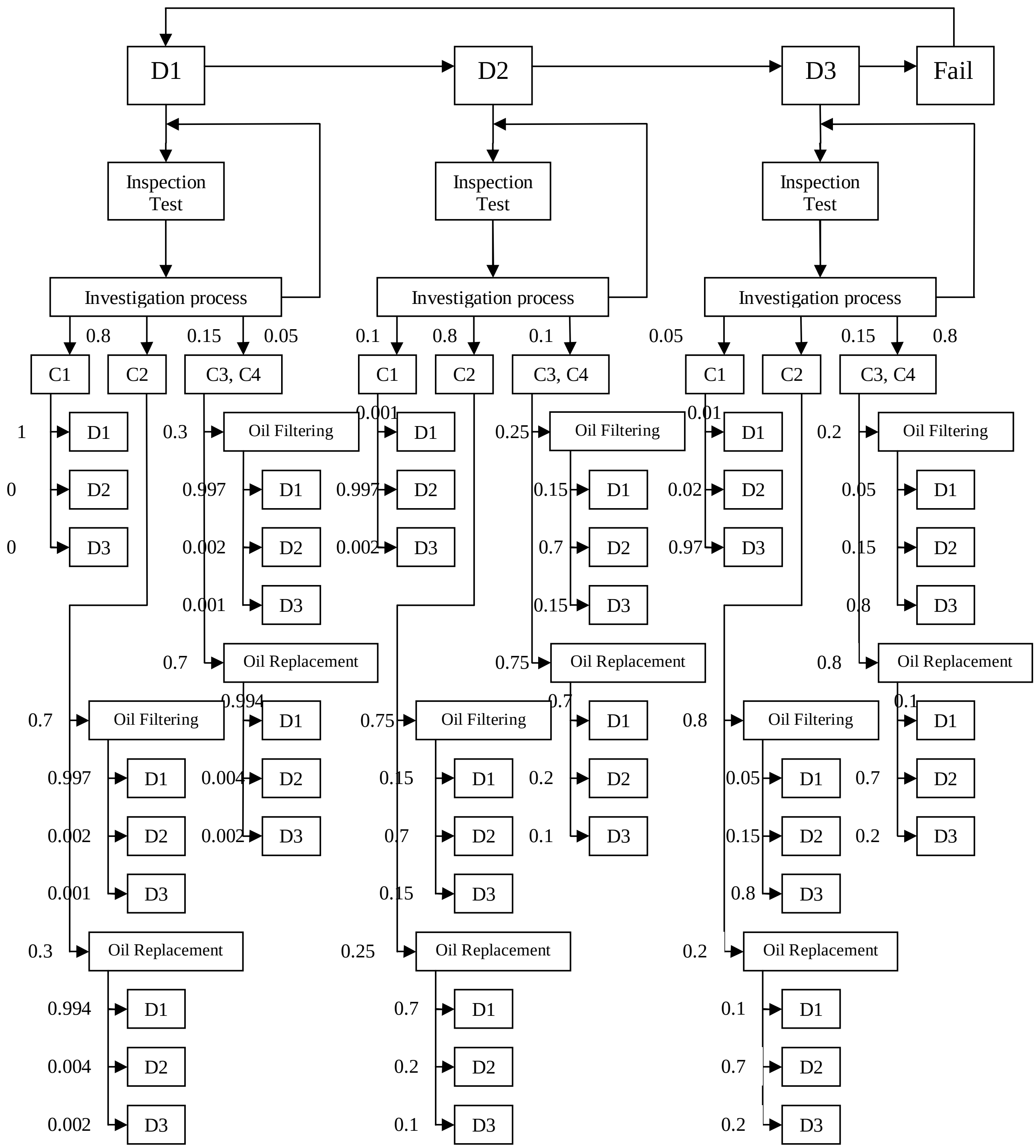

Fig. 6.42: Transformer model Parameters

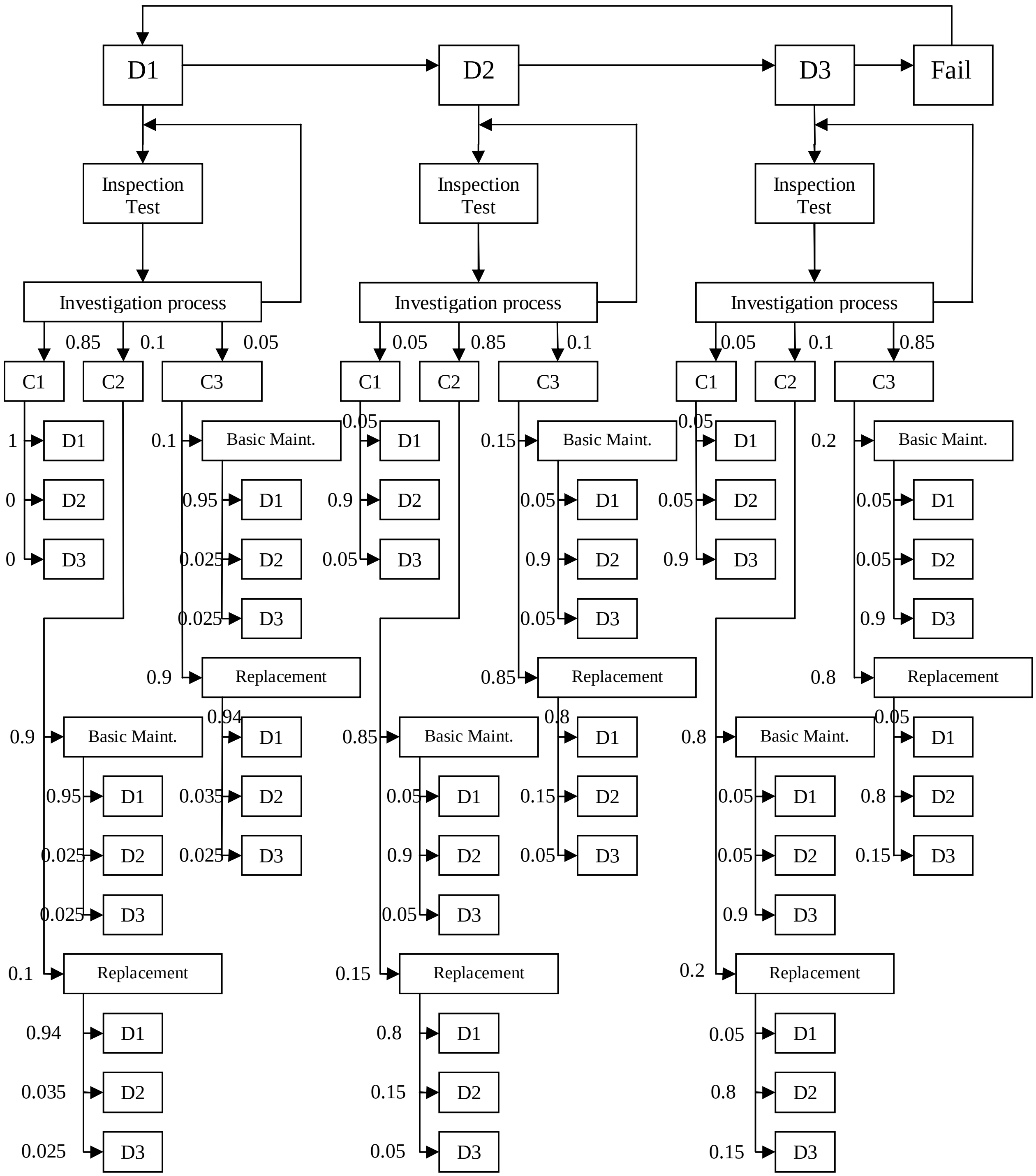

Fig. 6.43: Circuit breaker model Parameters

Cost parameters of transformer maintenance model

Inspection cost = 100 $
Oil Filtering cost = 1,000 $
Oil Replacement cost = 10,000 $
Failure cost = 100,000 $
Mean time in D1 = 10 years
Mean time in D2 = 7 years
Mean time in D3 = 3 years

Cost parameters of circuit breaker maintenance model

Inspection cost = 100 $
Oil Filtering cost = 1,000 $
Oil Replacement cost = 10,000 $
Failure cost = 100,000 $
Mean time in D1 = 12 years
Mean time in D2 = 9 years
Mean time in D3 = 4 years

7. Condition Data Integration for Failure Rate Estimation of Power Transformers

7.1 Introduction

In previous chapters we have investigated the methods and models in condition assessment of transmission components and the information were applied in the maintenance asset management. We can see that data plays an important role in the asset management. The asset management challenge common to all is a set of decision problems related to operation, maintenance, and planning of those assets where decision-makers must identify alternatives and for each one, assess costs, benefits, and risks. Quality of resulting decisions depends on quality of information used in the assessments and how that information is processed. However, information collection is difficult because we are managing a huge system with a large number of distributed, interdependent, capital-intensive physical assets such as transformers and circuit breakers that can fail in catastrophic ways. This makes the data collection is difficult because unselective manner of information gathering will increase the communication burden and increase the difficulty of data analyzing, and inadequate data will reduce the accuracy of our analysis. Central, and essential, are information characterizing the health, or condition, of the assets. For example, often-used indicators of asset condition are age and time since the last inspection and maintenance. Therefore “nameplate” data and maintenance histories have always been highly influential in the decision process. Condition data from manual inspections are also incorporated if available. It has been only recently, however, that sensing, communication, and database technology has evolved to the point where it is feasible for decision-makers to access operating histories and asset-specific real-time monitoring data. Creative use of this data via processing, fusion, assessment, and decision algorithms can significantly enhance the quality of the final actions taken and the confidence of the decision-makers, and, for even one of the aforementioned industries, result in very large national impact in terms of more economic and reliable system performance.

Against this background, in this chapter we investigate a federated, query-centric approach to information integration and knowledge acquisition from autonomous, distributed, and heterogeneous data sources for condition monitoring and failure mode estimation of power transformers. These data sources may include intelligent electronic devices (IEDs) local to the equipment or data repositories in corporate servers. Unavoidably in real life situations, the related data sources maintained by different institutions often differ in structure, organization, query capabilities, and more importantly ontological commitments [130] – assumptions concerning the objects that exist in the world, the properties of the objects and their possible values, relationships between them, and their intended meaning. In other words, data sources often do not agree on using a shared vocabulary of terms and concepts in a coherent and consistent manner. As a result of this, it becomes increasingly difficult for different individuals and autonomous software entities to query the data sources or assert facts about them seamlessly. Our approach to this problem has resulted in the design and development of a system called INDUS[5] (Intelligent Data Understanding System) [131, 132]. INDUS imposes a clear separation between the data and semantics (or intended meaning) of data, which allows the users to reconcile semantic differences between multiple heterogeneous data sources from their own point of view. With the help of specific software wrappers, the system exposes autonomous data sources (regardless of their location, internal structure, and query interfaces) as though they were relational databases (i.e., a collection of inter-related tables), structured according to an ontology supplied by the user. INDUS when equipped with data mining and decision-making algorithms for ontology-driven knowledge acquisition can accelerate the pace of discovery in many data-rich domains. We have used INDUS to integrate power transformer condition data for training Hidden Markov Models [133], a model effective in characterizing discrete state random processes where the mapping between states (deterioration levels in this case) and observations is uncertain.

The rest of the chapter is structured as follows: Section 7.2 describes the data integration component of INDUS, whereas a detailed description of failure rate probability estimation using HMM is given in Section 7.3. In Section 7.4 we describe the implementation details of our framework and show how transformer failure rate can be estimated from condition monitoring data. Finally, we summarize our work and provide a brief discussion about future work in Section 7.5.

7.2 Data Integration in INDUS

The estimation of the state of an asset (e.g., transformer, circuit breaker, underground cable, insulator, etc.), is typically made using a variety of data. In general, there may be up to four classes of this data: equipment data, operating histories, maintenance histories, and condition histories. The equipment data comprises the so-called 'nameplate' information including manufacturer, make, model, rated currents, voltages, and powers, equipment's age, and manufacturer's recommended maintenance schedule. The operating histories capture the electrical and environmental conditions to which the equipment has been subjected in the past, e.g., temperatures, loading histories and through faults for transformers, and operations and I^2t for circuit breakers. The maintenance histories contain records of all inspections and maintenance activities performed on each piece of equipment. Condition histories are comprised of measurements providing information about the state of the equipment with respect to one or more failure modes. Common condition data information for a transformer includes that coming from tests on: oil (dissolved gas, moisture, hydrogen, and furan), power factor, winding resistance, partial discharge (acoustic emissions, spectral decomposition of currents), and infrared emissions. All of this data can be collected either manually via inspections/ laboratory tests; in addition, continuous monitors are available for most of it and are increasingly being used. Usually, these four classes of information are maintained in multiple database systems distributed between the substation and corporate headquarters using various commercially available storage technologies (e.g., Oracle) together with a variety of data standards and proprietary systems. Effective use of this data demands for versatile data integration and management systems that can efficiently extract the relevant information

[5] The acronym INDUS should not be confused with a suite of commercial service delivery and asset management solutions provided by Indus (www.indus.com).

from the disparate sources *on-demand*. In practice, data integration systems [134,135,136,137,138,139] attempt to provide users with seamless and flexible access to information from autonomous, distributed, and heterogeneous data sources through a unified query interface. Ideally, such systems should allow the users to specify *what* information is needed instead of *how* it can be obtained. In other words, it should provide mechanisms for:

- Specification of a query expressed in terms of a user-specified vocabulary (ontology).
- Specifying mappings between user ontology and data-source specific ontologies.
- Automatically transforming user queries into queries that can be answered/understood by the respective data sources.
- Hiding the complexity of communication and interaction with heterogeneous, distributed data sources.
- Mapping the results obtained into the form expected by the user and storing them for future analysis.
- Allowing effortless incorporation of new data sources as needed, and supporting sharing of ontologies between different users.

