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Condition-based hazard rate estimation and optimal maintenance scheduling for electrical transmission system

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Table of Contents

Chapter 1 Introduction 1
1.1 Research Motivation and Objective 1
1.2 Background of research 2
1.3 Contents of the dissertation 4
Chapter 2 Failure modes, maintenance and monitoring of power transformers 5
2.1 Transformer Failure Modes and corresponding maintenance 5
2.1.1 Definition and cost of transformer failures 5
2.1.2 Transformer Failure Modes and Mechanisms 6
2.2 Typical maintenance activities 10
2.3 Condition monitoring techniques for transformer failures 11
2.3.1 Operating Condition Monitoring 12
2.3.2 Temperature Monitoring 13
2.3.3 Dissolved Gas-in-oil Analysis 13
2.3.4 Moisture-In-Oil Monitoring 15
2.3.5 Partial Discharge Monitoring 16
Chapter 3 Transformer Failure Modes and Failure Probability 19
3.1 Introduction 19
3.2 Definition of instantaneous failure probability 20
3.3 Overview of hazard rate estimation 22
3.3.1 Failure based estimation 22
3.3.2 Loading condition based estimation: Hottest-spot Temperature Model 25
3.3.3 Condition based hazard rate estimation 27
3.3.4 Hazard rate and its reduction estimation based on Markov model 30
3.3.5 Hidden Markov Models 33
3.4 Application of Hidden Markov model in hazard rate estimation 40
3.4.1 Estimation based on DGA data 40
3.4.2 Estimation based on score system (health index) 51
3.5 Bayesian Updating 55
Chapter 4 Mid-Term Maintenance scheduling 57
4.1 Introduction of Maintenance Asset Management 57
4.1.1 Asset management in electrical transmission system 57
4.1.2 Current maintenance scheduling methods 58
4.1.3 Maintenance scheduling in different time horizons 61
4.1.4 Structure of the Mid-term maintenance scheduling 63
4.2 Risk assessment of electrical system 64
4.2.1 Computation of risk 64
4.2.2 Modeling of severity 65
4.3 Risk based long term simulation 66
4.3.1 System severity 67
4.3.2 Component severity function 71
4.3.3 Components modeled in the simulation 73
4.3.4 Speed enhancement 74
4.4 Quantification of maintenance benefits- Risk reduction calculation 76

4.4.1 Risk reduction due to hazard rate decrease 77
4.4.2 Risk reduction due to life extension 80
4.4.3 Risk variation caused by the maintenance 80
4.5 Optimization 81
4.5.1 Objective function and constraints..81
4.5.2 Security impact due to maintenance scheduling 83
4.5.3 Relaxed linear programming with dynamic programming 83
4.5.4 Discussion of optimality of the algorithm..86
4.6 Incorporation of long-term and mid-term maintenance..89
4.7 Results...93
4.7.1 Description of contingencies and maintenance activities 94
4.7.2 Hazard rate determination and effect of maintenance......................................95
4.7.3 Maintenance activities..97
4.7.4 Description of results 98
4.7.5 Risk reduction with maintenance 100
4.7.6 Maintenance task pre-selection 101
4.7.7 Maximum risk reduction with budget and labor constraints...........................102
4.7.8 Optimality of our program 105
4.7.9 Optimization results with different resource allocations...............................107
4.7.10 Continuously scheduling maintenance activities with "rolling" procedure..112
4.7.11 Resource reallocation based on Lagrange Multipliers 114
4.7.11 Effect of constraints on optimization results...117
4.7.12 Decision making on resource scheduling and allocation 125
4.8 Maintenance scheduling coordination between transmission owners 128
Chapter 5 Conclusion...132
Appendix 1: Transformer Failure modes, causes, effects and maintenance activities 136
Appendix 2: Proposed transmission component maintenance tasks 138
Reference 141

List of Tables

TABLE 2.1: NUMBER AND COSTS OF POWER TRANSFORMERS FAILURES BY YEAR 6
TABLE 2.2: KEY GAS INTERPRETATION 15
TABLE 2.3: FAILURE MODES OF TRANSFORMER AND CORRESPONDING CONDITION MONITORING TECHNIQUE AND MAINTENANCE ACTIVITIES 18
TABLE 3.1: DETERMINE TRANSFORMER CONDITION BASED ON DGA (IEEE STD. C57.104-1991) 41
TABLE 3.2: DGA TEST DATA FOR TRANSFORMER 42
TABLE 3.3: ESTIMATED TRANSITION INTENSITIES FOR MARKOV MODEL 42
TABLE 3.4: COMPARISON OF OBSERVATION AND FORECAST. 42
TABLE 3.5: FIRST PASSAGE TIME FOR EACH STATE 43
TABLE 3.6: TRANSITION RATE OF DIFFERENT STATES FOR TRANSFORMER INSULATION DETERIORATION 45
TABLE 3.7: FIRST PASSAGE TIME BETWEEN DIFFERENT STATES 46
TABLE 3.8: MEAN VALUE AND CONFIDENCE INTERVAL OF FIRST PASSAGE TIME BETWEEN DIFFERENT STATES 50
TABLE 3.9: INSPECTION FORM FOR POWER TRANSFORMER 52
TABLE 3.10: NORMALIZATION FOR CRITERION 'AGE' 52
TABLE 3.11: INSPECTION TIMES AND CONDITION INFORMATION REFLECTED BY THE INSPECTION 53
TABLE 3.12: INSPECTION RESULTS AND WEIGHTED AVERAGE SCORE FOR TRANSFORMER........ 53
TABLE 3.13: MARKOV MODEL LEVEL CRITERION BASED ON WEIGHTED AVERAGE SCORE........ 54
TABLE 3.14: TRANSITION RATE AND FIRST PASSAGE TIME OF TRANSFORMER BASED ON SCORE RANKING SYSTEM 54
TABLE 4.1: EXAMPLE OF INCREMENTAL COST OF MACHINE WITH THE INCREASE OF THE OUTPUT 68
TABLE 4.2: SYSTEM SEVERITY SCALING FACTORS 72
TABLE 4.3: FAILURE MODES AND CORRESPONDING MAINTENANCE ACTIVITIES 73
TABLE 4.4: HIGHEST-RISK CONTINGENCIES FOR OVERLOAD RISK AT DIFFERENT LOAD LEVELS 99
TABLE 4.5 SELECTED TRANSFORMER MINOR MAINTENANCE TASKS AND OPTIMAL MAINTENANCE INTERVALS 102
TABLE 4.6: CONSTRAINTS FOR MAINTENANCE SCHEDULING 103
TABLE 4.7: TRANSMISSION MAINTENANCE SCHEDULE 103
TABLE 4.8: CASES WITH DIFFERENT RESOURCE ALLOCATION 107
TABLE 4.9: COMPARISON OF RESULTS BETWEEN RLP-DPH AND CPLEX 107
TABLE 4.10 QUARTERLY PERFORMANCE OF MAINTENANCE ACTIVITIES 110
TABLE 4.11 QUARTERLY PERFORMANCE OF MAINTENANCE SCHEDULING WITH "ROLLING" PROCEDURE 113
TABLE 4.12: RESOURCE ALLOCATION AMONG MAINTENANCE CATEGORIES......................... 116
TABLE 4.13: REALLOCATION OF RESOURCES BASED ON LAGRANGE MULTIPLIERS................. 116
TABLE 4.14: LABOR LEVEL FOR BUDGET VARIATION 118
TABLE 4.15: INDICES CALCULATED FROM DIFFERENT BUDGET SETTINGS 118
TABLE 4.16: BUDGET LEVEL FOR LABOR VARIATION 122
TABLE 4.17: INDICES CALCULATED FROM DIFFERENT LABOR SETTINGS............................. 123
TABLE 4.18 EXAMPLE OF MAINTENANCE OUTAGE SCHEDULING 130

List of Figures

FIG. 1.1: MAINTENANCE APPROACH OVERVIEW 3
FIG. 3.1: PROBABILITY OF FAILURE CAUSED BY AGING AND DETERIORATION 20
FIG. 3.2: RELATIONSHIPS BETWEEN H(T), F(T), AND R(T) 22
FIG. 3.3: BATHTUB CURVE 24
FIG. 3.4: WEIBULL DISTRIBUTIONS 25
FIG. 3.5: POSSIBLE SHAPES FOR UNIVARIABLE DEGRADATION CURVES. 28
FIG. 3.6: MAINTENANCE-INDUCED IMPROVEMENTS IN FAILURE PROBABILITY AND TIME 29
FIG. 3.7: COMPUTING CONTINGENCY PROBABILITY REDUCTIONS 30
FIG. 3.8: EXAMPLE OF HIDDEN MARKOV MODEL 34
FIG. 3.9: HAZARD RATE OF TRANSFORMER OIL DETERIORATION 43
FIG. 3.10: NORMAL PROBABILITY PLOT FOR FIRST PASSAGE TIMES 48
FIG. 3.11: LOGNORMAL PROBABILITY PLOT FOR FIRST PASSAGE TIMES 48
FIG. 3.12: WEIBULL PROBABILITY PLOT FOR FIRST PASSAGE TIMES 489
FIG. 3.13: EXPONENTIAL PROBABILITY PLOT FOR FIRST PASSAGE TIMES 49
FIG. 3.14: LOGISTIC PROBABILITY PLOT FOR FIRST PASSAGE TIMES 49
FIG. 3.15: LOG-LOGISTIC PROBABILITY PLOT FOR FIRST PASSAGE TIMES 50
FIG. 3.16: HAZARD RATE OF TRANSFORMER INSULATION DETERIORATION WITH SCORE RANKING SYSTEM 54
FIG. 4.1: CLASSIFICATION OF MAINTENANCE 59
FIG. 4.2: TRANSMISSION MAINTENANCE INCORPORATION FOR DIFFERENT TIME SCALES 62
FIG. 4.3: INTEGRATED MAINTENANCE SCHEDULER (IMS) 63
FIG. 4.4: ILLUSTRATION OF RISK CALCULATION FOR A GIVEN OPERATING CONDITION 64
FIG. 4.5: PIECEWISE LINEAR COST FUNCTIONS 68
FIG. 4.6: SIMULATION MODEL FOR LONG-TERM MAINTENANCE PLANNING 90
FIG. 4.7: INTEGRATION OF DATA PROCESS, LONG-TERM MAINTENANCE AND MID-TERM MAINTENANCE 92
FIG. 4.8: ONE YEAR LOADING TRAJECTORY OF TESTING SYSTEM 93
FIG. 4.9: HAZARD RATE ASSUMED FOR TRANSFORMERS CORE PROBLEMS 96
FIG. 4.10: COMPOSITE SYSTEM RISK 98
FIG. 4.11: YEARLY RISKS OF CONTINGENCY 66 100
FIG. 4.12: YEARLY RISKS OF CONTINGENCY 21 100
FIG. 4.13: RISK REDUCTION OF CONTINGENCY 66 100
FIG. 4.14: RISK REDUCTION OF CONTINGENCY 21 100
FIG 4.15: YEARLY OPERATION COST VS. MAINTENANCE INTERVAL OF OIL FILTERING 101
FIG 4.16: QUARTERLY ALLOCATED CRR AND RESOURCE ALLOCATION FOR CASE B 1018
FIG 4.17: QUARTERLY ALLOCATED CRR AND RESOURCE ALLOCATION FOR CASE C 1018
FIG 4.18: QUARTERLY ALLOCATED CRR AND RESOURCE ALLOCATION FOR CASE D 1019
FIG 4.19: QUARTERLY ALLOCATED CRR AND RESOURCE ALLOCATION FOR CASE E 10109
FIG 4.20: QUARTERLY ALLOCATED CRR AND RESOURCE ALLOCATION FOR CASE F 10110
FIG 4.21: QUARTERLY CRR AND RESOURCE ALLOCATION FOR CASE A WITH "ROLLING" PROCEDURE 114
FIG. 4.21: CUMULATIVE RISK REDUCTION 12121

FIG. 4.22: CRR/COST 12121
FIG. 4.23: CRR/LABOR USED 12121
FIG. 4.24: COST/BUDGET 12121
FIG. 4.25: CRR/POSSIBLE CRR 1211
FIG. 4.26: LABOR USAGE 1211
FIG. 4.27: UNSCHEDULED MAINTENANCE 1222
FIG. 4.28: CUMULATIVE RISK REDUCTION 1244
FIG. 4.29: CRR/COST 1244
FIG. 4.30: CRR/LABOR 1244
FIG. 4.31: COST/BUDGET RATIO 1244
FIG. 4.32: LABOR USAGE 1255
FIG. 4.33: CRR/POSSIBLE CRR 1255
FIG. 4.34: UNSCHEDULED MAINTENANCE 1255
FIG. 4.35: CRR SURFACE WITH DIFFERENT RESOURCE CONDITIONS 1266
FIG. 4.36: EFFICIENCY RATIO WITH DIFFERENT RESOURCE ALLOCATIONS 1288
FIG. 4.37: FLOWCHART OF MAINTENANCE OUTAGE COORDINATION 13030

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Chapter 1 Introduction

1.1 Research Motivation and Objective

In the United States and many parts of the world, the trend toward a deregulated electricity market has put the utilities under severe stress to reduce operation and maintenance (O&M) costs in order to maximize returns and stay ahead of competition. Maintenance of transmission system, which may cost more than 40% of the total budget of the operating expenses [1], can be among the first categories of improving efficiencies and lowering the budget. On the other hand, the reliability of power system is still the most important factor of making maintenance schedules due to the tremendous amount of cost of blackouts. The traditional scheduling method is mainly based on conservative deterministic security assessment, by emphasizing the most severe, credible event [2]. However, under the pressure of market competition, 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 always 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.

Motivated by this requirement of industry, our objective in this research is to develop a method of allocating economic resources and scheduling maintenance tasks among bulk transmission system equipment so as to optimize the effect of maintenance with respect to the mitigation of component failure consequences. My work mainly includes the following parts:

1. Failure mode identification: Taxonomies are essential in identifying the effects of maintenance tasks on hazard rates. Taxonomies of failure modes associated with power transformers together with maintenance tasks that address those failure modes are provided.
2. Hazard rate estimation: Hazard rates and time-to-failure reductions from each maintenance task are used in optimizing resources. Methods have been developed, to

estimate probabilistic indices such as hazard rate and time to failure for power transformers, 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 hazard rate and time to failure for each component.

3. Risk reduction from expected redispatch costs: I 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 period such as a year. For each hour, the simulator evaluates each contingency in terms of the cost of redispatch necessary to eliminate violations of reliability criteria. These costs, when multiplied by contingency probability, provide the expected contingency cost, or risk, for the hour, and summed over the time period (e.g., year) provides the expected contingency cost, or risk, for the year. The effect of a specified maintenance task can be quantified based on the amount of risk cumulative reduction obtained from it.
4. Midterm 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.

1.2 Background of research

The effectiveness of 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: (1) time based maintenance (TBM) or scheduled 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; (2) condition-based maintenance (CBM) initiates a maintenance activity when data from monitoring the equipment indicates a need; (3) 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 [3].

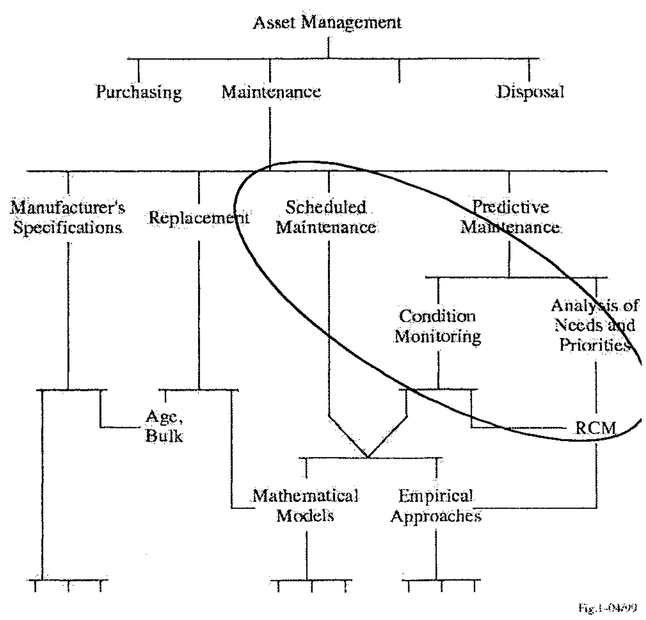

Fig. 1.1: Maintenance approach overview

In the context of deregulated electrical market, equipment monitoring has attracted considerable attention in the past decades. By monitoring of important functions of those equipments, developing faults can be detected before costly outages and/or equipment failures occur, thus cost saving can be realized through a delay in the procurement of transformers and reduction in maintenance effort. However, the high investment of condition monitoring equipment forbids its application on all equipments in transmission system. Reliability centered maintenance, on the other hand, is more practical since it 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.

In this thesis, new technologies are introduced to develop a system wide maintenance allocation and scheduling system based on automated integration of condition monitoring with an RCM-based optimized scheduler for transmission components. This framework will help utilities to reduce 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 personnel, the public, and the environment.

In order to limit the work to what can be accomplished within the designated duration, I focused my research of failure mode analysis and hazard rate estimation on transformers since it is the most important and expensive components in the transmission system. Furthermore its failure can have significant system reliability impact and the cost. Besides, the analytic models and procedures for using conditions of the monitored equipment in decision making related to a maintenance allocation and scheduling function based on transformers can be used on other types of equipments.

1.3 Contents of the dissertation

In this thesis, chapter 2 introduces the failure modes, maintenance activities, and condition monitoring techniques for transformers. Chapter 3 compares the methods of linking transformer condition monitoring information to the time-dependent failure probability. A hazard rate estimation method based on hidden Markov model (HMM) with condition monitoring data is also introduced. Chapter 4 presents the system risk simulator based on dispatch cost due to the contingencies. Mid-term maintenance scheduling problem is formulated and optimization technique to solve the high-dimensional integer programming problem is investigated and applied to a US utility system. In chapter 5, conclusions and suggestions for future work are presented.

Chapter 2 Failure modes, maintenance and 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 [4].

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 [5]:

- 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 [5]. Reference [6] 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 decreasing or constant failure probability over the transformers lifetime and maintenance cannot reduce the failure probability. In this 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 probability. 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 transformers 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 [7]. 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.

Generally, insulation deterioration is a mixed, complicated physical-chemical process that it is difficult to simulate with a laboratory model. As a result, the gases produced in this process, have been used as the most common criteria in judging the severity of the deterioration.

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 buildup on the winding and may damage 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 [8]. 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 otherwise cause the paper insulation to fail. 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 probability 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 [9]. 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 [10]. 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 [11].

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

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:

1. 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:

   - Remove oxygen and other gases from transformer or LTC oil.
   - Reduce the acid and moisture contents in the transformer or LTC oil
   - 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.

2. Mechanical maintenance

Maintenance of mechanical parts of transformer includes the following activities:

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

Appendix 1 summarizes typical failure modes, causes, effects as well as corresponding maintenance activities for power 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 [12]:

(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). I review some of these forms in the following five subsections [13, 14, 15].

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 [16]. 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 usually key to a transformer owner's loss prevention program [17].

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 [18].

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 [7]. 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 [13].

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 [18]. 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 [7].

TABLE 2.2: KEY GAS INTERPRETATION

Key Gas	Characteristic Fault
H_2	Partial Discharge
C_2H_6	Thermal Fault $< 300°C$
C_2H_4	Thermal Fault $300°C - 700°C$
C_2H_2, C_2H_4	Thermal Fault $> 700°C$
C_2H_2, H_2	Arcing

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.

2.3.5 Partial Discharge Monitoring

Partial Discharge (PD) is an electrical discharge that only partially bridges the insulation between conductors as introduced in 2.1.2.4. PD 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 PD. 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 PD activity. A significant increase either in the PD level or in the rate of increase of PD level can provide an early indication that changes are evolving inside the transformer. Since PD can deteriorate into complete breakdown, it is desirable to monitor this parameter on-line. PD 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 PD 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 [19] describes the instrumentation, test procedures, and results interpretation for the acoustic emissions detection of PD 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 PD Analysis (PRPDA [20]). 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 [21]. Also for each condition monitoring technique, the feasibility of online monitoring is listed.

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 DGA analysis, 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	P (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

Chapter 3 Transformer Failure Modes and Failure Probability

3.1 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. The power transformer is a critical and capital intensive asset within a power system. Due to the limited capital investment for new facilities, many transformers are close to or beyond their designed life. As transformers age beyond their expected life, there is a risk of an increasing number of catastrophic transformer 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 [22], six types of patterns are given that represent most kinds of aging and deterioration, as shown in Fig. 3.1. Pattern A is the well-known bathtub curve. It begins with a high incidence of failure (known as infant mortality) followed by a constant or gradually increasing failure probability, then by a wear-out zone. Pattern B shows constant or slowly increasing failure probability, ending in a wear-out zone. Pattern C shows slowly increasing failure probability, but there is no identifiable wear-out age. Pattern D shows low failure probability when the item is new, then a rapid increase to a constant level, while pattern E shows a constant failure probability at all ages. Pattern F starts with high infant mortality, which drops eventually to a constant or very slowly increasing failure probability. For a random failure, the failure probability in any short time interval, assuming that the device has been working up to that time, is constant. The time until failure is exponentially distributed and the hazard rate has the same shape of Pattern E. 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.

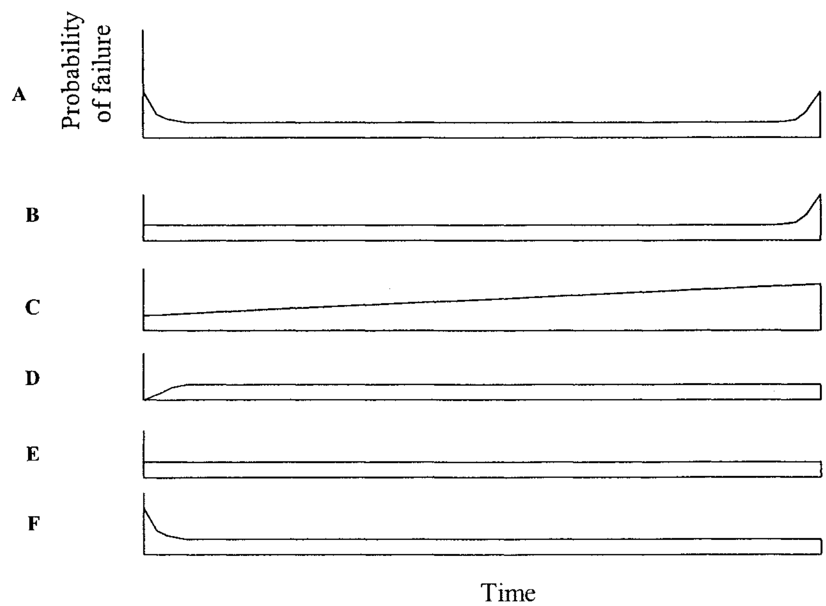

Fig. 3.1: Probability of failure caused by aging and deterioration

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.

3.2 Definition of instantaneous failure probability

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, I will present models for linking the transformer condition monitoring information to its time-dependent failure probability. I 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) $F(t) = \Pr(T \leq t)$, or the probability density function $f(t) = dF(t)/dt$. The probability density function $f(t)$ may be expressed as:

$$f(t) \approx \frac{P(t < T \leq t + \Delta t)}{\Delta t} \tag{3.1}$$

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:

$$R(t) = \Pr(T > t) = \int_t^{\infty} f(\tau) d\tau \tag{3.2}$$

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

$$h(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} \Pr[t < T \leq t + \Delta t \mid T > t] \tag{3.3}$$

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. 3.2 [23].

