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Maintenance Optimization for Substations with Aging Equipment

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MAINTENANCE OPTIMIZATION FOR SUBSTATIONS WITH AGING EQUIPMENT

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MAINTENANCE OPTIMIZATION FOR SUBSTATIONS WITH AGING EQUIPMENT

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Today's electric utilities are confronted with a myriad of challenges that include aging infrastructure, enhanced expectation of reliability, reduced cost, and coping effectively with uncertainties and changing regulation requirements. Utilities rely on Asset Management programs to manage inspections and maintenance activities in order to control equipment conditions. However, development of strategies to make sound decisions in order to effectively improve equipment and system reliability while meeting constraints such as a maintenance budget is a challenge.

The primary objective of this dissertation is to develop models and algorithms to study the impact of maintenance toward equipment/system reliability and economic cost, and to optimize maintenance schedules in a substation to improve the overall substation reliability while decreasing the cost.

Firstly, stochastic-based equipment-level reliability and economic models are developed depending on maintenance types. Semi-Markov processes are deployed to represent deteriorations, failures, inspection, maintenance and replacement states for reliability modeling; semi-Markov decision processes are implemented for economic cost

evaluations considering capital investment, operations and maintenance cost, and outage cost.

Secondly, substation level reliability and economic cost models are established based on equipment level models. Sensitivity studies for analyzing the impact of equipment maintenance toward system level reliability and overall system cost are conducted.

Finally, maintenance optimization scenarios and solutions are developed, to determine optimal equipment maintenance rates that maximize substation reliability or minimize overall cost, while meeting operational and economic cost constraints, based on Particle Swarm Optimization techniques.

Moreover, fuzzy Markov and Markov decision processes are designed to calculate fuzzy reliability indices and economic cost; a parallel Monte-Carlo simulation method is also proposed to perform reliability evaluations through simulation method, in which the accuracy and computation speed are testified.

The algorithms developed in this dissertation are valuable for system reliability evaluation, maintenance planning, maintenance prioritizations, and maintenance policy. The programs developed can assist asset managers in making maintenance-related decisions, to effectively balance the system level reliability and associated maintenance cost.

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I will always be proud as a graduate of the University of Nebraska-Lincoln, and will think of this place as my hometown in the U.S.

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CHAPTER 1
INTRODUCTION

Most of the current electric utility transmission and distribution equipment in the United States is over 30 years old [1]. As more and more equipment and systems age, electric utilities will be required to develop and implement asset management strategies and practices to balance their investment and operation and maintenance (O&M) costs to increase earnings while meeting reliability requirements and operation under budget constraints[2], [3].

1.1 Asset Management

Asset management is a program in which an organization make spending decisions that aligns all asset-level spending budget with high-level business objectives [4]. Asset management defines the process of guiding the acquisition, use and disposal of assets to make the most of their future economic benefit, and manage the related risks over entire asset life [5]. Asset management is a combination of *managerial* view and *technical* view of assets.

The diagram in Figure 1.1 presents the asset management activities related with maintenance, and organization levels in utilities.

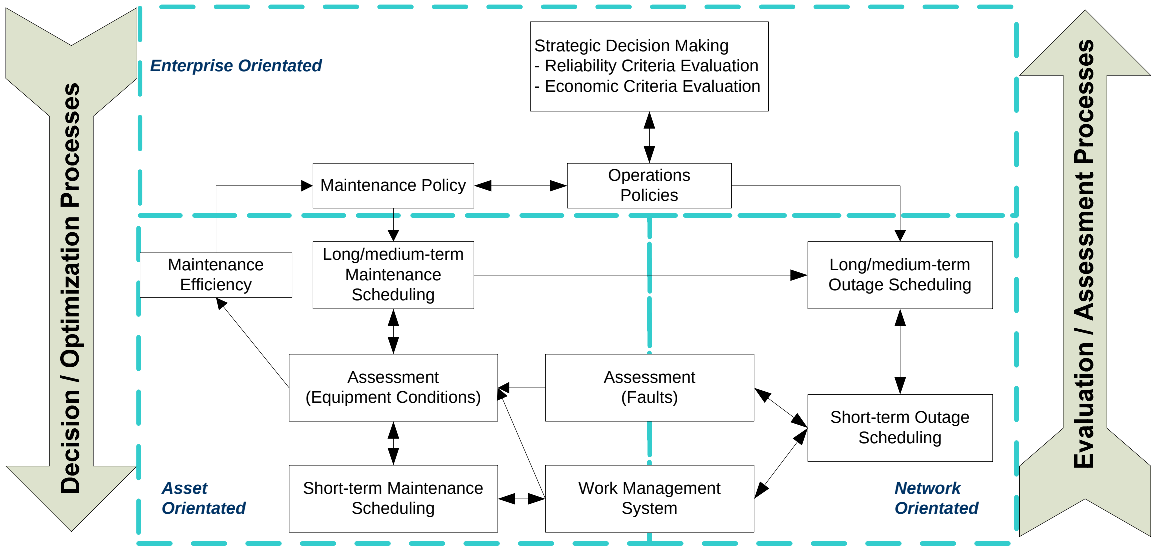


Figure 1.1 Maintenance related Activities in Utilities Asset Management Process

From an organizational standpoint, activities in Figure 1.1 are categorized into three parts [5]:

- *Asset-Oriented* activities focus on asset as individual component (for managing critical equipment), or the population of assets of similar type (for managing a group of equipment). Usually they are the responsibilities of maintenance department.
- *Network-Oriented* activities emphasize on outage scheduling with respect to system operation constraints. They are the responsibilities of operations, and some time coordinated with maintenance department.
- *Enterprise-oriented* activities involve strategic decision on capital investment, overall reliability and policy setup. Generally they are managing activities.

From engineering stand point, the activities in Figure 1.1 have other meanings. On the one hand, the processes from top to bottom are maintenance optimization related activities. The purpose from top to bottom is to optimize the limited maintenance and budget resources, to ensure reliable power supply and decrease interruption frequency/durations. On the other hand, the activities from bottom to top are evaluation processes. Detailed modeling of aging / maintenance / failure histories will more accurately represent asset values/conditions, in order to better support maintenance resources optimization described before.

1.2 Maintenance Models

Maintenance is defined as an activity to arrest, reduce or eliminated device deteriorations. The purpose of maintenance is to extend equipment lifetime, increase asset values (equipment conditions), and avoid costly consequences of failures [6].

Models to establish connections between maintenance and the corresponding lifetime extension, asset condition, and reliability improvement are required in order to make sound decisions related to maintenance activities.

Empirical Approaches and Mathematical Models

The relationship between maintenance and its impact can be based either on empirical approaches or mathematical models [6].

Empirical approaches are based on experience and manufacturers' recommendations. A widely used empirical approach is *reliability centered maintenance* (RCM). RCM is based on condition monitoring, failure cause analysis, and investigation for operation needs and priorities, in order to select critical components and prioritize maintenance steps [6].

In contrast, mathematical models are more flexible than heuristic policies. A distinct advantage of mathematical models over empirical approaches is that the outcomes can be optimized. Mathematical models include deterministic or probabilistic -

based methods. Since maintenance models are used for predicting the effects of maintenance in the future, probabilistic methods are more appropriate than deterministic methods, even through probabilistic methods may increase complexity and loss in transparency.

Probabilistic Mathematical Models

Recently many utilities have replaced the scheduled maintenance activates by predictive maintenance, in which the schedule is based on analysis of periodic inspections or condition monitoring results [6]. For these applications, quantitative correlation between reliability and maintenance has to be developed. Probabilistic maintenance models are usually adopted to quantify the above correlations, as generally the models deal with random deteriorations, failures, aging processes, etc [7].

1.2.1 Reliability and Economic Modeling with Maintenance for Equipment

Equipment Reliability Modeling

In earlier reliability research, the states of equipment were usually categorized as fully successful or fully failure state [8]. Maintenance was also included but only as an active failure [9]. However, two states are not sufficient to reflect real working conditions of power systems equipment. For example, equipment can still work while part of their material deteriorates. Recently, “imperfect repair” or “imperfect preventive maintenance” has been introduced into the research [10], in which deterioration states are added into equipment modeling [11], and minor or major maintenance was introduced into preventive maintenance strategies [12]. These improvements make evaluation of maintenance’s impact on individual equipment more practical [13].

Endrenyi reported that probabilistic maintenance models would provide the highest flexible and economical solutions to utilities maintenance policies [6]. While considering equipment deterioration, maintenance, failures and other states, Markov processes and semi-Markov processes are powerful tools for modeling the transition of these states [14]. In previous work, optimal maintenance policy evaluation techniques for power equipment have been studied using minor maintenance or major maintenance [15-18]. This dissertation includes the addition of inspection state in equipment modeling, in order to better represent predictive maintenance and condition monitoring.

Equipment Maintenance Cost Modeling

From the diagram presented in Figure 1.1, it is evident that maintenance cost assessment is an indispensable part of asset management. Generally cost and reliability objectives are in conflict, as increased reliability usually means higher maintenance cost, especially for distribution systems with aging equipment.

The costs associated with equipment not only include inspection / maintenance / repair costs that are apparent, but also contain penalty costs associated with failures/maintenance outages that are unapparent [19]. Brown divided the maintenance related costs into Utility Cost of Reliability (UCR) and Customer Cost of Reliability (CCR), and claims that one of the objectives of making maintenance decisions is to minimize the Total Cost of Reliability (TCR) combined above two costs [20].

This dissertation adopts this idea to develop equipment economic model to study the impact of maintenance schedules toward the equipment cost. In addition, the dissertation presents how to minimize maintenance cost and to maximize the benefit under target availability.

1.2.2 Reliability and Economic Modeling with Maintenance for Substation

Substations play a vital role in both transmission and distributions (T&D) systems. Traditional reliability studies focus on generation, transmission or distribution, mainly for system planning [1]. Previous work on switching station or substation reliability evaluation incorporates maintenance as active failure or forced outage [21-25]. Recently, more maintenance planning is considered and evaluated in transmission planning and operation [26] [27]. Industry has also developed several tools for maintenance planning [28] [20]. Our previous works involve development of a Fuzzy-based technique, for determining the impact of maintenance on substation reliability evaluation including uncertainty of model parameters [29] [30]. However, there are certain shortcomings in previous research for evaluating the impact of maintenance on load point availability as stated below:

- Maintenance is treated the same for the equipment life duration, while in practice different types of maintenance may be performed at different stages, such as useful-life period and wear out period.
- Maintenance is assumed to be perfect. Traditional methods assume that equipment enters fully success state again after maintenance; but in practice, maintenance may not be perfect, in which equipment can enter a state in different conditions after maintenance, or enter other types of maintenance states.
- Previous studies didn't provide a rank or priority of the equipment. Determining which component is more critical for a specific load and which one should be maintained first are common problems in utilities asset management.

- There are no economical analyses of the substation maintenance cost, as well as other costs related to the equipment outage. In practice, economical evaluation is indispensable for utilities to make maintenance decision under limited budget.

Based on reliability and economic models developed for equipment while incorporating maintenance, similar models are established for substations in this dissertation. This dissertation also quantifies the importance of every component in a substation, from the perspective of load point or entire substation.

1.2.3 Modeling Uncertainty

Accurate modeling of aging equipment requires historical data related to deterioration, failures and maintenance in order to statistically reflect the stochastic processes of the equipment and systems. In practice, however, historical data is either insufficient or uncertain. Imprecision or ambiguity is the characteristic of many reliability model parameters, generally because of insufficient historical data.

Fuzzy mathematics has been developed to model these types of uncertainties [31-33]. Recently, fuzzy mathematics has been applied successfully to power systems, e.g., optimal power flow [34], [35], transformer condition monitoring and diagnosis [36], electric machine controls [37], [38], and reactive power compensation [39].

The inherent parameter of uncertainty in reliability evaluation techniques has also led several researchers to apply fuzzy set methods. Fuzzy logic was introduced to represent uncertain information, and basic models are presented for calculation of different reliability indices [33], [40]. In [41], [42], the uncertain load information is represented by fuzzy values while the bulk system reliability indices are calculated using fuzzy arithmetic. These papers initiate application of fuzzy mathematics in reliability evaluation, but with relatively simple models and specific applications.

Markov models with fuzzy inputs have also been developed in which uncertainties in transition rates/probabilities are represented by fuzzy values [43-45]. Generally in existing models, the methods for calculating the fuzzy outputs can be categorized into two classes. In class one, the uncertain transition rates/probabilities in the matrix of Markov equation are replaced directly by fuzzy membership functions, and fuzzy logic or arithmetic are utilized to mimic the Markov processes calculation [43][45]. This approach is computationally tedious and requires complex fuzzy logic calculations, and is only applicable for small scale Markov models with limited states. In class two, the reliability indices are derived, as functions of transitions rates / probabilities and then fuzzy arithmetic is applied to compute the fuzzy indices [44]. However this approach requires deriving explicit equations, which is impractical in some cases especially in system level models. In general, the standard framework of Markov processes with fuzzy transition probabilities or fuzzy transition rates is not pursued.

In this dissertation, a general approach to develop a fuzzy Markov model is proposed. This approach incorporates parameter uncertainty and probability in aging equipment models and existing reliability models. The proposed method can also be used for determining the optimal maintenance rates that maximizes specific reliability indices.

1.3 Maintenance Optimization

As described in Section 1.2, for mathematical maintenance models, maintenance optimization with regards to changes in some basic model parameters (such as maintenance rates) can be carried out for evaluating maximum reliability or minimum costs [11].

It is pointed out that preventive maintenance optimization (PREMO) can be more efficient than RCM. Preventive maintenance optimization is based on extensive task analysis rather than system analysis, with a capability of drastically reducing the required number of maintenance tasks in a plant. Therefore, it can be very useful in ensuring the economic operation of power stations [6].

For maintenance optimization studies, Hilber, Bertling [46] presented a concept of applying a multi-objective optimization method for maintenance optimization in distribution systems. The process is similar to that carried out during distribution planning. Jiang and McCalley [47] developed a risk-based method for transmission system maintenance optimization, by studying the cumulative long-term risk caused by failure of each piece of equipment, which considers equipment failure probability, deterioration and outage consequence. Yang and Chang developed several approaches to include stochastic-based equipment models for substation and system maintenance optimizations, and implement evolutionary-based optimization techniques [48] [49].

Based on the works cited and similar researches it is evident that the outcome of maintenance optimization approaches can improve equipment or system interruptions while decreasing maintenance related cost. This dissertation also studies maintenance optimization process for substations, with detailed modeling of equipment aging and maintenance processes.

1.4 Overview of Dissertation

The organization of this dissertation is as follows:

- Chapter 2 provides an introduction to the problem of power equipment aging and deterioration. A number of stimulants that contribute to the aging process are discussed. Maintenance that mitigation deterioration is presented, and a comparison of existing maintenance policies are provided.