There are two broad approaches to data integration: *Data Warehousing* and *Database Federation*. In the data warehousing approach, data from heterogeneous information sources is gathered, mapped to a common structure and stored in a central location. Periodic updates are required to ensure that the information contained in the warehouse is up-to-date with the contents of the individual sources. However, the data replication/updating process can be quite expensive in case of large information repositories. Also, this approach relies on a single common ontology for all users which is specified as part of the warehouse design. As a result, the system tends to be less flexible. On the other hand, in case of database federation, the information needed to answer a query is gathered directly from the data sources in response to the posted query. Hence, the results are up-to-date with respect to the contents of the data sources at the time the query is posted. More importantly, this approach is being more readily adapted to applications where users are able to impose their own ontologies and specify queries using the various concepts in those ontologies. Because our focus is on data integration for scientific applications, which requires users to be able to flexibly interpret and integrate data from multiple autonomous sources, we adopt the federated architecture for our system.

Typically, a query posted by the user must be decomposed into a set of operations corresponding to the information that needs to be gathered from each data source and the form in which this information must be returned to the system. These operations should be capable of dealing with syntactic (or structural) and semantic (or intended meaning) mismatches by transforming the queries expressed in terms of the user ontology into data source-specific execution plans. These plans describe what information to extract from each data source and how to combine the results. In general, there are two basic approaches for dealing with semantic mismatches for query answering: Source-Centric approach and Query-Centric approach. In the case of the source-centric approach, each individual data source determines how the terms in a data source ontology (or vocabulary) are mapped to terms in the user (or global) ontology. Thus, the user has little control on the true meaning of concepts, and hence the results of a query. In other words, this approach puts the information sources in control of the semantics. In contrast, in the query-centric approach to information integration, concepts in the user ontology are defined in terms of concepts in data source-specific ontologies. Thus, the query-centric approach is better suited for data integration applications in which the users need the ability to impose the ontologies (and semantics) of their choice to flexibly interpret and analyze information from autonomous sources. However, this requires the user or administrator of the integration system to specify precisely how concepts in the user ontology are mapped to data source ontologies. As a result, the user controls/specifies the semantics because of which we adopt the query-centric approach to data integration in INDUS. A simplified architecture of INDUS is shown in Fig. 7.1.

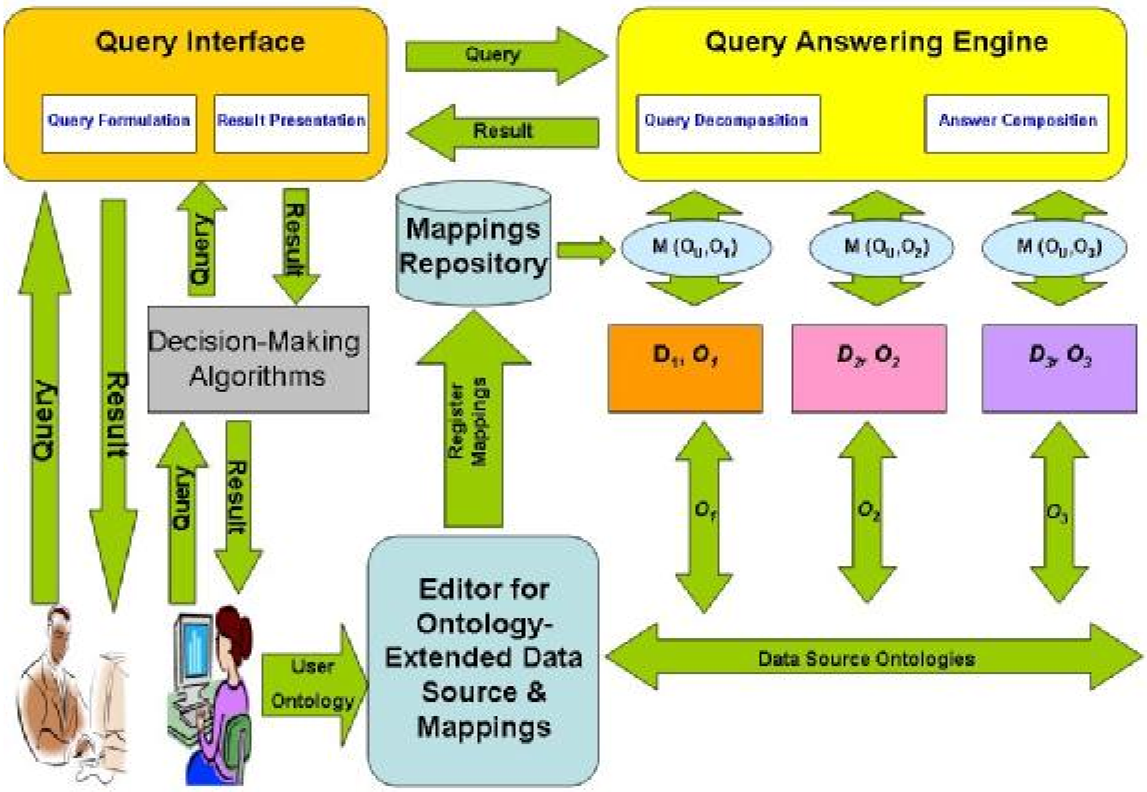

Fig. 7.1: Simplified INDUS Architecture

Typically, several related distributed and semantically heterogeneous *data sources* can be available to *users* who may want to query the data sources of interest via a *query interface*. Each user has the ability to impose his or her semantics by defining *user ontologies*. The system provides a user-friendly *ontology* and *mapping* editor [140] via which the users of the system can specify mappings between the concepts in the user ontology and data source ontologies. These ontologies and mappings are stored in the *mapping repository*. Once a query is posed by the user, it is handled by the *query answering engine* which acts as a middleware between the users (or clients) and data sources (or servers). This engine has access to the data sources as well as the set of user-specified mappings. Thus, when the engine receives a user query, it decomposes the query into distributed sources, maps the individual queries into data source-specific semantics, and finally composes the partial answers of each sub-query into final result that is sent back to the user. There are several features that distinguish INDUS from several other data integration systems:

- INDUS imposes a clear separation between data and the semantics of data. Such an approach allows users to specify mappings from the concepts in their ontologies to the data source ontologies.
- Instead of having a single global ontology (common to all users), INDUS allows users to specify their ontologies and mappings to the data source ontologies.
- The user-interface provides a tool to specify the ontologies and set of mappings.
- INDUS can be hooked up with various knowledge acquisition and decision-making algorithms (e.g., data mining algorithms) whose information requirements can be formulated as statistical2 queries [141].

We discuss these features in the remainder of this section.

7.2.1 Ontology-extended data sources

Assume that we have a set of physically distributed data sources, $D_1, \cdot\cdot\cdot, D_n$, such that each data source D_i contains only a fragment of the whole data D. In general, two common types of data fragmentation are defined [142]: horizontal fragmentation, where each data fragment contains a subset of data tuples, and vertical fragmentation, where each data fragment contains subtuples of data tuples. However, one can envision a combination of the two types of data fragmentation, and also more general relational data fragmentations. Formally, ontology can be defined as a specification of objects, categories, properties and relationships used to conceptualize some domain of interest [130]. Let D_i be a distributed data source described by the set of attributes $\{A_1^i, \quad \mathbf{L}, \quad A_m^i\}$ and $O_i = \{\Gamma_1^i, \quad \mathbf{L}, \quad \Gamma_m^i\}$ ontology associated with the data source. The element $\Gamma_j^i \in O_i$ corresponds to the attribute A_j^i and defines the type of that particular attribute. These types can be either linear (e.g., String, Integer etc.), or an ordering (or ***hierarchy*** [141]) of a set of terms (e.g., attribute value taxonomies). The schema S_i of a data source D_i is given by the set of attributes $\{A_1^i, \quad \mathbf{L}, \quad A_m^i\}$ used to describe the data, together with their respective attribute types $\{\Gamma_1^i, \quad \mathbf{L}, \quad \Gamma_m^i\}$, defined by the ontology O_i, i.e., $S_i = \{A_1^i : \Gamma_1^i, \quad \mathbf{L}, \quad A_n^i : \Gamma_n^i\}$

We define an *ontology-extended data source* as a tuple $\mathcal{D}_i = \langle D_i \quad S_i \quad O_i \rangle$, where D_i refers to the data contained in the data source, S_i is the schema of the data source, and O_i is the ontology associated with D_i ***i***. In addition, the following condition also needs to be satisfied: $D_i \subseteq \Gamma_1^i \times \mathbf{L} \times \Gamma_m^i$, which means that the set of values each attribute A_j^i can have is determined by its type Γ_j^i defined in the ontology O_i.

7.2.2 User perspective and ontology mapping

Suppose $D_1, \cdots, D_n$ be an ordered set of ontology extended data sources and U an user who wants to query $D_1, \cdots, D_n$ semantically heterogeneous data sources. A user perspective is given by the user ontology O_U and a set of interoperation constraints that define the correspondences between the terms and concepts in $O_1, \cdots, O_n$ respectively, with the user ontology O_U. These interoperation constraints can take one of the following forms [143]: $x : O_i \subseteq y : O_U$ (x is semantically subsumed by y), $x : O_i \supseteq y : O_U$ (x semantically subsumes y), $x : O_i \equiv y : O_U$ (x is semantically equivalent to y), $x : O_i \neq y : O_U$ (x is semantically incompatible to y), $x : O_i \approx y : O_U$ (x is semantically compatible with y). As shown in [141], the set of mappings can be semi-automatically inferred from the set of interoperation constraints. INDUS also provides a graphical user interface to specify the interoperation constraints [140].

7.2.3 Knowledge acquisition algorithms

It has been shown in [141] that the functioning of various knowledge acquisition and decision-making algorithms (e.g., classifier learning algorithms) can be reduced to answering queries from distributed data sources by decomposing it into two sub-tasks: information extraction and hypothesis generation. The information extraction component identifies the required sufficient statistics information, whereas, the hypothesis generation component uses this information to generate a predictive model (Fig. 7.2).

The information extraction component typically involves a procedure for determining the sufficient statistics as a query and a procedure for answering these queries from the distributed data sources. The process of answering queries from distributed data requires decomposition of the original query into sub-queries, for which the individual data sources can respond. These responses are then composed into a final answer for the original query. In case of semantically heterogeneous, distributed data sources, the mappings between the user ontology and data source ontologies also need to be applied. Thus, through the means of a query answering engine, this process can be made transparent to the functioning of the knowledge acquisition algorithms, and hence such algorithms can be regarded as pseudo-users in INDUS.

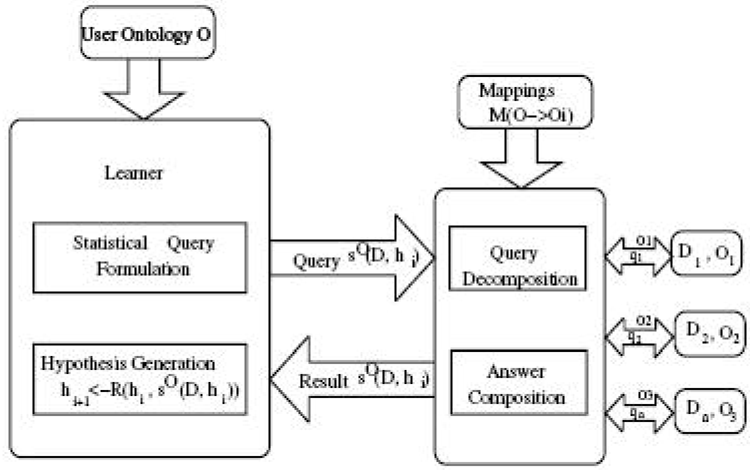

Fig. 7.2: Learning from Distributed, Semantically Heterogeneous Data Sources

Designing models for estimating probabilistic failure indices of power system equipment by capturing the uncertainty relationship between the observations and actual deterioration states is important for representing equipment state in system-level decision algorithms. The procedure for generating such models can be similarly decomposed into information extraction and hypothesis generation components. As a result, such algorithms can be easily connected to INDUS for efficient knowledge acquisition from distributed, semantically heterogeneous data sources. In what follows, we will show how we have used Hidden Markov Models with INDUS for failure rate probability determination for power transformers.

7.3 System Design and Experimentation

7.3.1 INDUS implementation

INDUS consists of five principle modules as seen in Fig. 7.3: graphical user interface, ontology & mapping repository, query answering engine, data mining algorithms & code repository and data source & wrappers registry. The modular design of INDUS ensures that each module can be updated and alternative implementation easily explored.

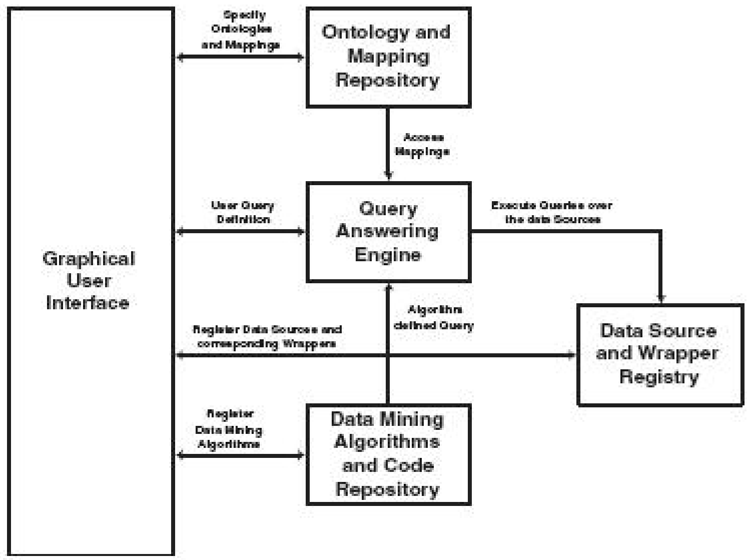

Fig. 7.3: INDUS Implementation Modules

The graphical user interface allows the users to interact with the system. It provides an editor [140] for specifying the ontologies and mappings. It also allows the users to register data sources (and their corresponding wrappers) and various data mining algorithms with INDUS. With the interface, the users can specify queries over distributed, semantically heterogeneous data sources using the interface. The ontology & mapping repository stores the various data source ontologies and user-defined ontologies. It also contains the set of mappings between the terms and concepts in the user ontology and data source ontologies. These mappings are accessed during query processing and execution.