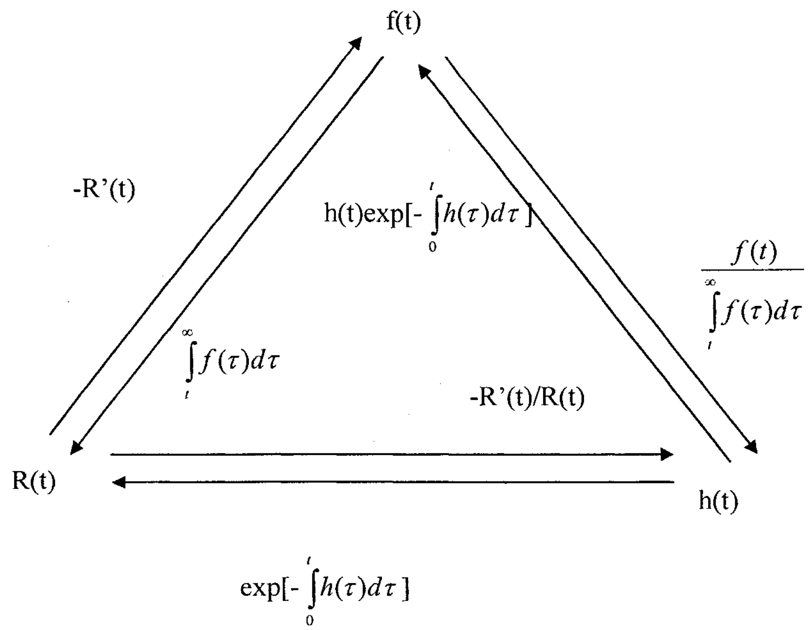

Fig. 3.2: Relationships between h(t), f(t), and R(t)

3.3 Overview of hazard rate estimation

Methods of estimating the proximity of equipment to failure usually depend on available data. Based on the available data source of the hazard rate estimation, we can classify the methods of hazard rate estimation into the following categories: 1) Failure based estimation; 2) Loading based estimation and 3) Condition based estimation.

3.3.1 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.

3.3.1.1 Non-Parametric Hazard Function Model

The most direct way of estimating hazard 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 hazard rate in [24]. 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 $[t_i, t_{i+1})$ [1], 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:

$$N_{i+1} = N_i - F_i - C_i \tag{3.4}$$

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:

$$t_{ij} = \begin{cases} t_{ijf}, & \textit{if jth transformer is observed to fail} \\ t_{ijc}, & \textit{if jth transformer is removed (censored)} \\ t_{i+1}, & \textit{if jth transformer survives till } t_{i+1} \end{cases} \tag{3.5}$$

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

$$TR_i = \sum_{j=1}^{N_i} (t_{ij} - t_i) \tag{3.6}$$

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

$$\tilde{h}_i = F_i / TR_i \tag{3.7}$$

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 hazard rate in $[t_i, t_{i+1})$ can take the form:

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

$$\hat{h}_i = \frac{F_i}{(t_{i+1} - t_i)(N_i - (F_i - C_i)/2)} \tag{3.8}$$

Although expression (3.8) is not as precise as (3.7), it is more precise than the estimation frequently use in engineering applications for the hazard rate:

$$\bar{h}_i = F_i / [(t_{i+1} - t_i) N_i] \tag{3.9}$$

With reasonably precise recordings of the failure or removal times of the transformers, we can use equations (3.7) or (3.8) to estimate the time-dependent hazard rate, h_i, as illustrated in Figure 3.3.

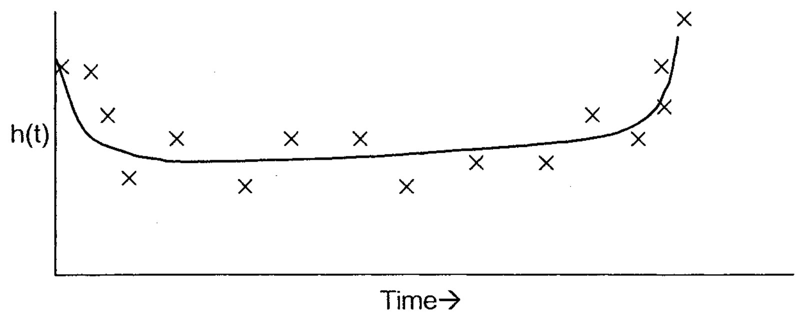

Fig. 3.3: Bathtub Curve

3.3.1.2 Parametric Hazard Function Model

The parametric estimation method [25] requires an assumption that the failure times due to 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:

$$f_T(t) = \begin{cases} \dfrac{\beta t^{\beta-1}}{\alpha^\beta} \exp\left[-\left(\dfrac{t}{\alpha}\right)^\beta \right], & t, \alpha, \beta > 0 \\ \\ 0, & otherwise \end{cases} \tag{3.10}$$

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 3.4 illustrates this feature by appropriately varying the shape and scale parameters.

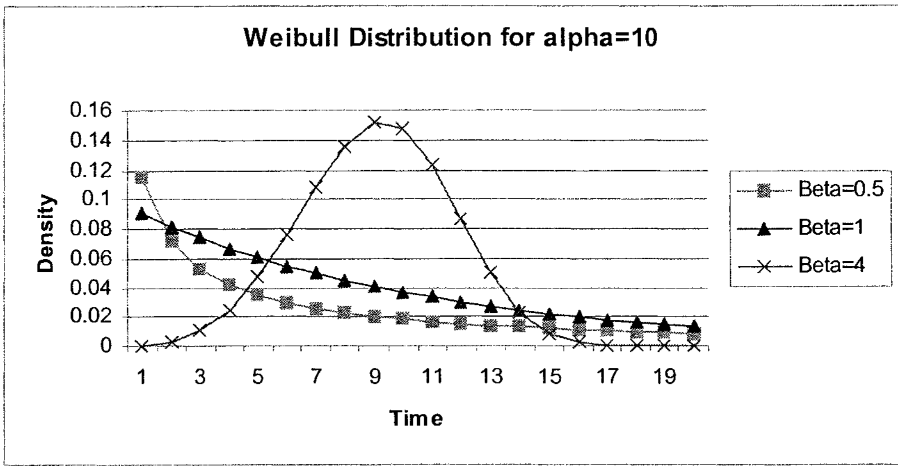

Fig. 3.4: Weibull Distributions

The Weibull hazard function is:

$$h(t) = \frac{\beta\, t^{\beta-1}}{\alpha^{\beta}}, \quad t > 0 \tag{3.11}$$

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

References [26, 27] report investigations into the feasibility of representing hazard 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 hazard rate (hazard function, h_i) has been shown to follow the so called "bathtub curve", as shown in Fig 3.3. The bathtub curve depicts equipment life in three stages. During the first stage, hazard rate begins high and decreases rapidly with time. This stage is known as the infant-mortality period, and it has decreasing hazard rate. The infant mortality is followed by nearly constant hazard rate period, which usually lasts for the longest period of time. Finally, the curve ends with an increasing hazard 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.

3.3.2 Loading condition based estimation: Hottest-spot Temperature Model

Loading information was first used to estimate the remaining life of transformer [28, 29].

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 [30]. 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:

$$\text{Per unit life} = 9.80\times 10^{-18} Exp(\frac{15000}{\Theta_H + 273}) \tag{3.12}$$

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 θ_u over ambient temperature is computed as:

$$\theta_u = \theta_{fl}(\frac{K^2+1}{R+1})^n; \qquad K = \frac{S}{S_{rated}} \tag{3.13}$$

where θ_{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:

$$\theta_0(t) = \theta_u(1-e^{-t/\tau_0}) + \theta_i e^{-t/\tau_0} \tag{3.14}$$

where τ_0 is oil thermal time constant for rated load, and θ_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:

$$\theta_g(t) = \theta_{g(fl)}K^{2m} \tag{3.15}$$

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

$$\theta_{hst}(t) = \theta_0(t) + \theta_g(t) + \theta_a(t) \tag{3.16}$$

where $\theta_0(t)$ is the ambient temperature. If the initial top oil temperature θ_i is unknown, then it can be estimated base on the knowledge of load cycle information using an iterative method [29]. And then the life expectation of transformer, with respect to the cellular decomposition, can be computed.

3.3.3 Condition based hazard rate estimation

Since power transformers are crucial and expensive equipment in transmission systems, they usually are well maintained and consequently have very high reliability. So in reality transformer 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. In this section, I will briefly describe a traditional degradation model to use such data to develop instantaneous hazard 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 [25]. 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.

3.3.3.1 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 3.5 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 [31] 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.

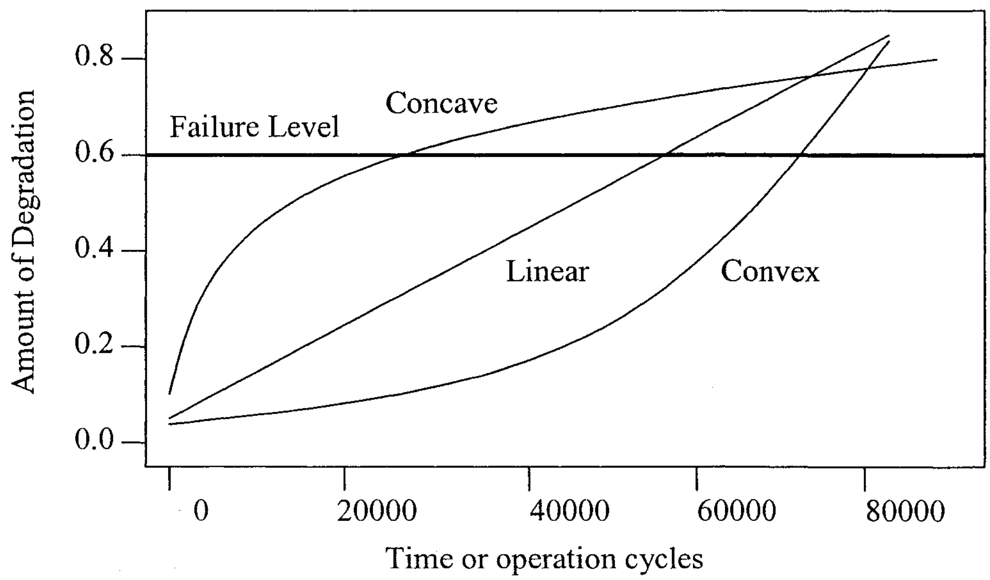

Fig. 3.5: Possible shapes for univariate degradation curves.

3.3.3.2 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. 3.6. In Fig. 3.6 we observe that there are 4 deterioration levels corresponding to four different hazard 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.

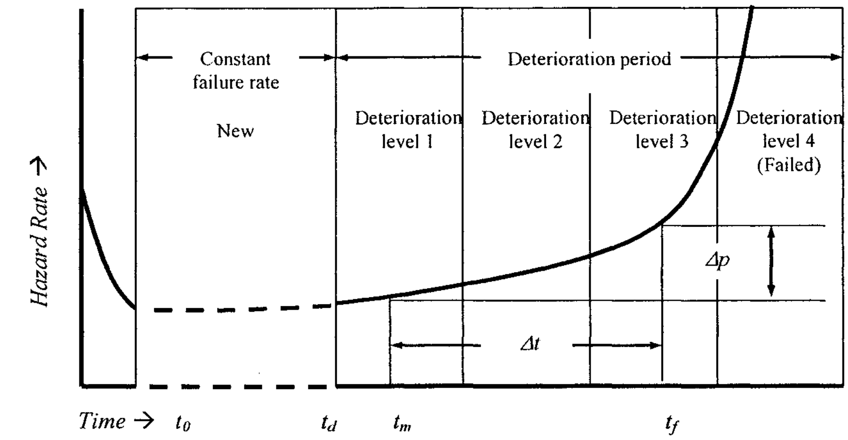

Fig. 3.6: Maintenance-induced improvements in failure probability and time

3.3.3.3 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. A method based on Markov model [32, 33] was found to be more attractive in our study. This method uses a multi-state Markov model [34] adapted from [35] to compute hazard rates from condition measurements.

Markov models provide an elegant and effective means of representing certain kinds of so-called "memory-less[2]" 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

[2] 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.

states and thus calculate time to failure from each state, and also the benefit from maintenance, which is the hazard rate reduction or the life extension of the transformer. This model, illustrated in Fig. 3.7, is more fully described in section 3.4.

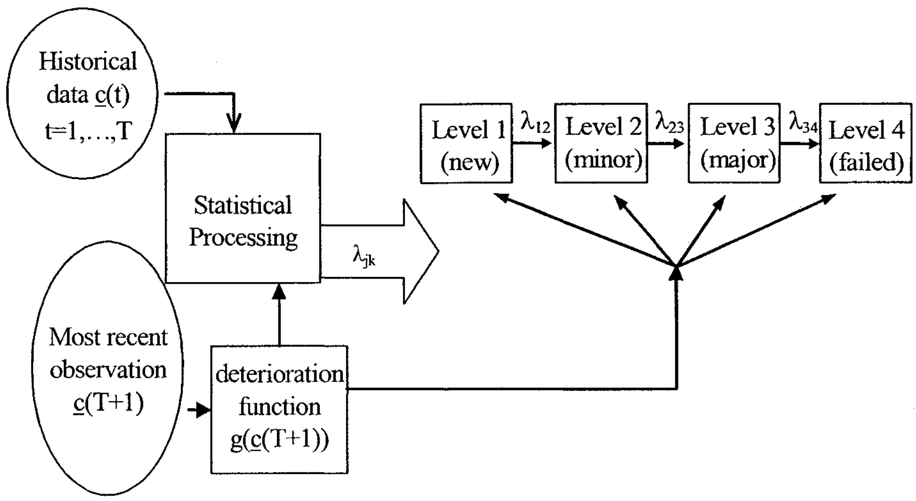

Fig. 3.7: Computing Contingency Probability Reductions

3.3.4 Hazard rate and its reduction estimation based on Markov model

Referring to the Markov model in Fig. 3.8, we assume that we have at our disposal a set of condition vectors $\underline{c}(t)=[\underline{c}_1(t),\underline{c}_2(t),...,\underline{c}_K(t)]$ for K similar components taken over an extended period of time $t=0,1,...,T$, where each vector $\underline{c}_k(t)$ provides M different measurements $c_{k1}(t)$, $c_{k2}(t),...c_{kM}(t)$, 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. 3.7 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. 3.7, 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 [36] 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. 3.7, λ_{12}, λ_{23}, and λ_{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. 3.7 is given by eq. (3.17).

$$\underline{P}=\begin{bmatrix} 1-\lambda_2 & \lambda_2 & 0 & 0 \\ 0 & 1-\lambda_3 & \lambda_3 & 0 \\ 0 & 0 & 1-\lambda_4 & \lambda_4 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3.17}$$

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 $P(0)=[1 \quad 0 \quad 0 \quad 0]$. The probability of finding the component in any deterioration level at time hT is then given by

$$P(hT) = P(0) * \underline{P}^h \tag{3.18}$$

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 [37] and to calculate the first passage time to failure as:

$$T_f = P(0) \times T \times (I - P_r(T))^{-1} \tag{3.19}$$

where T_f is the vector of time to failure from different states, and $Pr(T)$ is a partition of the transition matrix $\underline{P}$ corresponding to non-failure states [38]. The life extension Δt_k is obtained by calculating difference of time to failure of the states before and after maintenance.

(e) Hazard 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. 3.6, the benefit comes mainly from the decrease of hazard rate, which results in a decrease in hazard rate Δp, but for maintenance performed during the constant hazard 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. 3.6). 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 [39]. For a 4-level model in Fig. 3.8, 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, $\Delta p(m,k)$, is given by the last element of the 1×4 row vector resulting from the calculation:

$$[1 \quad 0 \quad 0 \quad 0]\underline{P} - [0 \quad 0 \quad 1 \quad 0]\underline{P} = [1 \quad 0 \quad -1 \quad 0]\underline{P} \tag{3.20}$$

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 [40]. Decreasing clearance intervals are assigned as discrete condition levels to conform to the model of Fig. 3.8, 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 [41].

3.3.5 Hidden Markov Models

The regular Markov model 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, I investigated the applicability of the hidden Markov model (HMM). While the component is in a particular state, the probability is characterized 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 [42]. As in Fig. 3.8, 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 $P(\text{'High'}|\text{'Low'})=0.7$, $P(\text{'Low'}|\text{'High'})=0.2$ 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. 3.8. However, there are some uncertainties of the relationship between the humidity and the pressure of air. The observation probabilities are: $P(\text{'Rain'}|\text{'Low'})=0.6$, $P(\text{'Dry'}|\text{'Low'})=0.4$, $P(\text{'Rain'}|\text{'High'})=0.4$, $P(\text{'Dry'}|\text{'High'})=0.3$.

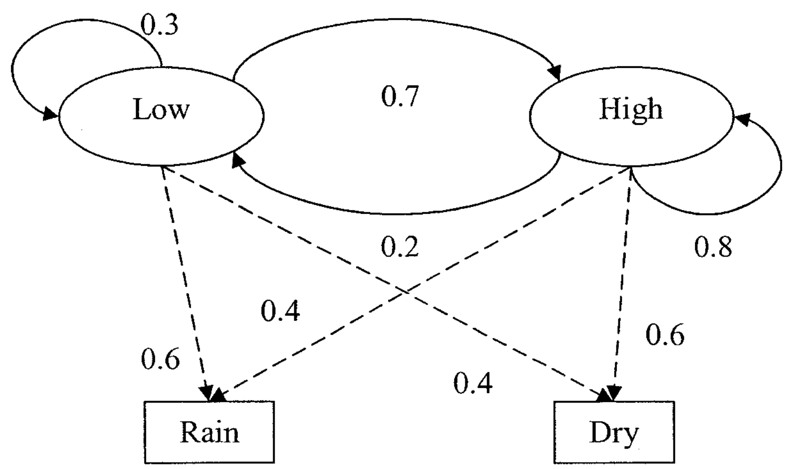

Fig. 3.8: Example of Hidden Markov Model

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 [43]. 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, I 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).

3.3.5.1 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 [44, 45, 46, 47] 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 [48] and acoustic vibration data [49]. I will use Hidden Markov model to investigate the hazard 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 $\theta = \{A, B, \pi\}$ 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 observation symbols. Here observation 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

$$a_{ij} = p\{q_{t+1} = j \mid q_t = i\}, \quad 1 \le i, j \le N \tag{3.21}$$

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

$$b_j(k) = p\{o_t = v_k \mid q_t = j\}, \quad 1 \le j \le N, \quad 1 \le k \le M \tag{3.22}$$

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 $\pi = \{\pi_i\}$, and defined by $\pi = p\{q_1 = i\} \quad 1 \le i \le N$. The parameter set $\theta = \{A, B, \pi\}$ is what we are going to estimate and the method is introduced in the following section.

3.3.5.2 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, 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 $\theta = \{A, B, \pi\}$ to maximize the likelihood of observation $L_{tot} = p(O \mid \theta)$. 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 of transformation of the data.

There have been well-developed methods of doing this, like Baum-Welch Algorithm (also known as forward-backward algorithm) [50]. 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. It can be explained into two-step procedures:

1. Transform the objective function $p(O \mid \theta)$ into a new function $F(\theta, \theta')$ that measures a divergence between the initial model θ and upgraded model of θ'.
2. Maximize the function $F(\theta, \theta')$ over θ' to improve θ in the sense of increasing the likelihood $p(O \mid \theta)$.

3. Continues by replacing θ with θ' and repeating the two steps above until some stopping criteria is met.

The following paragraphs give a detail 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 in our study. 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 $A=\{a_{ij}\}$

$$a_{ij} = p\{q_{t+1} = j \mid q_t = i\}, \quad 1 \le i, j \le N \tag{3.23}$$

where q_t denotes the current state.

We also have probability getting an observation with a symbol under specific state. $B=\{b_j(k)\}$

$$b_j(k) = p\{o_t = v_k \mid q_t = j\}, \quad 1 \le j \le N, \quad 1 \le k \le M \tag{3.24}$$

And so $\sum_{j=1}^{N} a_{ij} = 1 \quad 1 \le i \le N$ and $\sum_{k=1}^{M} b_j(k) = 1 \quad 1 \le j \le N$

And we also have the initial state distribution $\pi = \{\pi_i\}$, where $\pi_i = p\{q_1 = i\} \quad 1 \le i \le N$.

The parameter set $\{A, B, \pi\}$ here are values that need to be estimated and thus we can assume an initial value here. They will be updated during the training process. In the hidden Markov training, we need to define two auxiliary variables: 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.

$$\alpha_t(i) = p(o_1, o_2, o_3, \ldots, o_t, q_t = i \mid \theta) \tag{3.25}$$

Then we can derive

$$\alpha_{t+1}(j) = b_j(o_{t+1}) \sum_{i=1}^{N} \alpha_t(i) a_{ij} \qquad 1 \le j \le N, \qquad 1 \le t \le T-1 \tag{3.26}$$

$$\text{where } \alpha_1(j) = \pi_j b_j(o_1) \qquad 1 \le j \le N \tag{3.27}$$

So the required probability is given by

$$p(O \mid \theta) = \sum_{i=1}^{N} \alpha_T(i) \tag{3.28}$$

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.

$$\beta_t(i) = p(o_{t+1}, o_{t+2}, o_{t+3}, \ldots, o_T \mid q_t = i, \theta) \tag{3.29}$$

There is a recursive relationship too here:

$$\beta_t(i) = \sum_{j=1}^{N} \beta_{t+1}(j) a_{ij} b_j(o_{t+1}) \qquad 1 \le i \le N, \qquad 1 \le t \le T-1 \tag{3.30}$$

$$\text{Where} \quad \beta_T(i) = 1, \qquad 1 \le i \le N \tag{3.31}$$

Further we can see that

$$\alpha_t(i)\beta_t(i) = p\{O, q_t = i \mid \theta\} \qquad 1 \le i \le N \qquad 1 \le t \le T \tag{3.32}$$

And two more variables are needed in the calculation:

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

$$\varepsilon_t(i,j) = p\{q_t = i, q_{t+1} = j \mid O, \theta\} \tag{3.33}$$

It can be derived as

$$\begin{aligned} \varepsilon_t(i,j) &= \frac{p(o_1, \ldots, o_t, q_t = i \mid \lambda) * p(o_{t+1}, \ldots, o_T, q_{t+1} = j \mid q_t = i, \theta)}{p\{O \mid \theta\}} \\ &= \frac{\alpha_t(i) a_{ij} \beta_{t+1}(j) b_j(o_{t+1})}{\sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_t(i) a_{ij} \beta_{t+1}(j) b_j(o_{t+1})} \end{aligned} \tag{3.34}$$

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

$$\gamma_t(i) = p\{q_t = i \mid O, \theta\} \tag{3.35}$$

It is derived that

$$\gamma_t(i) = \frac{p(O, q_t = i \mid \theta)}{p\{O \mid \theta\}} = \frac{\alpha_t(i)\beta_1(i)}{\sum_{i=1}^{N} \alpha_t(i)\beta_1(i)} = \sum_{j=1}^{N} \varepsilon_t(i,j), \qquad 1 \le i \le N, 1 \le t \le M \tag{3.36}$$

With the assumed starting model $\theta = \{A, B, \pi\}$, we can start the training in the following way:

1) Use (3.26) and (3.30) to calculate the serial variable 'α's and 'β's.

2) Using (3.34) and (3.36) to update the HMM parameters:

$$\bar{\pi}_i = \gamma_1(i), \quad 1 \le i \le N \tag{3.37}$$

$$\bar{a}_{ij} = \frac{\sum_{t=1}^{T-1} \varepsilon_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)} \qquad 1 \le i \le N, \qquad 1 \le j \le N \tag{3.38}$$

$$\bar{b}_j(k) = \frac{\sum_{\substack{t=1 \\ O_t = v_k}}^{T} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(j)} \qquad 1 \le i \le N, \qquad 1 \le j \le N \tag{3.39}$$

3) Update the HMM model parameters with (3.37)-(3.39).