- The first part in Chapter 3 gives a complete description of how to utilize Markov processes to study the impact of maintenance toward equipment reliability, as well as determine the optimal maintenance rates to maximize equipment availability.
- The second part in Chapter 3 provides how to implement Markov decision processes to model the economic cost for aging equipment with maintenance.
- The first part in Chapter 4 gives the approaches of how to extend equipment reliability and economic modeling to substation level, and study the impact of equipment maintenance toward load points or overall substation reliability or cost.
- The second part in Chapter 4 illustrates different optimization scenarios as well as optimization techniques that can solve these problems.
- The first part in Chapter 5 gives an approach to calculate fuzzy reliability indices by fuzzy Markov and Markov decision processes.
- The second part in Chapter 5 presents a parallel Monte-Carlo simulation approach for system level reliability studies, which can significantly reduce the computation comparing to traditional Monte-Carlo simulation.
- Chapter 6 provides the complete case studies for each approaches developed through Chapters 3-5. Sensitivities studies are also conducted.

CHAPTER 2
AGING EQUIPMENT

This chapter describes the aging problem in power system with emphasis on power transformers and circuit breakers. Different maintenance policies that are utilized to mitigate the aging process are also compared and summarized.

2.1 Aging Power Equipment

2.1.1 Concept of Aging Process

In electric power industry, most electrical equipment or other assets are kept under service. During operation, the physical and electrical strengths of equipment are gradually deteriorated, until some point of deterioration failure, or other types of failures. This process can be called as *aging process* [50]. The word "*aging*" means that the strength of components deteriorates, as a function of chronological time in service.

Based on the physical causes, power system aging process can be categorized into four types. Table 2.1 presents the meaning and impact of four types of aging processes [50].

TABLE 2.1 CATEGORIES OF EQUIPMENT AGING AND THEIR IMPACT

Category	**Meaning and Impact**
Chronological Age (CA)	Aging since construction. Certain materials deteriorate over time due to natural causes, most directly associated with chronological age.
Cumulative Service Stress (CSS)	The cumulative effect of the time that the unit has been energized, and the load (mechanical, electrical) it has served in that time.
Abnormal Event Stress (AES)	The cumulative impact of severe events generally not considered as "normal service". This includes through-faults for transformers, storm and auto-accident stress for poles, etc.
Technical Obsolescence (TO)	Digital and data communications can become old by virtue, or not being compatible with new systems and equipment.

Although aging process has different categories as presented in Table 2.1, the term "aging" is generally referred to combination of all four effects.

2.1.2 Contributing Factors to Aging

In order to understand, identify, and manage aging or deterioration, it is necessary to develop mathematical models that represent the aging process to show the deterioration of power equipment, and determine the cause of aging.

Aging can be the result of the obvious process of the passing of time. As the age of equipment increases, the equipment slowly deteriorates correspondingly. Table 2.2 shows several types of deterioration that affect old equipment in power system [50].

TABLE 2.2 TYPES OF DETERIORATION CAUSED BY AGING

Type of deterioration	Caused by			Comments
	CA	CSS	AES	
Corrosion	X	X	X	Chemical decomposition or combination with oxygen or other ambient elements, until the material loses its required mechanical or electrical strengths, or qualities
Dielectric loss	X	X	X	Various mechanisms (treeing, contamination) that lead to the loss of electrical withstands strength
Shrinkage/Hardening	X	X		Paper rubber, synthetic gaskets and seals harden or shrink with age, losing their ability to keep out moisture or contain pressure.
Wear		X	X	Mechanical components lose tolerance and bind, or do not hold with the same bond as they once did.
Moisture retention	X			Water is gradually absorbed into a material, degrading its mechanical or electric strength

In addition to the classification according to physical causes, aging agents can also be classified as either environmental aging or operational aging [51].

Environmental aging agents exist continuously in the environment surrounding the equipment, whether it is in an operational state or not. Examples include vibration, temperature, radiation, humidity, or simply the passing of time.

Operational aging agents exist primarily when the equipment is under operation. Examples of operational agents include internal heating from electrical or mechanical loading, physical stresses from mechanical or electrical surges, and abrasive wearing of parts.

For example, *deterioration of power transformers* is primarily due to environmental aging agents. The deterioration failures of power transformers are usually due to degradation and aging of cellulose and oil used for transformer insulation [52]. The transformer failure has been found to be proportional to the dielectric response of the insulation system. The aging of the insulation is a complex process and it is irreversible. The aging of insulation paper and cellulose is actually a function of temperature, moisture, and oxygen.

For example, for the Furan analysis that is widely utilized for assessing oil-immersed insulation paper conditions, a study summarized the relationship between concentrations of furans in the transformer oil and degradation time, as presented in (2.1), [53]. *Furans* are major degradation products of cellulose insulation paper and are found in the insulation oils of operational transformers.

$$F_t = A(N_c)_0 t + (Akt^2)/2 = bt + ct^2 \tag{2.1}$$

Degradation of other parameters mostly used in transformer condition assessment can be found in [54].

Deterioration of circuit breakers is an example of power equipment that age more with repeated usage, rather than with the passing of time [55]. Heavily used power circuit breakers may age and deteriorate at a faster rate than ones not used very often. Every time that a circuit breaker performs its function, the circuit breaker deteriorates, until eventually reach a non-operable state.

2.1.3 Modeling Aging Process by Bathtub Curve

Previous research on aging process has validated the relationship between the equipment likelihood of failure over a period of time. This relationship is represented by the well known "bathtub curve", and can be used for all types of devices. [50].

Figure 2.1 [50] illustrates the bathtub curve for aging equipment hazard rate or failure rate modeling.

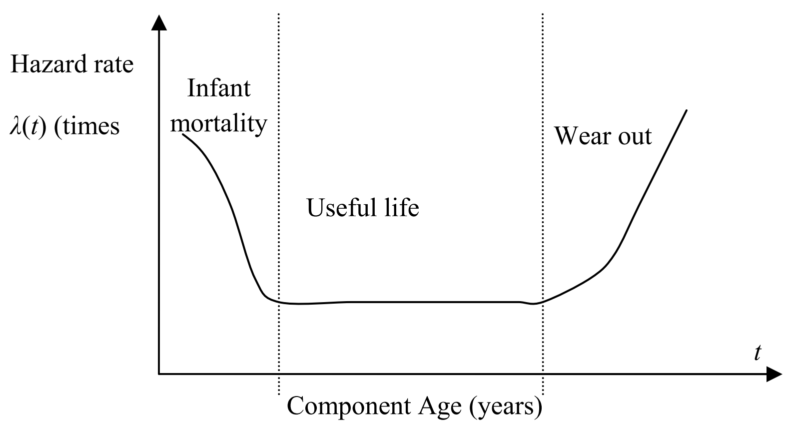


Figure 2.1 Traditional Bathtub Failure Rate Curve

Systems having this hazard rate function experience decreasing failure rate in their early life cycle (infant mortality), followed by a nearly constant failure rate (useful life), then by an increasing failure rate (wear out). This curve may be obtained as a composite of several failure distributions [11].

During useful life period, exponential distribution is usually used to model the probability of time to failure, or constant failure rates. Most equipment reliability models will use this useful life period, as the failure rate within this period is constant.

Assuming the useful life period, the hazard rate or failure rate is λ, then the time to failure follows an exponential distribution, modeled in (2.2) [56]:

$$f(T) = \lambda e^{-\lambda T}, T > 0 \tag{2.2}$$

For the infant mortality or wear out periods, log-normal or Weibull distribution are frequently deployed to model this nonlinear failure rates.

For example, at wear out period, the time to failure *T* may follow Weibull distribution, with scale parameter *α* and shape parameter *β* in (2.3) [56]:

$$f(T) = \alpha\beta T^{\beta-1} e^{-\alpha T^{\beta}} \tag{2.3}$$

In some cases, a function of piecewise linear failure rates is also utilized to represent the non-linear failure rates, such as using following piecewise linear equations in (2.4), to mimic the bathtub function[57].

$$\lambda(t) = \begin{cases} c_0 - c_1 t + \lambda, & 0 \le t \le c_0 / c_1 \\ \lambda, & c_0 / c_1 < t < t_0 \\ c_2(t - t_0) + \lambda, & t_0 < t \end{cases} \tag{2.4}$$

Then the time to failure follows the following distribution:

$$f(t) = \begin{cases} \exp-\{(c_0 + \lambda)t - c_1(t^2 / 2)\} & 0 \le t \le c_0 / c_1 \\ \exp-[(\lambda t + c_0^2 / (2c_1)] & c_0 / c_1 < t < t_0 \\ \exp-\{(c_2 / 2)(t - t_0)^2 + \lambda t + c_0^2 / (2c_1)\} & t_0 < t \end{cases} \tag{2.5}$$

2.2 Equipment Maintenance Strategies

Maintenance is defined as any activity that will restore or retain a unit so that it may perform its designed function. The type and extent of the maintenance determines how much the condition of unit is improved.

2.2.1 Mitigating Aging Effects

Although aging and deterioration effects are unavoidable, it is desirable to find a way to slow down the deterioration rate, and to prolong equipment's service life.

The aging mitigating actions are typically attempt to eliminate the stressors that cause the aging in the first place. This includes reducing the environmental or operational agents that cause deterioration. Environmental stressors such as heat and radiation are known to induce aging degradation, particularly in organic materials. Examples of adjustments in the operating environment include adding thermal insulation, venting electrical enclosures, or adding radiation shielding [58], [51]. However, these adjustments only slightly prolong the deterioration process. Deterioration failure is still the inevitable fate of the equipment.

Another way to mitigate the aging effect is through maintenance. Effects of different maintenance policies can be studied by comparing their impacts on the equipment life curve.

As equipment deteriorate further, its asset value (or condition) decreases. The relationships among asset values and maintenance are shown in Figure 2.2, which is called *equipment life curve* [11].

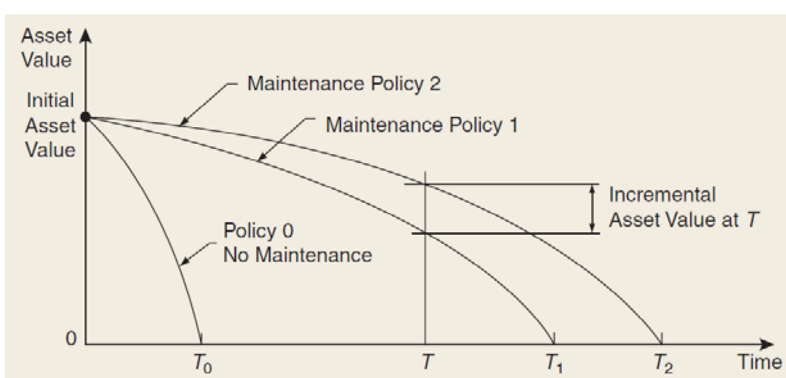


Figure 2.2 Life Curve and the Impact of Maintenance Policies

Figure 2.2 illustrates the effect of two different maintenance policies. Clearly, policies 1 and 2 are far superior relative to policy 0 (no maintenance) as they extend the equipment life. Compared with Policy 1, Policy 2 is better as it increases the asset value at time T.

However, doing maintenance may require de-energizing equipment, which will decrease the availability of the equipment. Maintenance may also increase the maintenance cost when it is carried out more frequently, and must be balanced against the gains resulting from improved reliability. Determining the optimal equipment maintenance policy, in order to prolong equipment life, improves equipment availability, increases the benefit, while balancing related maintenance cost. This is one of the major goals in this dissertation.

2.2.2 Equipment Maintenance Classification

A classification of various maintenance approaches is presented in Figure 2.3[6].

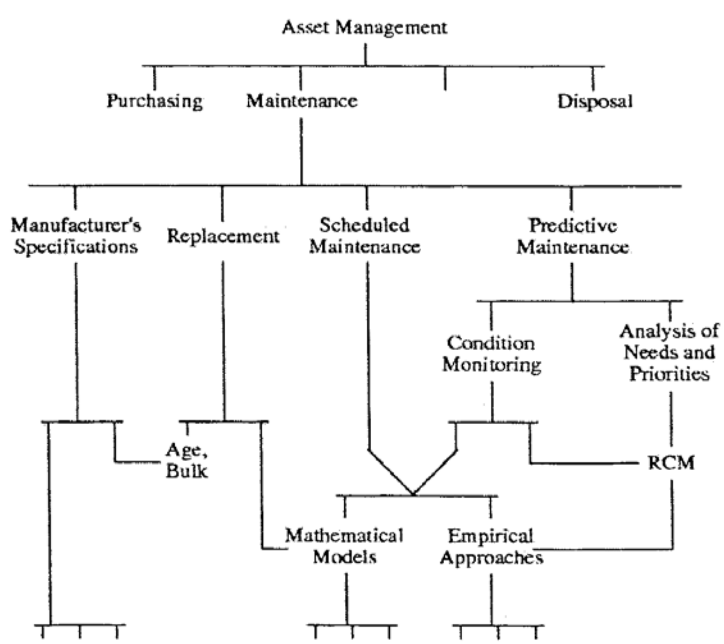


Figure 2.3 Overview of Maintenance Approaches

The chart in Figure 2.3 illustrates that in utility asset management different types of maintenance are utilized depending on their specific requirements and different characteristics.

Unplanned Maintenance

The restorations or replacement after failure are also called unplanned maintenance. *Unplanned maintenance* is a corrective maintenance, which is costly and should be avoided if possible. Once equipment reaches a completely failed state and is no longer in working condition, corrective maintenance is needed. The equipment may have reached a failed state due to either deterioration or random unexpected event. In either case, corrective maintenance is conducted for restoration.

Restoration is an activity which improves the condition of a device. If the device is in a failed condition, the intent of restoration is the re-establishment of a working state. This maintenance disregards the possibility where less improvement is achieved at lower cost. Also, this maintenance is costly and should be avoided if possible.

Scheduled Maintenance

On the other hand, equipment may be replaced or repaired at predetermined intervals. This type of maintenance is called scheduled maintenance. *Scheduled maintenance* (also known as *preventive maintenance*) is a maintenance carried out at regular intervals (rigid schedule) [6]. Scheduled maintenance can be used to upgrade equipment's current state. As frequency of preventive maintenance increased, the probability of having deterioration failure is reduced. Preventive maintenance can be time-based, or condition-based. Time-based preventive maintenance is executed on pre-determined date (usually constant frequency); condition-based preventive maintenance is performed depending on the condition of equipment. Generally preventive maintenance is pre-scheduled.

Predictive Maintenance

Recently, engineers discovered that the most effective maintenance is done only when needed, and not necessarily conducted routinely. This is called predictive maintenance. *Predictive maintenance* is a maintenance carried out based on periodic inspection, diagnostic test or other means of condition monitoring. Usually predictive maintenance is carried out when necessary; compared with preventive maintenance, usually the time to execute the predictive maintenance is not predefined.

Inspection and Condition Monitoring

Inspection is the process of seeking the condition of equipment or vital indications of the residual life (or remaining working time).

Condition monitoring is the periodic inspection of equipment to determine whether further maintenance is required to ensure the continuous operation of equipment without the risk of failure. Maintenance is then performed when required.

There are certain advantages that inspection-based maintenance has over preventive maintenance. The type of indication of equipment condition found during inspection determines the type of maintenance to perform. Unnecessary maintenance should not be done on parts of the equipment that is still adequately operable. Inspection provides the operators or engineers with a choice or a decision. Maintenance can either be done or not. If maintenance is chosen, the extent of maintenance needs to be selected as well. These decisions allow the engineers to have more control during the maintenance process [58].

Inspection provides the equipment operator with control over the maintenance schedule. A high rate of inspection gives greater control, because the operator is given more frequent decisions. As the time between periodic inspections is reduced and the inspection rate approaches infinity, called *continuous monitoring*, the operator is given ultimate control. In continuous monitoring, the instant in which equipment shows signs of deterioration, the operator is notified and may choose to implement maintenance [7].