The data source & wrapper registry allows the users to register various data sources and wrappers with the system. These wrappers provide a set of functions to interact with the individual data sources. Each wrapper is implemented by a Java class. During the registration of the data sources, the users also provide a capability description of the data sources. Such descriptions provide information about the structure of the data source (e.g., relational, XML), querying capabilities (e.g., different types of functionalities the data source provides), querying restrictions (e.g., various constraints on the usage of data by external applications), infrastructure (e.g., CPU speed, RAM size of the server hosting the data source) etc. This information is used during query execution.

The data mining algorithms and code repository allows users to register various data mining and knowledge acquisition algorithms. These algorithms act as pseudousers in INDUS. This repository also allows users to store application-specific functionalities that might be used in querying the registered data sources.

Finally, the query answering engine accepts a query either from an user or from data mining algorithms (i.e., the information extraction component). This engine acts as a middleware between the users and data sources, and utilizes the functionalities of the data source wrappers for query processing. There are two main aspects of the engine. Firstly, it translates the user queries (which are specified using the concepts in the user ontology) into data-source specific queries via the interoperation constraints (or ontology mappings), hence allowing the users to view the data source from their own point of view. Secondly, the engine adopts a hybrid query answering approach, which allows it to choose to perform some query execution at the data source server, and some portion of the execution at the client location. The rationale behind this design choice is that, this approach allows the engine to decide whether to ship executable code (for query answering) to the data source server location, or ship raw data to the client location for local processing based on the dynamics of the query and various querying capabilities of the data source (as specified in the data source description). The engine comprises of 4 sub-components: Query Decomposition, QueryTranslation, Query Execution and Answer Composition. Upon receiving a query Q (based on concepts in user ontology O_U) from the user/application, the query decomposition component identifies the data sources, $D_1, \cdots, D_n$, that need to be queried, and decomposes the original query into sub-queries, $Q_{D1}, \cdots, Q_{Dn}$, that are sent to the query translation component. For each sub-query, Q_{Di}, received by this component, it is translated (or re-written) in terms of the concepts specified in the data source ontology, O_i. The translated sub-query is then sent to the query execution component which enumerates alternate plans for processing the query, and executes the one which is most efficient. Finally, the result of the sub-query is sent to the answer composition component. This component composes the partial answers (i.e., the results of all the sub-queries) into a final answer for the original query Q, and sends it back to the user.

In what follows, we demonstrate an application of INDUS for failure rate estimation using condition monitoring data.

7.3.2 Transformer failure rate estimation based on condition monitoring data

We have developed an INDUS application on data integration of condition monitoring with an optimized maintenance selection and scheduling for circuit breakers and power transformers. It can set up the mappings between user ontology and data-source specific ontologies and thus can collect data from diverse data sources. And also it provides the ability of estimating the failure rate of the transformer based on gas analysis data, using hidden Markov models (HMM) (described in chapter 4). Figure 7.4 depicts the interface of the software, which is accessed through password protection, collects data based on ontology relationships, and performs failure rate estimation of the equipment. Figure 7.5 shows the query results of one transformer gas analysis. Figure 7.6 shows the failure rate estimation based on the gas analysis data from the query.

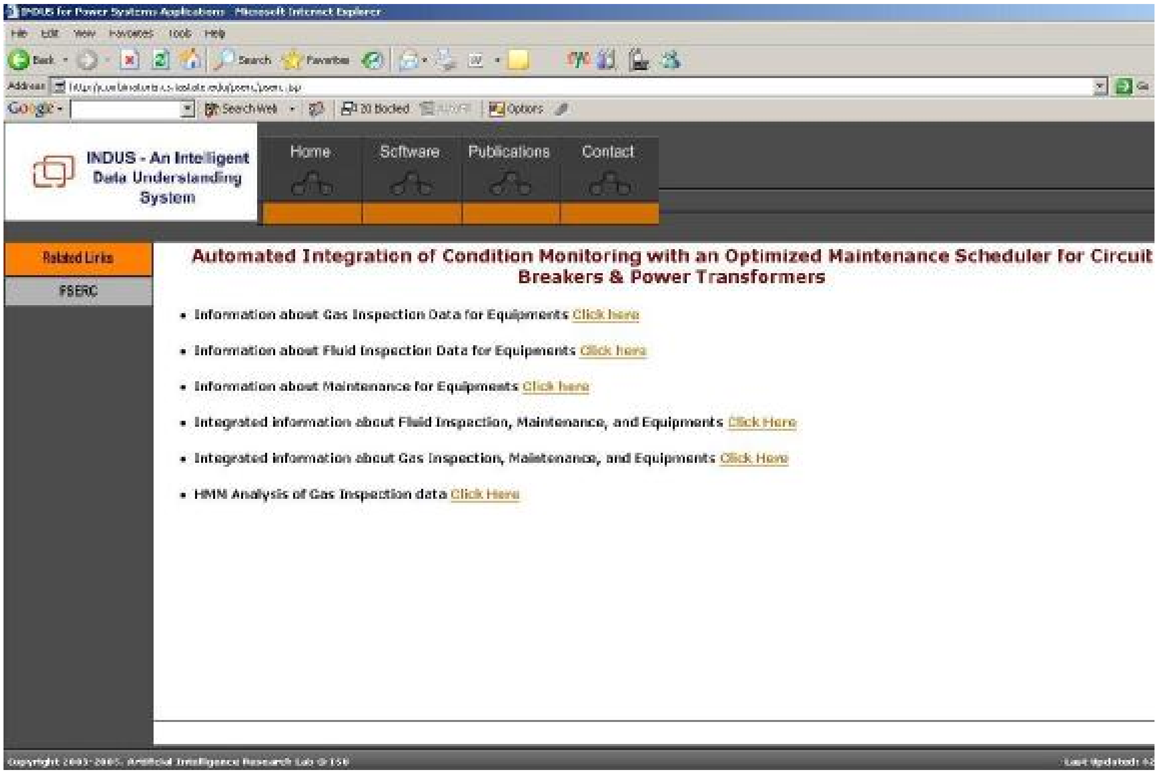

Fig. 7.4: Interface of the software

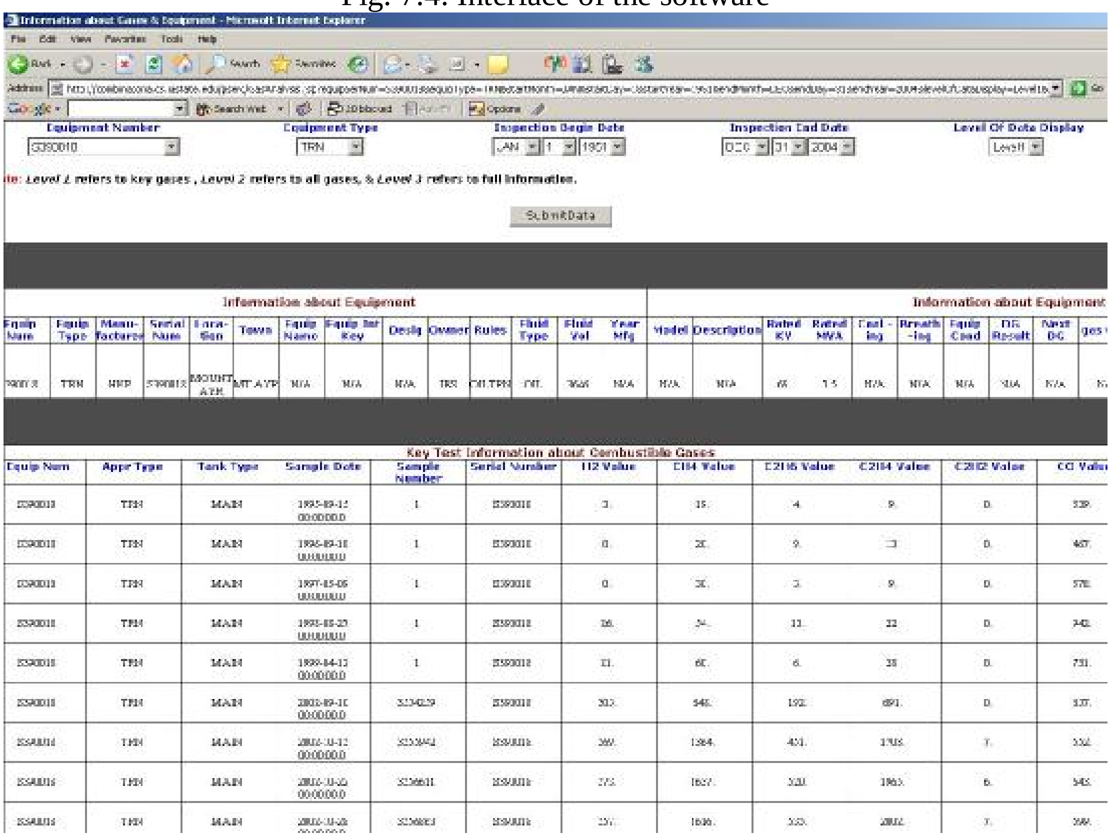

Fig. 7.5: Query results of gas analysis

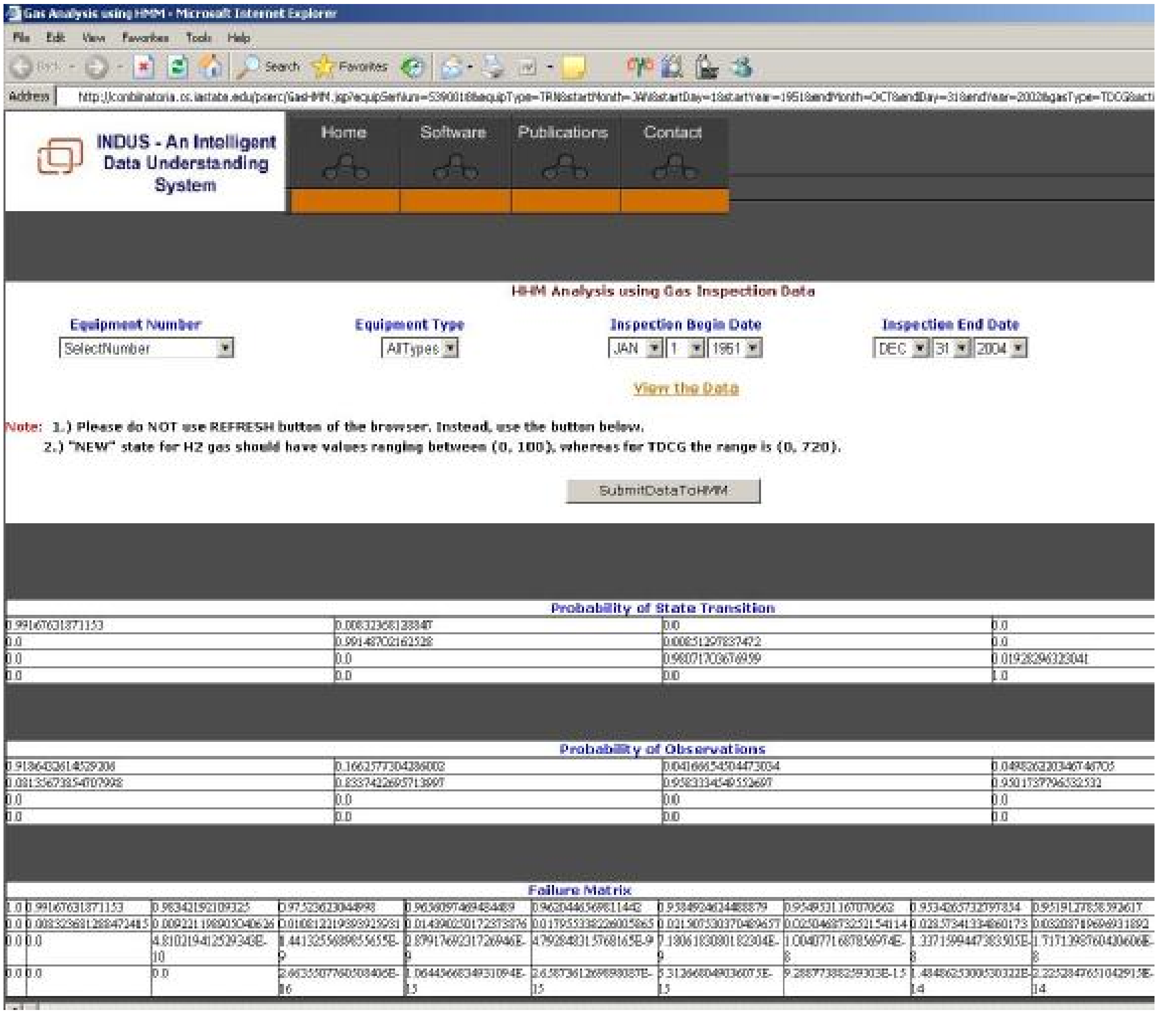

Fig. 7.6: Failure rate results based on queried gas data

7.4 Summary and Discussion

We have addresses a highly complex dynamic data-driven decision problem associated with a critical national infrastructure - asset management for the electric power system. Solution to this problem involves 6 main issues:

1. Sensing and diagnostics
2. Data accessibility, communication, and integration
3. Data transformation
4. System simulation across multiple decision horizons
5. Decision making
6. Information valuation and sensor deployment or re-deployment

There are four different kinds of decisions to be made. Operational decisions are made within the hour to week time frame and require trading off risk associated with potential equipment failure with the short term economics of generation dispatch. Maintenance decisions are made within the week to year time frame and require allocating financial and human resources to maximize benefits in terms of operational reliability and equipment life. Planning decisions are made within the 1-10 year time period and require determining the necessary and most effective capital improvements in terms of facility investments to continue supply of the growing load from expanding energy resources. Each of these decisions affects the others, and so the capability to capture the interaction of different policies in one decision-horizon with those of another decision-horizon is essential. Finally, it is through the simulation and inter-related decision that one may be able to determine where additional information would be valuable. This information valuation problem, #6 on the above list, determines where to deploy new sensors and associated infrastructure to collect additional information. In a real sense, then, this dynamic data driven decision problem is closed, i.e., it feedbacks on itself.