It has been proved [46] that after each iteration described above, either the re-estimated parameter set $\theta' = \{A', B', \pi'\}$ is more likely than original set $\theta = \{A, B, \pi\}$ in the sense that $p(O \mid \theta') > p(O \mid \theta)$ or we have reached a stationary point of the likelihood function at which $\theta' = \theta$.

The Baum-Welch learning process updates the parameters of the HMM to maximize the quantity $p\{O \mid \lambda\}$. But first, we need initial values for the model $\theta = \{A, B, \pi\}$. Initial values for parameters of A can be obtained using the method of regular Markov model [34], 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 π 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 $\theta = \{A, B, \pi\}$ will be updated during the HMM training and will not affect the final result of parameter estimation.

3.3.5.3 Incomplete data and local maximization

For hazard rate estimation based on condition data, the observations might be incomplete, which means there are some periods t that we don't have the observation data 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 than those with observations), this might cause significant error in the HMM model training because the preset initial value will determine the stochastic process., since there is no observation in most period t to adjust the parameter set $\lambda = \{A, B, \pi\}$ in the training. So we must eliminate the effects of unobserved initials. Solution is to set the observation probability in each state will as 1 (or 1/N) at time t when there is no observation, which is:

$$b_j(k) = p\{o_t = v_k \mid q_t = j\} = 1/N,\ \ 1 \le j \le N,\ \ 1 \le k \le M, t \in \{unobserved\ \ period\} \qquad (3.40)$$

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.

3.4 Application of Hidden Markov model in hazard rate estimation

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 thesis, I will provide the applications of HMM in hazard rate estimation based on DGA data and on a scoring system, which is a combination of health data on insulation material.

3.4.1 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 [49], as shown in Table 3.1. Here conditions 1, 2, 3, 4 correspond to the deterioration levels 1, 2, 3, 4, respectively, in our Markov model.

TABLE 3.1: 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[3]
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

3.4.1.1 Parameter estimation

Table 3.2 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 I use all records taken between two maintenance tasks to simulate the deterioration process. The transition rates for the Markov model are given in Table 3.3.

To validate the HMM performance, I compare the observation with the HMM results. In Table 3.4, *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.

[3] 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 3.2: 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 3.3: ESTIMATED TRANSITION INTENSITIES FOR MARKOV MODEL

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

TABLE 3.4: COMPARISON OF OBSERVATION AND FORECAST.

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

The probability we need to calculate 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 given by (3.41)

$$p(hT) = \Pr(hT < x \leq (h+1)T \mid x > hT) = \frac{P((h+1)T) - P(hT)}{1 - P(hT)} \tag{3.41}$$

where $P(hT)$ is the failure probability *calculated* in (3.19). Calculated instantaneous failure probability vs. time is shown in Fig. 3.9.

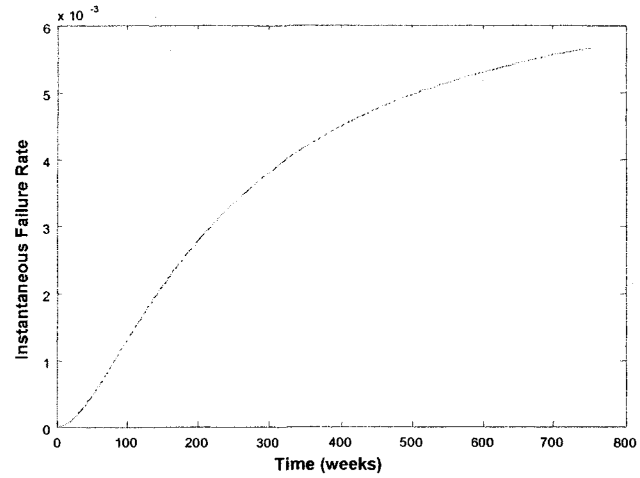

Fig. 3.9: Hazard rate of transformer oil deterioration

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 3.2 shows the maintenance (an oil change) was performed 377 weeks after the first record, which is the time of the previous maintenance. From Fig. 3.9, we observe that the failure probability at 377 weeks is about 4E-3, and exact calculation yields $p(377)$=0.004354. Also the DGA records just after the maintenance were checked, and they indicated the oil was of course in very good condition, so that the computed failure probability was very close to 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, (3.19) provides an estimate of the component's remaining life. Table 3.5 gives the results for components in each state, the average time to next state and the estimate time to failure.

TABLE 3.5: 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 3.4 may differ significantly from the expected time between states per calculation as given in Table 3.5. For example, referring to Table 3.4, 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 3.4 are not necessarily at the time the deterioration process first enters the indicated state. Returning to our 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 3.5 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.

3.4.1.2 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 3.3, 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. My 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 as initial input for HMM training, for a particular transformer when the historical data for that transformer does not allow it otherwise.

I 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 3.6, with mean and standard deviation for each transition intensity given at the bottom of the table. I have also used (3.19) to calculate the first passage time between different states, and these calculations are provided in Table 3.7.

TABLE 3.6: TRANSITION RATE OF DIFFERENT STATES FOR TRANSFORMER INSULATION DETERIORATION

ID	λ_{12}	λ_{23}	λ_{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		
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 3.7: 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	
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. I 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.

Fig 3.10 – 3.15 are probability plots of first passage times between different states (which are the inverse of the corresponding transition intensities λ_{12}, λ_{23}, *and* λ_{34}). The distributions I have tested are: Normal, Lognormal, Weibull, Exponential, Logistic and Loglogistic distribution.

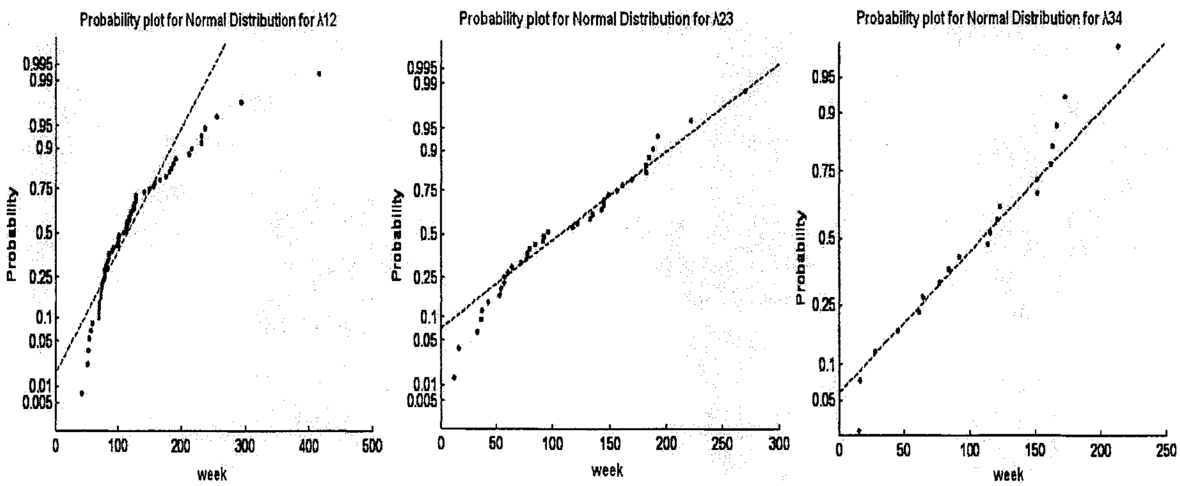

Fig. 3.10: Normal probability plot for first passage times

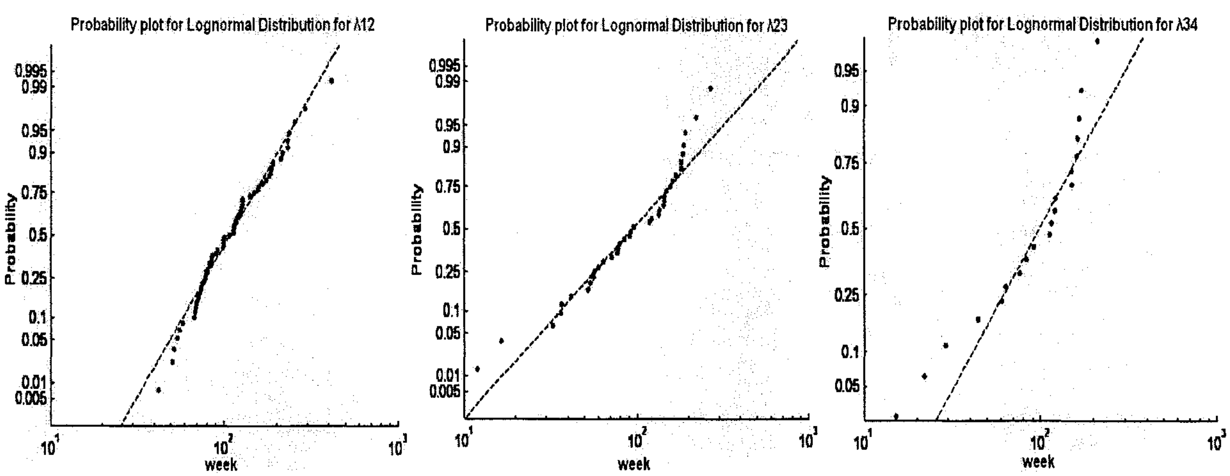

Fig. 3.11: Lognormal probability plot for first passage times

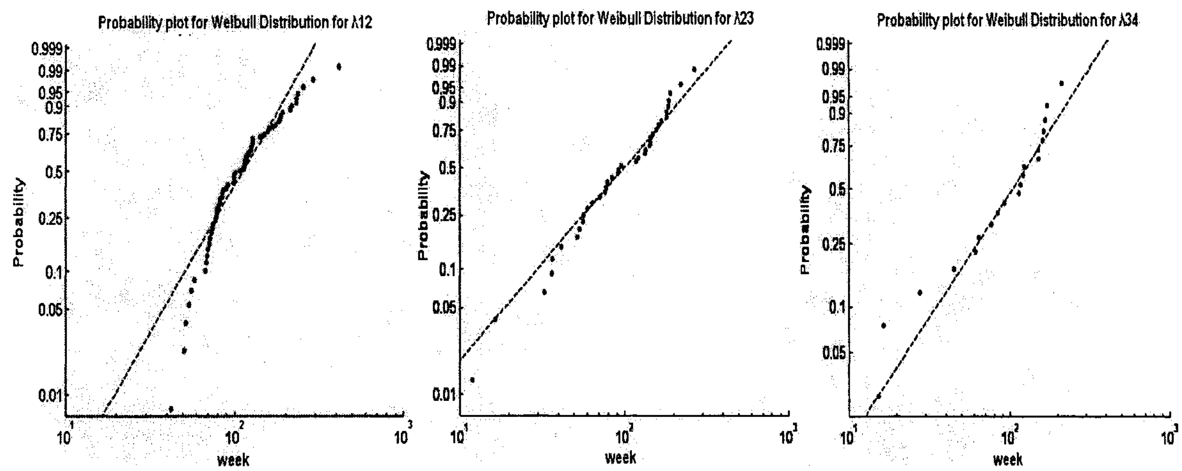

Fig. 3.12: Weibull probability plot for first passage times

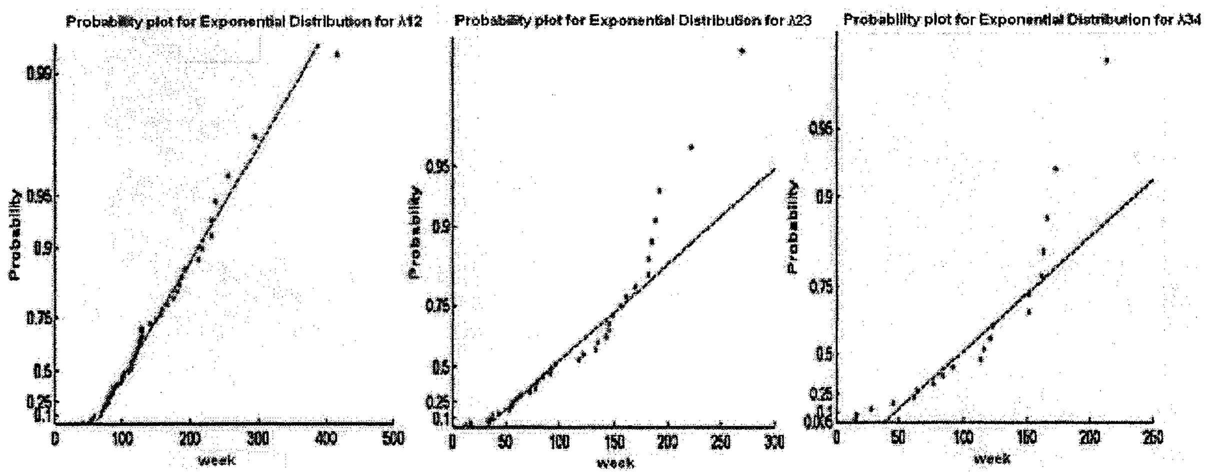

Fig. 3.13: Exponential probability plot for first passage times

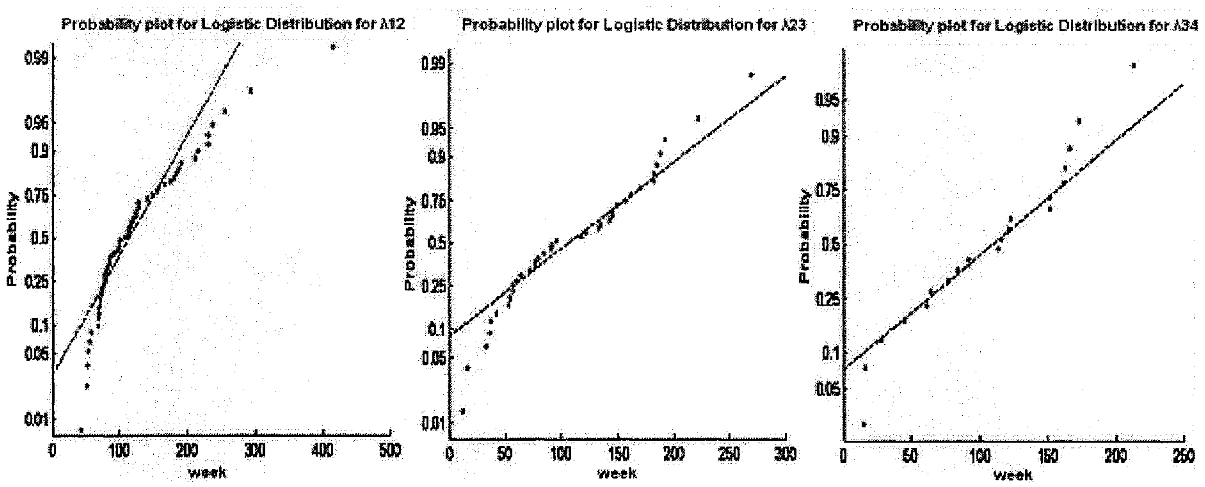

Fig. 3.14: Logistic probability plot for first passage times

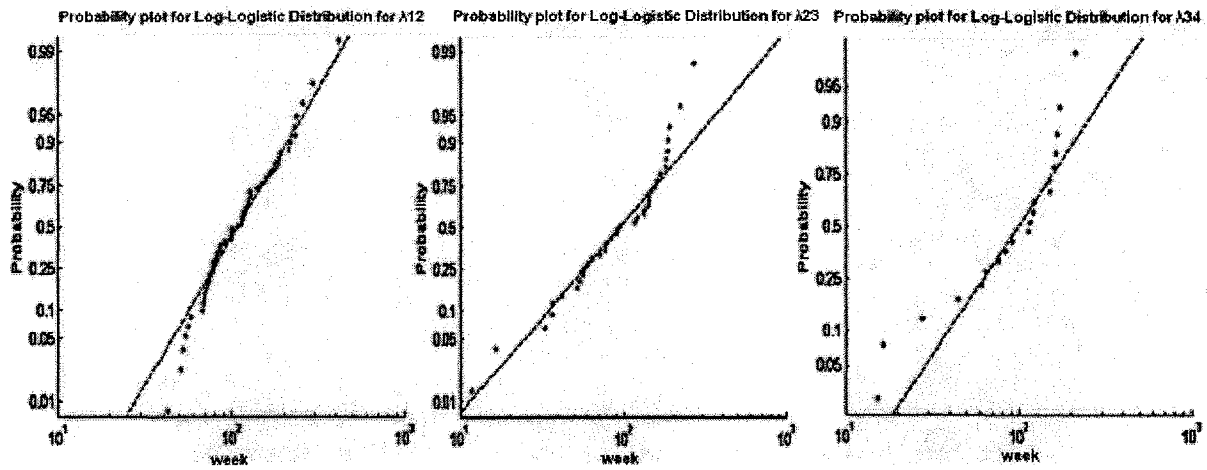

Fig. 3.15: Log-logistic probability plot for first passage times

Comparison of the plots in Fig. 3.11 to those of Fig 3.12-15 suggests that the log normal distribution may provide the best fit to the data. This finding is consistent with experience in modeling of other degradation processes [25].

$$Log(x) \sim Normal(\mu, \sigma) \tag{3.42}$$

Also, with statistics tools, we can estimate the parameter of the lognormal distribution to describe the first passage time between different states, as in Table 3.8.The parameters ($\hat{\mu}, \hat{\sigma}$) is based on maximum likelihood estimation [25] and the 95% upper and lower confidential intervals were achieved with:

$$CI = \exp(\hat{\mu} \pm Z_{1-\alpha/2} \times \hat{\sigma} / \sqrt{n}) \tag{3.43}$$

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

TABLE 3.8: MEAN VALUE AND CONFIDENCE INTERVAL OF FIRST PASSAGE TIME BETWEEN DIFFERENT STATES

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).

It should be noted here that this result is corresponding to the transformer oil insulation failure. It can develop fast if not well maintained, comparing with 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.

3.4.2 Estimation based on score system (health index)

In the previous sections of this chapter, it has been 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, I will make use of such a scoring system describe some testing towards that end that I have performed.

Some research has been done on obtaining such a relative condition or health index for a failure mode. For example, [51] proposes a concept of health indices and developed rules of health indices, and [52] 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 [51]. Suppose we have n inspection indicators (r1, r2,..., rn) 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. 3.7.

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 (3.44), calculated by taking the weighed average of inspection item results.

$$\text{Condition Score} = \sum_{i=1}^{n} w_i r_i \div \sum_{i=1}^{n} w_i \tag{3.44}$$

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 3.9 gives an inspection form for power transformers. Table 3.10 illustrates normalization for the criteria 'age.' Table 3.11 gives the inspection items and the information they carry for transformer insulation deterioration conditional assessment. Table 3.12 summarizes the condition scores for a single transformer (18 in Table 4.6) taken over a period of time from 1994 to 2000.

TABLE 3.9: 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 3.10: 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 3.11: INSPECTION TIMES AND CONDITION INFORMATION REFLECTED BY THE 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 cellulose.
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 3.12: INSPECTION RESULTS AND WEIGHTED AVERAGE SCORE FOR TRANSFORMER

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

From the data we can see that not every condition indicator shows the same deterioration trend. This is because each indicator carries information on a specific portion of the deterioration process. For example, loading history gives the thermal effect of heavy load on solid insulation material, whereas DGA provides information on oil condition under thermal and electrical stresses over time.

To inject a degree of conservatism into the interpretation of the condition scores, we map the condition score to the various states according to Table 3.13, based on industry experience and field engineer suggestions. This mapping will provide that the failure state is reached when two or more of the individual scores are 4.

TABLE 3.13: 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 3.12, mapped to states via Table 3.13, in developing the HMM model. Resulting transition rates and first passage times between different states are shown in Table 3.14, and the corresponding hazard rate is shown in Fig. 3.16.

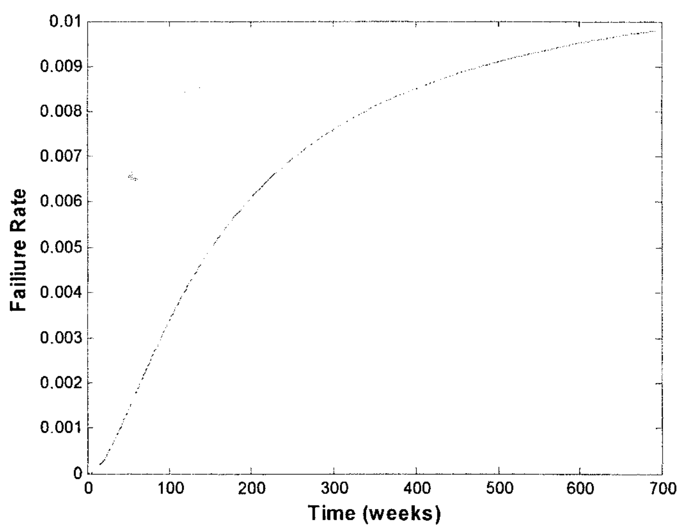

Fig. 3.16: Hazard rate of transformer insulation deterioration with score ranking system

TABLE 3.14: TRANSITION RATE AND FIRST PASSAGE TIME OF TRANSFORMER BASED ON SCORE RANKING SYSTEM

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

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.

3.5 Bayesian Updating

Another method of estimating hazard rates, is Bayesian updating based on condition test data. A Bayesian approach was developed in [53] for estimating the hazard 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 τ is an unknown parameter in our probability model. We first define a distribution, $P(\tau)$, which generally aim to be as uninformative as possible. $P(\tau)$ is the prior distribution which represents uncertainty about τ based on prior knowledge, e.g. historical information. Then, the posterior distribution of τ, given some observations of transformer condition monitoring data, is given by Bayes' Rule:

$$P(\tau|data) = \frac{P(data|\tau)P(\tau)}{P(data)} \tag{3.45}$$

Here $P(data) = \int P(data|\tau)P(\tau)d\tau$. 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

$P(data|\tau)$ takes the form of $P(x_1, x_2, x_3, x_4|\tau)$. By the product rule of probability, the conditional distribution can be factored as:

$$P(x_1, x_2, x_3 x_4|\tau) = P_{X_4}(x_4|x_1, x_2, x_3, \tau) \times P_{X_3}(x_3|x_1, x_2, \tau) \times P_{X_2}(x_2|x_1, \tau) \times P_{X_1}(x_1|\tau) \tag{3.46}$$

If x_1, x_2, x_3, x_4 are independently distributed, Eq. (3.46) can also be written as:

$$P(x_1, x_2, x_3, x_4|\tau) = P(x_1|\tau)P(x_2|\tau)P(x_3|\tau)P(x_4|\tau) \tag{3.47}$$

The resulting posterior distribution in (3.47) 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. 3.17.

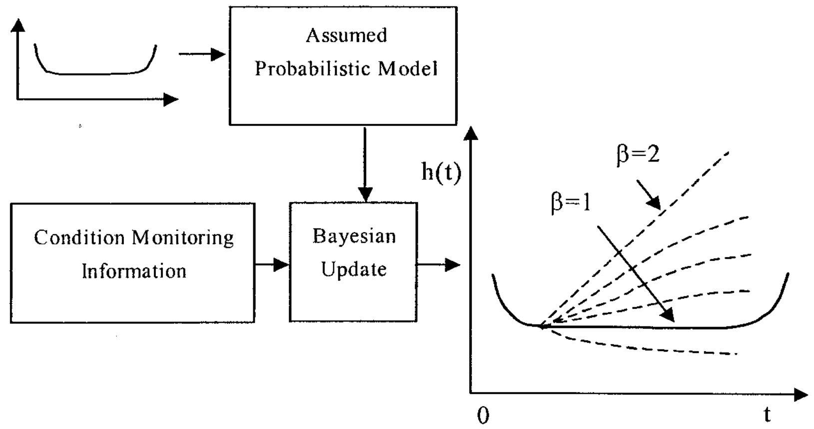

Fig. 3.17: Bayesian Analysis of Equipment Hazard rate

Reference [53] provides a Bayesian example for estimating transformer hazard 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 difficulty of this approach lies in the need of establishing the relationship (conditional distributions) between the monitoring data and the equipment's failure probability.