Reliability Centered Maintenance (RCM)

RCM is a structured process which determines the best and most cost-effective maintenance approaches, based on regular assessments of equipment condition. RCM does not always based on condition monitoring, but on other features, such as failure modes and effect analysis, and an investigation of operation needs and priorities.

A typical RCM process includes the following steps [6]:

- System identification and the listing of critical components and their functions.
- Failure mode and effects analysis for each selected component, determination of failure history, and calculation of mean time between failures.
- Categorization of failure effects (by using appropriate flow charts) and determination of possible maintenance tasks.
- Maintenance task assignment.
- Program evaluation, including cost analysis.

In power systems, equipment maintenance can also be categorized into different levels, according to characteristics of maintenance, and their impact on equipment after maintenance. Table 2.3 summarizes the characteristics and effects of different levels of maintenance for power equipment [57].

TABLE 2.3 COMPARISONS OF DIFFERENT LEVELS OF MAINTENANCE

Category	Personnel that perform the tasks	Contents	Impact and Effect on Equipment
Inspections	• Often accomplished by using condition monitoring or other diagnosis instrument, and performed on site	• Operation personnel frequently performing the maintenance tasks, such as lubrication, routine services, adjustments, removal & replacement of minor parts	• The MTTR is small, the cost of inspection is relatively less than doing maintenance; many inspections do not require de-energizing of equipment, thus will not bring in outages or overhaul of the equipment. Inspections will not directly bring in improvement of equipment conditions.
Minor Maintenance	• Maintenance personnel that are employed specifically to perform the repair task. They have higher skills levels than those in inspections	• Repair may be performed on removal components, or other the system itself. For non-moveable system, maintenance personal may travel to site to perform the repair.	• Minor maintenance requires de-energizing of equipment for repair; the duration and cost of maintenance is higher than inspection and less than major maintenance.
Major Maintenance	• Usually the work is taken by manufactures' professional personnel or contractors' factor in a specialized depot	• Completely overhaul of equipment, consisting of complete tear down and rebuilding of units.	• Major maintenance can effectively improve the health condition of equipment and prolong life. Major maintenance usually include costly and complex components refurbishment/replacement

2.2.3 Typical Inspections for Power Transformers and Circuit Breakers

For the power substations studied in this dissertation, the key equipment such as power transformers and circuit breakers are selected for development of mathematical models. Therefore, the typical inspection, maintenance, and repair processes for power transformers and circuit breakers are briefly summarized below.

Transformers are the basic building blocks of power systems. They alter the voltage-current constitution of alternating current power, and essentially change the economy of scale of transmission of power from one side of the transformer to another. Typical inspection and diagnosis processes of power transformers include [50]:

- Oil Quality Assessment
- Power Factors, Interfacial Tension (IFT)
- Moisture
- Dissolved Gas in Oil Analysis (DGA)
- Analysis of particles in transformers oils
- Transformers turns ratio test (TTR)
- Infrared Thermograph Analysis
- Assessment of thermal Properties

After inspection, various activities such as repair, maintenance or other refurbishment related work can be conducted on transformers. Typical maintenance and repair work for transformers include [50]:

- Minor maintenance of components (bushing & joint, motor drive unit, cooler, etc)
- Oil reclaiming
- On-site drying
- Disassembly and drying
- High voltage testing

Circuit breakers are also critical components in substations. *Circuit breakers* are electromechanical devices. They are tested for both mechanical & electrical performance and for signs of deterioration. Inspection techniques for circuit breakers include [50]:

- Visibly check for noticeable corrosion, deterioration or damage, and infrared examination; These inspections do not require de-energizing of the equipment
- Temperature rise test

- Electrical test, which include insulation resistance test, AC high potential test, and contact resistance test. Usually these tests require de-energizing of the equipment

2.3 System Maintenance Strategies

Most maintenance programs and algorithms focus on equipment, and the objective is to extend equipment life, improve equipment reliability, or both. However, from enterprise leader's perspective, reliability or condition of single equipment might not be top priority; asset managers wish to know the overall reliability performance of their asset, from system perspective. They prefer to have programs to optimize maintenance resources, and allocate maintenance budget into individual systems or equipment, to ensure successful operation of a system, while meeting mandatory reliability target, and resources/budget constraints.

This dissertation intends to provide an optimization program to efficiently dispense the available resources to individual equipment while considering detailed modeling of individual equipment in a substation and its configuration.

The following aspects need to be determined, while performing system level maintenance optimization.

- *Maintenance Prioritization*

  Due to limited maintenance resources and budget, asset managers need to determine which equipment or set of equipment should receive the maintenance first, based on condition of equipment, importance of the equipment location within the system, etc.

- *Maintenance Frequency*

For equipment which will be maintained, how can the frequency of maintenance be determined? This should avoid the over-maintenance that utilizes the budget and creates unnecessary failure time, and under-maintenance that could not effectively reduce the equipment deterioration process.

- *Maintenance Type (or Maintenance Level)*

  For each equipment, what level of maintenance or what type of maintenance should be taken (doing nothing, minor maintenance or major maintenance)? The determination of the level of repair is often an economical decision in order to maximize the reward or minimize the cost.

This chapter focuses on summarizing contributing factors toward power equipment aging and maintenance actives only. Next chapter will focus on studying the impact of aging and maintenance toward equipment reliability and correlated economic cost.

CHAPTER 3
RELIABILITY AND ECONOMIC MODELING OF AGING EQUIPMENT WITH MAINTENANCE

In order to study the effect of maintenance toward aging equipment, detailed mathematic models to evaluate equipment reliability and economic cost with consideration of maintenance need to be established. This is chapter focus on how the models are developed, as well as their potential applications.

3.1 Reliability, Maintainability, and Availability

The purpose of maintenance is to extend equipment life and reduce frequency of service interruption and undesirable consequences. For the purpose of quantifying the effect of maintenance on equipment performance improvement, definitions of reliability indices need to be addressed [57].

In general**,** *reliability* is defined as the probability that a component or system will perform a required function, for a given period of time, when used under stated operating conditions [57]. In power system engineering, it is the probability of equipment or system that can stay in normal operating conditions [59].

Maintainability is defined as the probability that a failed component or system will be restored or repaired to reach a specified condition, within a period of time when maintenance is performed in accordance with prescribed procedures.

In power industry, there are various indices used to measure the reliability of systems. IEEE developed three standards, for term definitions in outage data reporting and reliability indices: IEEE Standard 762 [60] for generation reliability indices; IEEE

Standard 859 [61] for transmission reliability indices; and IEEE Standard 1366 [62] for distribution reliability indices.

Among the reliability indices defined, availability is an important index. *Availability* is the probability that a system or component is performing its required function at a given point in time, or over a stated period of time when operated and maintained in a prescribed manner [57].

Availability is the preferred measure when system or component can be restored, since it accounts for both failures (reliability) and repairs (maintainability). Therefore, availability is a popular adopted index for repairable equipment or systems.

Typically, the common used term *mean time to failure* (MTTF) index is utilized to measure reliability, because reliability focused on success or failures. In the contrast, availability includes the consideration of both reliability (quantified by MTTF) and maintainability (quantified by *mean time to repair*, MTTR), and usually calculated by MTTF/ (MTTF+MTTR). Therefore, availability is the most important index to examine the impact of maintenance toward reliability [57].

According to application specifications, availability may be interpreted at a given point in time (point availability), or over time intervals (average availability), or in the long run (steady-state availability).

- *Point Availability* $A(t)$ is the availability at time t.
- A*verage Availability* $A(T)$ is the average availability over the interval $[0, T]$, defined by (3.1)

$$A(T) = \frac{1}{T}\int_{o}^{T} A(t)dt \tag{3.1}$$

- *Steady-state Equilibrium Availability* A is defined by (3.2)

$$A = \lim_{T \to \infty} A(T) \tag{3.2}$$

In power systems, long-run equilibrium availability is usually used as a basic reliability index for reliability assessment of aging equipment and systems, as the purpose of the maintenance is to improve equipment condition, prolong its life, and increase long-run availability [59].

Besides availability, average outage duration and outage frequency are other basic reliability indices commonly examined.

- *Average Outage Duration r*

  r is also called *Mean Outage Duration*, or *Mean Time to Repair* (MTTR) in some literatures [63]. r is calculated by (3.3)

$$r = \frac{\sum_{i=1}^{M} D_i}{M} \tag{3.3}$$

  where D_i (hour) is the outage time for each outages; M is the number of outage events in the time span considered. The unit of r is hours per outage.

- *Outage frequency f*

  f which is the average number of outages in one year. In adequacy studies, the steady-state reliability indices are of particular interest. The system failure frequency in steady-state is defined as $f=f(\infty)$.

It should be noted that outage frequency is not the failure rate. *Failure rate λ* is defined as the number of visits from success state S to failure state in unit time. Conceptually an outage frequency is different from a failure rate. Their values are only very close, if the average repair time is very short compared to operating time [63].

From the above definitions, it can be seen that availability, average outage duration and outage frequency are related. The mathematical relationship among these indices is presented in (3.4).

$$r = \frac{1 - A}{f} \tag{3.4}$$

As long as any two are obtained from statistics, the other one can be calculated.

3.2 Markov Processes

Markov processes are widely adopted in power system reliability assessment. This dissertation also utilizes the Markov processes for modeling aging and maintenance of equipment. Therefore, it is necessary to provide a brief introduction of the definitions and calculations of various Markov processes.

At the beginning of the 20th century, Andrei Andreevich Markov introduced a model that was the simplest generalization of the probability model of independent trials in which outcomes of successive trials are only dependent on the preceding trial [64].

A *stochastic process* is a family of random variables based on time. Stochastic processes are called *Markov processes* if the process possesses the Markovian property. The *Markovian property* states that the probability that a system will undergo a transition from one state to another state depends only on the current state of the system, and not on any previous states the system may have experienced. In other words, the transition probability is not dependent on the past (state) history of the system. This is also known as a '*memory-less*' property [64].

1) Discrete-time Markov processes

A standard *discrete-time Markov process* is a process in which the state of the system changes at fixed time intervals [8]. A discrete-time Markov chain assumes that the component will transit to future state after a given interval of time. Discrete-time Markov chains are useful when the initial state distribution and transition probabilities are known. Then, the state probabilities can be calculated step by step. The future state *j,* can be a different state or the same state for successive steps [8]. However, this is not applicable in many situations, such as power equipment maintenance, since the state of the system may change at any time, rather than being fixed in a given time interval.

Mathematically, a discrete-time Markov chain is represented by a *transition probabilities matrix P*. In *P,* each element P_{ij} represents the probability of transition from state *i* to state *j*. The size of the matrix is *s* by *s,* where *s* is the total number of the states in this Markov chain.

The steady-state probability Π of a discrete-time Markov Chain can be calculated by Gauss - Jordan elimination method, by solving linear equations (3.5),

$$\begin{cases} \Pi P = \Pi \\ \sum_{k \in s} \pi_k = 1 \end{cases} \tag{3.5}$$

or by matrix calculation of (3.6),

$$\Pi = e \cdot (I+E-P)^{-1} \tag{3.6}$$

where *e* is a “1 × s” row vector with all elements are “1”; *I* is a “s × s” identity matrix with diagonal elements of “1”; *E* is “s × s” square matrix, and all elements are 1.

2) Continuous-time Markov Processes

A *continuous-time Markov process* is a stochastic process that assumes the time spent in each state is exponentially distributed. In continuous-time Markov processes, *transition rate* is defined as the rate at which the system moves from state *i* into state *j.* In continuous-time Markov processes, *i* cannot be equal to *j* [14].

The state probabilities can be found for any specific time (as long as it is after the initial start time) using a *continuous-time Markov chain*, sometimes called *homogeneous Markov chain* [14]. This means that the behavior of the system must be the same at all points of time irrespective of the point of time being considered [8].

A continuous-time Markov process provides an easy way to calculate the state probabilities by using a transition matrix. This is useful in large complex systems. For this reason, Markov processes have been widely used to solve numerous probability problems, including the reliability assessment of power systems.

A continuous-time Markov chain has a *transition rates matrix* Q, where the element q_{ij} is the transition rate from state i to state j ($i \neq j$); for $i=j$(diagonal elements), $q_{ii} = -\sum_{i \neq j} q_{ij}$. (3.7) is used for calculating the steady-state probabilities.

$$\begin{cases} \Pi Q = 0 \\ \sum_{k \in s} \pi_k = 1 \end{cases} \tag{3.7}$$

The steady-state distribution can also be acquired by (3.8),

$$\Pi = e \cdot (Q+E)^{-1} \tag{3.8}$$

where e is a "1 × s" row vector with all elements are "1"; E is "s × s" square matrix, and all elements are 1.

3) Semi-Markov Processes

A *semi-Markov process* (SMP) improves a standard Markov process by incorporating sojourn time. *Sojourn time* refers to the length of a visit in a particular state of a system. This is the major difference between a semi-Markov process and a standard Markov process. Notice that if the sojourn times of each state are equal to 1, then the semi-Markov process is actually a standard Markov process [65].

A semi-Markov process can use any positive random variable for the sojourn time distribution where a continuous-time Markov process is limited to using only exponential distribution [65]. In other words a standard Markov process (continuous-time Markov process) is a special case of a semi-Markov process, when sojourn times are exponentially distributed.

One of the advantages of using semi-Markov processes is that transition times among states follow non-exponential distributions [66]. The disadvantage is the additional requirement of accurately representing sojourn time. The sojourn times often have certain distributions and are represented by a random distribution with a calculated mean value. The accuracy of estimating the mean sojourn times directly results in the accuracy of the overall models [14].

A semi-Markov chain has two matrices: the transition probability matrix P (or *embedded matrix*), and the *expected holding time matrix* $H[E(h_{ij})]$. The element $E(h_{ij})$ is defined as expected time the equipment spends in state i, before making a transition to state j, given that it has just made a transition to state i.

Given $E(h_{ij})$, one can also calculate $E(h_i)$, which is defined as the *expected time that the chain spends in state i* before making a transition, irrespective of destination state (including the departure state i itself).

The steady-state probabilities of a semi-Markov chain can be calculated by the following steps:

Step1: Calculate the steady-state probabilities of the embedded matrix P, by Gauss-Jordan elimination of (3.9),

$$\begin{cases} \Pi^e P = \Pi^e \\ \sum_{k \in s} \pi^e{}_k = 1 \end{cases} \tag{3.9}$$

or by matrix calculation of (3.10),

$$\Pi^e = e \cdot (I + E - P)^{-1} \tag{3.10}$$

Step 2: Calculate the steady-state probabilities of entire semi-Markov chain, by the (3.11),

$$\pi_i = E\,(h_i) \cdot \pi^e{}_i / \sum \pi_k^e\, E(h_i) \tag{3.11}$$

In conclusion, Table 3.1 summarizes the characteristics, meaning, mathematical modeling, and solution methods, for various types of Markov processes.