In this chapter, we have addressed two of the issues listed above: #2 (data integration) and item #3 (data transformation). The data federation approach of the INDUS platform provides a rich alternative to the data warehousing approach used in industry today, with important benefits being that data need not be moved except at the instant it is needed, and as a result, simulation models are always making use of the very latest equipment condition measurements. The HMM provides an essential bridge between condition data and the probabilistic failure indices required by the system simulation tools of issue #4 above. It is quite natural that the data integration tools would interface closely with the data transformation applications, as illustrated by the design presented in this chapter. We intend to continue expanding this prototype to include application software associated with the other issues listed above.

7.5 Conclusion

Cost effective equipment maintenance requires ongoing integration of information from multiple, highly distributed, and heterogeneous data sources storing various information about equipments. This chapter describes a federated, query-centric data integration and knowledge acquisition framework for condition monitoring and failure rate prediction of power transformers. Specifically, our system uses substation equipment condition data collected from distributed data resources, some of which may be local to the substation, to develop Hidden Markov Models (HMMs) which transform the condition data into failure probabilities. These probabilities provide the most current knowledge of equipment deterioration, which can be used in system-level simulation and decision tools. The system is illustrated using dissolved gas-in-oil field data for assessing the deterioration level of power transformer insulating oil.

8. Multiagent System Based Condition Monitoring

8.1 Introduction

Chapter 7 established that effective use of transmission equipment condition monitoring data requires the acquisition and integration of heterogeneous data residing at multiple locations. In response, we developed a software system capable of performing this function using a federated approach where each user query initiates a direct transfer of data from the raw sources. An important functional associated with such a query is the operation on the raw data that results in estimation of equipment failure indices. We have built into our software system the ability to perform this estimation using Hidden Markov Models. Repeated operation on multiple pieces of equipment at multiple substations would result in failure rate estimations of all equipment. The intention would then be to use such data in system decision-making algorithms for operations, short-term and long-term maintenance, and facility planning. We have described such algorithms for short-term and long-term maintenance in Chapters 5 and 6, respectively. In contrast to allowing decision-algorithms to interface with condition monitoring in an ad-hoc fashion, it is prudent to design the overall software system so that the decision-algorithms may interface, each leveraging the information obtained from the others. In designing this software system, one must account for the need to communicate between algorithms, from algorithm to data repository, and to do so in a way so that promotes maintainability and evolution. Multiagent systems provide a powerful vehicle for accomplishing this.

In this chapter, we provide in Section 8.2 a conceptual design of the overall software system we believe necessary for managing large quantities of condition monitoring data and associated decision-algorithms that use such data. Section 8.3 gives a high-level summary of software agents and multiagent systems. Section 8.4 describes some recently-developed multiagent system platforms. Section 8.5 gives a 4-stage approach for designing multiagent systems. Section 8.6 summarizes some preliminary work done at Iowa State University to implement such a design.

8.2 Conceptual Design of Software System

We focus on the needs of the most critical electric transmission equipment, including power transformers, circuit breakers, and transmission lines. Figure 8.1 illustrates the conceptual design of the software system. We conceive of this software system as a dynamic data-driven software system whereby sensing technologies collect data which is transformed and used to drive decision algorithms that provide information which in turn is used to identify effective sensing locations. We overview intended implementation of the 5 different layers of this software system in what follows.

<u>Layer 1, The power system</u>: Layer 1 represents the power system as it operates from day-to-day, from hour-to-hour. In a prototype phase, this layer could be represented by a simulator, such as those used for dispatcher training.

Layer 2, Condition sensors: This layer contains the sensors and data repositories local to the substation equipment.

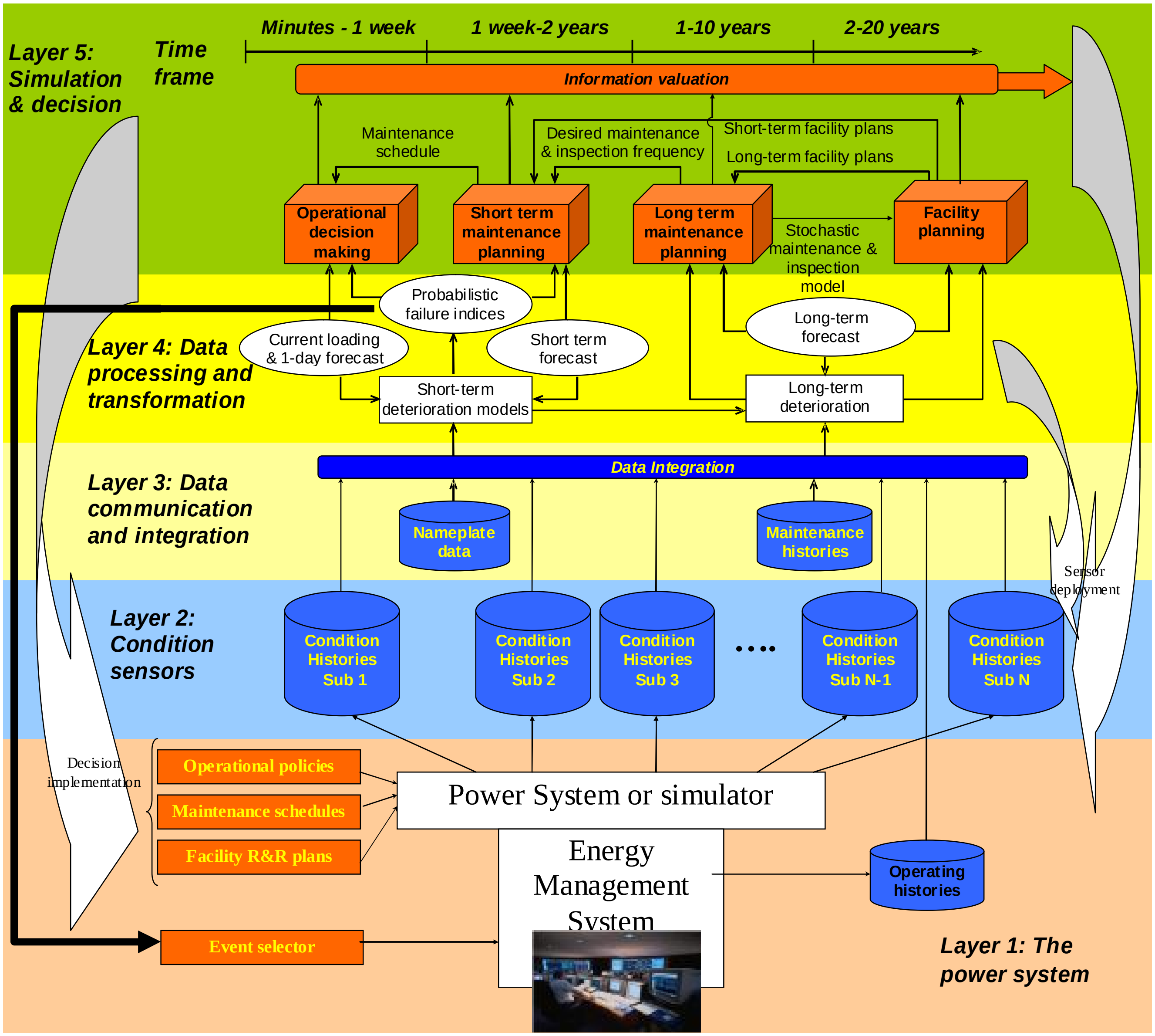

Fig. 8.1: Conceptual design of software system

§ Layer 3, Data communication and integration: This layer entails intra-substation communication, possibly using wireless between IEDs, and the substation server, together with federated data integration to provide mechanisms for interfacing Layer 4 data transformation algorithms with the data resources.

Layer 4, Data processing and transformation: This layer operates on the integrated data from layer 3 to produce, for each component/failure mode/time, an estimate of that particular component/failure mode deterioration level at the given time. This requires deterioration models and stochastic estimation algorithms such as the hidden Markov models described in Chapter 4.

§ Layer 5, Simulation and decision: This layer utilizes the component probabilistic failure indices from layer 4 together with short and long-term system forecasts to drive integrated stochastic simulation and decision models. These models operate interactively, so that simulation and decision in each time frame utilizes information from simulation and decision within other time frames. Resulting operational policies, maintenance schedules, and facility reinforcement plans are implemented on the power system (or the power system simulator). The decision models can also be used to discover the value of additional information. This information valuation is used to drive the deployment of new sensors and redeployment of existing sensors, impacting Layer 2.

8.3 Software Agent and Multiagent Systems

The most popular definition of intelligent software agent is given in [144]:"An autonomous agent is a system situated within and a part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future. "As widely recognized, an intelligent software agent enjoys several properties, such as Autonomy, Social Ability, Reactivity, and Proactiveness, Mobility etc [145]. While these terms can be descriptive in distinguishing agents from ordinary software programs, it is not realistic to assume that the actual agents will satisfy all these characteristics in their full sense. Fundamental concepts and definitions of software agents and multiagent systems (MAS) together with detailed descriptions can be found in [146,147,148]. Software agents have the ability to persistently sense its environment. The environment of an agent includes both the physical hosting environment and other agents in the system. These percepts together with the agent's own domain knowledge contribute to the agent's internal states. Based on its internal states, an agent will employ a decision-making procedure to determine the actions necessary to best achieve its objectives.

Software agents have the capability of traveling among the substation computers, the maintenance system and the maintenance crew computers to collect and process information. Having software agents traveling among different sources has formed a loosely coupled distributed information processing system. The software agent platform will provide the necessary services to encrypt, transmit, authenticate and authorize software agents.

Adequate agent-based representations of many complex physical systems must involve multiple agents within a multiagent system. The rationale for designing environments of multiple agents is to enable the individual agents to share expertise, cooperatively solve problems, and represent multiple viewpoints. Agents communicate with each other using an agent communication language (ACL), and frequently occurring communication patterns can be encoded as conversation protocols. This flexibility MAS offers in providing global and virtually unlimited communication ability among all entities represented as agents has tremendous significance with respect to power systems, which have for so long depended on a ubiquitous mix of various forms of expensive telemetry to satisfy its communication needs.

8.4 Multiagent Platforms

There are several agent development tools available ranging from research applications to commercial products [149,150,151]. The majority of the latest systems are Java based reflecting the current move towards Java as the language of choice for developing network solutions. This also illustrates the fact that the Internet is a major application area for agent technologies at the moment. These systems will usually use Java's Remote Invocation Method (RMI) to provide support for mobile agents. These are agents, which can suspend their execution on a host and then move to another host computer and resume execution with the same program state, i.e. data. Some of the available tools are described in this section.

8.4.1 Aglets

The Aglets Software Developer Kit (ASDK) [152] was one of the first Java-based systems developed at the IBM Research Laboratory in Japan. The first version was released in 1996. ASDK requires the JDK 1.1 or higher to be installed. IBM has developed the Aglets Workbench, which enables Java based agents called Aglets to move from one host on the Internet to another. These agents can execute on a host, halt, and then move to another host and execute there. The agent brings its program code and state with it as it moves from one host to another, and security mechanisms are provided so that a computer can host previously unknown aglets. The ASDK provides a modular structure and an easy-to-use API for the programming of Aglets. This platform has extensive support for security and agent communication and provides an excellent package of documentation.

8.4.2 Concordia

Mitsubishi Electric has developed a system called Concordia [153], which is a "full-featured framework for development of network-efficient mobile agent applications for accessing information". It requires the JDK 1.1 or higher to be installed. It is a Java-based mobile-agent system that has a strong focus on security and reliability. Like most other Java-based systems, it moves an agent's object code and data, but not thread state, from one machine to another. This platform provides a rich set of features, like support for security, reliable transmission of agents, access to legacy applications, inter-agent communication; support for disconnected computing, remote administration and agent debugging. Agents can communicate with each other using high-level protocols based on Java API's, and lower level network details are shielded from the developer. Facilities are also provided for agent cloning and resumption of computation following network or system failure. This system also provides good documentation.

8.4.3 D'Agents 2.0 (Agent TCL)

D'Agents 2.0 [154], which was formerly known as Agent TCL, supports transportable agents written in Tcl, Java and Scheme, as well as stationary agents written in C and C++. D'Agents provides a go instruction for each language, and automatically captures and restores the complete state of a migrating agent. Agents can suspend execution; transport themselves to another machine and resume execution again. The

D'Agent server uses public-key cryptography to authenticate the identity of an incoming agent's owner. Only the D'Agent server is multi-threaded; each agent is executed in a separate process, which simplifies the implementation considerably, but adds the overhead of inter-process communication. Agents can pass messages to each other and can use the Tk toolkit to create graphical user interfaces on the machine they are currently residing on. The system is composed of two main components. An extended TCL interpreter is provided to interpret the agent code, and a server is provided which runs on each machine, which will be a host for agent programs.

8.4.4 JAFMAS

JAFMAS (A Java-based Agent Framework for Multiagent Systems Development and Implementation) [155] provides a "framework to guide the coherent development of multiagent systems along with a set of classes for agent deployment in Java". The system encourages development from a speech-act point of view. The developer can construct scalable fault-tolerant multiagent systems using the system. KQML is the language used to implement speech-act theory.

8.4.5 Java Agent Template (JAT)

The Java Agent Template (JAT) [156] is a Java application, which provides basic agent functionality. The user can execute JAT agents as either applets or applications via an applet viewer. Agents can communicate with each other via KQML. These agents are not mobile unlike in other systems. The JAT is designed in such a way that the GUI can be replaced with a developer’s own interface, as can the other main functional components such as message interpretation and resource handling. Agents can exchange resources such as files or other data by in-lining them in KQML messages.

8.4.6 Jumping Beans

The Jumping Beans platform [157] is another Java-based framework for mobile agents, commercially distributed by AdAstra. It requires JDK 1.1.2 or higher to execute. The main strengths of this platform include the support for security, agent management, easy integration with existing environments and a small footprint. However, this platform uses a domain server approach for the agent migration: if an agent wants to migrate between two agencies it has to go first to the Agent Manager. Thus the server becomes a central point for tracking, managing, and authenticating agents. This approach may represent a central point of failure or a performance bottleneck in large-scale applications. Security and reliability are key aspects of Jumping Beans. Public-key cryptography is used to authenticate agencies to the server and vice versa, and access-control lists are used to control an agent's access to resources, based on the permissions given to the agent's owner.