Chapter 4 Mid-Term Maintenance scheduling

4.1 Introduction of Maintenance Asset Management

4.1.1 Asset management in electrical transmission system

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 [54].

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 such as budget and labor, 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 [55] 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.

4.1.2 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 [3]. 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) [56]. 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 [57]. Condition based maintenance triggers a maintenance from information characterizing the equipment condition, since condition monitoring may identify incipient failures [58]. 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. Fig 4.1 gives the overview of the classification of different maintenance strategies [59]. From this figure, we can see that the reliability centered maintenance accounts for both importance and condition of the facilities.

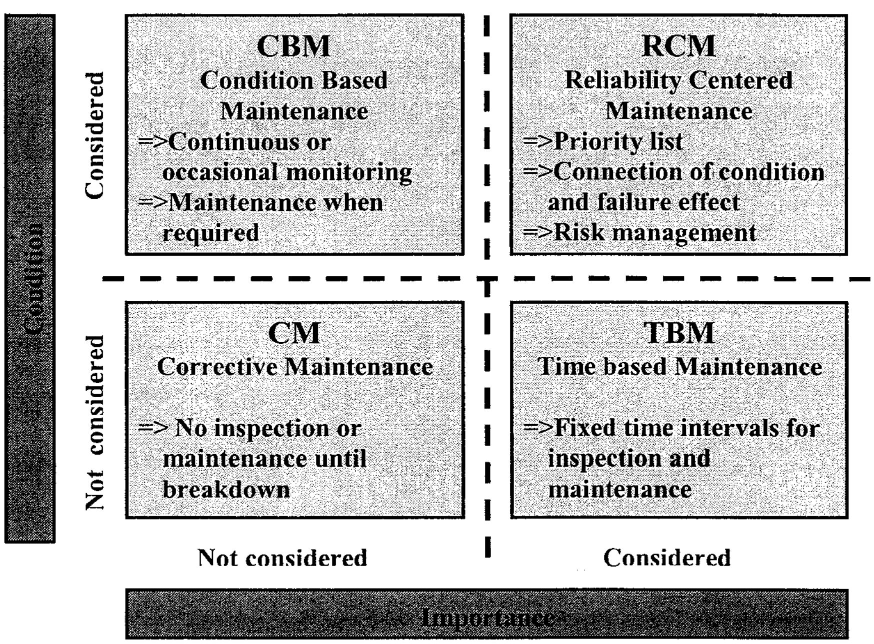

Fig. 4.1: Classification of maintenance

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 [60]. Today, a number of processes called RCM are applied in nearly every major sector of industry, such as gas pipelines [61], mass traffic system [62], and telecommunications [63]. 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 different heuristic indices to represent the priority of the maintenance tasks, such as using a benefit-cost ratio [64], health index (probability of system being in 'healthy' state) [65], expected energy not supplied [66], and some weighted combinations of statistics of component performance [67]. Other methods use objectives like minimizing the cost of maintenance and operation, while satisfying system reliability constraints [68]. Shahidehpour [69] 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 [66] 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 hazard rate estimation instead of constant hazard 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.

4.1.3 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. Shahidehpour has worked on maintenance scheduling under deregulated market and developed a means of coordinating maintenance scheduling for mid-term and short-term transmission maintenance [69]. Maintenance scheduling strategies with different time scale and their scheduling constraints and methods are introduced as follows:

1. Long-term transmission maintenance scheduling: 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. Mid-term transmission maintenance scheduling: 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 redispatch and component damage) so as to minimize risk of wide-area 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 [69].

So we can see that maintenance scheduling with different time scale 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 4.2 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.

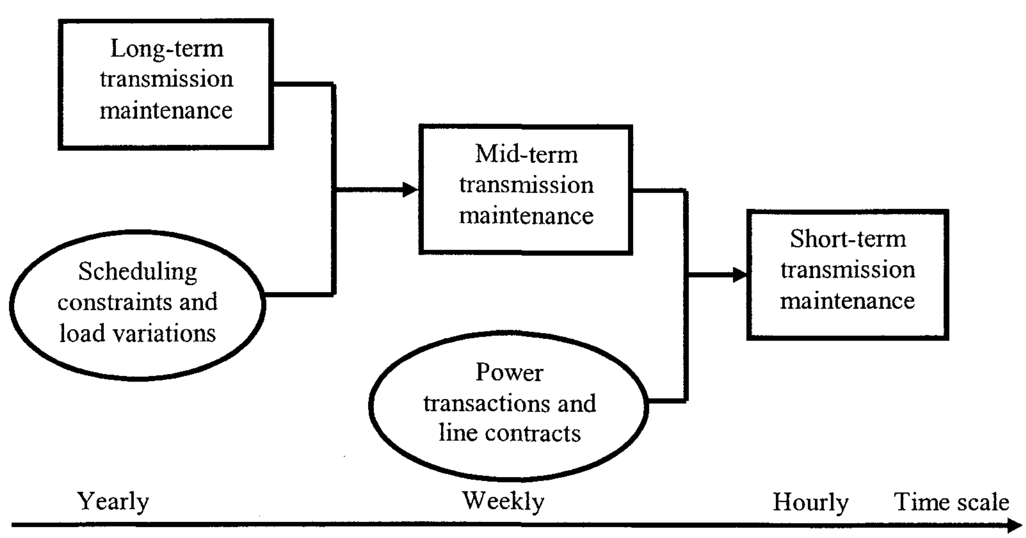

Fig. 4.2: Transmission maintenance incorporation for different time scales

4.1.4 Structure of the Mid-term maintenance scheduling

The risk-based maintenance approach has three steps: 1) long-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. 4.3, 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.

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.

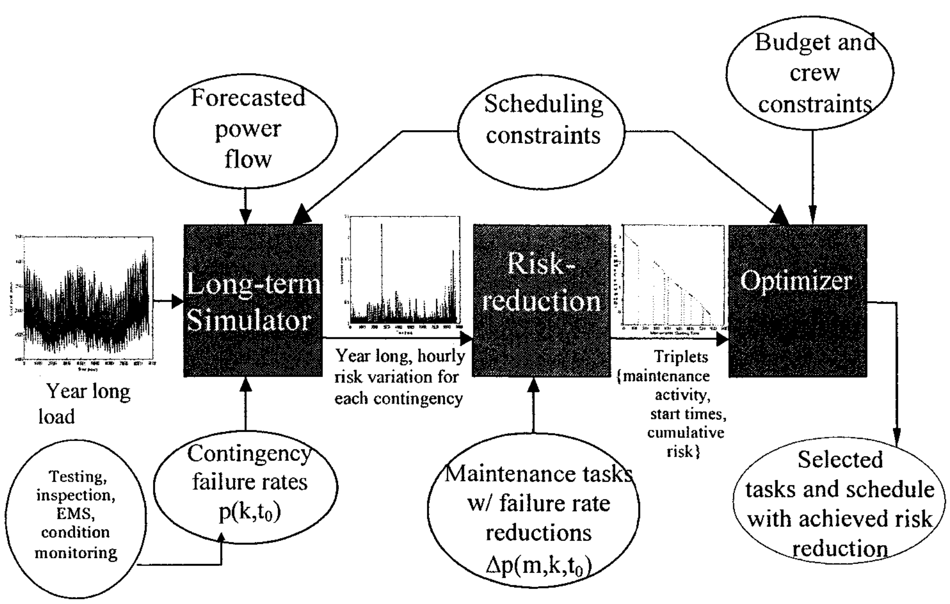

Fig. 4.3: Integrated Maintenance Scheduler (IMS)

4.2 Risk assessment of electrical system

The deterministic method, where all contingencies in a designated category, or llist, 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, I have used the risk-based security analysis on transmission maintenance scheduling [70] in the process developed to optimize maintenance resources.

4.2.1 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 4.4. 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. 4.1:

$$\mathrm{Risk}(\mathrm{Sev} \mid X_t) = \sum_i \Pr(E_i)\mathrm{Sev}(E_i \mid X_t) \tag{4.1}$$

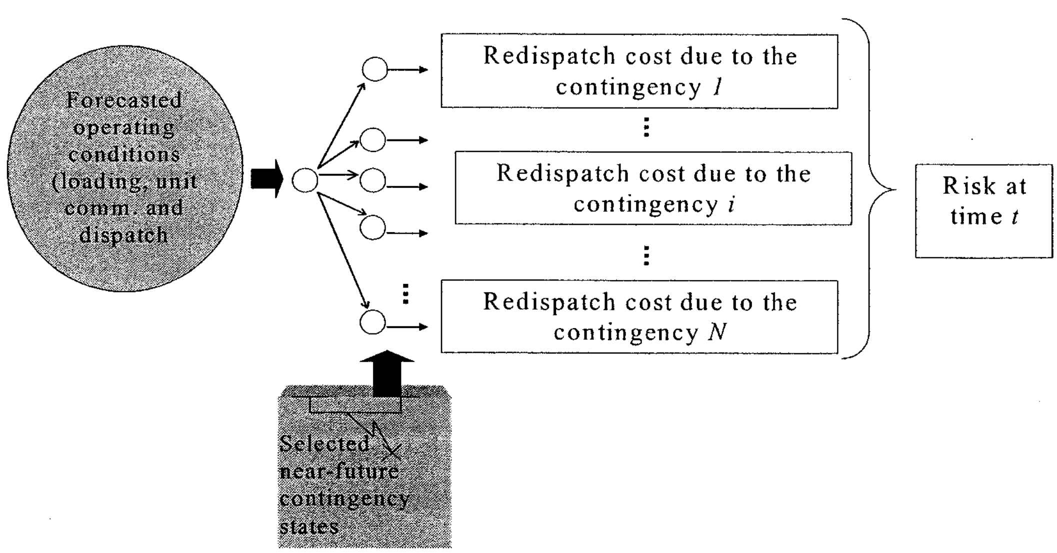

Fig. 4.4: Illustration of risk calculation for a given operating condition

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 instantaneous 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. I will further describe the severity functions in the next section.

4.2.2 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 [71] 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, which are especially important in modeling the severity of a transformer failure. As a result, I decompose the evaluation of consequence following failure of a component as summation of its system and component impacts.

$$\mathrm{Sev}(\mathrm{E_i},\mathrm{X_{t,j}})=\mathrm{Sev}_{\mathrm{system}}(\mathrm{E_i},\mathrm{X_{t,j}})+\mathrm{Sev}_{\mathrm{component}}(\mathrm{E_i},\mathrm{X_{t,j}}) \tag{4.2}$$

4.3 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 such as redispatch cost 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 "basecase" 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:

$$R(m,t)=\sum_{k=1}^{N} p(k)\left[sev_{sys}(k\mid m,t)+sev_{comp}(k\mid m,t)\right] \tag{4.3}$$

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. (4.3). 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.

4.3.1 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, I 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:

$$Sev(E_i \mid X_t) := Cost(E_i \mid X_t) - Cost(0 \mid X_t) \tag{4.4}$$

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 DC Optimal Power Flow (DC OPF) and the objective function is:

$$Min : Cost = \sum_{m=\{1,\ldots,N_g\}} Cost(PG_m) \tag{4.5}$$

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. 4.5.

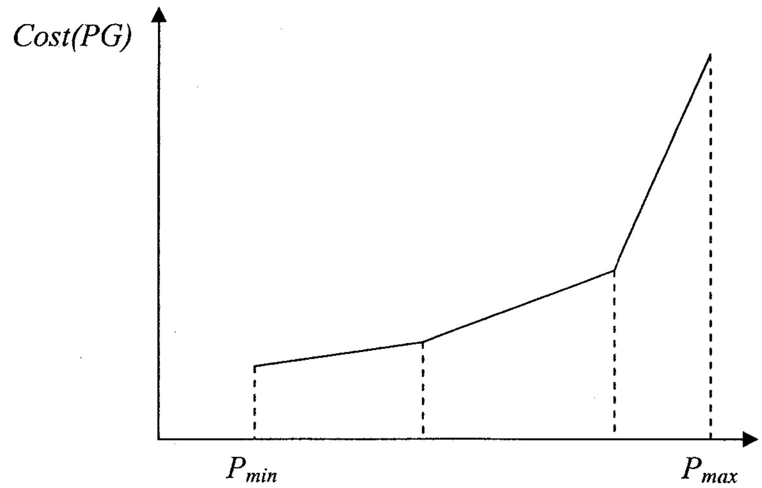

Fig. 4.5: Piecewise linear cost functions

Table 4.1 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:

$$Cost(PG_m) = \sum_{i=1}^{N_{Gm}} \alpha_i P_m(i) \tag{4.6}$$

where N_{Gm} is the total number of the segments in Fig 4.5, 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 4.1, the optimal programming will guarantee that for each generator output $P_m(j)=0, (j>i)$ before $P_m(i)$ reaches its maximum.

TABLE 4.1: 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

$$PG = (PG_1, PG_2, \Lambda, PG_{N_G})^T \tag{4.7}$$

where $N_G = \sum_{m=1}^{N_g} N_{Gm}$ is the total cost function segments for all the generators in the system, and PG_i is the output of each segment accordingly.

The objective function in (4.5) is subject to the following constraints:

$PG_m^{\max} \geq PG_m \geq 0, \quad m \in (1, \Lambda, N_G)$ Each generator generates between 0 → $PG_m^{\max}$

$\gamma_i PB_i^{\max} \geq PB_i \geq -\gamma_i PB_i^{\max}, \quad i \in (1, ..., N_B)$ The power flow in each branch (line or transformer) is limited by its rating;

$B^T \times \theta = P^{inject} = (PG - PD)$ DC power flow equations;

$(D_B \times A) \times \theta - PB = 0$ Branch flow equations;

where

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*;

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

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;

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

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:

$$\max f^T \cdot x \tag{4.8}$$

Constraints:

$$A_{eq} \cdot x = b_{eq} \tag{4.9}$$

$$lb \le x \le ub \tag{4.10}$$

We define

$$PG = \begin{pmatrix} PG_1 \\ PG_2 \\ \vdots \\ PG_{N_G} \end{pmatrix}_{(N_g \times 1)} ; \quad PB = \begin{pmatrix} PB_1 \\ PB_2 \\ \vdots \\ PB_{N_B} \end{pmatrix}_{(N_B \times 1)} ; \quad \theta = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_N \end{pmatrix}_{(N \times 1)} \tag{4.11}$$

$$PG^{\max} = \begin{pmatrix} PG_1^{\max} \\ PG_2^{\max} \\ \vdots \\ PG_{N_G}^{\max} \end{pmatrix}_{(N_g \times 1)} ; \quad PB^{\max} = \begin{pmatrix} \gamma_1 PB_1^{\max} \\ \gamma_2 PB_2^{\max} \\ \vdots \\ \gamma_{N_B} PB_{N_B}^{\max} \end{pmatrix}_{(N_B \times 1)} ; \quad \theta^{\max} = \begin{pmatrix} \pi \\ \pi \\ \vdots \\ \pi \end{pmatrix}_{(N \times 1)} \tag{4.12}$$

$$PG^{\min} = \begin{pmatrix} PG_1^{\min} \\ PG_2^{\min} \\ \vdots \\ PG_{N_G}^{\min} \end{pmatrix}_{(N_g \times 1)} ; \quad PB^{\min} = \begin{pmatrix} -\gamma_1 PB_1^{\min} \\ -\gamma_2 PB_2^{\min} \\ \vdots \\ -\gamma_{N_B} PB_{N_B}^{\min} \end{pmatrix}_{(N_B \times 1)} ; \quad \theta^{\min} = \begin{pmatrix} -\pi \\ -\pi \\ \vdots \\ -\pi \end{pmatrix}_{(N \times 1)} \tag{4.13}$$

$$x = (PG^T \quad PB^T \quad \theta^T) \tag{4.14}$$

$$f_i = \begin{cases} \alpha_m^T & \text{when } i \in [1, N_G] \\ 0 & \text{when } i \notin [1, N_G] \end{cases} \tag{4.15}$$

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

$$A_{eq} = \begin{pmatrix} 0 & I_{N_B \times N_B} & -D_{N_B \times N_B} \times A_{N_B \times N} \\ I_{N \times N_G} & 0 & -B^T{}_{N \times N} \end{pmatrix}_{(N_B+N)\times(N_G+N_B+N)} \tag{4.16}$$

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

$$B_{eq} = \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}_{(N_B+N)\times 1} \tag{4.17}$$

$$ub = \begin{pmatrix} PG^{\max} \\ PB^{\max} \\ \theta^{\max} \end{pmatrix} \tag{4.18}$$

$$lb = \begin{pmatrix} PG^{\min} \\ -PB^{\max} \\ \theta^{\min} \end{pmatrix} \tag{4.19}$$

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 current 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 (4.3) and (4.4).

4.3.2 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

I make two modifications to the severity function to account for these issues. First, to account for transformer damage, a non-zero value of component severity function $Sev_{component}$ in eq. (4.2) is provided. Assuming, conservatively, that any transformer failure requires its replacement, the component severity function, which represents the cost of purchasing a new transformer of the same MVA rating, is given by eq. (2.4):

$$Sev_{component}(E_i \mid X_t) = C \times MVA_{rated} \tag{4.20}$$

where MVA_{rated} is the MVA rating of the transformer and C is a constant of proportionality that can be obtained based on eq. (4.21):

$$\mathrm{C} = \frac{\text{replacemen t cost of a 100 MVA xfmr}}{100} \tag{4.21}$$

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

Second, it is also reasonable 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 4.2.

TABLE 4.2: 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 4.2 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.

4.3.3 Components modeled in the simulation

Different types of equipments and the consequences of their failures should be modeled in the simulation. In my simulation, I have modeled several failure modes of the components in transmission system, as listed in Table 4.3.

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

In utility maintenance practice, they usually perform a package of maintenance activities at the same time instead of performing each preventive maintenance corresponding to each failure mode at different time. This is because many inspection or maintenance activities may request the component to be removed out of service, or even opened or disassembled. So by 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 breaker, the failure which is caused by mechanical excessive wear and maladjustments is a major failure mode and could cause the failure of protection action. Here, I only consider the failure to open of circuit breaker, which is failure to isolate the fault location, as the result of this failure mode. Because it could result in high cost of repair, damage to other components and instability of the system.

In simulator, the failure of transmission lines and transformers are similar as the outage of the equipment and thus the outage of corresponding transmission lines. The failure of circuit breaker should be combined with other failure during its protection region. So this is a higher order contingency and its hazard rate should be achieved with the information of system configuration and topology data, together with probability analysis [72]. In the simulator, an assumption was made that for each fault circuit breaker, all of its neighboring circuit breakers function well and will open to isolate the fault area. The fault area was searched in the simulation to get the system configuration of post contingency and corresponding redispatch cost was calculated.

4.3.4 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 I 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.

$$abs\left(\frac{P_{gki}-P_{gkj}}{P_{gki}}\right)<\varepsilon \text{ and } abs\left(\frac{P_{gki}-P_{gkj}}{P_{gkj}}\right)<\varepsilon \tag{4.22}$$

$$abs\left(\frac{P_{lki}-P_{lkj}}{P_{lki}}\right)<\varepsilon \text{ and } abs\left(\frac{P_{lki}-P_{lkj}}{P_{lkj}}\right)<\varepsilon \tag{4.23}$$

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

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. I have used β=0.1 in my studies.

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.

4.4 Quantification of maintenance benefits- Risk reduction calculation

A table has been developed [73] 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 has been used to illustrate these benefits. A hazard function for a typical transmission equipment failure mode has been shown in Fig. 3.6. This curve can be divided into two periods: 1) almost constant hazard rate period and 2) deterioration period with increasing hazard 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. 3.6, the benefit comes mainly from the decrease of hazard rate, which results in a decrease in failure probability Δp, but for maintenance performed during the constant hazard 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. 3.6).

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 hazard rate reduction and life extension, as $CRR(m,k,t) = CRR_1(m,k,t) + \alpha \times CRR_{.2}(m,k,t)$

CRR_1 is the risk reduction from failure probability reduction, CRR_2 is the risk reduction from life extension, and α is the corresponding weight chosen to reflect the user's relative emphasis on long term component life extension versus near-term system reliability enhancement.

4.4.1 Risk reduction due to hazard rate decrease

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 $\Delta p(m,c,t)$. Here Δp is the maintenance induced hazard rate reduction. The cumulative-over-time risk reduction due to maintenance task m is $\Delta CR(m,t_f)$, computed as a function of the completion time t_f according to:

$$\begin{aligned}\Delta CR(m,t_f) &= \Delta CR_{during}(m,t_f) + \Delta CR_{after}(m,t_f) \\ &= \int_{t_f - T_d}^{t_f} (R(0,t) - R_{during}(m,t))dt + \int_{t_f}^{8760} (R(0,t) - R_{after}(m,t))dt\end{aligned} \tag{4.24}$$

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 (4.24) is the risk reduction during the maintenance period, always non-positive indicating that risk may increase during the maintenance period. The second integral in (4.24) is the risk reduction after completion of the maintenance activity, always positive due to the decrease in failure probability. In each integral, $R(0,t)$ is obtained from the long-term simulator. If, during the maintenance period, no component is outaged, then $\Delta CR_{during}=0$. However, if the maintenance task requires removal of component k (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:

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

$$= \int_{f - T_d}^{t_f} [p(k)sev(k\,|\,0,t) + \sum_{c=0,c\neq k}^{N} p(c)\big(sev(c\,|\,0,t) - sev(c\,|\,m,t)\big)]dt \tag{4.25}$$

Now consider the second integral in (4.24), the risk reduction after the maintenance activity. Here, the maintenance activity *m* reduces contingency *k* probability by $\Delta p(m,k)$ 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

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

$$= \int_{t_f}^{8760} \{[p(k)sev(k \mid 0,t) + \sum_{\substack{c=0 \\ c \neq k}}^{N} p(c)sev(c \mid 0,t)] - [(p(k) - \Delta p(m,k))sev(k \mid 0,t) + \sum_{\substack{c=0 \\ c \neq k}}^{N} p(c)sev(c \mid m,t)]\} dt \tag{4.26}$$

where we have pulled from each summation the risk associated with contingency *k*, since contingency *k* is the only one having a probability affected by the maintenance activity. After t_f, component *k* is back in service, and the operating conditions are unchanged relative to the case of no maintenance; therefore $sev(c|0,t)=sev(c|m,t)\ \forall c=1,\ldots,N$, and the two summations within the integral of (4.26) are equal so that:

$$\begin{aligned} \Delta CR_{after}(m,t_f) &= \int_{t_f}^{8760} \{p(k)sev(k \mid 0,t) - (p(k) - \Delta p(m,k))sev(k \mid 0,t)\} dt \\ &= \int_{t_f}^{8760} \{\Delta p(m,k))sev(k \mid 0,t)\} dt \end{aligned} \tag{4.27}$$

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

$$\Delta CR_{after}(m,t_f) = \int_{t_f}^{8760} \Delta p(m,k) \left\{ \frac{R(0,k,t)}{p(k)} \right\} dt = \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t) dt \tag{4.28}$$

Substituting (4.26) and (4.28) into (4.24), and replacing $p(k)sev(k|0,t)$ in (4.25) 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:

$$\Delta CR(m,t_f)$$
$$= \int_{t_f - T_d}^{t_f} [R(0,k,t) + \sum_{c=0,c\neq k}^{N} p(c)\left(sev(c \mid 0,t) - sev(c \mid m,t)\right)]dt + \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t)dt \qquad (4.29)$$

There are three main terms in the risk reduction expression of equation (4.29). The first term inside the first integral represents the reduction in risk, relative to the basecase, 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 basecase configuration $(0,t)$, and the severity of all contingencies occurring under the weakened configuration (m,t). The contingency severities associated with the basecase configuration 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 can 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 and thus 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 (4.29) is 0. This might be true as a result of, for example, operator initiated system adjustments during the maintenance period. I accept this assumption in my work. Under this assumption, the total risk reduction associated with maintenance task m completed at time t_f is

$$\Delta CR(m,t_f) = \int_{t_f - T_d}^{t_f} R(0,k,t)dt + \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t)dt \tag{4.30}$$

Thus, we need $R(0,k,t)$, the risk variation for each contingency affected by a maintenance task under the basecase network configuration, which is information obtained from a simulator run. In (4.30), the first term indicates the risk reduction accumulated 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 (4.30), which is:

$$CRR_1(m,t_f) = \frac{\Delta p(m,k)}{p(k)} \int_{t_f}^{8760} R(0,k,t)dt \tag{4.31}$$

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

4.4.2 Risk reduction due to life extension

The risk reduction due to the life extension Δt, due to the delay of deterioration, is:

$$CRR_2(m,t) = RC(k) \times \frac{\Delta t_k}{MTTF} \times (1+r)^{-(t+\Delta t)} \tag{4.32}$$

Here, CRR_2 is the risk reduction due to the delay of the deterioration and $RC(k)$ is the restoration (repair) cost of the component after the failure. Δt_k is the length extension, with respect to failure mode k, and $MTTF$ is the component mean time to failure. r is the inflation rate. So the risk reduction due to delay of deterioration can be explained as the saving of extending the life of this component from deterioration.