TABLE 3.1 SUMMARIES OF MARKOV PROCESSES AND CORRESPONDING SOLUTIONS

Name	Characteristics	Mathematic Model	Solution	Application Filed
Discrete time Markov Processes	• The time to transition are the same and the chance is defined by the probability • Simple but not very practical.	$\begin{cases} \Pi P = \Pi \\ \sum_{k \in s} \pi_k = 1 \end{cases}$	$\Pi = e \cdot (I + E - P)^{-1}$	• Calculate the system probability at discrete time point. • Not very applicable
Continuous-Time Markov Processes	• The time to transition belongs exponential distribution • Advantages: Easy for calculating, especially in large complex systems • Broadly applied in Power System	$\begin{cases} \Pi Q = 0 \\ \sum_{k \in s} \pi_k = 1 \end{cases}$	$\Pi = e \cdot (Q + E)^{-1}$	• Widely used in power system reliability assessment. However, not applicable for modeling aging equipment, where the time to failure may be non-exponential
Semi-Markov Processes	• Introducing sojourn time • Can model more complicated stochastic processes • More general type of Markov processes, in which the continuous-Markov process and discrete-Markov processes are special cases • Requires modeling sojourn times. Accuracy of this parameter directly impact the overall model accuracy	$\begin{cases} \Pi^e P = \Pi^e \\ \sum_{k \in s} \pi^e{}_k = 1 \end{cases}$	$\Pi^e = e \cdot (I + E - P)^{-1}$ $\pi_i = E\,(h_i) \cdot \pi^e{}_i / \sum \pi_k^e\, E(h_i)$	• More suitable to model aging processes and maintenance, where the times to transitions are sometime non-exponential

3.3 Modeling of Aging and Failures

In conventional reliability studies, the states of equipment were usually categorized into fully successful or fully failure state, which is presented in Figure 3.1 [67].

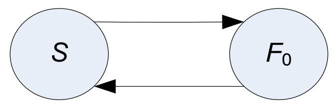


Figure 3.1State-Space Diagram of Binary-State Model: Success and Random failure

In this binary-state model, usually the MTTF and MTTR are assumed to follow exponential distributions. Therefore, this simple model is appropriate to represent random failure mainly because of its memory-less characteristics. *Random failure* is defined as the failure whose rate of occurrence (intensity) is constant, and independent of device's condition. A failure is random if the density of the conditional probability that it occurs in the interval (*t, t+Δt*), given that the device was in a working condition at *t*, is constant (independent of *t*) [6].This model also agrees with practical experience; it gives rise to the widely known piece of wisdom: "if it isn't broke, don't fix it!" [6]

However, two states are not sufficient to reflect real working conditions of power systems equipment. For example, equipment can still work while part of their material deteriorates. A simple failure-repair process for a deteriorating device is shown in Figure 3.2. The deterioration process is represented by a sequence of stages of increasing wear, finally leading to equipment deterioration failure [11].

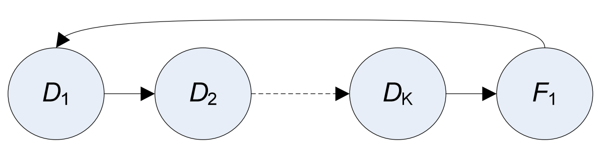


Figure 3.2 State-Space Diagram Including Deterioration and Deterioration Failure

In Figure 3.2, $D_1, D_2, \ldots, D_k$ are consecutive deterioration but workable states, and F_1 are deterioration failure. There are two ways of defining deterioration stages: either by duration, or by physical signs (corrosion, wear, etc.) of appropriate level [6]. In practical applications, the second approach is more favorable, and various condition-monitoring processes are combined in which the information can be used to determine the current deterioration stage.

However, one cannot neglect the differences between random failures and deterioration failures, while modeling aging equipment/system [6]. This can be explained as follows:

1) First, the roots of random failures and deterioration failures are different.

   In a broader sense, failures whose origins are not well understood and therefore are perceived as being able to occur at any time, are often said to be random. In mathematical modeling, it is assumed that such failure can occur at any time. And, the rate of random failure may depend on external conditions (i.e., lightning or ice storms in which the resulting random failures would be different in each season) [6]. In contrast, deterioration failure is caused by aging processes, where the condition and trend can be measured and predicted.

2) Second, in Markov modeling, random failure has constant failure-rate while deterioration failure is not.

   For deterioration failure, the times from the new condition to failure are not exponentially distributed, even if the times between subsequent stages of deterioration are. In such process the hazard function is increasing. In contrast, due to features of randomness of roots described in 1), usually random failures will be treated with constant failure rates, even in wear out stages.

3) Third, the effect of maintenance on two types of failures is different.

   For random failure, the constant failure-rate assumption leads to the result that maintenance cannot produce any improvement, because the chances of a failure occurring during any future time-interval are the same with or without maintenance.

   But for deterioration failure, maintenance will make an improvement on the condition of equipment to bring it to the previous stage(s) of deterioration. Therefore, maintenance has an important role to play, when failures are the consequence of aging.

Table 3.2 Summarizes the characteristics of random and deterioration failures [6].

TABLE 3.2 COMPARISON OF RANDOM AND DETERIORATION FAILURES

	Random Failures F_0	**Deterioration Failures F_1**
Definition	A failure whose rate of occurrence (intensity) is constant, and independent of device's condition.	A failure resulting from the deterioration of a device, which is related with effects of usage, environmental exposure or passage of time, material deterioration, etc.
Maintenance's Impact	Condition cannot be improved by maintenance for random failures.	Assumed that effective maintenance will bring an improvement to the conditions in the previous stage of deterioration.
Characteristics	Constant failure rates.	Increased failure rates when the equipment enters further deterioration stages.

Endrenyi developed a model for analysis of aging equipment, which includes both failures F_1 and F_0 that are presented in Figure 3.3 [7].

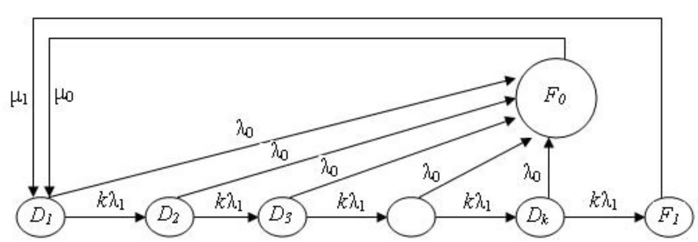


Figure 3.3 State-Space Diagram for Deteriorating Power Equipment

In this model, equipment is represented by natural wear and deterioration which can eventually cause the component to fail, state F_1, making the entire system unavailable. Equipment can also fail randomly and enter state F_0 due to an unexpected exterior event. Unfortunately, this random failure cannot be prevented and must be considered as a possible transition from each working up-state, states D_1 to D_k.

After k deterioration stages, with no preventive maintenance, the component reaches F_1, deterioration failure. From this state, corrective maintenance is needed to return the component to the working state D_1. The corrective maintenance transition rates to the 'like new' state from the deterioration failure state is μ_1 and from the random failure state is μ_0. The random failure transition rate from any up-state is λ_0 [58].

3.4 Maintenance Modeling

3.4.1 Basic Markov Models of Maintenance

Based on the above assumptions, a maintenance state can be added into the state diagrams of Figure 3.1 and Figure 3.2, which are shown in Figure 3.4 and Figure 3.5 [59][67].

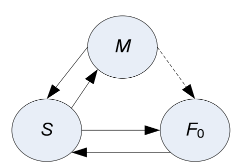


Figure 3.4 State-Space Diagram Including Success (S), Random Failure (F_0) and Maintenance (M)

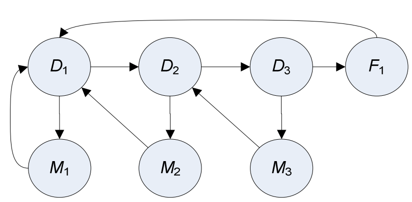


Figure 3.5 State-Space Diagram Including Success (S), Deterioration Failure (F_0) and Maintenances (M_i)

In Figure 3.4, equipment or system could enter the maintenance state. The time to transition from S to M state follows a specific type of distribution, for example exponential distribution. After carrying out maintenance, equipment/system is restored to success state again. In Figure 3.4, it is also possible that after maintenance, due to human error or other reasons, the device enters the failure state. The detailed model of including human error is given in the following sections.

However, the tri-state Markov model presented in Figure 3.4 does not recognize the deterioration of aging equipment, and the model assumes that all maintenances performed are the identical (same effect, same duration and same economic cost), which are inaccurate and impractical. Therefore, the model in Figure 3.4 is only applicable in cases where deterioration and various types of maintenance are neglected.

The Markov model in Figure 3.5 enables modeling of equipment/system deterioration, and modeling of various types of maintenance. Comparing with the basic maintenance model in Figure 3.4, this model enables the study of deterioration and maintenance at each deterioration stage. Therefore, it can be used in determining the maintenance policies in simple applications [58].

3.4.2 Advanced Equipment Maintenance Models

In conventional maintenance models, there are no quantitative relationships involved. The capability is very limited for making predictions about the effectiveness of the policy or carrying out any sort of optimization. To make numerical predictions and carry out optimizations, mathematical models are needed which can represent the effects of maintenance on reliability [6].

In order to design general models, considering equipment deterioration, inspections, maintenance, replacement, failures, human errors and etc, various Markov-based models are developed in this dissertation.

1) *Minor and Major maintenances*

Figure 3.6 present a Markov model, which can examine the effect of minor (state M_i) and major maintenances (state MM_i) [58].

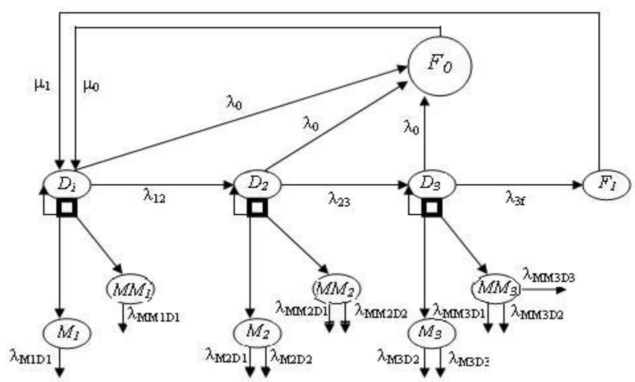


Figure 3.6 General State-Space Diagram of Deteriorating Power Equipment with Minor and Major Maintenance

In Figure 3.6, in each deterioration state, there is a decision making option (represented as rectangle), to determine which type of maintenance to select, or just doing nothing. After performing maintenance, equipment returns either to the current state, or to better/worse D-state, depending on actions and probabilities. λ_{MiDj} or λ_{MMiDj} is the rate in which after minor maintenance (state M_i) or major maintenance (state MM_i), the process enters deterioration state D_j.

The motivation of adding different types of maintenance is to recognize their differences in condition improvement and economic cost. Theoretically, the deeper the levels of maintenance, the better improvement it will have, towards the equipment conditions. However, the deeper levels of maintenance might bring longer time in which equipment is unavailable, as well as the higher maintenance/penalty cost.

2) *Inspection Modeling*

The above models neglect the process of inspection, as the inspection won't bring equipment condition improvement. Compared with various types of maintenance, inspections time is much shorter; many inspections will not overhaul or de-energize the equipment; also the cost of doing inspections is much less compared with maintenance. Therefore, in many studies the inspection process is neglected.

However, in practice many utilities will make the maintenance decisions after doing the inspection. In addition, the development of the Smart Grid will enable more condition-monitoring instruments installed in substations, in which the inspection will be conducted automatically and in real-time. Therefore, it is necessary to consider inspection in existing models. A Markov model with inspection added is presented in Figure 3.7.

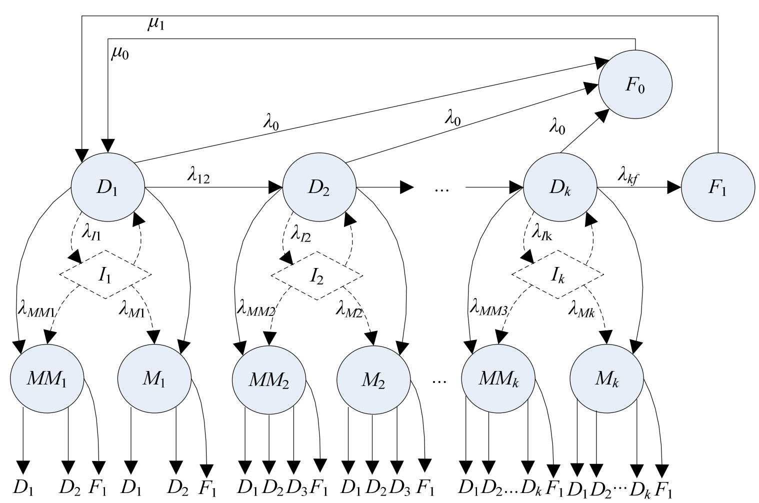


Figure 3.7 State-Space Diagram of Semi-Markov Model for Aging Equipment with Maintenance and Inspection

By adding I_1, I_2,…, I_k states for each stage of deterioration, the previous Markov model can be easily extended to include inspection states. This model is shown in Figure 3.7 where the inspection rate at each stage is denoted by λ_{Ii}.

3) Human Induced Error

The above models assume that inspections / maintenances / replacements can be conducted correctly. However, errors committed by personnel during the inspection or maintenance procedures have often left initial good equipment in the further deterioration condition or even failed state. Two accidents in the nuclear power stations in 1980's, for instance, were partially due to human-induced errors [59].

The impacts of Human error toward the equipment operation are:

i) In general, maintenance should bring a machine to better conditions. But due to human error, it may not improve its condition, or it may even worsen it to further deterioration state.

ii) Occasionally, a machine is possible to be identified in a failure state where it is actually not. This human error may result in taking the machine into "random failure" state.

Based on the above assumptions, human error state is added into the existing maintenance models, with inspections, minor and major maintenances, presented in Figure 3.8.

In Figure 3.8, $F_{i\mathrm{H}}$ represents a failure that is caused by human error, after inadequate maintenance. This failure is different than the random failures F_0 and deterioration failure F_1, as the root cause and the economic cost for restoration are different than F_0 and F_1.

To quantify the human error, two probabilities (the probability of going from MM_k to F_{kH} , and M_k to F_{kH}) are included. These two probabilities describe the extent in which human error occurs during maintenance. The detailed sensitivity studies of the probabilities are given in Chapter 6.