8.4.7 Odyssey (Telescript)

Telescript [158], developed at General Magic, Inc., was the first commercial mobile-agent system. A Telescript agent is written in an imperative, object-oriented language, which is similar to both Java and C++, and is compiled into bytecodes for a virtual machine that is part of each server. It was one of the most secure, fault-tolerant and efficient mobile-agent systems. However largely because it was overwhelmed by the rapid spread of Java, it has been withdrawn from the market. And General Magic re-implemented its ***Telescript*** language as Odyssey, which has support for mobile agents, and is Java based. It requires JDK1.1 or higher to execute. The platform has a transport-independent API that work with Java RMI, IIOP and DCOM. The system can run on any platform, which supports the Java Development Kit (JDK), and it uses RMI to transport agents from one location to another.

8.4.8 Voyager

Developed by ObjectSpace, Voyager [159] is an object request broker with support for mobile objects and autonomous agents. It requires the JDK 1.1 or higher to be installed. Voyager has a comprehensive set of fundamental ORB features: remote enabling objects, message support (synchronous, one-way, future), automatic network class loading, socket factories; Voyager allows agents to move themselves and continue executing as they move. The agent transport and communication is based on a proprietary ORB on top of TCP/IP. Voyager uses RMI and provides full CORBA support. It provides a convenient way to interact, somewhat transparently, with remote objects (via proxy objects called “virtual” references), and for objects to move from host to host. It also provides federated directory service, a naming service, which allows users to build and link together hierarchies for the management of objects in a distributed system. Voyager has a pluggable security manager to restrict the operations of foreign objects. Its innovative dynamic proxy generation, naming service, synchronous and asynchronous messaging support simplifies the development of a distributed multiagent system.

There are some comparisons between these agent platforms in [149]. A performance study of some Java-based systems was also presented in [150]. Among those most famous platforms, Voyager and Odyssey are considered better in terms of robustness and performance. Based on Voyager, we have developed our own multiagent infrastructure – *MASPower* [160].

8.5 Multiagent System Methodology

MAS is a new field and as yet has not converged on a universally accepted design methodology. Several MAS paradigms and methodologies have been proposed in the literature, e.g. MASSIVE [161], DESIRE [Brazier, 1997], Gaia [162] and MaSE [163], based on different notions of agents and multi-agent organizations. We feel it is appropriate to use a 4-stage methodology for constructing MAS for power systems applications: Analysis, Design, Implementation, and Deployment.

8.5.1 Analysis: environment and tasks

This is the first stage which identifies the application domain, overall problem, objectives, MAS application environment, i.e., information that will be available to an agent, actions required of the agents, and operational (e.g., security) and performance constraints. Task decomposition is performed to determine what the system is supposed to do (and not how it is supposed to do it) to achieve overall MAS objectives.

8.5.2 Design: roles, interactions and organizations

Having decomposed the problem into constituent tasks, the next stage is to identify the agents required to effectively perform the tasks in terms of (a) definition of agent roles (data, functional, decision, mediator, facilitator, etc.) linking domain-dependent application features to appropriate agent technology, and specifying services to be associated with each agent; (b) identifying the types of interactions needed between different agents in order to achieve individual or joint goals; and (c) specifying the organization of the different agents in terms of a society of agents that is consistent with the various defined roles and that achieves the overall objectives.

8.5.3 Implementation: architecture

A key requirement for implementing a MAS is the selection of system and agent architectures. System architecture includes such aspects as multi-agent organization (e.g., hierarchical versus flat), agent management, and coordination mechanisms, including such things as directory services (or yellow pages) that enable each agent to know the capabilities and location of other agents, and the Agent Communication Language (ACL) that provides the common basis for inter-agent communication. The most common ACLs include Knowledge Query and Manipulation Language (KQML) [164] and Foundation for Intelligent Physical Agents (FIPA) ACL [165]. There are a number of available agent platforms for implementing MAS including Voyager [159], Concordia [166], Aglets [167] and SMART [168] etc. Based on an agent platform, individual agents can be extended with abilities to process specific messages and communicate with other agents. In order to enable inter-agent communication, besides ACL, it is also essential to define an appropriate ontology, or vocabulary, for the MAS that specify all possible message contents. In addition, some kind of inter-agent coordination strategy must be in place.

A broad range of architectures for agents (including reactive, deliberative, adaptive, communicative) have been studied in artificial intelligence. Properties that distinguish the various agent architectures include reasoning capabilities, resource limitations, control flow, knowledge handling, autonomy, user interaction, temporal context, and decision making.

8.5.4 Deployment

Here, actual agents are instantiated to cooperatively solve the problem. Testing is done to validate the model. We have implemented one approach. However, we recognize that another group has moved much faster than us in implementing a multiagent system for condition monitoring [169, 170, 171, 172], and this work should be studied closely before making further efforts along these lines.

8.6 Multiagent System Implementation

We have built a platform independent Java-based API called *MASPower* on top of the commercial distributed computing platform Voyager ORB [159] to instantiate agents and multiagent systems for eliciting coordinated and negotiated decision-making from power system decision-makers. Voyager supports dynamic proxy generation, naming services, synchronous and asynchronous messaging, management of multiple concurrent tasks and multiple conversation protocols, and preceptors for accessing local and remote percept sources for distributed MAS.

In this framework, we used object-oriented software design methods to develop agents representing different power system entities, e.g., suppliers, transmission owners, system operators, and delivery companies. The developed software is organized into eight packages: basic and collaborative agent classes to implement agents with different functionalites, agent GUIs, tasks carried out by agents, functionalities for enabling interagent messaging, functionalities for enforcing conversation protocols, interfaces for directory services, interfaces for distributed computing inter-agent messaging, and classes for enabling interagent negotiations. Individual agents may reside on any CPU within a network as long as the CPU is running *MASPower* on top of Voyager.

We extended the federated directory service implementation of Voyager ORB to provide the ability to maintain names of currently active agents together with keywords to identify the agent's area of expertise. *MASPower* stores the directory location as an XML document, read by every newly created agent, to avoid the need to recompile a program every time the directory location is changed.

Agent communication is performed using inter-agent messaging with message interpretation being private to each agent, providing the ability to interpret the same message differently under different agent internal states. Structural elements of an inter-agent message are per FIPA-2000 recommendations [165]. Multiagent conversations are managed using thread, tagged by unique conversation identifiers generated by the agent initiating the conversation. Conversation protocols were designed as finite state machines (FSM) following the COOL notations [173]. The FSM for a conversation protocol is characterized by a START state, END state, FAIL state, and a variable number of intermediate states. Transition between one state to another occurs by either sending or receiving a message with a particular performative. For example, the FIPA recommendation for the contract net protocol [174, 175] can be encoded as the FSM in Fig. 8.1. This protocol is useful for automated contracts in environments where all agents cooperatively work toward the same goal. The manager proposes a task, announces it, and potential contractors evaluate it (together with other announcements from other managers) and then submit bids on the tasks for which they are able to perform.

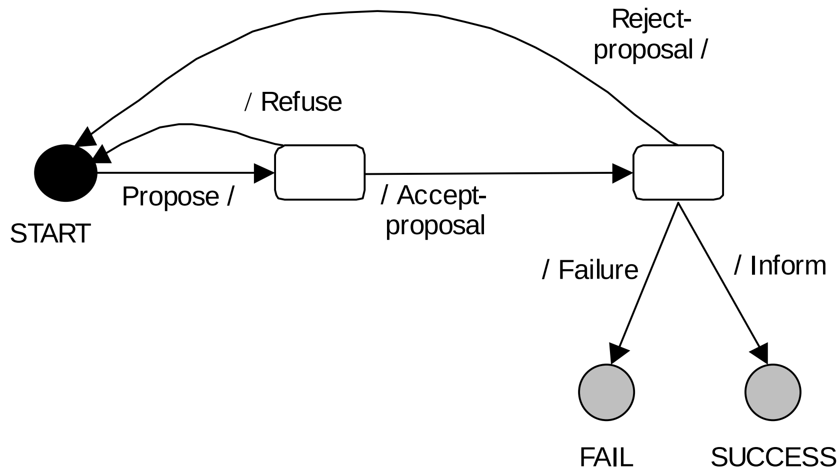

Fig. 8.2: FSM of Contract Net Protocol in COOL Notations

The FSM to be used by an agent depends on the role that the agent is playing in the conversation: the FSM in Fig. 1 is used by the agent responding to the initiating agent. The initiating agent uses the same FSM except that “send” and “receive” labels are interchanged for all transitions.

Each activity that can be undertaken by an agent in its lifetime is organized as tasks. Whenever a new task instance is created, the object registers with the agent’s task manager. A key attribute of *MASPower* is that many tasks can run concurrently within the agent.

8.7 Multiagent Framework of Transformer Condition Monitoring and Maintenance System

A platform-independent, object-oriented software infrastructure called MASPower [160] was developed previous to initiating the project for which this report was generated. MASPower can be used to rapidly instantiate software agents and multiagent systems for eliciting complex information processing and negotiated decision-making scenarios. Based on this software agent infrastructure, we have designed a multiagent based condition monitoring and maintenance system (MCMMS) with focus on power transformers. The framework of MCMMS is shown in Fig. 8.2.

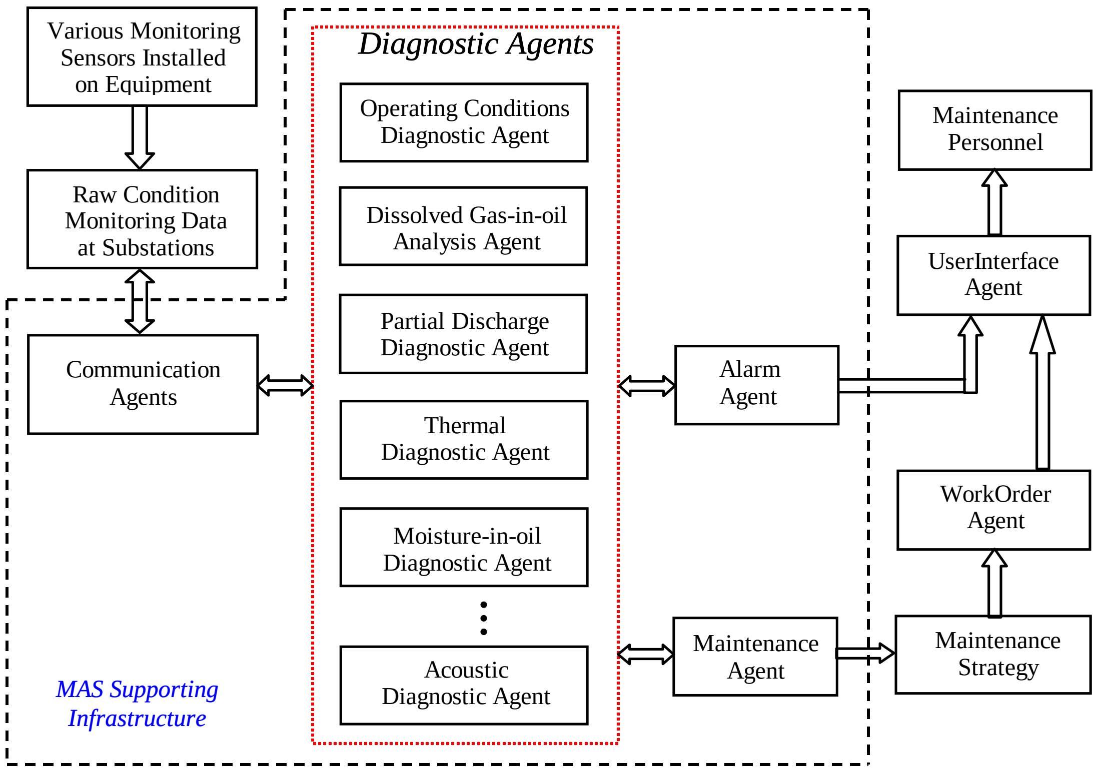

Fig. 8.3: Multiagent based Condition Monitoring and Maintenance System (MCMMS)

8.7.1 Model of communication agent

Large amounts of equipment monitoring data are gathered at monitoring equipment, operational hardware, software systems and databases that are not easily accessed or generally available. Intelligent communication agents, capable of accessing distributed, heterogeneous, proprietary data sources, can extract all related transformer condition monitoring information and communicate with diagnostic agents. The model of the communication agent is shown in Fig. 8.3.

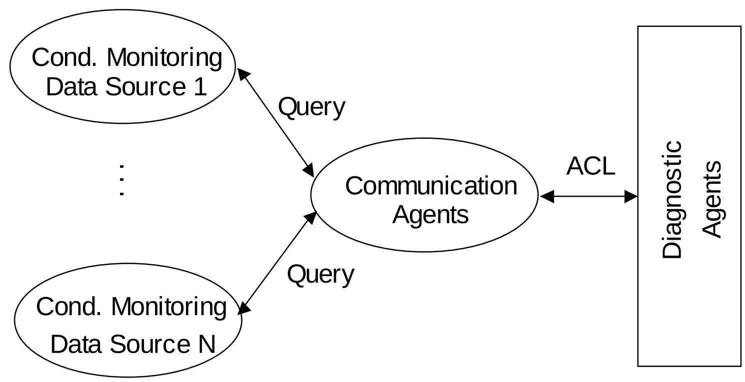

Fig. 8.4: Model of Communication Agent

8.7.2 Model of diagnostic agent

The model of diagnostic agent is shown in Fig. 8.4. Diagnostic agents possess knowledge of the necessary monitoring techniques as previously described. Based on the queried monitoring data, diagnostic agents can cooperatively perform diagnostic functions. Because monitoring systems continuously collect real-time data, the amount of data is enormous, and the diagnosis can be data and computation intensive. MAS architecture enables diagnostic agents to cooperatively detect abnormal situations and identify possible transformer failure modes. Once certain predefined operating thresholds have been violated, the alarm agent alerts the operating personnel at a central control room.