4.4.3 Risk variation caused by the maintenance

While the maintenance requests the service to be removed out of service temporarily, it also may need some dispatch actions so that no security violation is made. Thus it will incur some cost associated with the dispatch, if necessary, and increase the risk at the time of the maintenance. The difference between this risk and the risk caused by the contingency is that this risk is incurred by the maintenance scheduling and its probability is 1 at the maintenance interval but 0 otherwise. I want to represent this effect of maintenance in the objective function, which reflects the redispatch cost of scheduling a maintenance task at a certain time t. So the total objective function becomes

$$CRR(m,k,t) = CRR_1(m,k,t) + CRR_{.2}(m,k,t) - C(m,k,t) \tag{4.33}$$

Here $C(m,k,t)$ is the increased risk due to dispatch cost needed to schedule outage of component k at time t.

Generally, the value of increased risk due to maintenance scheduling should be non-positive, and might has a high value at time t whenever there is a peak load, or some other forced outage. By adding this option the utilities to could be permitted to schedule maintenance even at critical time, with the cost that they are willing to pay.

For most the components in transmission system they have all of three risk reduction in the (4.33). But for tap changer, since its failure usually does not cause outage immediately, there is no security risk associated with tap changer. Therefore its CRR_1=0 and the benefit of maintenance is credited to the life extension, which means CRR_2>0.

4.5 Optimization

4.5.1 Objective function and constraints

As indicated in Figure 4.3, first the simulator is run to compute risk as a function of time for each hour over a long-term such as a year and then, for the example of this paper, use (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; $m=1,...L_k$ 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

$$Ia(k,m,t) = \sum_{j=t-d(k,m)+1}^{t} Is(k,m,j), \forall (k,m,t) \tag{4.34}$$

Equation (4.34) 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, $b \in 1, 2, 3, 4,$ where 1=transformer maintenance, 2=tree-trimming, 3=insulator cleaning, and 4=circuit breaker maintenance. *Crew(k,m)* is the required number of crews for m^{th} task for component k. *TotCrew(b,t)* is the number of labors available for maintenance category b at time t. Then the objective function and constraints become:

$$Max(\sum_{k=1}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} CRR(k,m,t) \times Is(k,m,t)) \tag{4.35}$$

subject to:

$$\sum_{m=1}^{L_m}\sum_{t=1}^{T} Is(k,m,t) \leq 1,\ k = 1,\Lambda\ ,N \tag{4.36}$$

$$Ia(k,m,t) = 0, \forall\ t \in Inf\ (k,m), \forall\ (k,m) \tag{4.37}$$

$$\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m} Ia(k,m,t) * Crew(k,m) < TotCrew(b,t), \forall t, b = 1,...4 \tag{4.38}$$

$$\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} cost(k,m) * Is(k,m,t) < TotCost(b), b = 1,...,4 \tag{4.39}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m} Ia(k,m,t) * SEV(k,m,t) \leq SEV_{\max}(t), \forall t \tag{4.40}$$

$$Is(k,m,t) \in \{0,1\}, \forall (k,m,t) \tag{4.41}$$

In this optimization problem, the objective (4.35) is to maximize total cumulative risk reduction. Constraint (4.36) restricts each component to be maintained at most once. Constraint (4.37) 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 (4.37). Constraint (4.38) stipulates the number of maintenance tasks ongoing during any period is limited by crew constraints.

Constraint (4.39) represents budget constraints for each budget category. Constraint (4.40) 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.

4.5.2 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, I have defined the security function with respect to the low voltage and voltage instability problem. The definition and simulation techniques were introduced in the previous report [70] about maintenance scheduling for transmission system. The principle here is: 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 is set so that no maintenance outage may violate the reliability criteria of low voltage or voltage instability, which is equation (4.40).

It must be illustrated that this is a "soft" constraint, which means it cannot guarantee that the bus voltage at each node is within the acceptable range. However, it can provide a systematic constraint to forbid a maintenance or a combination of maintenance actitives to be scheduled at a critical time. Stricter constraint on feasible time for each maintenance activity should be implemented with the infeasible constraint (4.37).

4.5.3 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. I 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 [58]. In comparing these methods, I 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 (4.39) and risk (4.40) 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 [74] over the labor constraints (4.38) 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 (4.36)-(4.41) in order to get approximations on budget and risk constraint Lagrange multipliers μ_1-μ_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 (4.38) for the first period (e.g., first week) to identify the maintenance tasks to be performed in that week. Then I 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 (4.38) is a classical knapsack problem, stated as follows:

$$\max\ F(Is(k,m,t))$$
$$=\sum_{k=1}^{N}\sum_{m=1}^{L_m}\Delta CR(k,m,t)\times Is(k,m,t)-\sum_{b=1}^{4}\mu_b\left\{\sum_{\substack{k=1 \\ (k,m):B(k,m)=b}}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T}cost(k,m)*Is(k,m,t)-TotCost\ (b)\right\}$$

$$- \sum_{t}^{t+T_{max}} \lambda_t \left\{ \sum_{k=1}^{N} \sum_{m=1}^{L_m} \Delta R(k,m,t) * Is(k,m,t) - \Delta R \max(t) \right\} \tag{4.42}$$

subject to

$$\sum_{\substack{m=1 \\ (m,n):B(m,n)=b}}^{M} \sum_{n=1}^{M_m} Ia(m,n,t) * Crew(m,n) \le Crew(b,t), \forall t, b = 1,\ldots,4 \tag{4.43}$$

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 $t+T_{max}$, where T_{max} is the longest duration for any task. Therefore, the third term in the objective function must sum over period t to t+Tmax. (d) Available hours for any period must be reduced by ongoing tasks that begin in earlier periods. (e) Infeasible periods from constraint (4.37) 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).

4.5.4 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 errors 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 always the convergence is a concern. This section gives some discussion on the situation that algorithm will provide optimal solution and the comparison between our method and Lagrange relaxation.

The major goal of optimization is to choose and find the best schedule of maintenance activities, to maximize the system reliability, with a bunch of constraints. The formulation of the problem is listed as (4.35)-(4.41)

Where constraint (4.41) 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 solve this problem and also reduce the calculation burden, I have coarsened the timeframe from hour to week. Since most maintenance task can be finished in one week, the decision variable in (4.41) can be dropped and simplify the algorithm discussion, the formulation above can be modified as:

$$Max\left(\sum_{k=1}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} a_{k,m,t} \times x_{k,m,t}\right) \tag{4.44}$$

Subject to:

$$\sum_{m=1}^{L_m}\sum_{t=1}^{T} x_{k,m,t} \leq 1,\ k = 1,\Lambda\ ,N \tag{4.45}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m} b_{k,m} * x_{k,m,t} < B(t), \forall t \tag{4.46}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m}\sum_{t=1}^{T} c_{k,m,t} * x_{k,m,t} < C \tag{4.47}$$

$$\sum_{k=1}^{N}\sum_{m=1}^{L_m} d_{k,m,t} * x_{k,m,t} \leq D(t), \forall t \tag{4.48}$$

$$x_{k,m,t} \in \{0,1\}, \forall (k,m,t) \tag{4.49}$$

From above formulation we can 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 [75].

To solve the integer programming, 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. Most commonly used method is linear programming relaxation (LP) and Lagrange relaxation (LR). LP relieves the needs of variables and solves the optimization problem in real number space. The results might not be correct because of the relaxation. LR 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. So combining the two methods may provide a way to overcome the shortcoming of both at the same time. What I did is to use linear programming relaxation with Lagrange multipliers. It can also be called as Lagrange relaxation without the integer constraint. To prove our results are same or similar with those from LR, I would like to discuss the solution of (4.44-4.49) in two cases:

A1) Change the constraint (4.45) as $\sum_{n=1}^{L_m}\sum_{t=1}^{T} x_{k,m,t} = 1,\ k = 1,\Lambda\ ,N$, which means all of the maintenance tasks will be scheduled. So this is a problem of scheduling without the choice of maintenance activities.

A2) Keep (4.45) as it was, which means not all of the maintenance tasks will be scheduled, as our problem.

Under the condition of A1), [75] has proved that the duality gap for LR and LP relaxations is exactly the same, or they provide the same upper bounds for the maximization problem. For our problem, we can convert the problem by relaxing the constraint (4.46)-(4.48):

$$\text{LR1} \quad \min_{\alpha,\beta,\chi \geq 0} \left\{ \begin{array}{l} Max(\sum_{k=1}^{N}\sum_{m=1}^{L_m}(\sum_{t=1}^{T}(a_{k,m,t} - \alpha_t b_{k,m,t} - \beta_t c_{k,m,t} - \chi_t d_{k,m,t})) \times x_{k,m,t} + \sum_{t=1}^{T}[\alpha_t B(t) + \beta_t C + \chi_t D(t)]), \\ s.t. \sum_{m=1}^{L_m}\sum_{t=1}^{T} x_{k,m,t} = 1, \ \forall k \quad and \quad x_{k,m,t} \in \{0,1\} \end{array} \right\} \tag{4.50}$$

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 $(m,t)_k = \text{argmax}(a_{k,m,t} - \alpha_t b_{k,m,t} - \beta_t c_{k,m,t} - \chi_t d_{k,m,t})$, 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 can 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 (4.45) means there need not to be exactly most 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, I convert the problem into the following formulation in LR2:

LR2:

$$\min_{\alpha,\beta,\chi,\lambda \geq 0} \begin{cases} Max(\sum_{k=1}^{N}\sum_{m=1}^{L_m}(\sum_{t=1}^{T}(a_{k,m,t} - \alpha_t b_{k,m,t} - \beta_t c_{k,m,t} - \chi_t d_{k,m,t} - \lambda_k) \times x_{k,m,t} + \sum_{t=1}^{T}[\alpha_t B(t) + \beta_t C + \chi_t D(t)] + \sum_{k=1}^{N}\lambda_k), \\ s.t \quad x_{k,m,t} \in \{0,1\} \end{cases} \quad (4.51)$$

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 in (4.49) cannot be dropped. But we can say in confidence that the linear relaxation with Lagrange multipliers should not provide 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, I have tested the result with some other mixed linear program in commercial software and got satisfying results. The comparison will be illustrated in the following section.

4.6 Incorporation of long-term and mid-term maintenance

As introduced in section 4.1.3, the utility companies always need to make long term maintenance schedules, e.g. 10 years or longer for their transmission components. The objective is to make long term budget investment schedule for their asset management. The long-term maintenance and inspection policy is used to optimize maintenance costs, failure costs and extend equipment life for gradually deteriorating equipment. There is a large literature on it based on system age and lifetime failure statistics from a population, but significantly less on developing improved maintenance policies [76,77,78] when condition measurements are available. For example, the model of Figure 4.6 below, suggested in [35], embeds decision within a Markov process, to setup a quantity connection between maintenance and reliability. Then use Monte Carlo simulation to choose the optimal long-term maintenance schedule for each component.

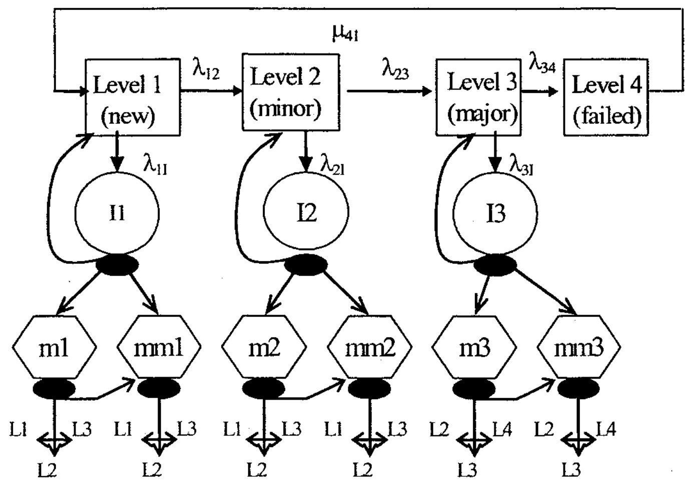

Fig. 4.6: Simulation model for long-term maintenance planning

The difference and relationship between long-term and mid-term maintenance are:

1. For long term maintenance, more uncertainties exist in the component deterioration process, available resources and system improvement by maintenance, over a much longer period.
2. The objective of long-term maintenance is to evaluate the optimal maintenance time for individual component, regardless the system operation condition at each specific moment.
3. The output of long-term scheduling is the recommended maintenance/inspection interval for component maintenance. We can also call this task pre-selection for mid-term scheduling. Long-term maintenance scheduling determines the specific "time

window" for maintenance scheduling, and mid-term maintenance determines proper maintenance time within that window.

My work here is to investigate the long-term maintenance method so that it can incorporate with the mid-term maintenance method described above. The objective function of long-term maintenance is for each maintenance activity, corresponding to each component *k* and failure mode *m*, to minimize the average cost of keeping the component in desired working condition:

$$C_a = \min_{T_m} \left(\frac{\frac{T}{T_m} C_m + \frac{T}{T_m} C_d + \frac{T}{MTTF(T_m)} C_f}{T} \right) = \frac{1}{T_m}(C_m + C_d) + \frac{1}{MTTF(T_m)} C_f \qquad (4.52)$$

where C_a is the yearly operation cost of maintaining the components in working condition; T is the total time scale we consider the long term maintenance. And T_m is the maintenance cycle ($1/\lambda$). It can be a value or vector of maintenance intervals for different maintenance activities. C_m is the cost per maintenance and C_d is the cost of corrective system actions due to the maintenance, which is usually the redispatch cost of the scheduled outage. C_f is the cost of repair after failure. *MTTF* is the mean time to failure of the component, with the maintenance cycle T_m. It can be evaluated with the Markov model in [79]. It is obvious that when T_m is small or the maintenance is performed frequently, the first part of (4.52) is very large because it is corresponding to the cost of maintenance, while the second part of (4.52) is very small because the probability of failure will be very low, and vise versa. So the objective here is to find the optimal T_m which minimize the total cost of keeping the components "healthy" in the life time.

It is possible to evaluate these costs by simulation, but in the long-term maintenance, it is not easy due to the high uncertainties in system working conditions over a long time frame. A good assumption is that these costs are related to the duration of maintenance and the average severity it caused by the maintenance activity:

$$C_d = \alpha * T_d * Sev(k,m) \qquad C_f = \beta * T_f * Sev(k,m) \qquad (4.53)$$

here, T_d is the duration of maintenance, T_f is the repair time and $Sev(k,m)$ is the average severity caused by the maintenance (if outage is needed) m for component k. This average severity does not depend on time because it is an average of severity function during one year, which is available in our risk simulation in 4.3:

$$Sev(k,m) = \frac{\sum_{t=1}^{8760} Sev(k,m,t)}{8760} \tag{4.54}$$

Fig 4.7 gives the total structure of the incorporation between long-term and mid-term maintenance activities. The contents in each rectangle are: 1) statistical process for hazard rate estimation based on condition data; 2) Long-term maintenance scheduling. 3), 4) and 5) are mid-term maintenance selector and scheduler and they are sequential simulator, risk assessment and optimizer respectively. These parts comprise the whole structure of the asset maintenance management of electrical transmission system.

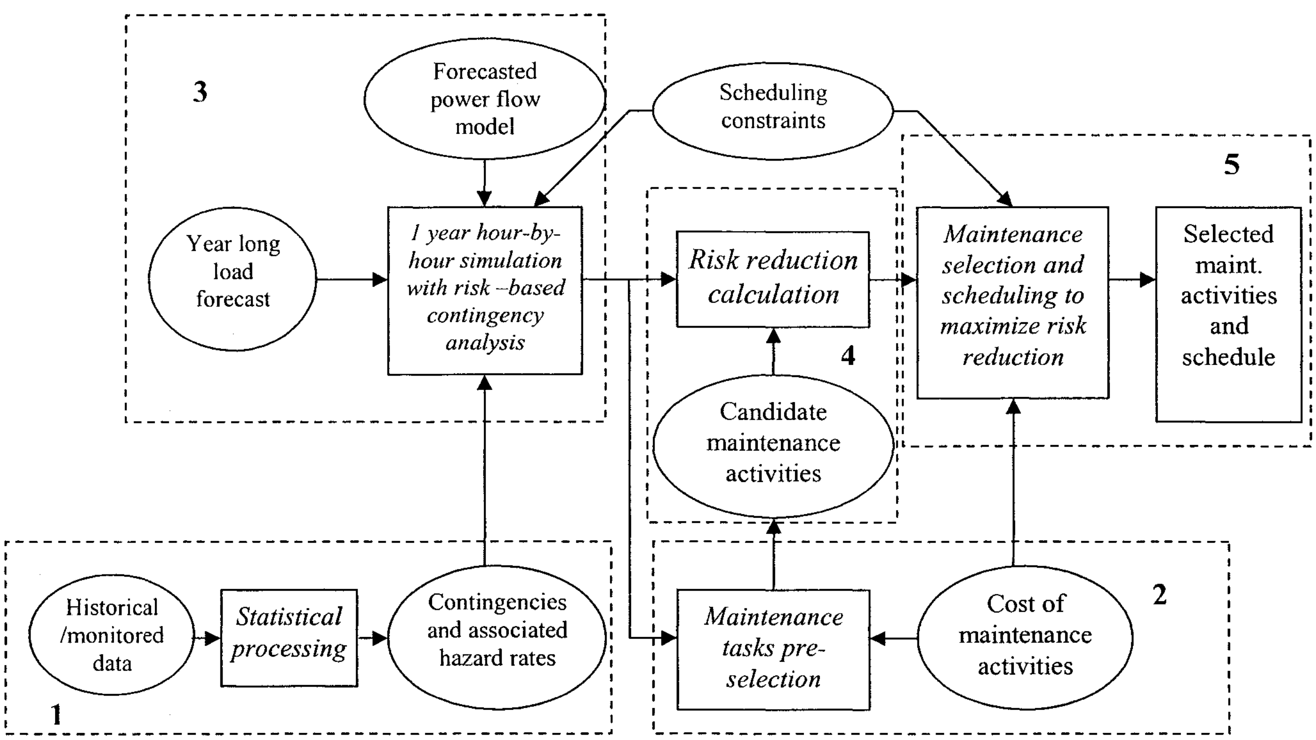

Fig. 4.7: Integration of data process, long-term maintenance and mid-term maintenance

4.7 Results

I have illustrated my 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 changed. 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. 4.8, was used as the next year's expected loading trajectory.

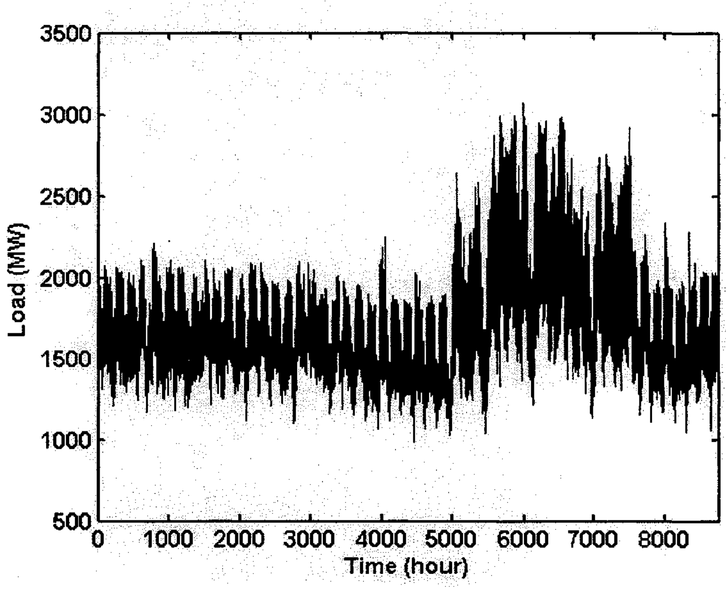

Fig. 4.8: One year loading trajectory of testing system

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.

4.7.1 Description of contingencies and maintenance activities

Contingency analysis must be done for any component that I am considering to maintain. Thus, I 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, I 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, the approach proposed in this thesis would also apply to the selection and scheduling of distribution equipment maintenance tasks as well.

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. I limit the maintenance tasks scheduled in our illustration to those affecting these four 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 4.3.

4.7.2 Hazard rate determination and effect of maintenance

With the method I introduced in Chapter 4, we can estimate the hazard 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 hazard 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 hazard rate and hazard rate reduction, based on the condition monitoring data. For example, based on the sample transformer result in chapter 4, and I 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 hazard rate of this transformer during the whole year, with the failure mode of oil deterioration with equation (3.41). And the change of hazard rate will be:

$$\Delta p = p(t_f) - p(t_m) \tag{4.55}$$

as depicted in Fig 3.6. For the maintenance of oil refinement (oil filtering and oil replacement) in the example of section 3.4.1.1, 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 hazard rate returns to 0. Thus we can calculate Δp, the change of failure probability after maintenance, as $\Delta p = p(t_f)$.

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

Reference [79] provides a typical MTTF for power transformers of 25 years. We assume in the work described 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 ages between 11 and 16 years.
4. Maintenance effects are as follows:

- Minor maintenance of a transformer reduces the hazard rate to the value of the previous year.
- Major maintenance of a transformer reduces the hazard 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. 4.9.

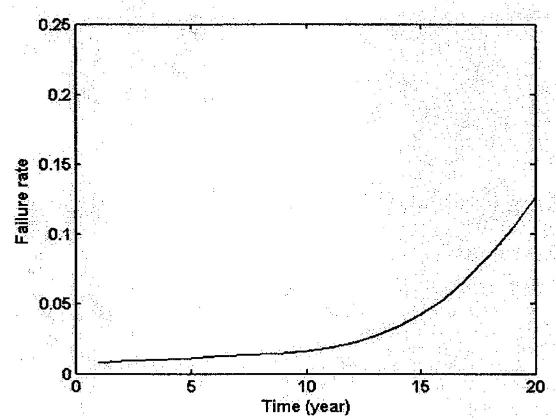

Fig. 4.9: Hazard rate assumed for transformers core problems

2) Transmission lines

Typical transmission line hazard rate data is 1 outage/100km/year for 345kV and 161 kV lines [80].

From [81], the typical hazard rate of tree contact is p=0.05 outages/100miles/year or 0.03125 outages/100km/year. It was assumed that after tree trimming, the hazard rate drops to zero so that the maintenance induced probability reduction is $\Delta p=p$. The hazard 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. I make the assumption that all tree-contact-related hazard rates are 1 outage/100km/year at the beginning of year, and if the tree trimming is not scheduled, the hazard rate increases linearly to 1.03125 occ/100km/year. Within the time frame, the hazard 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 hazard rate is set to be p=0.26 occurrences/100miles/year. For 345KV, the typical hazard rate is set to be p=0.20 occurrences/100miles/year.