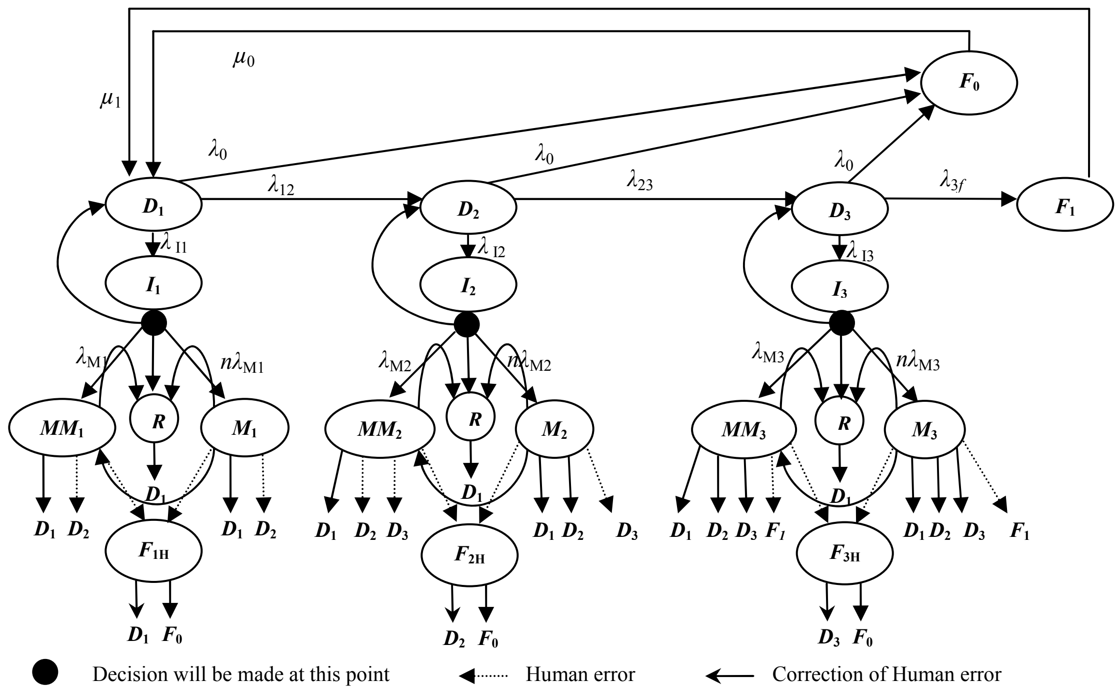


Figure 3.8 State-space Diagram of for Aging Equipment with Human error, Inspections, Minor, Major Maintenance and Replacement

In addition to human errors, predictive replacement is also added. In practice, the utility owners might perform scheduled replacement of old equipment, in order to prevent costly deterioration failures. However, the challenge is how to determine the retirement age for minimum *life cycle cost* (LCC) [57]. Too early replacement is a waste of investment and unnecessary overhaul cost due to replacement; too late replacement increases the risk of having vast failures.

In this model, a possibility of transition to replacement state is added, based on the conditions of equipment after inspections. Also a replacement rate λ_R is assigned similar to the maintenance rates. Values of λ_R can be acquired from historical schedule replacement record, or from optimization, in order to minimize LCC. It should be noted that the retirement age is not directly related to the inverse of λ_R. The optimal age of equipment is the expected mean time between visiting two retirement states.

3.4.3 Comparison of Markov Models

Table 3.3 summarized the comparison of various maintenance models.

TABLE 3.3 COMPARISONS OF MARKOV MODELS USED IN RELIABILITY ASSESSMENT

#	Markov model type	Characteristics	Advantages and Disadvantages
1	• Binary state Markov process (Figure 3.1)	• Only two state, • usually assumed exponential distributions of MTTF and MTTR	• Simple and clear. Can be easily implemented in system level reliability assessment, in both in analytical method and Monte-Carlo simulation method. • Not feasible to study the effect of aging and maintenance for equipment
2	• Three state Markov process (Figure 3.4)	• Add of maintenance state.	• Enable studying the impact of maintenance
3	• Markov model with multi-stages of deteriorations and only random failure (Figure 3.2)	• Using successive deterioration stages, to model the aging process	• Enables using Markov model to model equipment in aging period, with increased failure rates. • Requires additional historical data, to determine the transition rate among different deterioration stages
4	• Markov model with multi-stages of deteriorations, random failure, and deterioration failures (Figure 3.3)	• Introduce deterioration failure and random failure	• For power equipment random failures and deterioration failures, the effects are typically different, and the related restoration cost and duration are usually not the same. • More appropriate to model aging equipment, where the root cause of failures can be either randomly (random failure) or deterioration (deterioration failure)
5	• Multi-stages of deterioration, both random and deterioration failures, minor & major maintenance, and inspection (Figure 3.7)	• Use separated maintenance states, instead of single maintenance. This action respects the impact, cost, duration and other differences among different maintenance. • Modeling the inspection, and condition monitoring	• Popular utilized in aging equipment modeling. • Accurately models the process of doing predictive maintenance, based on equipment conditions. • Enables optimal maintenance policy determination • Requires more reliability history data, for the added states. Sometime, parameter uncertainty will even decrease the accuracy of entire model.
6	• Based on the Markov model in Figure 3.7, and adding replacement and human error (Figure 3.8)	• Add predictive replacement, in order to distinguish the corrective replacement after deterioration failure • Enables modeling of failures caused by human error	• Enables the life cycle cost analysis of the equipment. • More historical data are needed to support the model

3.5 State Reduction of Multi-state Markov Models

While the increase number of states improves the accuracy of modeling equipment aging and maintenance, it also brings the problem of whether proposed multi-state models can be compatible with practical reliability studies. Moreover, for system reliability evaluations, most tools and programs are designed based on binary-state equipment models. Therefore, it is necessary to find a method to reduce the multi-state Markov models into binary-state or three-state models, to ensure proposed models are practical.

According to [59], condition of *lump ability* (or *merge ability*) must be satisfied in order to lump two or more state together: A group of states can be lumped if the transition rate to any other state (or group of lumped states) is the same from each state in the group.

1) *Probability*

If a number of states j can be combined into a single state J, the probability of J, p_J is obtained by adding all the probabilities p_j,

$$p_J = \sum_{j \in J} p_j \tag{3.12}$$

The probabilities p_j can be summed up because the events of being in any of the states j are mutually exclusive.

2) *Frequency*

The frequency of state J, f_J, is the total frequency of leaving state j from state i that are out side state J

$$f_J = \sum_{j \in J, i \notin J} f_{ji} = \sum_{j \in J} p_j \sum_{i \notin J} \lambda_{ji} \tag{3.13}$$

For power equipment modeling, the transition rates can be derived between two combined state S and F, each of which is composed of several original states with no over lap. Then the failure rate can be computed by

$$\lambda_{SF} = \frac{\sum_{i \in S} p_i \sum_{j \in F} \lambda_{ij}}{\sum_{i \in S} p_i} \tag{3.14}$$

If the conditions of lump ability are satisfied, (3.15) can be reduced to

$$\lambda = \sum_{j \in F} \lambda_{ij} \tag{3.15}$$

It should be noted that although above equation was derived from the knowledge of Markov processes and the underlying assumption of exponential distributions, they are equally suitable for evaluating the long-term mean values of other distributions [69].

3.5.1 State-Reduction of Continuous Markov Processes with Maintenance

For an eight-state continuous-time Markov process model with maintenance in Figure 3.9, it can be assumed that besides D_1, D_2 and D_3, all other states are failure states (illustrated in Figure 3.10). The above state reduction techniques can then be applied to obtain availability, failure rate, and duration.

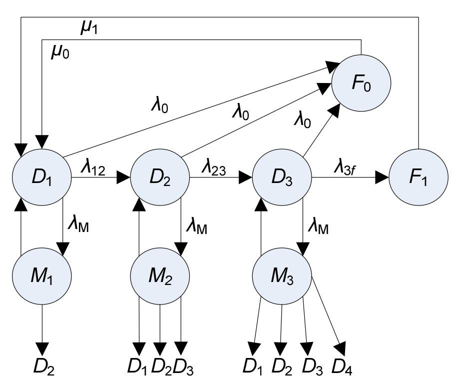


Figure 3.9 Eight-state Continues-time Markov Process

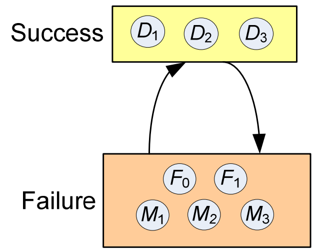


Figure 3.10 Equivalent Two-state Markov Process from Eight-state Markov Process

Availability, *A,*

$$A= \pi_{D1} + \pi_{D2} + \pi_{D3} \tag{3.16}$$

where π_{Di} is the steady-state probability of being in D_i state.

Frequency of Success (or Failure), f_{success},

$$\begin{aligned} f_{\text{success}} &= \sum_{i\in \mathrm{S}} \sum_{j\in \mathrm{F}} f_{ij} \\ &= \pi_{D1}(\lambda_{D1F0} + \lambda_M) + \pi_{D2}(\lambda_{D2F0} + \lambda_M) + \pi_{D3}(\lambda_{D3F0} + \lambda_{D3F1} + \lambda_M) \end{aligned} \tag{3.17}$$

Failure rate λ,

$$\lambda = \frac{f_{\text{success}}}{A} \tag{3.18}$$

Expected duration between failures T_{failure},

$$T_{\text{failure}} = \frac{1-A}{f_{\text{success}}} \tag{3.19}$$

3.5.2 State-Reduction of Semi-Markov Processes with Maintenance

For the 14-state semi-Markov process model presented in Figure 3.11, it is assumed that besides deterioration states D_1, D_2, D_3, and inspection states I_1, I_2 and I_3, all other states are failure states. Figure 3.11 gives the reduced binary-state Markov process.

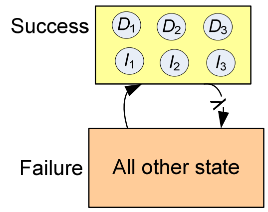


Figure 3.11 Reduced Two-state Markov Process for Fourteen-state Markov Process

Generally, it is not appropriate to reduce a multi-state semi-Markov process, because of existing non-exponentially distributed transitions among states. However, if the transitions among the lumped states are still represented by exponential distributions, it is possible to reduce a semi-Markov process into a two-state Markov process.

Similar to the equations derived in case 1, the following equations can be derived for case 2.

Availability A,

$$A = \pi_{D1} + \pi_{D2} + \pi_{D3} + \pi_{I1} + \pi_{I2} + \pi_{I3} \tag{3.20}$$

π_i is the steady-state probability of being in state i.

Frequency of Success (or Failure), f_{success},

$$\begin{aligned} f_{\text{success}} &= \sum_{i \in \mathrm{S}} \sum_{j \in \mathrm{F}} f_{ij} \\ &= \pi_{D1}(\lambda_0 + \lambda_I) + \pi_{D2}(\lambda_0 + \lambda_I) + \pi_{D3}(\lambda_0 + \lambda_{3f} + \lambda_I) + \\ &\quad \pi_{I1}(\lambda_M + n\lambda_M) + \pi_{I2}(\lambda_M + n\lambda_M) + \pi_{I3}(\lambda_M + n\lambda_M) \end{aligned} \tag{3.21}$$

Failure rate, λ,

$$\lambda = \frac{f_{\text{success}}}{A} \tag{3.22}$$

Duration, T_{failure},

$$T_{\text{failure}} = \frac{1 - A}{f_{\text{success}}} \tag{3.23}$$

In some applications, the maintenance time/cost is also desired. In these cases, the multi-state Markov model should be reduced to three-state equivalent model.

For example, in Figure 3.12, an equivalent "Maintenance" state is introduced, which incorporates M_1, M_2, M_3 and the major maintenance states MM_1, MM_2, MM_3. Figure 3.12 presents the equivalent model after state reduction. Reliability indices related with failures and maintenance can then be computed.

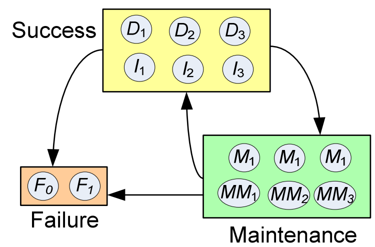


Figure 3.12 Reduced Three-state Markov Process for Fourteen-state Markov Process

Availability, A,

$$A = \pi_{D1} + \pi_{D2} + \pi_{D3} + \pi_{I1} + \pi_{I2} + \pi_{I3} \tag{3.24}$$

π_i is the steady-state probability of being in i state

Frequency of Failure, f_{failure},

$$f_{failure} = \sum_{i \in \mathrm{S}} \sum_{j \in \mathrm{F}} f_{ij} = \pi_{D1}\lambda_0 + \pi_{D2}\lambda_0 + \pi_{D3}(\lambda_0 + \lambda_{3f}) \tag{3.25}$$

Frequency of Maintenance, $f_{\text{maintenance}}$,

$$f_{\text{maintenance}} = \sum_{i \in \mathrm{S}} \sum_{j \in \mathrm{M}} f_{ij} = \pi_{I1}(\lambda_M + n\lambda_M) + \pi_{I2}(\lambda_M + n\lambda_M) + \pi_{I3}(\lambda_M + n\lambda_M) \tag{3.26}$$

When calculating the duration of outage (T_{failure}+$T_{\text{maintenance}}$), Figure 3.13 can be further reduced to Figure 3.13.

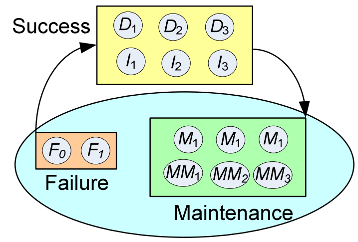


Figure 3.13 Reduced Two-state Equivalents

The frequency of transition from Success to Outage is

$$f_{\text{outage}} = f_{\text{failure}} + f_{\text{maintenance}}$$

$$f_{\text{outage}} = \frac{1}{T_{\text{success}} + T_{\text{outage}}} = \frac{T_{\text{outage}}}{T_{\text{success}} + T_{\text{outage}}} \bullet \frac{1}{T_{\text{outage}}} = \frac{1-A}{T_{\text{outage}}} \tag{3.27}$$

$$T_{\text{outage}} = \frac{1-A}{f_{\text{outage}}} = \frac{1-A}{f_{\text{failure}} + f_{\text{maintenance}}} \tag{3.28}$$

3.6 Maintenance Optimizations for Maximum Equipment Availability

In power systems, there is critical equipment, for which the grid owners prefer to improve their availability, regardless of the economic costs or other budget constraints.

In the previous sections, it is clear that maintenance can be utilized as a control mechanism that affects the reliability of equipment. Alternation of maintenance can either improve the reliability or decrease the reliability of equipment, in which the relationship is presented in Figure 3.14.

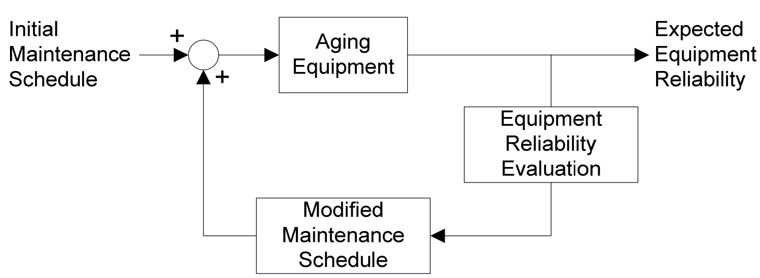


Figure 3.14 Loop Relationship of Maintenance and Equipment Reliability

In Figure 3.14, the relationship between maintenance and equipment reliability is similar to the negative feedback: altering the value of maintenance schedules, until the desired equipment reliability is achieved.

3.6.1 Mathematical Model

The following optimization problem can be formulated to maximize the equipment reliability by optimizing the maintenance rates.

Objective functions:

Maximize equipment availability, or minimize equipment frequency of failure / expected duration between failures.

Decision Variables:

Maintenance / inspection / replacement rates.

Constraints:

The lower and upper bound of Maintenance/Inspection/Replacement rates.

For example, for aging equipment modeled by an eight-state continues-time Markov process presented in Figure 3.9, the optimal maintenance rate which can achieve the maximum availability is determined. Then the optimization problem is defined as

Objective functions:

Maximize availability, A, as a function of maintenance rate λ_M: $A=f(\lambda_M)$.