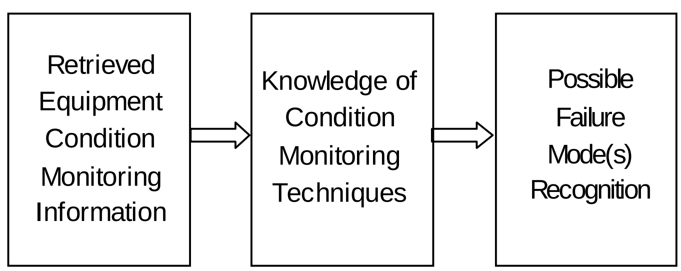

Fig. 8.5: Model of Diagnostic Agent

8.7.3 Model of maintenance agent

Based on the result of diagnosis, maintenance agents recommend appropriate maintenance activities for the equipment. And the transformer failure probabilities will also be refined based on acquired condition monitoring information. The number of maintenance agents serving each utility depends on the amount of equipment the utility owns. Among the maintenance agents which belong to the same utility, they could simply rank their maintenance activities according to certain criterion, e.g. equipment failure probability, available budget etc. The model of maintenance agent is shown in Fig. 8.5.

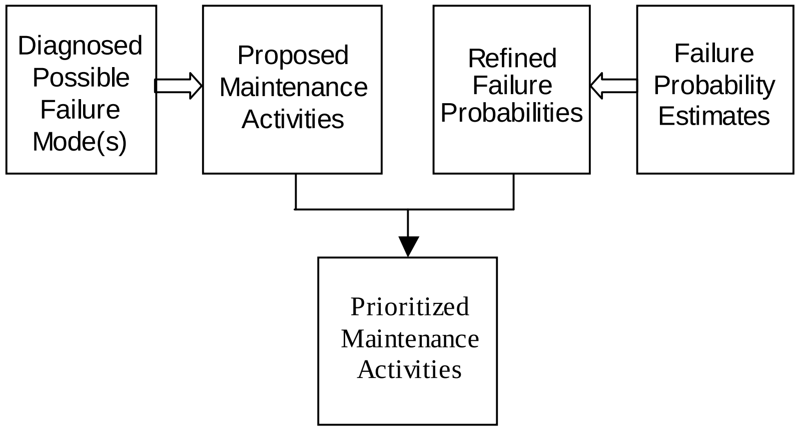

Fig. 8.6: Model of Maintenance Agents

8.7.4 System-wide maintenance scheduling

There are thousands of high voltage power transformers in a bulk transmission system. Although power transformers have proven to be reliable in normal operating conditions with a global failure rate of 1~2% per year, the large investment in generating capacity after World War II, and continuing into the early 1970's has resulted in a large transformer population which now is fast approaching the end of life [[176]]. Therefore, with large number of aged electrical equipment in a system, certainly there would be numerous maintenance scheduling conflicts. For the sake of system security, it is important that priority be placed on scheduling system-wide maintenance activities to maximize the achieved overall risk reduction. Here we are interested in using multiagent negotiation to solve this equipment maintenance-scheduling problem. The multiagent socially rational negotiation is suitable in this situation because maintenance activities would not only save money for each utility (by avoiding costly equipment failures and extend the life of electrical equipment), but also significantly improve the system reliability.

While in order to carry out the maintenance activity, the corresponding maintenance agent must get approval from the ISO-Agent, who is responsible for the entire system security. Using system network information and expected load profile, the ISO-Agent identifies time slots allowing transformer maintenance (number and duration) for certain time periods; the requesting maintenance agents, which represent various independent organizations, negotiate among themselves to obtain more rapid approval for their maintenance activities, as shown in Fig. 8.6. For example, one maintenance agent having urgent maintenance activity may be willing to negotiate with other related agents using monetary compensation in order to obtain higher priority for its maintenance activity.

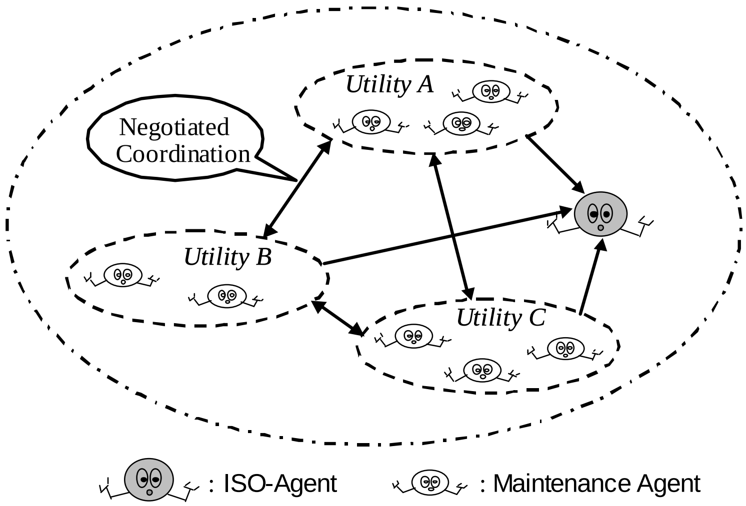

Fig. 8.7: Maintenance scheduling based on MAS Negotiation

8.8 Conclusions

The development in sensor and computer technology allows the realization of on-line monitoring systems for power transformers, in order to use this most expensive transmission equipment in the optimum technical and economical manner. With copious amount of condition monitoring data available at substation IEDs, we propose a multiagent based equipment condition monitoring and maintenance system with several autonomous diagnostic agents to perform the condition-monitoring task as well as recommend an optimal maintenance strategy. Based on our previous research experience [146,147,148] with multiagent systems, we envision that the application of multiagent system in this area will be effective in facilitating the maintainability of highly modularized software systems such as that envisioned in Fig. 8.1. This will enable utilities to move away from the traditional calendar-based maintenance strategy to a more flexible and efficient condition-based maintenance (CBM) philosophy with the benefits of both cost saving and system reliability enhancement.

9. Conclusions and Future Work

This project report proposes a rigorous method of allocating economic resources for bulk transmission system maintenance, based on condition data of equipments and resource limitations, to maximize the system performance. Failure mechanics of circuit breakers and power transformers are analyzed and methods of obtaining condition monitoring information of components are investigated. An integrated maintenance scheduler to identify the most effective selection and schedule of maintenance tasks associated with bulk transmission equipment is developed in this project.

Fundamental to the solution approach implemented in this project are the ideas that: (a) condition monitoring information is useful in estimation of component status in deterioration. Understanding of each specific deterioration process is important in setting up translation functionality used to connect the condition monitoring data and deterioration status of the components; (b) maintenance reduces the "cumulative-over-time" risk caused by the equipment being maintained, where risk is the product of failure probability and failure consequence; (c) failure consequence is assessed in terms of redispatch cost and component damage; and (d) different maintenance tasks at different times cause different risk reduction.

The work of this project has made several distinct contributions to the need to manage transmission assets through the strategic and systematic allocation of resources. Of most importance, we have provided analytical models for use in addressing resource allocation for managing transmission assets. We expect these analytical models to facilitate the development of commercial tools that practitioners can regularly use, resulting ultimately in increased reliability per dollar expended. More specifically, we point to the following:

1. <u>Failure rate estimation</u>: Two models have been developed to convert condition data into failure rates. One model is based on a standard Markov process, and the other one is based on a so-called hidden Markov process. The second model better characterizes uncertainty in the resulting failure rates.

2. <u>Optimization</u>: An optimization algorithm with associated code was developed to systematically identify optimum maintenance task selection and scheduling so as to maximize the risk reduction achieved from a given allocation of financial and human resources. The optimization problem is integer, with multiple constraints, has high dimension, and therefore is quite challenging to properly solve. Different solution methods have been utilized and investigated, and we have concluded that relaxed linear programming with DP knapsack solutions is a very effective solution method in that it provides very good solutions in a computationally feasible way.

3. <u>Resource allocation</u>: Lagrange multipliers, obtained from the optimization problem, are very useful in providing insight into the effects on solution quality of different resource allocations. Such insight is useful in managerial decision-making associated with company budgeting processes where one is continuously trying to identify how to reallocate resources in order to gain improvement in reliability.

4. <u>Long-term maintenance scheduling</u>: We developed an approach for planning long-term policies associated with inspecting and maintaining power transformers and circuit breakers. Results of this approach serve to provide a list of candidate

maintenance tasks as input to the mid-term scheduler. Integrate the maintenance asset managements in different time scales. Long-term and mid-term maintenance planning is coordinated to result in a complete strategy to achieve balance between different optimization objectives cost, component lifetime, and system reliability.

5. Data integration: We developed a federated, query-centric data integration and knowledge acquisition method of integrating information from multiple, highly distributed, and heterogeneous data sources storing different information about equipment.

6. Multiagent systems: Multiagent systems are a promising software development approach to address the communication, coordination, and software maintainability in complex software systems as we see developing for managing transmission assets.

Although this project focused on maintenance, it motivated the recognition that the state of different transmission-level equipment, in terms of tendency to fail as characterized by condition measurements, is information that is, or at least should be, utilized in three system-level decision problems: operational security assessment, maintenance, and facility planning. It is through the equipment condition that each of these three decision problems affect and are affected by policies resulting from the other two decision problems, improved analysis can be obtained by capturing this coupling between these different decision-problems in a simulation environment. Building simulation capability that does this and at the same time interfaces with communication equipment and condition monitoring hardware, is a formidable task and well outside the scope of this project, but two of the investigators of this project will pursue this effort, funded by a recent National Science Foundation Award. Figure 8.1 in Chapter 8 of this report illustrates the objective of this work. Six different companies, including two large utilities, have agreed to participate as advisors in this NSF project, which was developed as a direct result of this PSERC-sponsored project T-19. More information about this project can be found at http://ecpe.ee.iastate.edu/powerweb/auto.htm.

References

[1] M. Gallaher, S. Johnston, B. Kirby, "Changing measurement and standards needs in a deregulated electric utility industry," Nov. 1999, Research Triangle Institute, http://www.rti.org/pubs/dereg.pdf.
[2] J. Endrenyi, S. Aboresheid, R. Allan, G. Anders, S. Asgarpoor, R. Billinton, N. Chowdhury, E. Dialynas, M. Fipper, R. Fletcher, C. Griggs, J. McCalley, S. Meliopoulos, T. Mielnik, P. Nitu, N. Rau, N. Reppen, L. Salvaderi, A. Schneider, and C. Singh, "The present status of maintenance strategies and the impact of maintenance on reliability," IEEE Trans. on Pwr Sys, Nov. 2001, pp. 638-646.
[3] W. R. Blischke, D.N. Prabhakar Murthy "Reliability, modeling, prediction and optimization," John Wiley & Sons, 2000
[4] M. Minhas, P. de. Klerk, J. Reynders, "A study of failure modes of large power transformer," Proc of 10th International Symposium on High Voltage Engineer, Montreal, Canada, Aug 25-29,1997,
[5] W. H. Bartley "Analysis of Transformer Failures," www.imia.com/documents/wgp33(03).pdf
[6] IEEE Std C57.104-1991, "IEEE Guide for the Interpretation of Gases Generated in Oil-Immersed Transformers,"
[7] Y.H. Oh, K.D. Song, B.Y. Lee, K.Y. Park, "Displacement measurement of high-voltage winding for design verification of short-circuit strength of transformer," Proc of 2003 IEEE PES Transmission and Distribution Conference and Exposition, Vol. 2, 7-12 Sept. 2003, pp 831 - 835
[8] M. D. Judd, L. Yang, C. J. Bennoch, I. B. B. Hunter, and T. Breckenridge, "Condition monitoring of power transformers using UHF partial discharge sensors: operating principles and site testing," Proc of EuroTech Con Conference., Manchester, U.K., Sept. 2003, pp. 67–92.
[9] "IEEE guide for partial discharge measurement in power switchgear," IEEE Std 1291-1993
[10] Trevor Lord, Graham Hodge, "On-Line Monitoring Technology Applied to HV Bushings," http://www.avo.co.nz/techpapers/online-monitor/onlinehvbushings.php
[11] W.J. Bergman, "Equipment Monitoring Selection As A Part Of Substation Automation," Proc. Of 1999 IEEE Power Engineering Society Winter Meeting, Vol. 2, 31 Jan-4 Feb 1999, pp 971 -973
[12] D. Chu, A. Lux, "On-Line Monitoring of Power Transformers and Components: A Review of Key Parameters," Proc of 1999 Electrical Insulation Conference and Electrical Manufacturing & Coil Winding Conference, 1999, pp 669 –675.
[13] C. Bengtsson, "Status and Trends in Transformer Monitoring," IEEE Trans. on Power Delivery, Vol. 11, Issue. 3, July 1996, pp 1379 –1384.
[14] T. Krieg, M. Napolitano, "Techniques and Experience in On-Line Transformer Condition Monitoring and Fault Diagnosis in ElectraNet SA," Proc of 2000 International Conference on Power System Technology, 2000. Vol. 2, pp. 1019 -1024
[15] ANSI/IEEE Std 943-1986, "IEEE Guide for Aging Mechanisms and Diagnostic Procedures in Evaluating Electrical Insulation Systems,"
[16] http://www.electricity-today.com/et/issue0203/i02_analysis.htm
[17] B. Pahlavanpour, A. Wilson, "Liquid Insulation (Digest No. 1997/003), IEE Colloquium on An Engineering Review of" 7 Jan. 1997 pp.1/1 - 1/5
[18] http://www.gepower.com/prod_serv/products/substation_md/en/downloads_en/hydran_201r.pdf
[19] http://tdworld.com/mag/power_maintenance_management_techniques/
[20] IEEE Std C57.127-2000, IEEE Trial-Use Guide for the Detection of Acoustic Emissions from Partial Discharges in Oil-Immersed Power Transformers, 2000
[21] T. Bengtsson, et al., "Identification of PD Sources in Solids," Proc of 6th DMMA Conf. IEE Conf. Publ. 363, 1992, p 29.
[22] M.Wang, A. J. Vandermaar, K. D. Srivastava, "Review of condition assessment of power transformers in service," Electrical Insulation Magazine, IEEE Vol. 18, Issue 6, Nov.-Dec. 2002 pp.12 – 25
[23] http://www.ptd.siemens.com/solutions/pwr_transformer.html
[24] http://www.serveron.com/products/TG-tga-main.asp
[25] http://www.gepower.com/syprotec/products/systems/hy201i.html
[26] http://www.gepower.com/syprotec/products/systems/hydran_multi_2010.html.
[27] http://www.gepower.com/syprotec/products/systems/aquaoil.html.
[28] http://global.mitsubishielectric.com/pdf/advance/vol77/77np2.pdf.
[29] S. Tenbohlen, F. Figel, "On-line Condition Monitoring of Power Transformers," Proc of 2000 IEEE Power Engineering Society Winter Meeting, Vol. 3, 2000, pp. 2211 -2216.