3) Circuit Breaker

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 hazard rate should be achieved with the information of system configuration and topology data, together with probability analysis. Suppose for a circuit breaker with hazard rate P_c, there are N components within its protection region and each with hazard rate P_i . And failure of each component requires the operation of trip of circuit breaker. It was assumed that the failures of all components are independent. So the rate of failure of this two order contingency is:

$$P = P_c \times \sum_{i=1}^{N} P_i \tag{4.56}$$

The hazard rate of circuit breaker can be achieved from failure reports and test. Typical hazard rate data for circuit breaker is 0.009-0.015 faults/year, depending on the voltage levels of the circuit breaker [82] [83].

4.7.3 Maintenance activities

Five categories of maintenance are considered. I desire to identify the maintenance tasks and their schedule that results in the largest risk decrease for the specified contingencies. I considered performing tree-trimming for every line, insulator cleaning for every line, minor and major maintenance for every transformer and maintenance of circuit breaker, where each task may be done at any time of the year. Possible tasks and their attributes, together with the corresponding contingencies are listed in Appendix 2.

In Appendix 2, *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.

4.7.4 Description of results

Using the previously described system data, the process of risk-based transmission component maintenance scheduling is illustrated. For the contingencies identified in Table 4.4 I performed risk assessment over one year. The composite risk variation through the year (the sum of risk over all contingencies) is shown in Fig. 4.10.

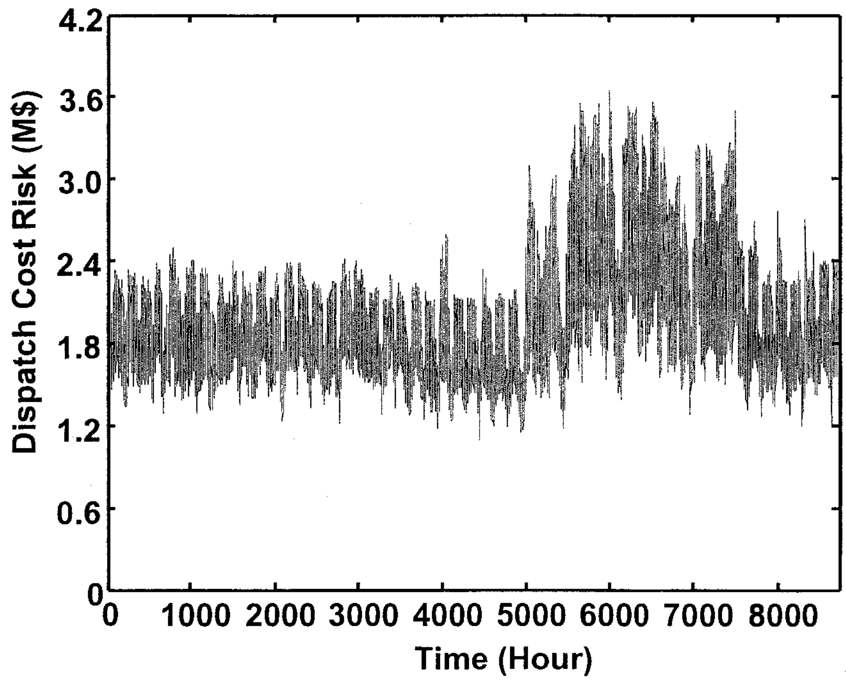

Fig. 4.10: Composite system risk

This Fig. 4.10 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. I have listed contingency-specific risk variation in table 4.4 and identified the highest risk contingencies for the specified problem-type at three different load levels (peak, minimum, and average). Fig 4.11 and 4.12 are the yearly risk curves for the two contingencies, 66 and 21, which have the highest risk and 10th highest risk at peak load.

TABLE 4.4: 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

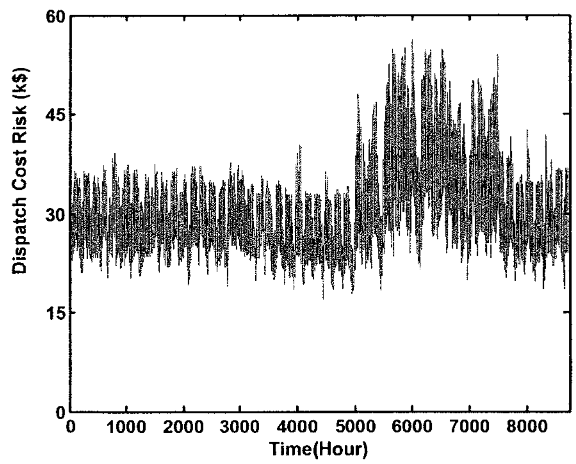

Fig. 4.11: Yearly risks of contingency 66

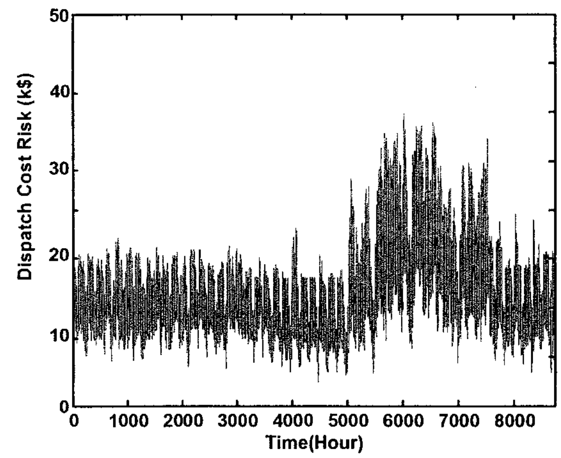

Fig. 4.12: Yearly risks of contingency 21

4.7.5 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. (4.33) are computed for each maintenance task. Figures 4.13 and 4.14 show the risk reduction curves for maintenance Trim66 and Trim21 (one such curve exists for each component *k*, task *m* combination). We can see it is non-increasing, indicating that the earlier the maintenance is scheduled, the larger will be the risk reduction. However, not all the maintenance start times indicated in Figures 4.13 and 4.14 are feasible because some of them incur very high risk due to maintenance-outage. This constraint is represented in the optimization model.

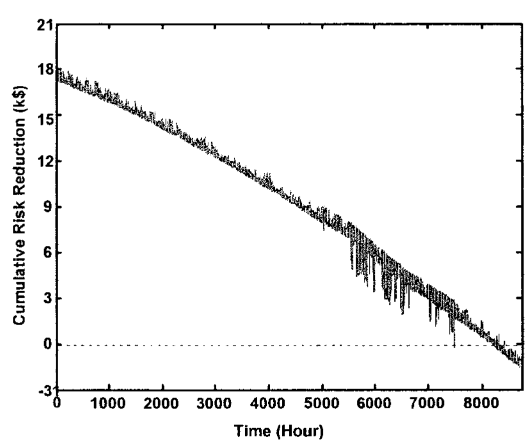

Fig. 4.13: Risk reduction of contingency 66

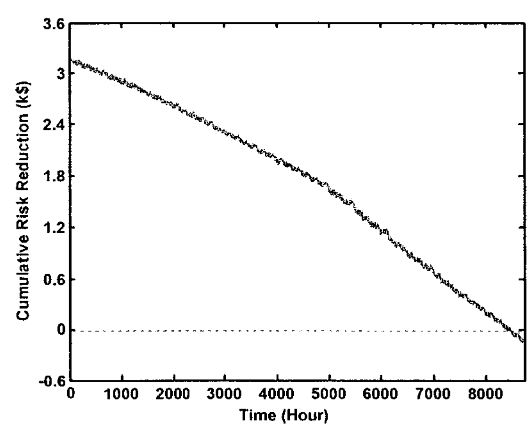

Fig. 4.14: Risk reduction of contingency 21

From Fig 4.13 and Fig 4.14 we can see that at the end of the year, the cumulative risk reduction falls below zero. This is because in (4.33), there is a non-positive item which is due to redispatch cost of aintenance itself. Since at the end of the year the cumulative risk reduction is very small, and the redispatch cost of maintenance itself might cause the benefit of maintenance lower than the risk increase by itself.

4.7.6 Maintenance task pre-selection

The task pre-selection is needed before we set up our mid-term maintenance scheduling problem, to reduce the calculation burden. As introduced in 4., a long term maintenance selection was performed based on components repair cost and failure cost estimated with (4.52) and (4.53). Fig 4.15 describes the relationship between the yearly average cost of maintaining the component in working condition and the maintenance cycle of oil filtering of transformer.

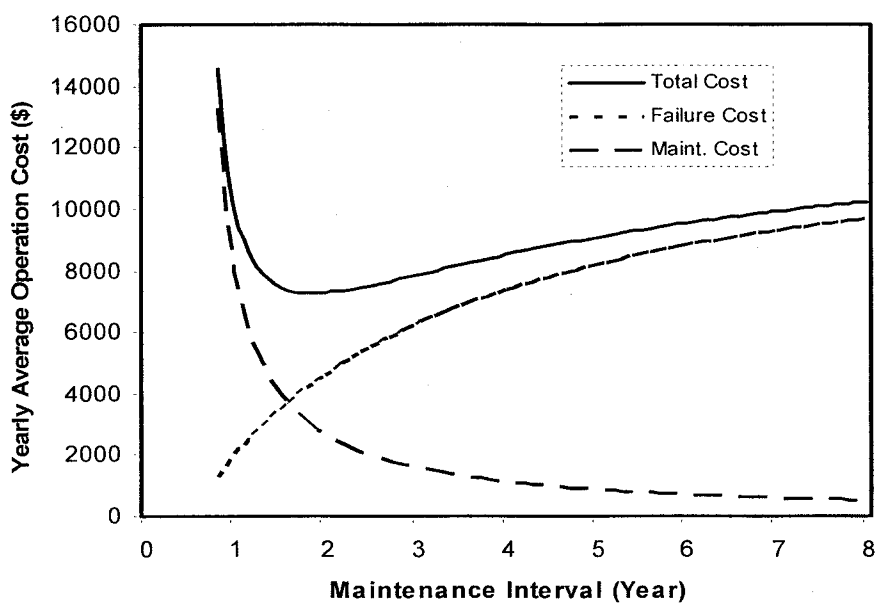

Fig 4.15: Yearly operation cost vs. maintenance interval of oil filtering

From Fig 4.15 we can see that there is an optimal maintenance interval with respect to the yearly average operation cost of the transformer. The optimal value in the figure is 2.11 years. That does not give a fixed time of maintaining the transformer but rather suggests a good time frame to perform the maintenance or inspection. In Fig. 4.15, the value should be between 1.5 to 3 years and the average cost will be between 7.3k and 8.1k dollars. Table 4.5 gives the selected transformer minor maintenance tasks and their corresponding optimal maintenance intervals.

TABLE 4.5 SELECTED TRANSFORMER MINOR MAINTENANCE TASKS AND OPTIMAL MAINTENANCE INTERVALS

Task	Cm ($)	Cd ($)	Cf (k$)	Tm (year)
Xrmi1	1000	2980	93.8	2.11
Xrmi2	1000	2350	74.0	1.93
Xrmi3	1000	2686	84.6	1.89
Xrmi4	1000	3590	113.1	1.82
Xrmi5	1000	1970	62.1	1.99
Xrmi6	1000	3025	95.3	1.86
Xrmi7	1000	3687	116.1	1.81
Xrmi8	1000	4890	154.0	1.76
Xrmi9	1000	5600	176.4	1.74
Xrmi10	1000	2080	65.5	1.97
Xrmi11	1000	3500	110.3	1.82
Xrmi12	1000	4235	133.4	1.78
Xrmi13	1000	2598	81.8	1.90
Xrmi14	1000	2600	81.9	1.90
Xrmi15	1000	2350	74.0	1.93
Xrmi16	1000	1970	62.1	1.99
Xrmi17	1000	3025	95.3	1.86
Xrmi18	1000	5625	177.2	1.74
Xrmi19	1000	2689	84.7	1.89
Xrmi20	1000	3698	116.5	1.81
Xrmi21	1000	4503	141.8	1.77
Xrmi22	1000	2680	84.4	1.89
Xrmi23	1000	2908	91.6	1.87
Xrmi24	1000	3758	118.4	1.81
Xrmi25	1000	3622	114.1	1.81
Xrmi26	1000	4020	126.6	1.79

4.7.7 Maximum risk reduction with budget and labor constraints

The labor and budget constraints are summarized in Table 4.6. 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 4.5.3, 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.

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

The maintenance task selection and schedule computed by the optimization program is shown in Table 4.7, 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 4.7: 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
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

Table 4.7 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. This will reduce those risks for the remainder of the year, which in turn tends to maximize the risk reduction achieved, in conformance with the objective.

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 blank periods although they have crews 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 that 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 Fig 4.13 and 4.14. So we can set that different constraints might have different effect on maintenance selection and scheduling, so their effects on optimization results should be analyzed.

4.7.8 Optimality of our program

To show the performance of our program, I have tested the result and compare those from other mixed linear program in commercial software. Since the size of our problem, the program should have ability to deal with large size integer programming. Two programs are tried. The first one is the *bintprog(),* a function in optimization toolbox of Matlab 7.0. It is based on branch and bound method, and could solve binary variable problem. However, it does not have good ability to deal with large size problem. When the projects size exceeds 5 (number of variables exceeds 5*52=206), the searching cannot be finished within limited time.

Another software to compare is 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 superior performance and reliability--particularly on large, difficult problem. From the introduction in its manual, the solver is based on branch and bound 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. This tool is powerful in solving industry-sized problem, but might encounter some performance problem such as out of memory for real large problem. And due to the facts of the mechanism, users can neither project how much further the process needed to go nor how much memory would be required to ultimately solve it.

I have tested the performance of both programs on different cases of our problem. Those cases have different resource allocation as in Table 4.8. The comparison of results from our program and CPLEX is listed in Table 4.9. In every case the CPLEX can give very good result. The errors are within 1%. The conclusion of CPLEX results and comparison of two results are as follows:

1) CPLEX can provide optimal result since it uses B&B method, but it is time and memory consuming because of the large size of tree it needs to build and search. In many cases optimal result are not reached before the memory is consumed. But CPLEX provides both best feasible solution and upper/lower limit for integer programming. Usually the gap (difference between the current best feasible solution and upper limit is less than 1%). And we can think this result is satisfying and can be deemed as optimal.

2) CPLEX uses much more time in searching since it uses B&B method, which is a partial enumeration method. Usually it will cost more than 6 hours until the memory is exhausted. Since our sample problem is still small compare to industry size problem. The feasibility of using CPLEX in real system maintenance selection and scheduling needs to be investigated.

3) Comparing to the optimal solution of CPLEX, our method of RLP-DPH can also provide good results. The error of the result with CPLEX solution always falls within 5%. And most of the error with the upper limit from CPLEX is less than 5% too. The advantage is the calculation time is much shorter and memory usage is much less. Although current computer technology can provide good support for heavy calculation burden, the searching size will increase exponentially with the increase of problem size, with the usage of B&B. So the computation burden is still a concern. But our method can solve this problem efficiently, because it divides the problem into smaller knapsacks and the calculation burden should increase linearly with the increase of problem size. Thus it provides very good speed performance with satisfying accuracy, as shown in Table 4.9.

TABLE 4.8: 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 4.9: 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 of RLP-DPH and CPLEX.

Gap*: The difference between solution of RLP-DPH and the upper-limit from CPLEX, actually it is the upper-limit of error of our solution with optimal result.

4.7.9 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 4.8. 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 4.16-4.20.