Decision Variables:

Maintenance rates, $\lambda_{M.}$

Constraints:

$\lambda_{M\_MIN} \leq \lambda_M \leq \lambda_{M\_MAX}$, where λ_{M_MIN} and λ_{M_MAX} are the lower and upper bound of maintenance rate λ_M.

3.6.2 Optimization Techniques for Equipment Maintenance Optimization

In the above optimization model, usually the objective functions have non-linear characteristics, and the increased number of states in Markov model typically increases the complexity.

There are several approaches available in solving the optimization problem:

1) *Equation Derivation*

Explicit equations of optimization function are required for this method. For example, the explicit equation of availability as a function of maintenance rate must be acquired. Then partial derivative of this equation is used to solve for the optimal decision variables. The optimal maintenance rates that will achieve the maximum availability values can be determined while satisfying the constraints.

This approach is accurate and straight forward. However, in many cases, deriving the explicit equations is always a challenge. In fact, in some large Markov models, deriving explicit equations take too much effort and time, and it is not worth doing this just for the optimization purpose. Therefore, this approach is only applicable for small Markov models with limited number of decision variables.

For example, in above example, the explicit objective function between availability A and maintenance rate λ_M can be derived through solving the Markov equation, which is presented in (3.29)

$$A = \frac{1.6 \cdot (9.2\mathrm{e}10^3 \lambda_\mathrm{M} + 5.8 + 5.5\mathrm{e}10^6 \lambda_\mathrm{M}^2 + 1.6\mathrm{e}10^9 \lambda_\mathrm{M}^3)}{1.5\mathrm{e}10^4 \lambda_\mathrm{M} + 9.4 + 8.8\mathrm{e}10^6 \lambda_\mathrm{M}^2 + 2.5\mathrm{e}10^9 \lambda_\mathrm{M}^3 + 2.5\mathrm{e}10^9 \lambda_\mathrm{M}^4} \tag{3.29}$$

The partial derivative of the equation with respect to λ_M is set to zero. The optimal maintenance rate is then calculated as λ_M= 0.00271 (1/day) and the corresponding maximum availability is 0.9936.

However, in larger Markov models, or Markov models with more decision variables, derivation of explicit equations is not an easy task. Moreover, using partial derivative method only local optimal points is determined. In some cases, especially in complex models, global optimization approaches will be more favorable.

2) *Exhaustive Enumeration*

In this approach, the search space of the decision variables is separated equally into several possible points, and the objective function is evaluated at every possible point. Then the maximum objective function as well as the corresponding optimal point can be determined.

For example, the search space of maintenance rate [0.0001 0.02] in the above case can be separated equally, and the availability of equipment are evaluated at every points. Then, the maximum availability as well as the corresponding maintenance rate (the optimal point) can be determined, as illustrated in Figure 3.15 [69].

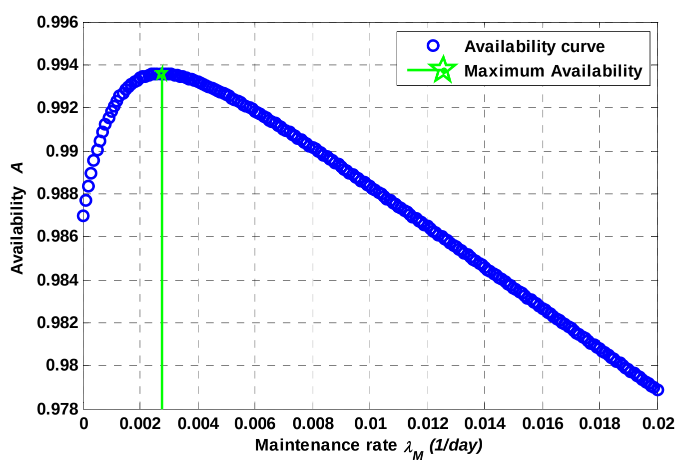


Figure 3.15 The Optimal Maintenance Rate that Maximizes Equipment Availability

Compared with the first approach, numerical evaluation approach is clear, and it avoids deriving the explicit equation of objective function. As long as the relationship between the equipment reliability and the maintenance rate is developed, it is not necessary to derive the explicit reliability equation. Moreover, the process of doing optimization can be conveniently visualized.

However, the accuracy of the result depends on the size of intervals, in which the searching space is separated. The optimal point might reside between adjacent interval points. Besides, this approach requires the evaluation of objective functions at every possible point within the searching space.

3) *Non-Linear Programming* (*NLP*)

Although NLP approach also avoids the derivation of explicit equations required in Approach 1), and redundant objective function evaluation in Approach 2), the NLP is still a local optimization method. In optimization of multi decision variable problems, the global optimization approach, such as Genetic Algorithm, may have more applications.

Table 3.4 summaries the features and applications of above three optimization approaches.

TABLE 3.4 COMPARISONS OF ANALYTICAL METHODS FOR POWER SYSTEM RELIABILITY ASSESSMENT

Approaches	Advantages	Disadvantages	Application Cases
Equation Derivation	• Accurate	• Requires deriving explicit equations • Local optimization	• Academic illustration • Small Markov model with limited number of decision variables
Numerical Evaluation	• Clear • Visualization • Global optimization	• High computation burden • Not as accurate as equation derivation approach	• Markov models with limited number of decision variables (usually less than 3)
Non-Linear Programming	• Accurate	• Local optimization	• Appropriate for both small and large models, and optimization with multiple decision variables

In addition to the above three approaches, there are other global optimization techniques, such as Genetic Algorithm, Simulated Annealing, and Particle Swarm Optimization, available to solve equipment maintenance optimization problems. However, compared with the complexity of system level maintenance optimizations (described in detail in Chapter 4), equipment level optimization is relatively low. Therefore it is reasonable to apply above simple but clear optimization approaches, to make the illustration easier.

3.7 Equipment Reliability, and Maintenance Evaluation Procedure

To conclude this Chapter, the procedure for equipment reliability evaluation and maintenance optimization is presented in Figure 3.16.

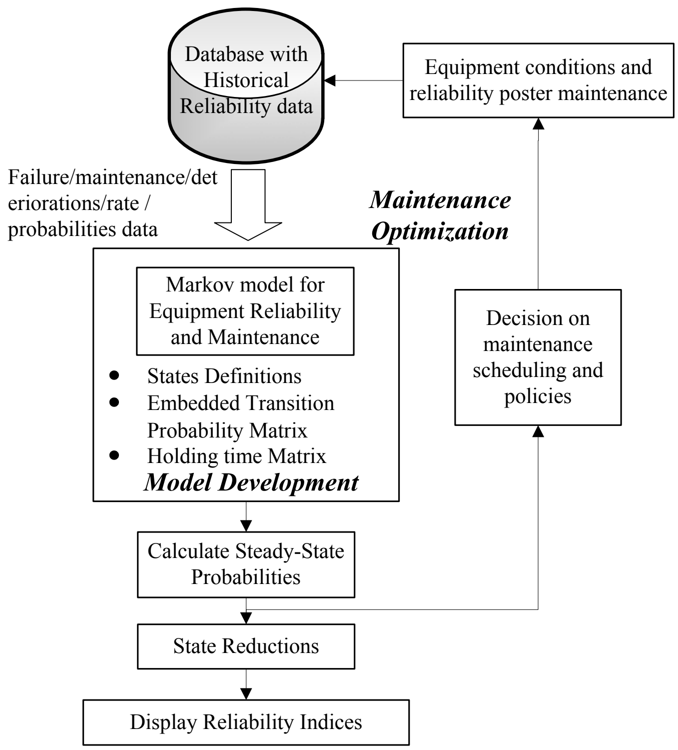


Figure 3.16 Flow Chart Diagram for Equipment Reliability / Maintenance Evaluation

The techniques discussed above can be combined, following above flow chart, for equipment reliability evaluation and maintenance decision making work.

3.8 Power System Economic Cost Analysis

Economic evaluation is crucial in power system reliability and maintenance engineering analysis. In fact, all maintenance optimization programs have to incorporate economic or cost-benefit analysis, to determine the optimal maintenance schedules. Economic analysis is quickly becoming an inextricable part of reliability assessment [70]. In power system reliability and maintenance analysis, not only the cost of maintenance should be consider, the penalty of unreliability due to maintenance outage cannot be neglected either.

Li [71] claimed that the economic cost model for optimal planning of power systems should incorporate following cost:

$$\textit{Economic Cost} = \textit{Investment Cost} + \textit{Operation \& Maintenance Cost} + \textit{Penalty Cost} - \textit{Salvage Value} \qquad (3.30)$$

In this dissertation Salvage Value is neglected, as compared with other cost related with investment and maintenance cost, salvage value is relative small.

For distribution substations that this dissertation focuses on, above economic cost can be further separated into two different parts: *Customer Cost of Reliability* (CCR) and *Utility Cost of Reliability* (UCR) [20].

Customer Cost of Reliability (CCR)

From the customers' perspective, their concerns are mainly whether the electricity will be served or not; if not, how much electricity is not served? How much is the frequency and duration of outages? Therefore, *Customer Cost of Reliability* contains primarily the Penalty Cost. In this dissertation, *CCR* is represented by (3.31)

$$CCR = C_{\mathrm{outage}} + C_{duration} + C_{kWh} \qquad (3.31)$$

where C_{outage} is the Cost of interruption power (unit: \$/outage); $C_{duration}$ is the Cost of interruption duration (unit: \$/hr); C_{kWh} is the Cost of interrupted energy (unit: \$/kWh).

Utility Cost of Reliability (UCR)

From grid owners' perspective, besides the penalty cost due to electricity outages, grid owners also have concerns on cost related with equipment operation/maintenance and their assets values (conditions). Therefore, the Investment Cost and Operation & Maintenance Cost makes the majority part of Utility Cost of Reliability (*UCR*).

In this dissertation, the *UCR* is represented by (3.32):

$$UCR = \textit{Capital Investment Cost} + \textit{Operation \& Maintenance Cost} \tag{3.32}$$

where *Capital Investment Cost* is the cost of purchasing new equipment (unit: $); *Operation & Maintenance Cost* is the cost of doing routine inspections repairs and any cost related with operation and maintenance of this equipment.

In [20] *Total Cost of Reliability* (*TCR*) is introduced, which is the sum of Utility Cost of Reliability (*UCR*) and Customer Cost of Reliability (*CCR*) as described in (3.33).

$$TCR = UCR + CCR \tag{3.33}$$

The introduction of *TCR* meets the needs for design maintainability and determining the maintenance schedules. *TCR* is utilized as one of the objectives in the maintenance optimizations process, especially in publicly owned utilities. However, utilization of *TCR* might emphasis too much on customers' benefit. According to [20], "without compensation, minimizing societal cost transfers wealth from utility owners to utility customers".

3.9 Economic Benefit Analysis

In many applications, grid owners prefer economic *benefit* models than economic *cost* models, as the expected benefit indices are more straight forward in enterprise-level analysis when make maintenance related decision [57].

The above Economic cost model can be easily transferred to Economic Benefit model, by adding the portion of benefit of successfully running the equipment in a given period, which is illustrated in (3.34):

$$\textit{Economic Benefit} = -(\textit{Economic Cost}) + \textit{Benefit of Successfully Running} \quad (3.34)$$

Benefit of Successfully Running represents the contribution of equipment toward the substation benefit when successfully operated.

For economic cost modeling of equipment based on Markov process, usually a simple economic model is applied. A typical method is direct convolution of the steady-state probabilities and the related cost of being in each state, such as the economic cost models in [72] [48] [49].

Through the studies in [72] [48] [49] realized the importance of having economic analysis, the models are relatively simple, and only considered the cost of residing in a state in per unit of time. The cost related with per-visiting, such as C_{outage} (Cost of interruption power, unit: \$/outage) is neglected. This dissertation will utilize Markov decision processes to for economic cost modeling.

3.10 Markov Decision Process

3.10.1 Introduction of Markov Decision Process

Engineers are often faced with the problem of modeling equipment with decision-making features. For example, in the multi-state Markov model presented in Figure 3.7, at each deterioration stages, what action (minor maintenance, major maintenance, or no action) to take?

In 1960, Howard developed a model based on the standard Markov model but incorporating a decision-making technique [73]. This became known as the Markov

Decision Process (MDP). Howard's Markov decision process is based on a reward scheme that provides a method of measurement and comparison for different equipment policies.

3.10.2 Solving Markov Decision Process

There are three iteration methods which are widely used to solve MDPs. *Linear Programming* is a method that solves for the policy with the greatest reward for problems in which a certain probabilistic constraints may exist [64]. *Value-iteration* method is a slightly more simple technique because it does not require the solution of a set of linear equations [74]. The *policy-iteration* method uses a policy to compute an average cost per unit of time to build another policy with a greater reward. This process continues until the optimal policy is obtained [65].

In comparing the above methods, linear programming tends to require more iteration to reach an optimal policy; value iteration method is more appropriate for discrete-time Markov decision processes, where in this dissertation the process is continuously.

On the other hand, the policy-iteration method is more appropriately fit this dissertation because it is a much more efficient search method for larger systems. The optimal policy is obtained in a minimal number of iterations and is directed more to analyzing a process of indefinite duration that makes many transitions before termination [73]. Policy-iteration method is utilized in this dissertation to solve Markov decision process.

3.10.3 Semi-Markov Decision Process

The semi-Markov decision process (SMDP) takes the above standard MDP to another level to more accurately model power equipment, in which decision-making traits are present.

Standard MDPs fails to include sojourn times for actual planning problems [75]. Semi-Markov processes improve upon standard Markov processes with inclusion of the sojourn times of each state in the state space

SMDPs can be used for both a discrete-time process in which the state transitions are made at specific time epochs and a continuous-time process in which the system may transition at any time. The *continuous-time SMDP*'s ultimate goal is to use the steady-state probabilities to find the long term maintenance policy for an infinite horizon problem.

An SMDP must possess the *uni-chain property* as well as the *Markovian property*.

The *Uni-chain property* declares that all the states in the state space of the model must be either a transient state or a recurrent state. Every state must be achievable in every possible policy [64].

The *Markovian property* proclaims that the future state of the model depends only on the present state and is independent of all past states. In addition, the reward also must possess a form of the Markovian property. The reward for a specific transition depends only on the present state and the future state. Past states cannot affect the cost or reward for that state in any policy.

3.10.4 Steps to Solve Semi-Markov Decision Process

For solving SMDP, the policy-iteration method can be separated into following four steps:

Step 1) Steady-state Probabilities

The first step is to solve for the state probabilities using the SMP. By using equations (3.9)-(3.11) in Section 3.2, the steady-state probabilities of a SMP can be solved.

Step 2) Initial Policy

For policy iteration, it is necessary to select an initial policy. Initial policy can be selected at random, but this may result in a number of unneeded iterations to reach to the final optimal policy. Therefore, in this dissertation the first step is to choose an initial policy based an educated guess. The initial policy $\mathbf{d}_1$ which the highest earning rate is selected for each state is selected in this dissertation.

Let Γ_{ji}^{a} be the probability of going from state *i* to state *j* when action *a* is chosen, and r_{ji}^{a} is the corresponding reward from a transition to state *j* from state *i*. Then the total reward of choosing action *a* while in state *i* is [17]:

$$r_i^a = \sum_{j=1}^{N} r_{ji}^a \Gamma_{ji}^a \tag{3.35}$$

where N = the total number of states in the model.