[30] A Report of the IEEE/PES Task Force on Impact of Maintenance Strategy on Reliability of the Reliability, Risk and Probability Applications Subcommittee, "The Present Status of Maintenance Strategies and the Impact of Maintenance on Reliability," IEEE Trans. on Pwr. Sys, VOL. 16, No. 4, Nov. 2001

[31] RTR-84 Circuit Breaker Response Recorder, Hathaway Systems Corporation, Belfast, Ireland, Hathaway, 1999.

[32] H. K. Høidalen, M. Runde, O. Haugland, G. Ottesen, and M. Öhlén, "Continuous Monitoring of Circuit Breakers Using Vibration Analysis," Proc. of 1999 Eleventh International Symposium on High Voltage Engineering. pp. 102 –106

[33] Daytime Corona Inspection, EPRISolutions, A Service of EPRISolutions, Inc.

[34] http://www.ir55.com/thermacam.html

[35] J. Moubray, Reliability-centered maintenance, Industrial Press INC, New York, NY 1997. pp. 409

[36] P. F. Gale, G. O. Hensman, "Extending SCADA Systems to Provide Cost Effective Distribution Switchgear Condition Monitoring," Proc of Third International Conference on Power System Monitoring and Control, 1991.

[37] J. P. Dupraz, A. Fanget, T. Jung, and G. F. Montillet, "Diagnostics and Monitoring Tools Applied to Asset Management: Applications to Circuit Breakers," Proc of Substation Equipment Diagnostic Conference XIII, March 6-9, Louisiana, 2005

[38] M. Kezunovic, G. Latisko, and N. Ved, "Real-Time Monitoring and Assessment of Circuit Breaker Operations for Diagnostics and Control Applications," Proc of Substation Equipment Diagnostic Conference XIII, March 6-9, Louisiana, 2005.

[39]IEEE standard C37.10-1995, December 1995, "IEEE Guide for Diagnostics and Failure Investigation of Power Circuit Breakers, "

[40] IEEE Guide for the Selection of Monitoring for Circuit Breakers, IEEE standard C37.10.1-2000, December 2000.

[41] Working Group A3.12, "Failure Survey on Circuit Breaker Control Systems Summary report for Electra," CIGRE, Electra No 216, October 2004.

[42] S. Natti, P. Jirutitijaroen, M. Kezunovic, and C. Singh, "Circuit Breaker and Transformer Inspection and Maintenance: Probabilistic Models," Proc of 8th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), September 13-16, Iowa, 2004.

[43] R. D. Garzon, High Voltage Circuit Breakers: Design and Applications, 2nd ed. New York: Marcel Dekker, 2002

[44] M. Runde, G. E. Ottesen, B. Skyberg, and M. Ohlen, "Vibration analysis for diagnostic testing of circuit-breakers," IEEE Trans. Power Delivery, vol. 11, no. 4, pp. 1816-1823, October 1996

[45] J. Moubray, Reliability-Centered Maintenance, Industrial Press INC, New York, NY 1997. pp. 404

[46] L. Balgard, L. Lundin, "Monitoring of Primary Circuit Temperatures and Breaker Condition in a Substation," Proc of 12th International Conference on Electricity Distribution, 1993.

[47] M. Kezunovic, C. Nail, Z. Ren, D. R. Sevcik, S. Lucey, W.E. Cook, E.A. Koch, "Automated Circuit Breaker Monitoring and Analysis," IEEE PES summer meeting, Chicago, July 2002

[48] IEEE Guide for Acceptance and Maintenance of Insulating Oil in Equipment, IEEE standard C57.106-1991

[49] IEEE Guide for Acceptance and Maintenance of Insulating Oil in Equipment, IEEE standard C57.106-2002, November 2002.

[50] J. Moubray, Reliability-Centered Maintenance, Industrial Press INC, New York, NY 1997. pp. 408 - 409

[51] IEEE Guide for Partial Discharge Measurement in Power Switchgear, IEEE Standard 1291-1993.

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

[53] L. Wolstenholme, "Reliability Modeling, A Statistical Approach," Chapman and Hall, New York, 1999

[54] G. Anders, H. Maciejewski, B. Jesus and F. Remtulla, "Analysis of failure rates of Air Blast breakers as a function of age and usage" , IEEE Bologna Power Tech Conference, June., 2003, Bologna, Italy

[55] V.I. Kogan, J.A. Fleeman, J.H.Provanzana, etc. "Failure analysis of EHV transformers," IEEE Trans. on Power Delivery, Vol 3, No.2, April 1988.

[56] W Q. Meeker, L A. Escobar, "Statistical Methods for Reliability Data" John Wiley & Sons, 1998.

[57] A.S. Farag, C. Wang, T. C. Cheng, etc. “Failure analysis of composite dielectric of power capacitors in distribution systems,” IEEE Trans. on Dielectrics and Electrical Insulation, Vol. 5, Issue 4, Aug. 1998 pp.583 - 588

[58] X Jin; C Wang; C Chen, etc. “Reliability analyses and calculations for distribution transformers“, Proc of 1999 IEEE Transmission and Distribution Conference, Vol. 2, 11-16 April 1999 pp.901 - 906

[59] C. R. Acker, “Transformer Insulation and Transformer Life Expectancy—A More Comprehensive Concept,” Paper Number A 76 021-6 presented at the IEEE PES Winter Meeting and Tesla Symposium, New York, NY, Jan. 25-30, 1976.

[60] W. Fu, J. McCalley, V. Vittal, “Transformer Risk Assessment,” IEEE Trans. on Pwr Sys.Vol. 16, No. 3, Aug., 2001, pp 346-353.

[61] IEEE Std C57.91-1995 “IEEE Guide for Loading Mineral-Oil-Immersed Transformers” 1995

[62] K. Abe, T. Maeda, T. Shimonaka, T. Umemura, ”A sensing system for degradation diagnosis of oil-filled transformers,” Conference Record of 1994 IEEE International Symposium on Electrical Insulation, 5-8 June 1994 pp.29 - 32

[63] S.H. Sim, J. Endrenyi, “A failure-repair model with minimal and major maintenance,” IEEE Trans. on Reliability, Vol. 42, Issue 1, March 1993 pp.134 - 140

[64] G.J. Anders, J. Endrenyi, G.L. Ford, G.C. Stone, “A probabilistic model for evaluating the remaining life of evaluating the remaining life of electrical insulation in rotating machines,” IEEE Trans on Energy Conversion, Vol. 5, Issue 4, Dec. 1990 pp.761 – 767

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

[66] J. Endrenyi, G. Anders, A. Leite da Silva, “Probabilistic Evaluation of the Effect of Maintenance on Reliability- An Application,” IEEE Trans on Pwr Sys, Vol 13 Issue 2, May 1998, pp 576-583.

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

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

[69] A. L. da Silva and J. Endrenyi, “Application of First Passage Times in the Markov Representation of Electric Power Systems,” Proc of the 4th International Conference on Probabilistic Methods Applied to Power Systems, Rio de Janeiro, Brazil, September 1994.

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

[71] V. Shvets, B. Zeide, “Investigating parameters of growth equations,” Canadian Jour. Forest Research., vol. 26, no. 11, pp. 1980–1990, Nov. 1996

[72] FERC report, “Utility Vegetation Management Final Report,” March 2004 http://www.ferc.gov/cust-protect/moi/uvm-final-report.pdf

[73] “Introduction to Hidden Markov Model,” www.cedar.buffalo.edu/~govind/CS661/Lec12.ppt

[74] L.E. Baum and T. Petrie, “Statistical inference for probabilistic functions of finite state Markov chains,” Ann. Math. Stat. vol.37, pp1554-1563, 1966

[75] L.E. Baum and T. Petrie, “Statistical inference for probabilistic functions of finite state Markov chains,” Ann. Math. Stat. vol.37, pp1554-1563, 1966

[76] L.E. Baum and J. A. Egon, “An inequality with applications to statistical estimation for probabilistic functions of a Markov process and to a model of ecology,” Bull, Amer. Meteorol, Soc. Vol.73, pp360-363, 1967

[77] L.E. Baum and G. R. Shell, “Growth functions on transformations on manifolds,” Pac. J. Math., vol. 27, no. 2, pp211-227. 1968.

[78] L.E Baum, T. Petrie, G. Soules, and N. Weiss, “A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains,” Ann. Maht. Stat. vol. 41, no.1, pp 164-171, 1970

[79] L.E. Baum, “An inequality and associated maximization technique in statistical estimation for probabilistic functions for Markov processes,” Inequalities, vol.3, pp.1-8, 1972.

[80] E. Hatzipantelis, J. Penman, “The use of hidden Markov models for condition monitoring electrical machines” Proc of Sixth International Conference on Electrical Machines and Drives, 8-10 Sep 1993 pp. 91 - 96

[81] L. Atlas, M. Ostendorf, G. D. Bernard, ”Hidden Markov models for monitoring machining tool-wear,” Proc of 2000 IEEE International Conference on Acoustics, Speech, and Signal Processing, Vol. 6 , 5-9 June 2000 pp. 3887 - 3890

[82] H. Lucke, “Which stochastic models allow Baum-Welch training?” IEEE Trans. on Signal Processing, Vol. 44 , Issue: 11 , Nov. 1996 pp. 2746 - 2756

[83] T. Hjartarson, B. Jesus, D. T. Hughes, R. M. Godfrey, “Development of health indices for asset condition assessment,” Proc of 2003 IEEE PES Transmission and Distribution Conference and Exposition, Vol 2, 7-12 Sept. 2003 pp.541 - 544

[84] R. E. Brown, G. Frimpong, H. L. Willis, ”Failure rate modeling using equipment inspection data,” IEEE Trans on Pwr. Sys. Vol. 19, Issue 2, May 2004 pp.782 – 787

[85] IEEE Std 493-1997, “IEEE Recommended Practice for the Design of Reliable Industrial and Commercial Power System,”

[86] IEEE Std 500-1984, “IEEE Reliability Data for Nuclear Power Generating Stations”

[87] P. L. Fletcher, W. Degen, “A Summary of the final results and conclusions of the second international enquiry on the reliability of high voltage circuit-breakers,” Proc of Second International Conference on the Reliability of Transmission and Distribution Equipment, 1995, pp. 24-30

[88] Z. Zhang, Y. Jiang, J. McCalley, “Condition-based Failure Rate Estimation for Power Transformers,” Proc. of 35th North American Power Symposium, Oct., 2003, Rolla, USA

[89] L. T. Rumfield “Circuit Breaker Diagnostic Response Testing Using the RTR-84 Response Time Recorder,” presented at the Sixty-First Annual International Conference of Doble Clients, June, 1994.

[90] M. Kezunovic, Z. Ren, G. Latisko, D.R. Sevcik, J. Lucey, W. Cook, E. Koch, “Automated Analysis of Circuit Breaker Operations,” Proc of 2003 EPRI Substation Equipment Diagnostics Conference, New Orleans, February 2003

[91] Z. Ren, “Wavelet based analysis of circuit breaker operation,” Masters thesis, Texas A&M University, 2003

[92] M. Kezunovic, Z. Ren, G. Latisko, D.R. Sevcik, J. Lucey, W. Cook, E. Koch, “Automated monitoring and analysis of circuit breaker operations,” IEEE Trans on Power Delivery, Vol 20, Issue 3, July 2005, pp 1910-1918

[93] http://www.bain.com/bainweb/consulting_expertise/capabilities_detail.asp?capID=31

[94] M. Gallaher, S. Johnston, B. Kirby, “Changing measurement and standards needs in a deregulated electric utility industry,” Nov., 1999, Research Triangle Institute, http://www.rti.org/pubs/dereg.pdf.

[95] J. Endrenyi, S. Aboresheid, J. McCalley, et al., “The present status of maintenance strategies and the impact of maintenance on reliability,” IEEE Trans., on Pwr Sys, Vol.16, No. 4, 2001.

[96] J. Moubray, “Reliability-Centered Maintenance.” Industrial Press Inc., New York, 1997.

[97] R. E. Barlow and F. Proschan, “Statistical Theory of Reliability and Life Testing” New York: Holt, Rinehart and Winston, Inc., 1975.

[98] E. Solvang, L. Lundgaard, L. B. Gustavsen, A. Eggen, S. Fretheim, “Risk management: cost minimization using condition-based maintenance Electricity Distribution, 2001. Part 1: Contributions.” Proc of 16th International Conference and Exhibition on CIRED (IEE Conf. Publ No. 482) , Vol. 3 , 18-21 June 2001 pp. 6

[99] M. Schwan, W. H. Wellssow, K. Weck “Probabilistic assessment of the impact of maintenance strategies on supply reliability,” Proc of the CIGRE 2000 Paris Session, Paris, France, 27 Aug-2 Sep. 2000.