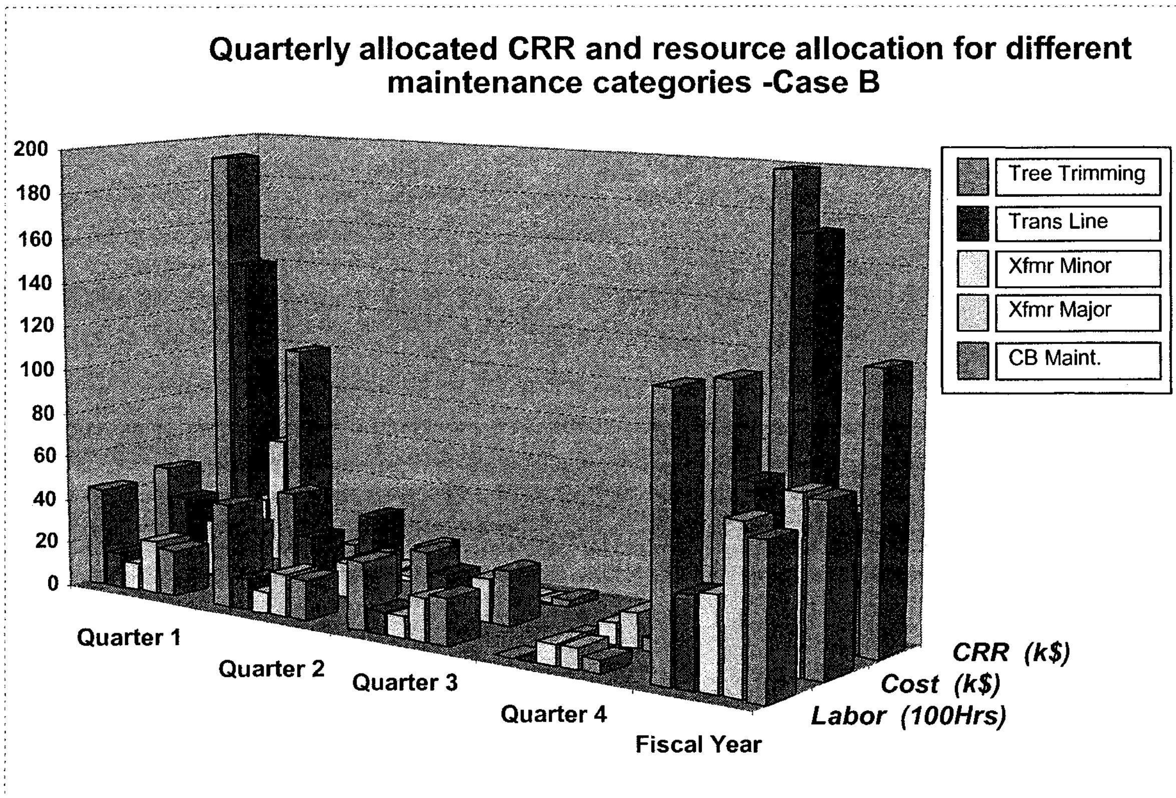

Fig 4.16 Quarterly allocated CRR and resource allocation for case B

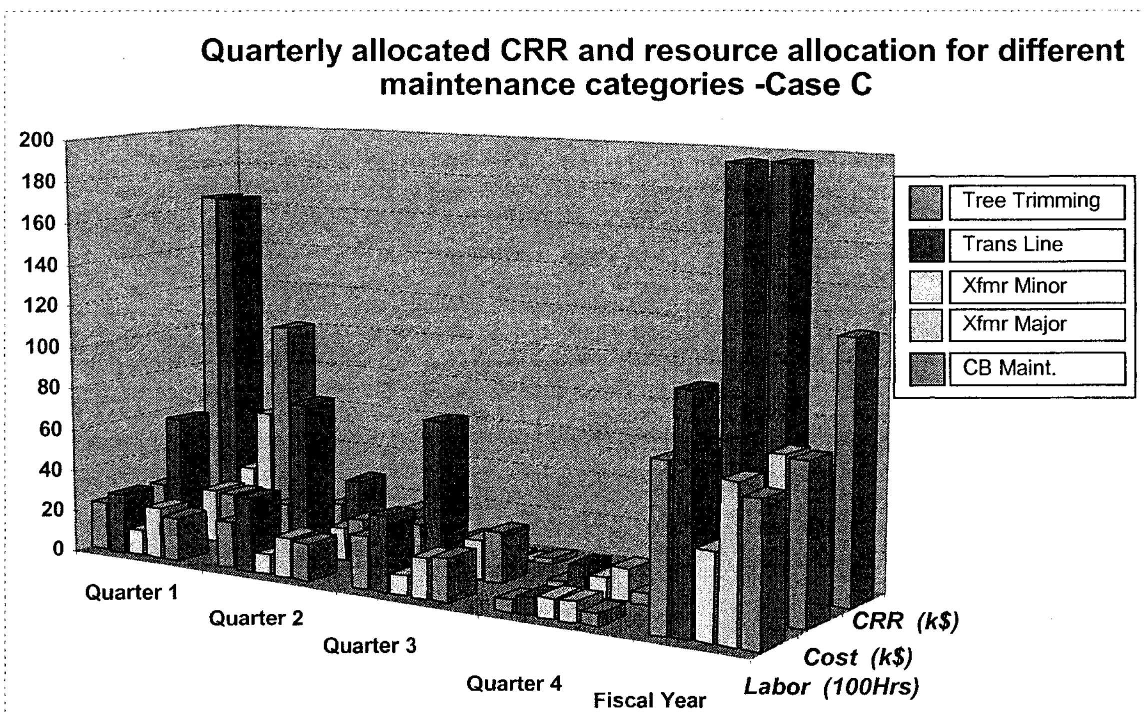

Fig 4.17 Quarterly allocated CRR and resource allocation for case C

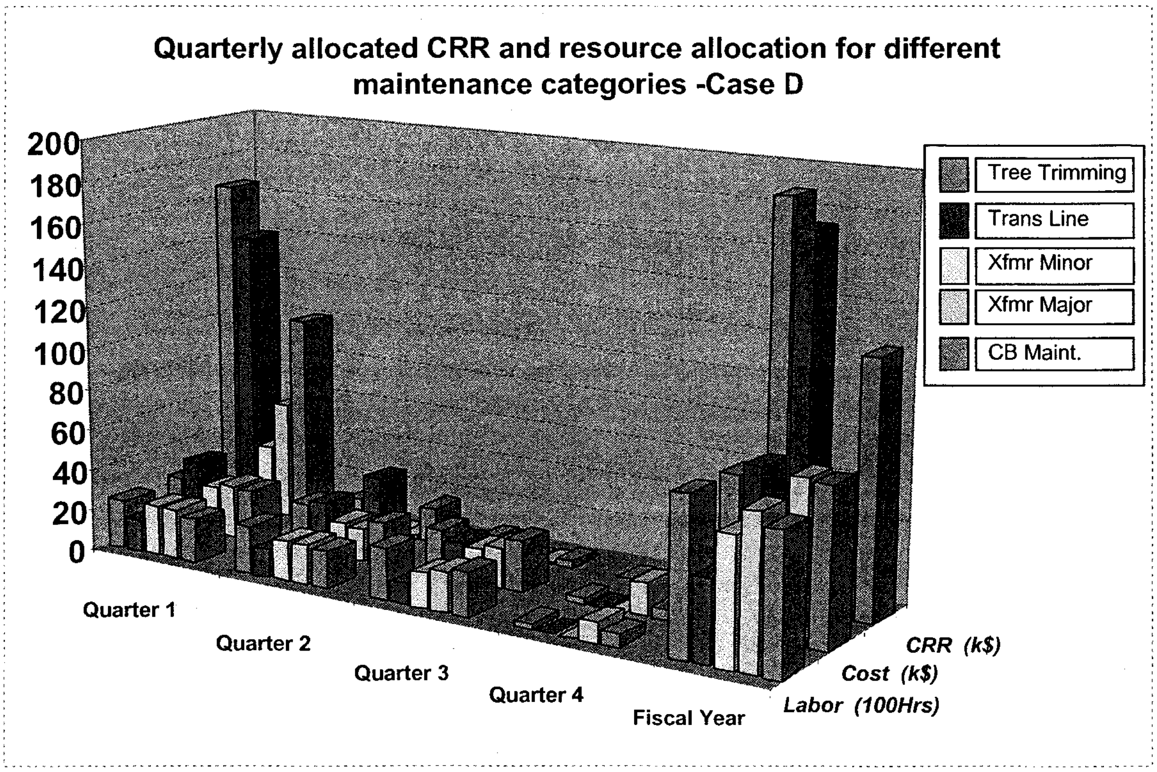

Fig 4.18 Quarterly allocated CRR and resource allocation for case D

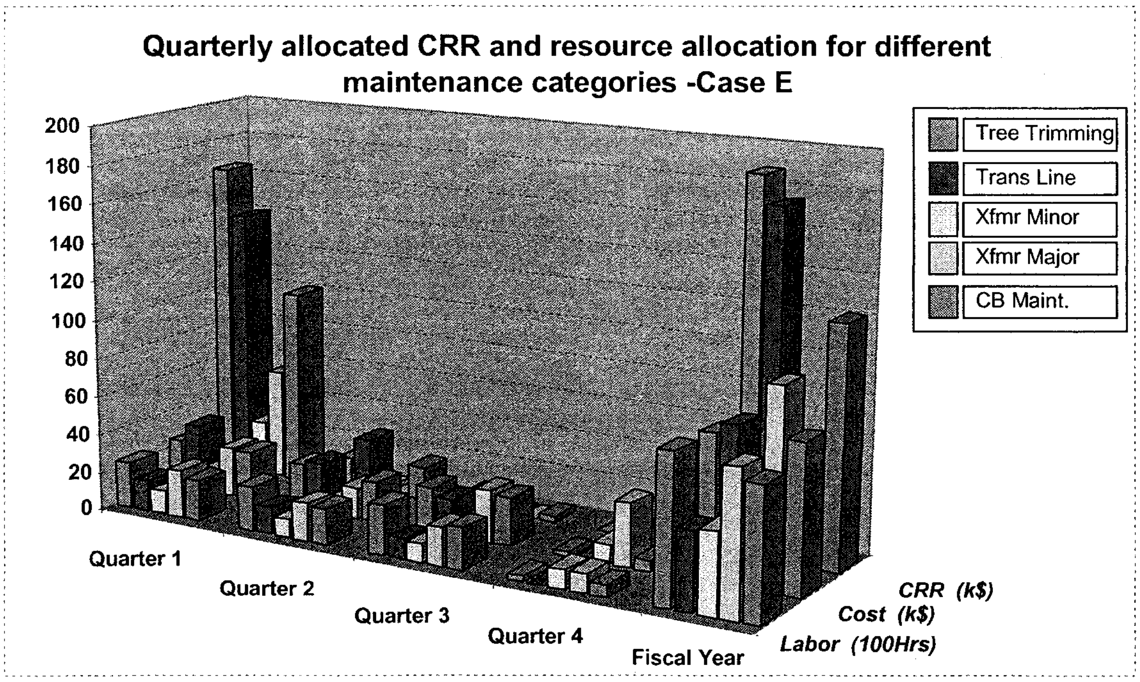

Fig 4.19 Quarterly allocated CRR and resource allocation for case E

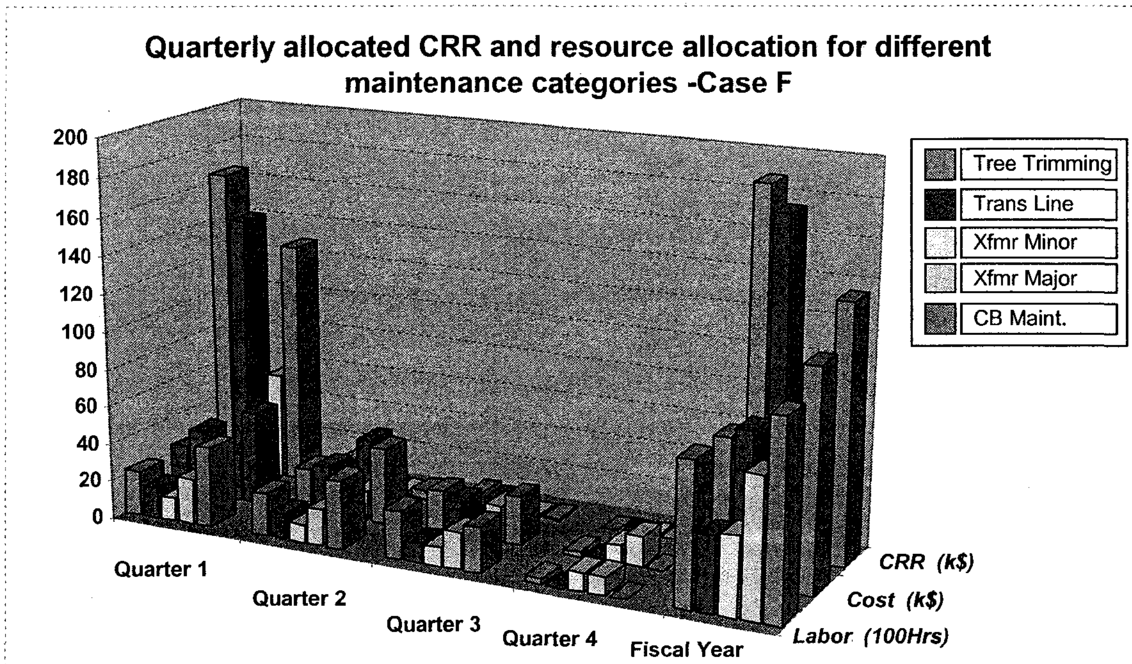

Fig 4.20 Quarterly allocated CRR and resource allocation for case F

Table 4.10 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 4.10 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 ratio	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 Figure 4.16-4.20 and Table 4.10, we can draw the following conclusions:

1. For each case, we can see that category 1 and 2 (tree trimming and transmission line maintenance) will consume more resource 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 permit several tasks to be scheduled at the same week as early as possible, as shown in Table 4.6.

2. For most categories, when more resource is allocated, more cumulative risk reduction is produced (Fig 4.16-4.20) but the general efficiency (CRR/Hour, CRR/Cost) of this category will drop, as shown in Table 4.10. This is reasonable because the optimal algorithm chooses most efficient tasks with available resources. When more resource is available, less efficient tasks will be chosen.

3. Category 4 (transformer major maintenance) does not show an increase with CRR with more allocated resources. This is because this category is much more labor constraint. We can see that in Table 4.6 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 at the same week. Therefore the category 4's result was not affected by our resource allocation from case B to F.

4. From Table 4.10 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 result gives us some direction in resource re-allocation between different categories.

5. When we compare the 5 cases in Table 4.10, we can see that case C, in which the category 2 (transmission line maintenance) is emphasized with more resource allocation, provides the highest output (599.78k$ of CRR). This is because it is category with most efficient resource characteristic, as stated in 5. But it also has the lowest general benefit/cost ratio (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 get performance of each category of maintenance activities in our objective function – cumulative risk reduction and their efficiency in utilizing the resources. And we can get direction of resource re-allocation between different categories based on it. However, such analysis is not enough to produce accurate resource reallocation because the scheduling program is constrained by two resources (labor and cost) and a good combination of resource allocation is needed to get better performance of the whole scheduling program. I will extend our effort with a more accurate method in the following section.

4.7.10 Continuously scheduling maintenance activities with "rolling" procedure

From the Fig 4.16-4.20 we can see that it is obvious in each case, 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: I) The optimization algorithm will choose the tasks which will produce the most objective values (CRR) to be scheduled as early as possible, since the risk reduction is cumulative over time. II). The tasks scheduled at the first quarter will be credit with the whole year's risk reduction but the tasks scheduled at the second quarter will only have the risk reduction of the next 3 quarters of the year credited. And the tasks scheduled at the last quarter of the year nearly have no risk reduction, comparing with the tasks scheduled at the beginning of the year. This is because we only evaluate the benefit in one year's horizon. A feasible solution of this issue might be a 'rolling' execution of this procedure, in which the whole year will be divided into different periods, such as quarters. For each quarter, we span the study period to one year from the start of that quarter and perform risk simulation and optimization accordingly. Table 4.11 gives an example of this rolling procedure of scheduling maintenance activities with resource allocation of case A in Table 4.8. It is a five-quarter maintenance scheduling with 2 years' time frame. With the first quarter, the maintenance scheduling is performed in the same procedure as illustrated in Table 4.7 but we only recorded the task scheduling for the first quarter. After each quarter, the scheduling program will be extended with another quarter with the same, with a full year's budget and labor. The only changes from quarter to quarter are the candidate tasks and their risk simulation results. The new problem excludes the tasks that already have been scheduled and will be set up as (4.35)-(4.41), with new simulation results of cumulative risk reduction and possible new task candidates. With this 'rolling' procedure, we can account for the yearly benefit for each maintenance activity more accurately.

In Table 4.11, quarter 1's result is based on one-year simulation result from the first quarter to the fourth quarter, and the quarter 5's result is based on simulation from the fifth quarter to the eighth quarter, which means the five quarters' maintenance scheduling is based on the system information of two year's time frame. Fig 4.21 gives the illustration of cumulative risk reduction achieved for each quarter in this rolling procedure, together with the resource consumed in each of the category. From the Fig 4.21 we can see that the benefit of maintenance in each quarter is more evenly distributed. This is because each quarter's result is based on one-year's risk reduction benefit. The difference of results among different quarters comes from the changes of maintenance tasks and different yearly system simulation starting from each quarter.

TABLE 4.11 QUARTERLY PERFORMANCE OF MAINTENANCE SCHEDULING WITH "ROLLING" PROCEDURE

	Category	Quarter 1	Quarter 2	Quarter 3	Quarter 4	Quarter 5	Total
CRR (k$)	1	164.14	154.46	139.26	149.12	85.83	692.81
	2	152.09	201.23	148.09	140.36	184.88	826.64
	3	28.17	18.91	21.98	29.65	24.63	123.34
	4	57.22	12.42	34.77	37.94	17.01	159.35
	5	101.35	88.58	136.64	96.86	44.06	467.49
Hour (100 Hours)	1	48.84	50.25	50.28	49.68	49.92	248.97
	2	60.66	60.96	60.69	61.14	61.62	305.07
	3	31.20	31.20	31.20	31.20	31.20	156.00
	4	62.40	62.40	62.40	62.40	62.40	312.00
	5	39.00	39.00	39.00	39.00	39.00	195.00
Cost (k$)	1	44.81	34.60	38.68	30.60	19.54	168.23
	2	51.55	45.12	51.28	49.93	55.69	253.57
	3	34.12	7.95	2.49	5.78	25.50	75.85
	4	43.20	11.41	32.65	5.89	3.67	96.82
	5	58.23	23.12	35.64	28.62	28.66	174.27

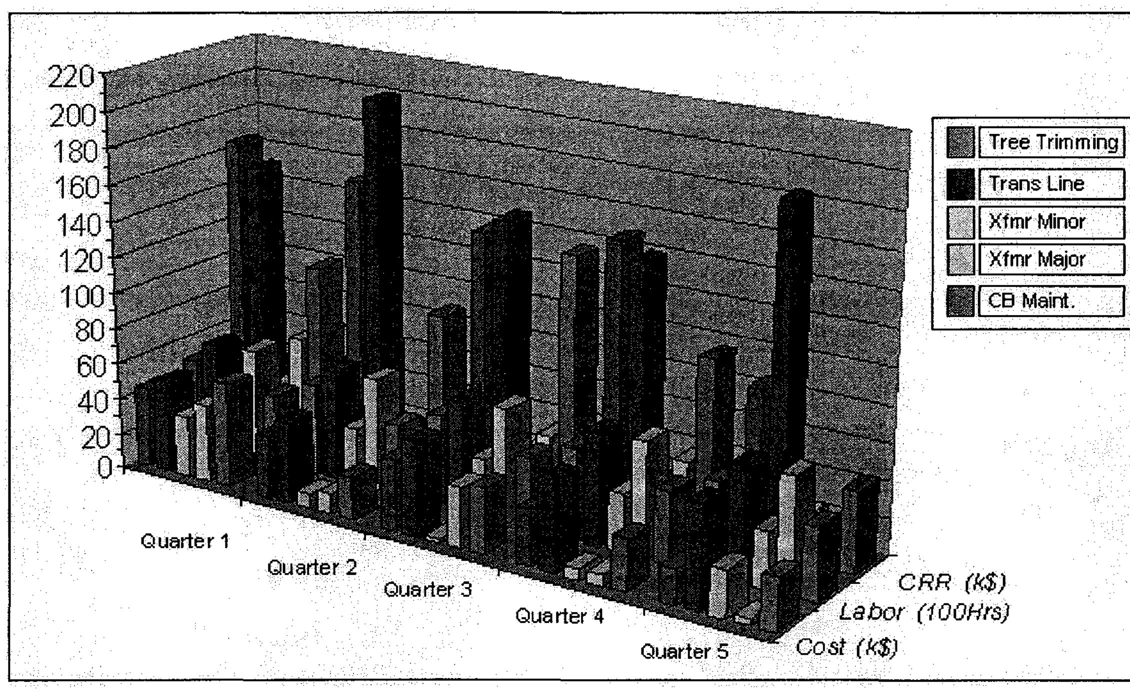

Fig 4.21 Quarterly CRR and resource allocation for case A with "rolling" procedure

4.7.11 Resource reallocation based on Lagrange Multipliers

From optimization results in Table 4.6 and analysis in section 4.6.8 we can see that the resource constraint has very important effect on the result of optimization. And it is very likely that there is 'imbalance' of the resource reallocation between the different categories. So the situation exists when one resource constraint is dominating while the other one is redundant. The reallocation of resource could make the resources more effectively distributed between different categories and thus maximize the optimization results.

In solving the linear programming of (4.35), Lagrange multipliers are solved 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 allocations, although they are only multipliers for the relaxed linear programming and thus may have some error with the real multipliers for the integer solution. The error may be fixed by the iteration of the resource allocation until an optimal point is reached. 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 $i=1...,N$, each with allocated resource C_i. The principle of the resource allocation is that resource is re-allocated from the categories with lower value of Lagrange multipliers to the category with the highest multiplier.

1) Solve the relaxed linear programming (4.35)-(4.41) of the problem. Get 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 redundant resource and all of the reallocated resource will come from that category.
3) If all of multipliers are less than zero, then the resource allocation will be determined by the difference between these multipliers with the maximum Lagrange multipliers:

$$\Delta C_i = \frac{\lambda_i - \lambda_{\max}}{\sum_{j=1}^{N}(\lambda_j - \lambda_{\max})} \times \Delta C \tag{4.57}$$

For labor constraint, since it is a weekly constraint, there is a lower limit of the resource allocated to each category, so that the labor in that week is enough to perform at least maintenance activity. This is especially important for transformer maintenance, which might need more people in each mission. When the lower limit is reached, then the labor in that category will be fixed at the lower limit and stop being adjusted.

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

Table 4.12 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 4.13, the Lagrange multipliers for every category, and for each case, are listed. Form the results we can see 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 4.12: 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 4.13: 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 4.13 we can see that we get significant increase of CRR by reallocating the resources between different maintenance categories, from 569.38k$ to 631.53k$ (10.9% increase). By tracking the reallocation, with reference of Table 4.10 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.

4.7.11 Effect of constraints on optimization results

I have investigated the effect of budget and labor reallocation between different categories, with fixed total available resources. However, in transmission asset management, a good investment level of the total resources needs to be found, to get best general performance of the maintenance scheduling. To help analyzing the performance of the maintenance-scheduling program, indices reflecting different attributes of the solution were introduced as described in what follows:

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 631.53 in the case scenario A5 in section 4.7.10.
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. I 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.

I computed and plotted these various indices for two scenarios based on the case A5, which has the best resource allocation. In Section 4.7.11.1, I will fix the labor constraints for each maintenance type and vary the budget constraint. In Section 4.7.11.2, I will fix the budget constraints for each maintenance type and vary the labor constraints.

4.7.11.1 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 4.14, and the budget is varied from \$246k to \$648k. The results in terms of the various indices are summarized in Table 4.15.

TABLE 4.14: 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 4.15: 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

Table 4.15 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. 4.22 to 4.28. I have made the following observations:

1. <u>CRR</u>: Fig. 4.22 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. <u>CRR/cost and CRR/total labor</u>: Figs. 4.23 and 4.24 indicate that as the budget increases, the CRR per dollar cost 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. 4.23 and 4.24. This does not necessarily imply that one should not utilize the greater resource levels. To this end, it can be commented 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. 4.25 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. 4.25 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*/Total possible *CRR*: Fig 4.26 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. Labor hours/available labor hours: Fig. 4.27 shows that as the budget increases, the (labor hours used)/(available labor hours) increases. This is reasonable as long as labor constraints are not active, implying crews are more fully utilized as budget increases.
6. Unscheduled maintenance: Fig. 4.28 shows that the percentage of unscheduled maintenance tasks decreases as the budget increases.

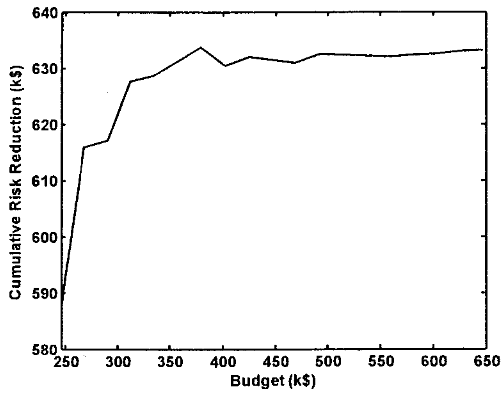

Fig. 4.22: Cumulative Risk Reduction

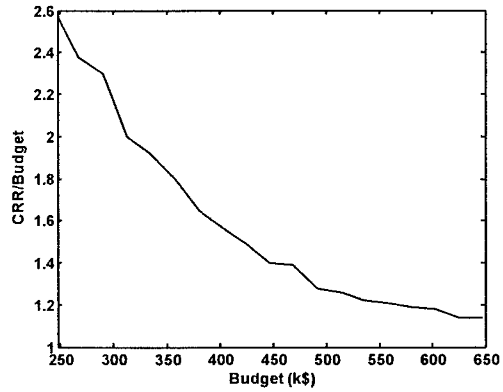

Fig. 4.23: CRR/Cost

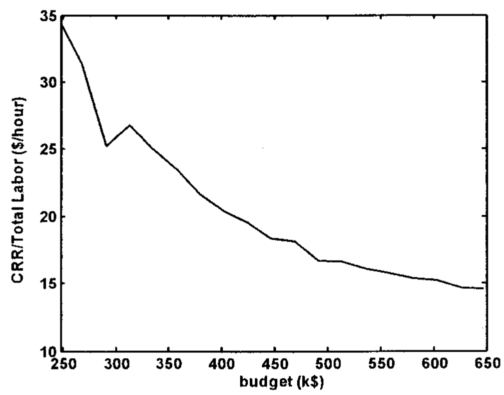

Fig. 4.24: CRR/Labor Used

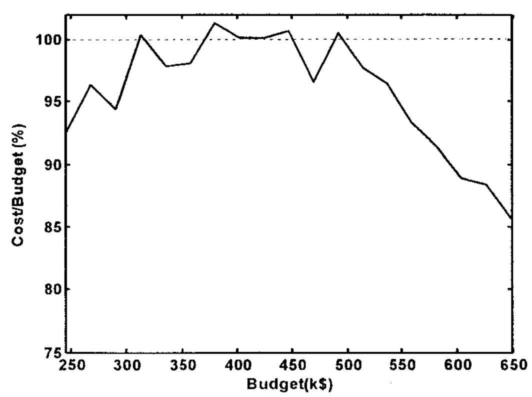

Fig. 4.25: Cost/Budget

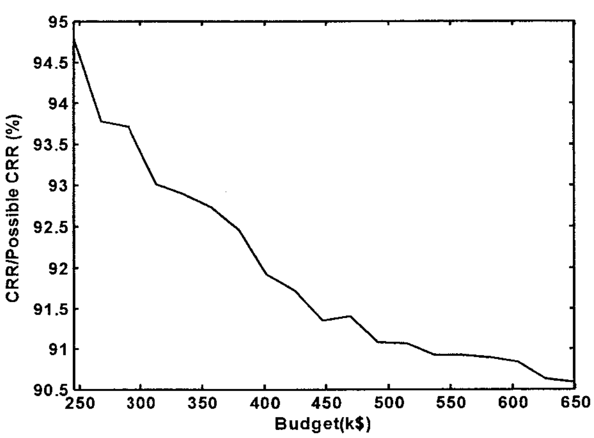

Fig. 4.26: CRR/Possible CRR

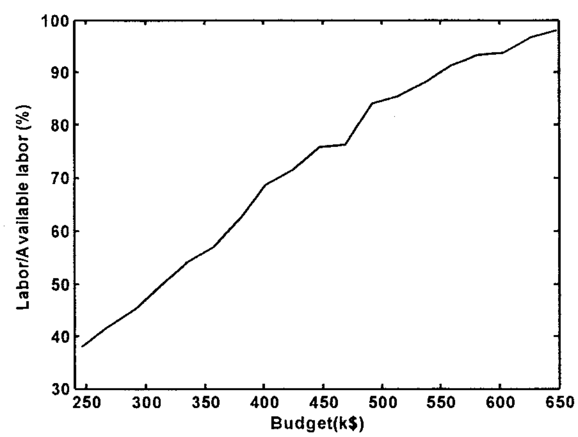

Fig. 4.27: Labor usage

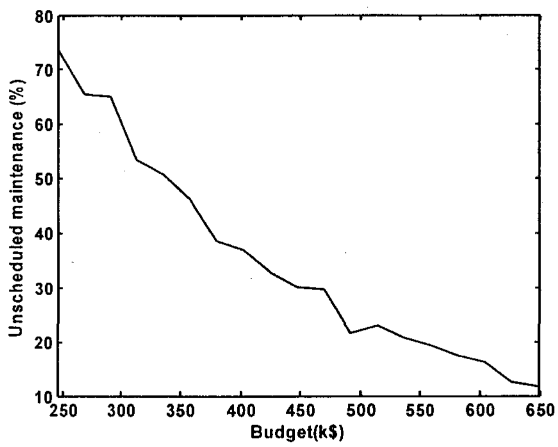

Fig. 4.28: Unscheduled maintenance

4.7.11.2 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 4.16, and the labor hour varies from 1798 to 3886 hour per week, as indicated in Table 4.17. The results in terms of the various indices are summarized in Table 4.17.

TABLE 4.16: 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 4.17: 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. 4.29 - 4.35. I make the following observations:

1. CRR: Fig. 4.29 shows that CRR increases with increasing labor. With increasing budget, we observed a leveling off of CRR (see Fig. 4.23) 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/cost and CRR/total labor: Fig. 4.30 and 4.31 show that as the labor increases, the CRR per dollar cost 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 4.23 and 4.24 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 Fig. 4.30 and 4.31.

3. Cost/budget: Fig. 4.32 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. 4.33 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 4.34 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. 4.35 shows that the percentage of unscheduled maintenance tasks decreases as the labor increases.