The time spent in each state must also be considered. So it is then necessary to find the reward per unit time called the earning rate while choosing action *a*. The initial policy found by [18]:

$$q_j^a = r_i^a / t_i \tag{3.36}$$

where t_i is the sojourn time of state *i*; r_i^a is the reward of choosing action *a* while in state *i*; q_i^a is the reward per unit of time.

Step 3) Policy Evaluation

The iteration process begins by the Policy Evaluation. It is necessary to obtain a measure that represents the gain of the selected alternative along with *N* relative values, v_i, for the system. This is achieved using (3.37).

$$v_i + g = q_i t_i + \sum_{j=1}^{N} v_j \Gamma_{ji} \tag{3.37}$$

Here the gain of the policy is the average reward per unit of time. Note that there are *N* relative values and one scalar *g* in which to solve, giving *N+1* unknown with only *N* equations. Therefore one of the relative values, usually v_N is arbitrarily set to zero [18].

Step 4) Policy Improvement

In policy improvement step, test quantity of alternative of state *i* G_i is calculated for each alternative of a given state. This is achieved using the relative values obtained from (3.38). The test quantities are compared for each alternative in a state. The lowest value for each state will be the best decision for that state in the next policy.

$$G_i^a = q_i + (1/t_i)[\sum_{j=1}^{N} v_j \Gamma_{ji} - v_i] \tag{3.38}$$

Policy Evaluation and Policy Improvement steps are repeated until the same policy results twice in a row. The process stops and the last iteration policy is the optimal policy. Figure 3.17 gives a flowchart of solving semi-Markov decision processes.

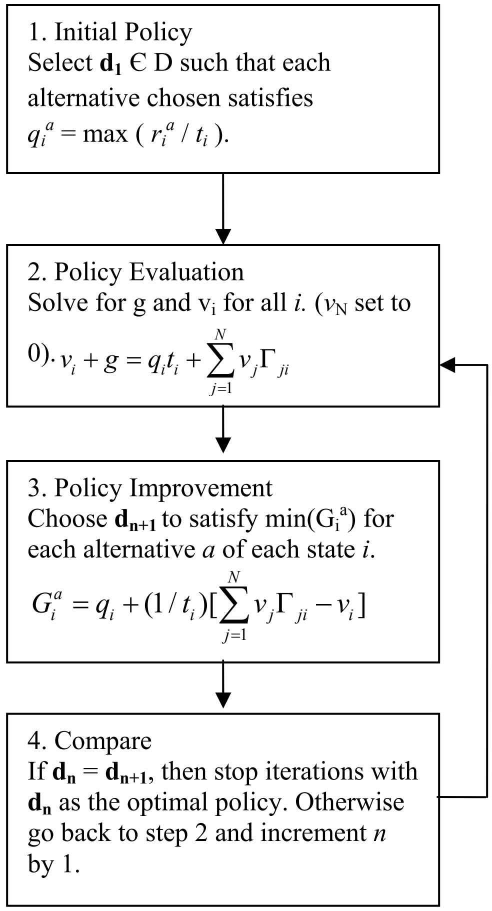


Figure 3.17 Flow Chart Diagram of Policy Iteration Method for Solving SMDP

3.11 Applying Semi-Markov Decision Process

The general semi-Markov model with inspection, minor and major maintenance states is used for illustrating how to apply Markov Decision Processes. In this model, equipment is represented by a series of deteriorating, maintenance, and failed states. It is assumed that the equipment can fail due to both deterioration and random causes.

In each deterioration state there exists the opportunity to do nothing, perform minor maintenance, or major maintenance. Each choice is marked with a bold circle in Figure 3.18. The action space is defined as:

A = {do nothing (I), do minor maintenance (II), do major maintenance (III)}

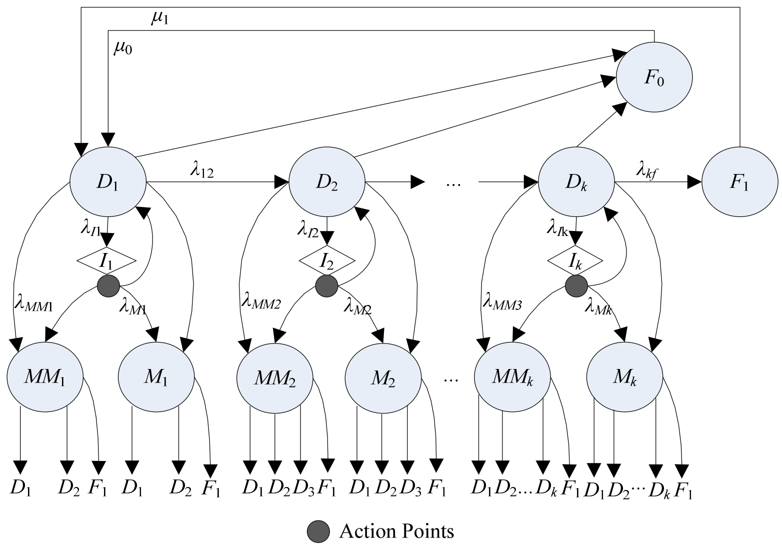


Figure 3.18 State-Space Diagram of a SMDP with Inspections, Minor and Major Maintenances

Here, the expected economic benefit will be calculated, based on the maintenance rate that can achieve maximum equipment availability. The explanation of every state this model is available in Section 3.2. Here the policy iteration method is utilized to determine the optimal policy, and number of deterioration states is 3 (when $k = 3$, N=14).

Determine the initial policy. Using (3.34) to determine the earning rate for each alternative in each state, the initial policy, $\mathbf{d}_1$, will be composed of the alternatives with the greatest earning rates for each of the three deterioration states.

Policy Evaluation. The next step in the process is to solve for the gain and the relative values associated with the current policy. Equations (3.36) and (3.37) give the gain, g, and the 14 relative values for the policy (v_{14} is set to 0). The gain can then be compared to future policies to find the most rewarding policy possible.

Through the iteration process, each step will produce a policy with a gain no less than the previous policy's gain. This can then be used to prove that the iteration process finds the global optimal policy and not a local optimal policy [65].

Policy Improvement. The gain and the relative values are used in Equation (3.37) to find the test quantity, G_i^a, of every alternative, a, for each state i, where a choice is to be made. In this case, nine test quantities will be solved for - three alternatives in three states. For example, G_2^1 (do nothing in D_2) is compared to G_2^2 (do minor maintenance in D_2) and G_2^3 (do major maintenance in D_2). The lowest test quantity of the three will determine the alternative to be chosen in the next policy, $\mathbf{d}_{\mathbf{n+1}}$.

Policy Comparison. If the two policies are different, then the next policy becomes the current policy and the policy evaluation step is implemented. However, if the policies are equal, then the current policy is the optimal policy.

After the policy iteration is completed, the optimal policy $\mathbf{d}_{\text{opt}}$. can be determined.

Then the sum of the expected reward per unit time q_i^a at deterioration states, corresponding to this optimal policy $\mathbf{d}_{\text{opt}}$, is the expected benefit that can be acquired by operating this equipment successfully. In summary, equation (3.39) gives the calculation of equipment benefit per unit time $B_{\text{Equ.}}$:

$$B_{\text{Equ.}} = \sum_{i=D_1, D_2, \ldots, D_k} q_i^a \text{ (} a \text{ is the actions under optimal policy } \mathbf{d}_{\text{opt}}\text{)} \qquad (3.39)$$

Appendix: List of Assumptions of the Proposed Method - Equipment Modeling

1. Assume equipment can failure due to both randomness and deterioration

   a. *Random Failure*

   Assume this type of failure can occur at any time, irrespective of the effect of maintenance. Generally random failure has constant failure rate.

   b. *Deterioration failure*

Assume the cost and severity of having deterioration failure are higher than random failure; the MTTR of deterioration failure is also longer than random failures.

c. Maintenance's impact on deterioration failure

Assume maintenance can improve equipment condition, prolong equipment life, and decrease probability of having deterioration failures.

2. Deterioration stages

   Assume aging equipment is separated into three deterioration stages, and the transition times between consecutive stages follow exponential distributions (therefore the corresponding transition rate can be modeled by a constant transition rate, such as λ_{12}, λ_{23} in Figure 3.7).

3. Human Error

a. Occurring during inspections

Due to human induced error, engineer may determine unnecessary outages of system/equipment after inspections. This type of human error will not have apparently impact on equipment condition.

b. Occurring during maintenance

Due to human error, after maintenance, the equipment condition may worse, or the equipment may enter further deterioration stages, or failures. This type of human error will change equipment condition.

Above development of reliability and economic cost models with respect to maintenance are only applicable in equipment level analysis. Chapter 4 will describe how these models are utilized in system level assessment.

CHAPTER 4
MAINTENANCE OPTIMIZATION FOR SUBSTATIONS

When make maintenance related decisions for entire system other than single equipment, it is desired to know the expected system reliability improvement and cost. Therefore, this chapter will focus on developing system level reliability and cost models with respect to equipment maintenance. Also, the chapter presents several scenarios about how to utilize the developed models to optimize maintenance decision.

4.1 Substations

Electricity is generated and delivered to end customers through generation, transmission and distribution systems. Generation systems produce enough power to meet customer demand; transmission systems transport bulk power without overheating or jeopardizing system capacity/stability over long distances; distribution systems distribute power and deliver electricity to end customer's service [70]. In terms of reliability, generation, transmission and distribution systems are referred to as functional zones [76]. A simple drawing of an overall power system in different zones is presented in Figure 4.1 [70].

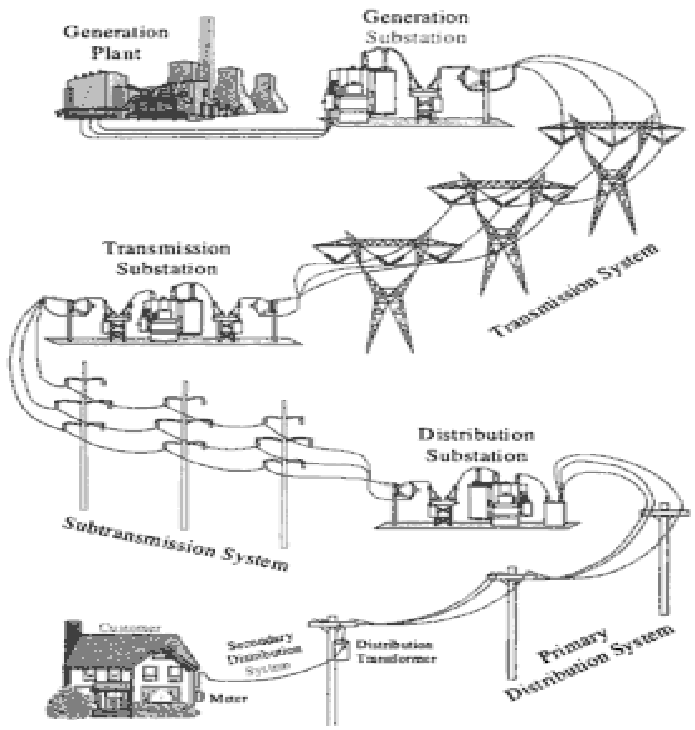


Figure 4.1 Typical Structures of Electric Power Systems

In Figure 4.1, substations play different roles in different systems: *generation substations* connect generation plants to transmission lines through step-up transformers, that increase voltage to transmission levels; *transmission substations* are transmission switch stations with transformers that step-down voltage to sub-transmission levels; there are also *transmission switch station*s which serve as nodes that allow transmission lines to be reconfigured; *distribution substations* are nodes for terminating and reconfiguring sub-transmission lines, with transformers that step-down voltage to primary distribution levels [70].

The dissertation focuses on the distribution substations, since most customer failures are related with distribution systems. However, the proposed methods are general, and can also be applied to substations in generation and transmission systems.

4.2 Substation Structure

There are various types of substations depending on functionalities. A popular and simple substation diagram is presented in Figure 4.2 [70].

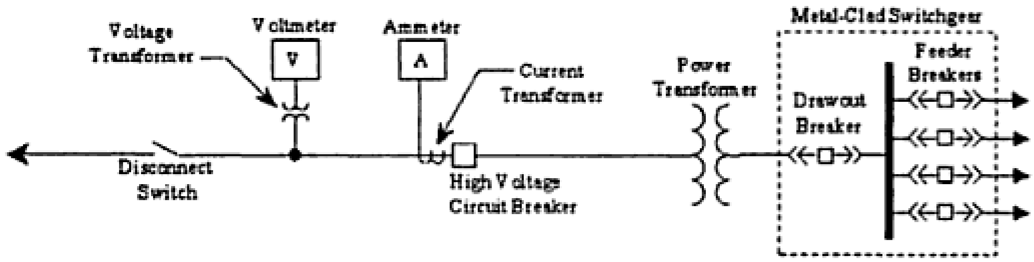


Figure 4.2 Single-line Diagram and Basic Components of a Distribution Substation

In Figure 4.2, the source of delivering power to the substation is a single sub-transmission line. Power is delivered across disconnect switch, through circuit breaker, and enters power transformer. Several current transformers (CT) and power transformers (PT) are connected in parallel, which are mainly for measurement purposes. The circuit breaker protects the transformer that steps voltage down to distribution level.

This single-line substation structure may cause reliability concerns, due to its simple configuration: any major component failure will results in all feeders to be de-energized. Consequently, many distribution substations are designed with redundancy, to allow portions of feeders remain energized if any major component fails or not available due to maintenance.

Figure 4.3 is an "H-station" or "transmission loop-through" design substation [70]. This substation is able to supply both secondary buses, after the loss of either transmission lines or transformer. This structure also has disadvantages that faults will generally cause one of secondary buses to be de-energized, until switching is performed [70].

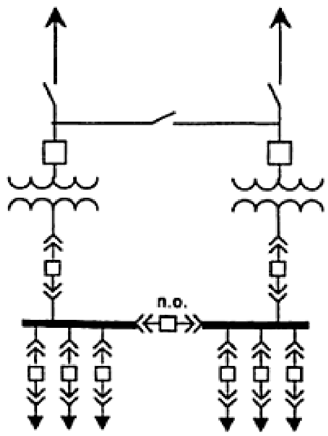


Figure 4.3 Substation with Two Sub-transmission Lines and Two Transformers

Figure 4.4 is a substation that further increases substation reliability, by having an additional transmission line, an energized spare power transformer, primary ring-bus protection, motor-operated switches, and a secondary transfer bus [70].