[100] F.S. Nowlan, H. Heap, “Reliability-Centered Maintenance,” US department of Commerce (NTIS), Springfield, VA, 1978

[101] G.P.P. Gunarathne, “Methods and reliability issues in the detection of mineral deposits in petroleum pipelines Inspection Reliability: State-of-the-Art,” (Digest No. 1996/178), IEE Colloquium on , 21 Nov. 1996 pp.4/1 - 4/7

[102]G. F. D'Addio, P. Firpo, S. Savio, ”Reliability centered maintenance: a solution to optimise mass transit system cost effectiveness” Proc of 1998 International Conference on Developments in Mass Transit Systems, (Conf. Publ. No. 453) , 20-23 Apr. 1998

[103] R. Sasisekharan, V. Seshadri, S.M. Weiss, ”Proactive network maintenance using machine learning” Global Telecommunications Conference, 1993, including a Communications Theory Mini-Conference. Technical Program Conference Record of 1993 IEEE GLOBECOM, Houston 29 Nov.-2 Dec. 1993 pp.217 - 222 vol.1

[104] E. Solvang, L. Lundgaard. B. Gustavsen, A.O. Eggen, "Risk management: Cost minimization using condition-based maintenance," Conference Publication No.482 of CIRED2001,18-21 June 2001, IEE 2001
[105] L. S. Low, L. Goel, "Incorporating deterministic criteria in the probabilistic framework for composite generation and transmission systems" Proc of 2000 IEEE Power Engineering Society Summer Meeting, Vol. 4 , 16-20 July 2000 pp.2069 - 2074
[106] W. Li; J. Korczynski, " A reliability-based approach to transmission maintenance planning and its application in BC hydro system," IEEE Trans. on Power Delivery, Vol. 19 , Issue: 1 , Jan. 2004 pp.303 - 308
[107] M. E. Beehler, "Reliability centered maintenance for transmission systems," IEEE Trans. on Power Delivery, Vol. 12 , Issue: 2 , April 1997 pp.1023 - 1028
[108] D. Chattopadhyay, K. Bhattacharya, J. Parikh, "A systems approach to least-cost maintenance scheduling for an interconnected power system" IEEE Trans. on Pwr Sys, Vol. 10 , Issue: 4 , Nov. 1995 pp.2002 - 2007
[109] M. Shahidehpour, M. Marwali "Maintenance scheduling in restructured power system," 2000 Kluwer Academic Publishers
[110] J. McCalley, T. Van Voorhis, A.P. Meliopoulos, Y. Jiang "Risk-Based Maintenance Allocation and Scheduling for Bulk Transmission System Equipment" PSERC Report 8/26/2004:
http://www.pserc.org/ecow/get/publicatio/reports/2003report/mccalley_final_report_s14.pdf
[111] CIGRE TF 38.03.12 (R. J. Marceau and J. Endrenyi, Chairmen), "Power System Security Assessment: A Position Paper," Electra, No. 175, pp. 48-78, December 1997.
[112] Q. Chen and J. McCalley, "Identifying high risk N-k contingencies for online security assessment," IEEE Trans. on Pwr Sys,Vol. 20, Issue 2, May 2005 pp. 823 - 834
[113] Y. Jiang, Z, Zhang, T. Van Voorhis, J. McCalley, "Risk-based maintenance optimization for transmission equipment," Proc of 35th North American Power Symposium, Oct., 2003, Rolla, USA
[114] G.L. Nemhauser, L.A. Wolsey, "Integer and combinatorial optimization," chapter 1, John Wiley & Sons, 1988
[115] P. Batra, "Modeling and efficient optimization for object-based scalability and some related problems" IEEE Trans. on Image Processing, Vol. 9, Issue 10, Oct. 2000 pp.1677 - 1692
[116] M. Wang, A. J. Vandermaar, K. D. Srivastava, "Review of condition assessment of power transformers in service," Electrical Insulation Magazine, IEEE , Vol. 18 Issue: 6 , Nov.-Dec. 2002 pp. 12 - 25
[117] IEEE Reliability Test System Task Force of the Application of Probability Methods Subcommittee, "The IEEE Reliability Test System – 1996," IEEE Trans. on Pwr. Sys, 1996.
[118] "MAPP bulk transmission system outage report," June 2001. MAPP Reliability Studies Subcommittee Report.
[119] T. Lindquist, L. Bertling and R. Eriksson "A feasibility study of probabilistic modeling of ageing circuit breakers for maintenance optimization," Proc of the 8th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS04), Ames, Iowa, USA, September 12-16, 2004.
[120] D. A. Crowl and J. F. Louvar "Chemical Process Safety, Fundamentals with Applications," Englewood Cliffs, N.J. : Prentice Hall, c1990.
[121] J. Lapworth, and T. McGrail, "Transformer failure modes and planned replacement," IEE Colloquium on Transformer Life Management, October 1998
[122] V. Wasserberg, H. Borsi, and E. Gockenbach, "An Innovation Online Drying Procedure for Liquid Insulated High Voltage Apparatus," Proc of 2001 International Symposium on Electrical Insulating Materials, 2001. (ISEIM 2001)., November 2001 pp. 587 -590
[123] C. Myers, "Transformers-Conditioning Monitoring by Oil Analysis Large or Small; Contentment or Catastrophe," IEE Conference Publication 452, April 1998, pp. 53-58
[124] Alfonso de Pablo, "Furfural and Ageing: How are they related," IEE Colloquium on Insulating Liquids, May 1999
[125] IEEE Std. C57.127-2000, IEEE Trial-Use Guide for Detection of Acoustic Emissions from Acoustic Emissions from Partial Discharges in Oil-Immersed Power Transformers.
[126] J. Endrenyi, G.J. Anders, and A.M. Leite da Silva, "Probabilistic Evaluation of The Effect of Maintenance on Reliability – An Application," IEEE Trans. on Pwr Sys, 13, 2, pp. 576-583, May 1998
[127] C. Singh & R. Billinton, "System Reliability Modeling and Evaluation," Hutchinson Educational, 1977, London

[128] S.H. Sim, and J. Endrenyi, “Optimal Preventive Maintenance with Repair,” IEEE Trans. on Reliability, 37, 1, pp. 92-96, April 1998

[129] IEEE Std. C57.100-1986, “IEEE Standard Test Procedure for Thermal Evaluation of Oil-Immersed Distribution Transformers,”

[130] P.M. Gruber and J.M. Wills. Handbook of Convex Geometry. Elsevier Science Publishers B.V,1993.

[131] J. Reinoso-Castillo, A. Silvescu, D. Caragea, J. Pathak, and V. Honavar. “Information Extraction and Integration from Heterogeneous, Distributed, Autonomous Information Sources: A Federated, Query-Centric Approach,” Proc of 2003 IEEE International Conference on Information Integration and Reuse, Sept. 2003

[132] J. Pathak, Y. Jiang, V. Honavar, J. McCalley, “Condition Data Aggregation with Application to Failure Rate Calculation of Power Transformers,” Proc. of the Hawaii International Conference On System Sciences, January 4-7, 2006, Poipu, Kauai, Hawaii.

[133] L. R. Rabiner and B. H. Juang. “An Introductionto Hidden Markov Models,” IEEE ASSP Magazine, pages 4–15, January 1986.

[134] E. Mena, V. Kashyap, A. Sheth, and A. Illarramendi. OBSERVER, “An Approach for Query Processing in Global Information Systems based on Interoperation across Pre-Existing Ontologies,” Intl. Journal of Parallel and Distributed Databases, 8(2):232–271, 2000.

[135] H. Garcia-Molina and et al. “The TSIMMIS Approach to Mediation: Data Models and Languages.” Journal of Intelligent Information Systems, 8(2), 1997.

[136] D. Draper, A. Y. Halevy, and D. S. Weld. “The Nimble XML Data Integration System,” Proc of 2001 International Conference on Data Engineering, pages 155–160, 2001.

[137] Y. Arens, C. Chin, C. Hsu, and C. Knoblock. “Retrieving and Integrating Data from Multiple Information Sources,” International Journal on Intelligent and Cooperative Information Systems, 2(2):127–158, 1993.

[138] J. Lu, G. Moerkotte, J. Schue, and V.S. Subrahmanian. “Efficient Maintenance of Materialized Mediated Views,” In Proceedings of 1995 ACM SIGMOD Conference on Management of Data, San Jose, CA, 1995.

[139] A. Levy. “The Information Manifold Approach to Data Integration,” IEEE Intelligent Systems, 13,1998.

[140] J. Bao and V. Honavar. Collaborative “Ontology Building with Wiki@nt,” Proc of 3rd International Workshop on Evaluation of Ontology Based Tools, held in conjunction with ISWC, 2004.

[141] D. Caragea, J. Pathak, and V. Honavar. “Learning Classifiers from Semantically Heterogeneous Data Sources,” Proc of the 3rd International Conference on Ontologies, DataBases, and Applications of Semantics for Large Scale Information Systems, 2004.

[142] S. Ceri, S. Navathe, and G. Wiederhold, “Distribution Design of Logical Database Schemas,” IEEE Trans. on Software Engineering, 9(3):487–504, 1983.

[143] F. Baader, D. Calvanese, D. McGuinness, D. Nardi, and P. Patel-Schneider, “The Description Logic Handbook,” Cambridge University Press, 2003.

[144] S Franklin and A. Graesser, “Is it an Agent, or just a Program? A Taxonomy for Autonomous Agents,” Proc of the 3rd International Workshop on Agent Theories, Architectures, and Languages, Springer-Verlag, 1996.

[145] M.J. Wooldridge and N.R. Jennings, “Intelligent agents: theory and practice,” The Knowledge Engineering Review, vol. 10-2, pp. 115-152, 1995.

[146] Z. Zhang, V. Vishwanathan, J. McCalley, “A Multiagent Security-Economy Decision Support Infrastructure for Deregulated Electric Power Systems,” Proc of 2002 Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Naples, Italy, 2002

[147] V. Vishwanathan, V. Ganugula, J. McCalley, and V. Honavar, “A multiagent systems approach for managing dynamic information and decisions in competitive electric power systems,” Proc. of the 2000 North American Power Symposium, Oct. 2000, Waterloo, Ontario

[148] V. Vishwanathan, J. McCalley, and V. Honavar, “A Multiagent Infrastructure and Negotiation Framework for Electric Power Systems,” Power Tech Proceedings, 2001 IEEE Porto, Vol. 1, 2001 pp. 438 –443

[149] R. Gray, D. Kotz, G. Cybenko, D. Rus, "Mobile Agents: Motivations and State-of-the-Art Systems," Dartmouth Technical Report TR2000-365, April 2000, This technical report will appear as a chapter in

Jeffrey M. Bradshaw, editor, Handbook of Agent Technology, AAAI/MIT Press, 2000. Available at: ftp://ftp.cs.dartmouth.edu/TR/TR2000-365.ps.Z
[150] Silva, G. Soares, P. Martins, V. Batista, L. Santos, "Comparing the Performance of Mobile Agent Systems: A Study of Benchmarking," Journal of Computer Communications, Special Issue on "Mobile Agents for Telecommunication Applications", Vol. 23, Issue 8, April 2000.
[151] J. Kiniry, D. Zimmerman, "A hands-on look at Java mobile agents," IEEE Internet Computing, Vol. 1 Issue: 4, July-Aug. 1997, pp. 21 –30.
[152] http://www.trl.ibm.co.jp/aglets/.
[153] http://www.meitca.com/HSL/Projects/Concordia/.
[154] http://www.cs.dartmouth.edu/~agent/agent2.0/
[155] http://www.ececs.uc.edu/~abaker/JAFMS
[156] http://cdr.stanford.edu/ABE/JavaAgent.html
[157] http://www.JumpingBeans.com/
[158] http://www.genmagic.com/technology/odyssey.html
[159] http://www.recursionsw.com/
[160] V. Vishwanathan, "Multiagent system applications to electric power systems: Negotiation models for automated security-economy decisions," M.S. thesis, Dept. Elec. and Comp. Eng., Iowa State Univ., Ames, 2001.
[161] Lind, Jürgen, "Iterative software engineering for multiagent systems – The MASSIVE Method," in "Lecture notes in Artificial Intelligence," Springer-Verlag, Berlin, 2001.
[162] M. Wooldridge, N.R. Jennings, D. Kinny, "The Gaia Methodology for Agent-Oriented Analysis and Design," Journal of Autonomous Agents and Multi-Agent System, 3(3), pp 285-312, 2000.
[163] M. F. Wood, and S. A. DeLoach, "An Overview of the Multiagent Systems Engineering Methodology," Proc of the 1st Internatioanl Workshop on Agent-Oriented Software Engineering, 2000, pp 207 – 221.
[164] M. R. Genereth, and S. P. Ketchpel, "Software Agents," Communications of the ACM, 37 (7), pp 48-53, 1994.
[165] FIPA, Foundation of Intelligent Physical Agents (FIPA) specifications available at: http://www.fipa.org
[166] Concordia: http://www.meitca.com/HSL/Projects/Concordia/
[167] Aglets: http://www.trl.ibm.co.jp/aglets/
[168] J. Wong, G. Helmer, V. Naganathan, S. Polavarapu, V. Honavar, and L. Miller, "SMART Mobile Agent Facility," Journal of Systems and Software, Vol. 56. pp. 9-22.
[169] S. McArthur; C. Booth, J. McDonald, I. McFadyen, "An Agent-Based Anomaly Detection Architecture for Condition Monitoring," IEEE Trans. on Pwr Sys, Vol. 20, Issue 4, Nov. 2005, pp. 1675 – 1682.
[170] S. McArthur, S. Strachan, G. Jahn, "The design of a multi-agent transformer condition monitoring system," IEEE Trans. on Pwr. Sys, Vol. 19, Issue 4, Nov. 2004, pp. 1845 – 1852.
[171] S. McArthur, V. Catterson, "Multi-agent systems for condition monitoring," Proc. of the 2005 IEEE Power Engineering Society General Meeting, June 12-16, 2005, pp. 1499 – 1502.
[172] V. Catterson, S. McArthur, "The practical implications of bringing a multi-agent transformer condition monitoring system on-line," Proc of 2004 IEEE/PES Power Systems Conference and Exposition, Oct. 10-13, 2004, pp. 12 - 16 vol.1.
[173] M. Barbuceanu, and M. S. Fox, "COOL: A language for describing coordination in multiagent domains," Proc of the 1st International Conference on Multi-agent systems, AAAI Press / MIT Press, 1999, pp. 17-24.
[174] R. Smith, "The Contract Net Protocol: High Level Communication and Control in a Distributed Problem Solver," IEEE Trans. on Computers, Vol. C-29, No. 12, pages 1104-1113, 1980.
[175] R. Smith, and R. Davis, "Negotiation as a metaphor for distributed problem solving," Artificial Intelligence 20, pp 60-109, 1983.
[176] B. Sparling, "Transformer Monitoring: Moving Forward from Monitoring to Diagnostics," Proc of 2001 IEEE/PES Transmission and Distribution Conference and Exposition Vol. 2, 2001, pp. 960-963.