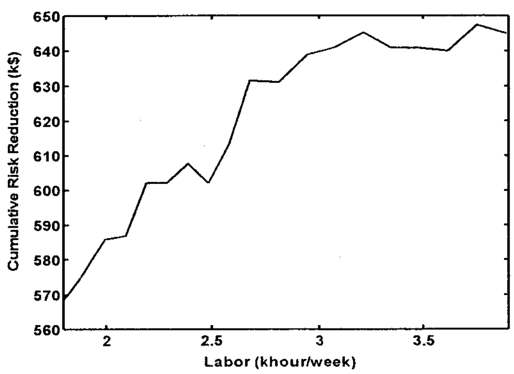

Fig. 4.29: Cumulative risk reduction

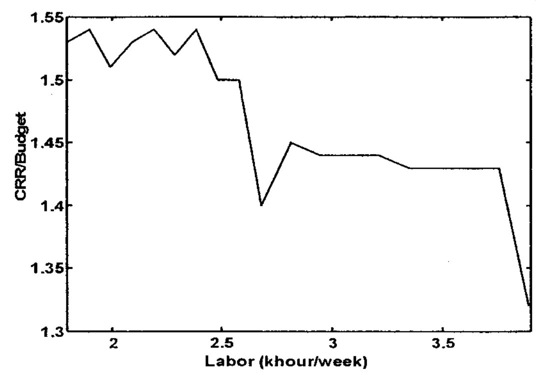

Fig. 4.30: CRR/Cost

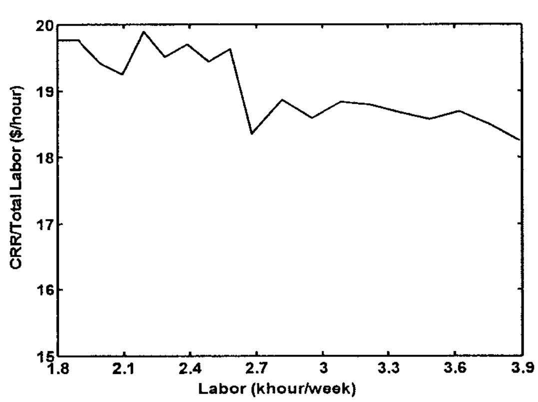

Fig. 4.31: CRR/Labor

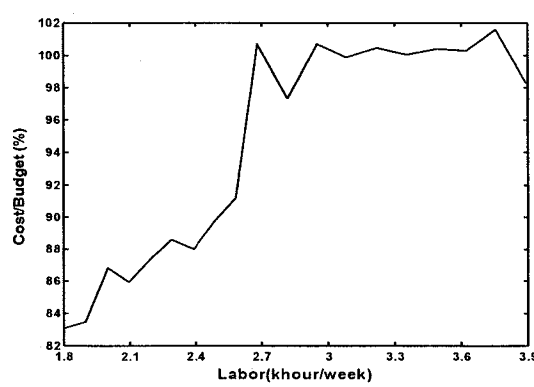

Fig. 4.32: Cost/Budget ratio

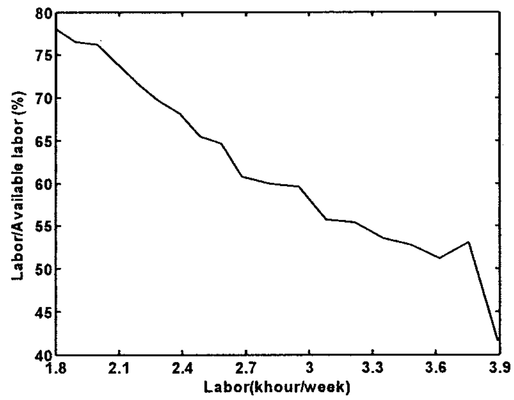

Fig. 4.33: labor usage

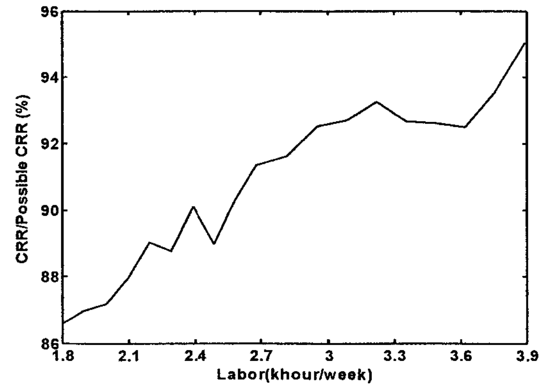

Fig. 4.34: CRR/Possible CRR

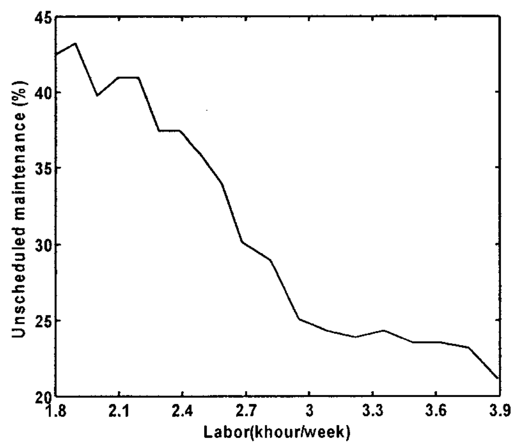

Fig. 4.35: Unscheduled maintenance

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.

4.7.12 Decision making on resource scheduling and allocation

Our program does not only provides the best selection and scheduling of current maintenance activities, with fixed resource allocations, it also provides useful information on how to make plans on how to make budget and labor resource scheduling, so that the maximum efficiency will be achieved. It should be based on calculation on optimization of different combination of resource allocations. Fig 4.36 gives the variation of the objective function with different resource scenarios. The total budget varies from 111k dollars to 961k dollars and the labor varies from 0.67k to 5.76k hours per week.

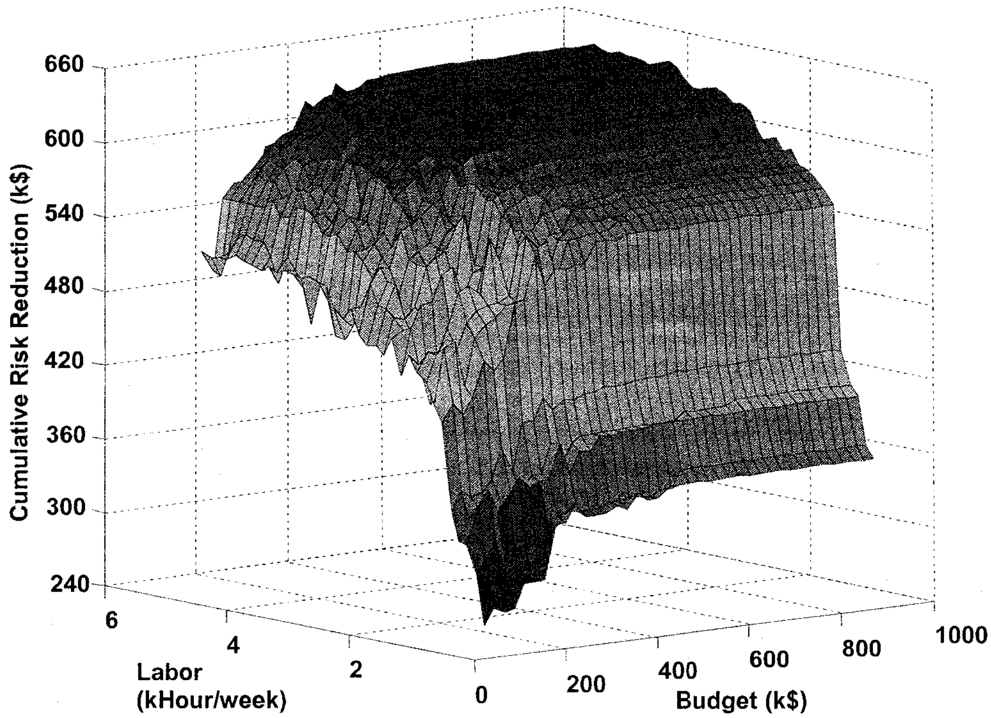

Fig. 4.36: CRR surface with different resource conditions

From Fig 4.36 we can see that the total objective function increase with the increase of the labor or budget constraint under most of the conditions. There is some lumpiness of the surface. This is due to the sub-optimal feature of our program. Under some conditions, the optimal solution cannot be found and is replaced with the sub-optimal solution found by our program. However, it achieves much faster speed. Otherwise, precise calculation with so many combinations of resource conditions for industry size problem is impossible. 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:

$$TotalCost = BudgetUsed(\$) + LaborUsed(Hour) * W(\$ / hour) \quad (4.58)$$

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:

$$E = CRR \,/\, TotalCost \tag{4.59}$$

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

1) Determine the required objective function threshold *CRR'* of maintenance scheduling.
2) Perform the maintenance scheduling with combination of different resource allocation within reasonable range, as in Fig 4.36
3) For each combination, calculation of the total cost of the scheduling and the efficiency ratio with (4.58) and (4.59) is performed.
4) Choose the scheduling scenario with the highest efficiency ratio with required objective function *CRR>CRR'*.

Suppose the hourly wage is set as 16$/hour, Fig 4.37 is the efficiency ratio of maintenance scheduling under different resource combinations. From Fig 4.37 we can see that maximum efficiency is achieved with the minimum resource allocation. However, we also need to meet the preset objective of our maintenance scheduling. Suppose we want to have a CRR>620k$, then we can use the Lagrange multipliers 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$ and efficiency ratio is 1.2609.

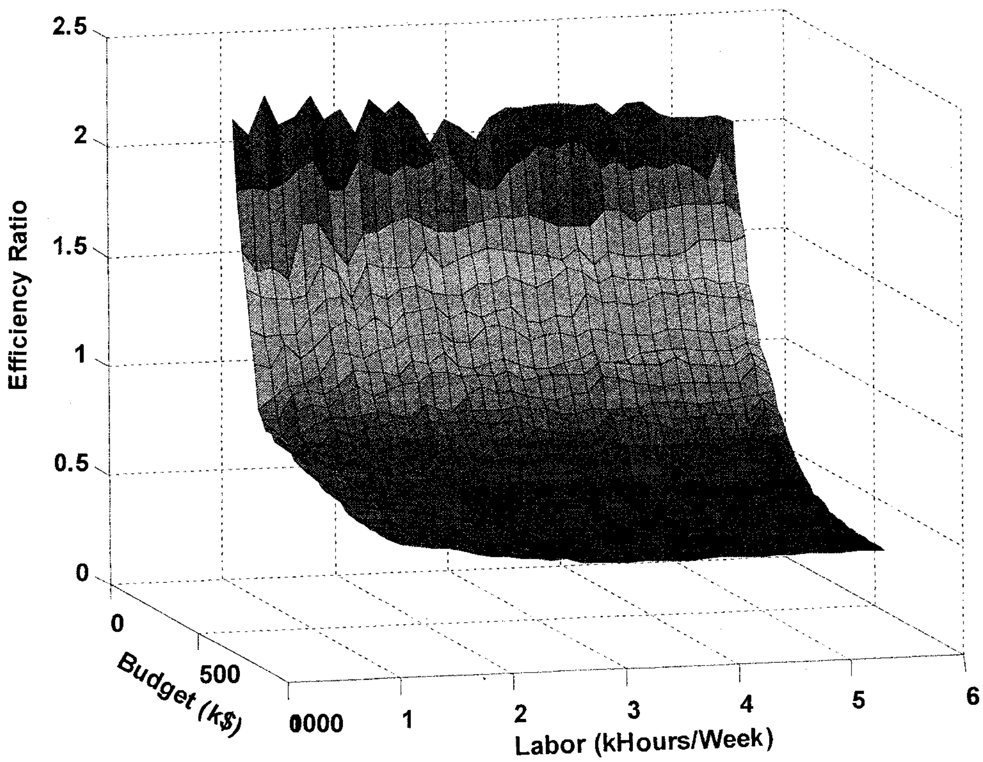

Fig. 4.37: Efficiency Ratio with different resource allocations

4.8 Maintenance scheduling coordination between transmission owners

Since the utility companies or transmission owners make their outage schedules according to their own sub-system and tie line information. It is possible that the outages of different transmission owners, when they are combined, will cause some problem to the security of the whole system. The activity of the outage planning should be coordinated with higher level of control, which is usually performed by the independent system operator (ISO).

ISO was setup according to the need of restructure of the power industry in 1990's, at different regions of power grids in US. They are charged with the responsibility of managing the flow of electricity along the long-distance, high-voltage power lines that make up the bulk of transmission system. The objective of this non-profit organization is to open the energy markets to competition and thus the transmission owners (Transco) turned their private transmission power lines over to ISO's management. The mission of ISO is to safeguard the reliable delivery of electricity, facilitate markets and ensure equal access to the transmission lines. So any outage scheduling of major transmission/generation component made by the transmission owners for should be submitted to the ISO for approval. ISO will investigate the impact of this outage and approve/deny the request based on system reliability requirement. Thus the coordination of the outages is an important task for ISO to assist the transmission owner customers to perform their duties while maintaining the system safe. Currently the ISO is using a first come, first serve policy, in which it means it approves the request submitted early and deny the request submitted later, if the later request is conflict with the previous request of outage. Our program can provide a more flexible solution to the system outage coordinator, since the tasks are scheduled based on redispatch cost induced risk and risk reduction. We can use the redispatch cost due to the outage conflict as a 'lever' to adjust the benefit of the transmission owner's maintenance scheduling and thus coordinate their outage request. The whole procedure is described in Fig. 4. 38.

As indicated in Fig 4.38, after the Transmission owners submit their scheduled outage request, the ISO can evaluate the impact of the outages to the system security. If any violation of reliability is found, the ISO will calculate the cost of the remedy actions to relieve the stress due to these outages. The remedy actions may contain generation redispatch, reactive power compensation and load shedding, etc. Then ISO will send this calculation back to the transmission owners as extra cost of scheduling this outage at the specific moment. This extra cost will force the transmission owners to change their estimated benefit from the maintenance, which is the cumulative risk reduction $CRR(k,m,t)$ in (4.35) to:

$$CRR'(k,m,t) = CRR(k,m,t) - C_r(k,m,t) \tag{4.60}$$

where C_r is the extra cost of remedy action and it might be a very large number. This will almost forbid that maintenance and corresponding outage to be performed at a specific time t, unless the transmission owner is willing to pay for it. After rescheduling, the transmission owners will submit their new schedules to the ISO and have the check again. This iteration will proceed until no violation is found. Then the final outage schedule will be approved by ISO.

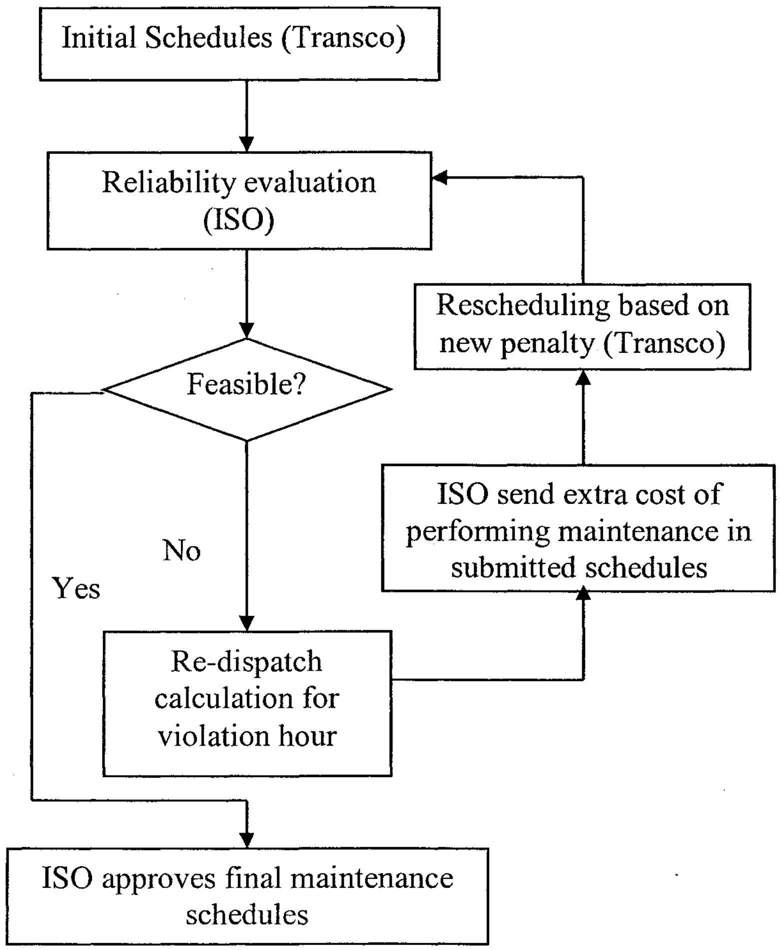

Fig. 4.38: Flowchart of maintenance outage coordination

A simple example has been setup to show this procedure. First the tasks in Appendix 2 are divided into two groups, simulating two Transco companies making their own maintenance scheduling with budget and labor resource limit respectively. The two lists of maintenance scheduling then was submitted to the ISO and evaluate their reliability impact within the whole system. An AC power flow is performed to calculate the outage impact for each hour. To simplify the problem, only overload problem is considered. If any overload is found due to some planned outage, an economic dispatch calculation is performed to calculate the cost of the redispatch to release the overload. The final result was shown in Table 4.18.

TABLE 4.18 EXAMPLE OF MAINTENANCE OUTAGE SCHEDULING

	CRR of Transco1 (k$)	CRR of Transco2 (k$)	Total CRR (k$)	Violation	Reason of the violation	Remedy cost needed
1	341.33	314.39	655.72	At week 2, overload at 69kv line (301-175)	Outage of transformer line 12	4721.3$
2	341.33	313.98	655.32	At week 3, overload at 161kv line(23-33)	Outage of transmission line 32	2659.8$
3	341.01	313.98	655.00	At week 4, overload at 161kv line(23-33)	Outage of transmission line 32	4243.9$
4	338.46	313.98	652.44	None		

In Table 4.18, two companies (Trnasco1 and Transco2) made their own scheduling of outages and then submit to the ISO. We can see that the initial submission of Transco2 caused some overload violation during week 2, which induced a redispatch cost of $4721.3. The new cost of this action forced Transco to reschedule their maintenance. In the second and third round of this iteration, an outage of Transco1 caused some violation in week 3 and week 4 respectively. Similar procedure made Transco1 to reschedule their maintenance outages until no violation was found. We can see from the results that the final total cumulative risk reduction, which is benefit of the maintenance scheduling, is reduced. It is the maximum benefit we can get from the maintenance while maintaining the system security.

Chapter 5 Conclusion

The purposes of our study are very simple. They can be concluded as two major objectives: 1) Quantify the maintenance benefit to the transmission system. 2) Setup the asset management model and maximize the benefit in 1) within given constraints. However, efforts should be made in many aspects in our study to achieve the goal. This dissertation proposes most of our work in finding a rigorous method of allocating economic resources for bulk transmission system maintenance. It can be concluded that there is significant potential for using the procedures and methods developed in this thesis to expend maintenance resources and therefore better manage aging assets. The salient points and major contributions of this approach are:

a. Maintenance Scheduling in Transmission Asset Management:

This thesis present a complete framework for maintenance asset management for electrical transmission system, based on estimation of components failure's impact to the system and resource constraints. This approach provides effective methods in allocating economic resources systematically and strategically. The inclusion of cumulative-over-time risk is essential to account for system failure consequences and its variation over time. A systematic procedure is given for including in the decision process the influence of undesired operational performance created by equipment failure in terms of system security and component damage.

b. Failure Mode and Effect Analysis for Power Transformers:

Mathematical models of transformer failures probabilistic analysis demand an extensive relationship among condition monitoring techniques, failure probabilities, and maintenance tasks of the device. Typical transformer failure modes along with their causes as well as corresponding maintenance activities are addressed. This thesis also provides the summation of the techniques of monitoring of transformer conditions and identification of failure modes, which are important to the maintenance engineer, to make decisions on maintenance activities and frequencies.

c. **Hazard rate estimation based on condition monitoring data.**

Different methods of estimating failure probability of transmission components were summarized and compared in this thesis. Markov model was set up to simulate the deterioration process of the transmission components. By utilizing the Hidden Markov Model (HMM) in the hazard rate estimation, we can get the best fit of the model parameters to the observations - this method can trace the component deterioration process in the sense of maximum likelihood with the observation data and thus provides relatively accurate estimation of instantaneous hazard rate of the transmission components. Also the HMM model can deal with incomplete observation data, which is almost unavoidable in condition monitoring or routine test. This HMM model can be extended to any deterioration model which can be represented by a Markov model with condition monitoring data.

d. **Long Term Sequential Risk Simulation:**

This thesis utilizes a sequential simulation to compute operational risk accounts for impacts of components failure to the system. Components failure consequences are analyzed with respect to system impacts and property damage. Benefit of maintenance are calculated as redispatch cost saving and the prevention of property damage. My work simulates the benefit incurred either due to the hazard rate reduction or life extension, based on the time horizon that the maintenance are performed. DC optimal power flow (OPF) algorithm is used in estimating the redispatch cost of the system. This simulator takes the probabilistic cost saving as the risk reduction benefit of maintenance, which provides a quantified, credible index for scheduling maintenance activities in the optimization procedure.

e. **Maintenance selection and scheduling**

This thesis develops a systematic way to identify the optimal selection and schedule of maintenance tasks 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 it is concluded that relaxed linear programming with DP knapsack solutions is a very effective solution method. It provides very good solutions in a computationally feasible way.

f. Resource allocation in maintenance asset management:

With the help of Lagrange multipliers, 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.

g. Maintenance Coordination:

This thesis uses the probabilistic redispatch cost as representative of reliability risk and thus the objective of our work to maximize. This is same with the industry goals and can easily coordinate the maintenance or other asset management activates between different industry utilities. The fast speed of our optimization algorithm provides the feasibility of this coordination.

Suggested follow-on work:

A good plan of maintenance scheduling depends on good understanding of the transmission system. The principle of effective maintenance asset management is the resource goes to the components which need the care mostly. This leads to the definition of 'risk'. A good modeling of 'risk' and accurate simulation is the key of success of maintenance asset management. The following proposed approach might improve the evaluation of risk and thus the efficiency of maintenance scheduler:

a. Hazard rate estimation

While in utilizing the Markov model to simulate the deterioration process of the components, we assume that each failure mode is independent with other mode and thus the deterioration process for each mode is also independent. In practice the mutual-effect of the failure modes might exist. For example, the cellulose decomposition can speed up the deterioration of oil and vise versa. It is difficult to find the relationship between different failure modes because it might be involved in complex physical or chemical processes. The utilization of the score system is a heuristic method of solving this problem but the rules to setup the criteria is generally based on experiences and need to be updated with most current field data and new experiences.

b. Long term simulator:

1. Optimal power flow: Our risk simulator utilized DC optimal power flow to calculate the redispatch cost. Under the condition of heavy load, the neglecting of system loss might cause some error in results. AC optimal power flow is desired but that could cause some problem in extra calculation burden for the year-long hourly simulation.

2. Outage duration: I have indirectly accounted for transformer outage duration via modifications in the severity function depending on the status of spares. However, I have assumed all other outages are uniform. Probabilistic treatment of outage duration is useful in getting the estimation of impact of those outages to the system reliability.

c. Incorporation of short-term maintenance scheduling

Incorporation of short-term maintenance scheduling will make the work a complete risk-based maintenance strategy which covers planning and operation horizon. [69] has introduced a scheduling model under restructured power system. Our optimization algorithm can be well applied to that method. However, the constraints of scheduled transactions and contracts need to be introduced into the optimization model.

Appendix 1: Transformer Failure modes, causes, effects and maintenance activities

Failure mode (criticality)	**Components**	**Failure cause**	**Failure effect**	**Detection**	**Maintenance Activity**	**Frequency (typical data)**
Insulation failure (high)	Insulation media (Transformer oil)	Oxidization of oil	Cause corrosion of the various metals within the transformer, particularly the iron	Oil screen test	Oil degasification; Oil filtering of non-pcb contaminated oil. Oil replacement	1 year
		Thermal decomposition of oil	Breakdown of the oil resulting in carbon formation, sludge and insulation deterioration.			
		Contamination from moisture	Possible catastrophic failure, winding to winding or winding to tank			
	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

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

Appendix 2: Proposed transmission component maintenance tasks

ID	Name	Type	Hour	Cost	Duration	Contingency	ID	Name	Type	Hour	Cost	Duration	Contingency
1	Trim1	1	120	1000	40	11 12	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
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
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								

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