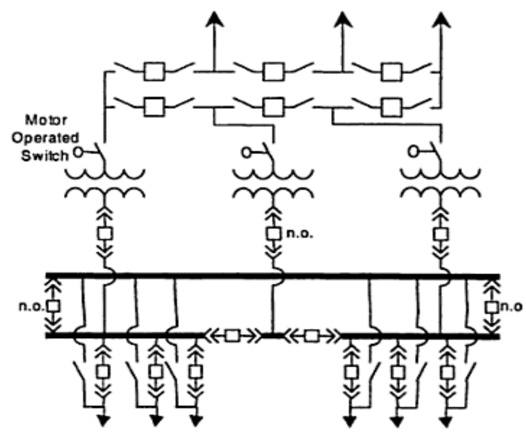
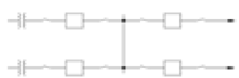
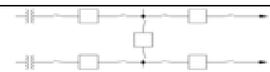
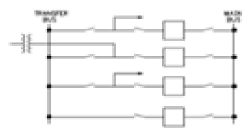
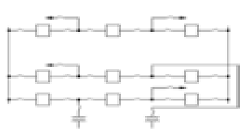


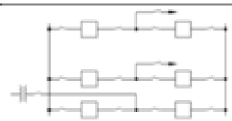
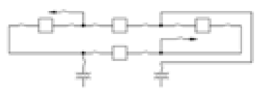
Figure 4.4 A Reliable Substation with a Primary Ring Bus, Switches, an Energized Spare Power Transformer and a Secondary Transfer Bus

The comparison of Figure 4.2 , Figure 4.3 versus Figure 4.4 indicates that reliability is improved when the number of buses or sections of buses increases. In fact, bus configurations play an important role for substation reliability, operational flexibility and economic costs [77].

Table 4.1 gives a summary of most commonly encountered substation structures utilized in substation design, as well as the advantages and disadvantages [77].

TABLE 4.1 SUMMARIES OF SUBSTATION BUS CONFIGURATIONS

Name	Typical Configuration	Description	Advantage	Disadvantage	Cost
Single Bus, Single Breaker		All connections terminate on a common bus	• Lowest cost • Small land area • Easily expandable • Simple operation • Simple for the application of protective relay	• Single bus arrangement, with the lowest reliability • Failure of a circuit breaker or bus causes loss of entire substation • Maintenance switching can be complicate, and disable some of the protection schemes	100% (Ref.)
Sectionalized Bus		Based on the Single Bus Single Breaker configuration; bus is split and connected by a switch or breaker	• Flexible operation • Isolation of bus sections for maintenance • Loss of only part of the substation, for a breaker failure or bus fault	• Additional circuit breakers needed for sectionalizing; high cost • Sectionalizing may cause interruption of non-faulted circuits	122%
Main and Transfer Bus		A transfer bus is connected to a main bus, through a tie breaker; circuits are normally connected to the main bus, but can be switched to the transfer bus, using sectionalizing switches	• Can maintain service and protection during circuit breaker outages • Reasonable in cost • Fairly small land area • Easily expandable	• Additional circuit breaker needed for bus tie • Protection and relaying may become complicated • Bus fault causes loss of the entire substation	143%
Breaker and a Half		Utilizes legs consisting of three series breakers, connected between two buses. On average,1.5 breakers are required per circuit	• Flexible operation and high reliability • Isolation of either bus or breaker without service disruption • Double feed to each circuit • Bus fault does not interrupt service to any circuits • All switching is done with circuit breakers	• More complicated relaying, as the center breaker has to act on faults for either of the two circuits it is associated with • Each circuit should have its own potential source for relaying	158%
Double Bus, Double Breaker		Each circuit is connected to two buses through dedicated circuit breaker. On average each circuit uses two breakers	• Flexible operation with very high reliability • Isolation of either bus, or any breaker without disrupting service • Double feeds to each circuit • No interruption of service to any	• Very high cost – 2 breakers per circuit	214%

			circuit from a bus fault • Loss of one circuit per breaker failure • All switching with circuit breakers		
Ring Bus		Arranges breakers in a closed loop with circuits placed between breakers. Only one breaker is required per circuit	• Flexible operation • High reliability • Double feeds to each circuit • No main buses • Expandable to breaker-and-a-half configuration • Isolation of bus sections and circuit breakers for maintenance without circuit disruption	• During fault, splitting of the ring may leave undesirable circuit combinations • Each circuit has to have its own potential source for relaying • Usually limited to 4 circuit positions, although larger sizes up to 10 are in service. 6 is usually the maximum terminals for a ring bus	114%

In practice, because of the high reliability and relatively low cost, it is common to initially build a substation as a ring bus, and convert it to breaker and a half when required [67].

4.3 Substation Component

Various types of equipment must be interconnected to construct a substation. A major distribution substation usually contains the following components:

- High Voltage Disconnect Switches
- High Voltage Buses
- High Voltage and Current Transformers
- Power Transformers
- Auto Transformers
- Protective Relays

From the standpoints of investment cost and failure effect, the most critical pieces are power transformers and circuit breakers, with most aging infrastructure problems occurring in old substations [70]. Therefore, transformers and circuit breakers are the primary objectives to be studied in this dissertation.

` Industrial surveys indicate that there are a lot of old transformers [50]. Also, in the past 15 years, utilities have generally loaded the transformers to higher levels. The combination of old chronological aging and increased thermal aging has created significant deterioration in many transformers. Therefore, usually the first concern of substations is related to aging power transformer [50].

From criticality perspective, circuit breakers are of special concern. This is because circuit breakers are often at the outset of the radial distribution systems. If a transformer fails, other transformers can generally serve the load entirely, while customer may experience momentary interruptions. However, if a feeder circuit breaker experiences an internal failure or deterioration failure, the entire feeder or even the entire bus will be de-energized.

4.4 Substation Reliability Evaluation

Previous researchers have developed many methodologies for substation reliability evaluation [78]-[81]. The methodologies can be categorized into Network Reduction, Markov Modeling, Minimum Cut-Set and Monte-Carlo Simulation approaches. Following is a brief descriptions and comparisons of these methodologies.

1) *Network Reduction*

This method uses an equivalent substation model to simplify the original substation, but excludes all feeder breakers. Equations are derived to calculate the equipment failure rates and durations [70]. However, this method ignores the impact of maintenance, and is therefore not appropriate for reliability modeling of substations with aging infrastructure and maintenance.

2) *Markov Modeling*

This method is based on a Markov model in which each state of the substation is a combination of specific states that are utilized in equipment Markov models. The reliability indices can then be calculated through solving Markov equations [59].

This method is straightforward and has several applications, especially in small scale substations with limited components. However, the increased number of equipment or states in equipment models will greatly increase the complexity in substation Markov models. (For example, if a substation has *m* equipment, and equipment is modeled by an n-state Markov model, then the substation Markov model contains n^m states) [59].

3) *Minimum Cut-Set*

Minimum cut-set method is an alternative network reduction method. A *cut-set* is a group of components that when fails causes the system to be unavailable. A *minimum cut-set* is a smallest set of components such that if they fail, the system fails. An *nth* order minimum cut-set is identified as those which consist of *n* components [67] [70].

The minimum cut-set method has the following advantages [67]: easy implementation; handles complex networks that cannot be characterized by either serial or parallel connections; gives insight into critical component dependencies. This dissertation implements a minimum cut-set method for substation reliability assessment.

4) *Simulation Method*

Simulation method is widely applied in system level reliability assessment, including substations. Sequential or non-sequential Monte-Carlo simulation techniques are used to sample the durations of events or the states of equipment, and the system reliability is calculated through the simulated event history [22] [82].

Again, the increased number states in modeling Equipment reliability by Markov process will increase computation burden; the simulation programs may experience long execution time, before converging to a satisfied value. One possible solution to decrease the executing time is using parallel computing techniques, in order to efficiently utilize the capacities of multi-processors and large memory resources.

4.5 Modeling of Substation Reliability

For analytical approaches, previous researchers either focus on network reduction techniques, which are based on the assumption of binary-state component model, or stochastic approaches which are limited by the size of systems [80] [59]. Neither of these approaches alone is appropriate for studying the impact of maintenance and aging equipment on reliability.

In this dissertation, a method of combining equipment Markov models and minimum cutest-based system reliability calculation is developed. The purpose of using Markov model is to study the aging process and maintenance, while applying minimum cut-set method to extend these studies to substation levels.

Figure 4.5 is the structure of the proposed method. The reliability index evaluated here is availability; as for the life cycle design of substation maintainability, availability is the most critical index. Also, the method developed is applicable for calculating substation failure frequency and average outage duration, based on some transformation techniques [83] [84].

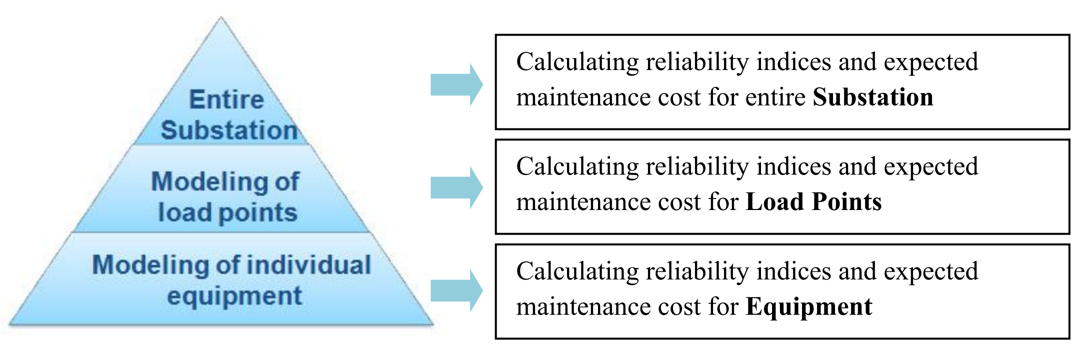


Figure 4.5 Connections of Equipment, Load Point and Substation Reliability Models

4.5.1 Reliability Modeling of Aging Equipment with Maintenance

The first step in Figure 4.5 is to perform reliability modeling of equipment with aging process and maintenance. Multi-state Markov process is utilized, which is described in Chapter 3. State-reduction technique is used to further reduce the multi-state Markov model into binary-state, as the minimum cut-set approach is based on binary-state equipment model.

For example, for the fourteen-state semi-Markov model in Figure 3.7, the equipment availability can be determined as a function of major maintenance rate λ_{MM} and inspection rate λ_I, presented in (4.1)

$$A_{equ.} = f(\lambda_{MM}, \lambda_I) \tag{4.1}$$

4.5.2 Load Point Availability Calculation

The second step in Figure 4.5 is calculating load point availability. Load point availability is of particular interest, since in distribution systems customers are directly connected to specific load points. The following is an example of using minimum cut-set method for calculating load point availability.

For a typical single-line structured substation presented in Figure 4.6, assuming sub-transmission lines are 100% reliable, the first and second order cut-sets can be derived, which is presented in Figure 4.7.

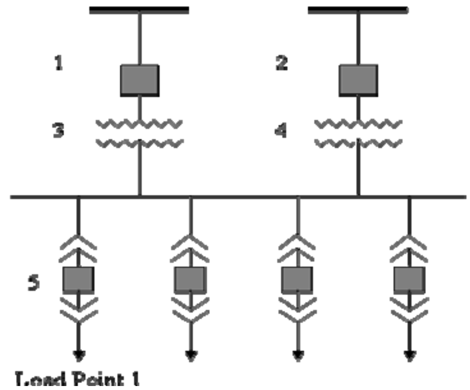


Figure 4.6 Configuration of a typical Substation

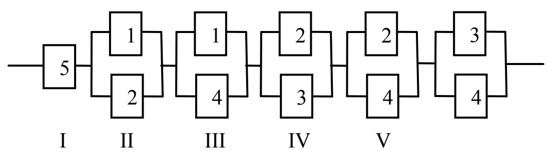


Figure 4.7 The First and Second Order Cut-sets for Load Point 1 in Figure 4.6

In Figure 4.7, "**I**" is the first order cut-set; "**II**" to "**V**" are the second order cut-sets. The serial connection between cut-sets "**I**" to "**V**" reflects the meaning of minimum cut-set's definition: failure of any cut-set will results in the failure of the entire system. For example, if component 5 in "**I"** fails, Load Point 1 will have interruption; if component 1 and 2 in "**II"** fail simultaneously, Load Point 1 will have interruption too.

From Figure 4.7, Load Point 1 unavailability U_{LP1} can be calculated by (4.2).

$$
\begin{aligned}
U_{\mathrm{LP1}} = {} & U(\mathrm{I}) + U(\mathrm{II}) + U(\mathrm{III}) + U(\mathrm{IV}) + U(\mathrm{V}) \\
& - U(\mathrm{I} \cap \mathrm{II}) - U(\mathrm{I} \cap \mathrm{III}) - U(\mathrm{I} \cap \mathrm{IV}) - U(\mathrm{I} \cap \mathrm{V}) \\
& - U(\mathrm{II} \cap \mathrm{III}) - U(\mathrm{II} \cap \mathrm{IV}) - U(\mathrm{II} \cap \mathrm{V}) \\
& - U(\mathrm{III} \cap \mathrm{IV}) - U(\mathrm{III} \cap \mathrm{V}) \\
& - U(\mathrm{IV} \cap \mathrm{V})
\end{aligned} \tag{4.2}
$$

It should be noted that U_{LP1} calculated by (4.2) is only an approximation. The probability of having three or more equipment fail simultaneously is small, and can be negligible. Therefore, the third and higher order cut-sets are ignored, and the unavailability value in (4.2) is only the lower bound value of load point unavailability (consequently, the upper bound of availability) [85].

4.5.3 Load Point Importance Quantification

After the load point availability is determined, the substation availability can be computed by combining the weighted load point reliability indices.

Here, the weight value for each load point is the load importance LI_j (j is the number of load points in a substation). The value reflects the load point's relative importance in a substation.

In current power system structure, electricity users and the power providers (grid owner or utilities) have different concerns about the unavailability, or outages of substations. The definition of the load point importance should include the following considerations:

- *Economic Importance of a load point: EI*

  EI is determined from the perspective of economic losses, when power supply for this load point is unavailable; the sum of the *EI* of all load point should be 1.

  The *EI* values for each load point can be determined, either by conducting surveys or by asset manager's decision. The determination of *EI* value should consider frequency, duration, expected energy losses, and other factors related to outages.

- *User Importance of a load point: UI*

  For electric utilities, it is reasonable to quantify the importance of users, according to some measures such as security, health, or convenience. *UI* is defined as the importance of users that the load point is connected to. For example, hospitals and airports should have higher *UI* values. The determination of the *UI* values can be based on mandatory decisions.

The load point importance values *LI* can be calculated by:

1) Calculate pre-processed load point importance values, *pre-LI,* by (4.3)

$$pre\text{-}LI_j = EI_{Lj} \times UI_{Lj} \tag{4.3}$$

2) Normalize:

$$LI_j = pre\text{-}LI_j / \sum pre\text{-}LI_j = EI_j \cdot UI_j / \sum EI_j \cdot UI_j \tag{4.4}$$

LI_j is the final value, which represents the relative importance of a load point j.

4.5.4 Substation Availability Calculation

After calculating the load point j, availability A_j, and load point importance factors LI_j, the substation availability can be evaluated by (4.5)

$$\begin{aligned} A_{Sub.} &= \sum A_j LI_j = \sum f_j(\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In},) LI_j \\ &= f(\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In}, EI_1, UI_1, EI_2, UI_2, ..., EI_j, UI_j ..., EI_J, UI_J) \end{aligned} \tag{4.5}$$

where, LI_j is the load point importance value; f_j is the availability function for load point j; $f()$ is the availability function for the entire substation; n is the total number of equipment in substation; J is the total number of load points.

Therefore, the substation availability can be expressed as a function of many decision variables: maintenance rates $\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}$ and user input values EI_1, UI_1, EI_2, UI_2, …, EI_j, UI_j.

Figure 4.8 presents a flowchart that describes the procedure of calculating substation availability.

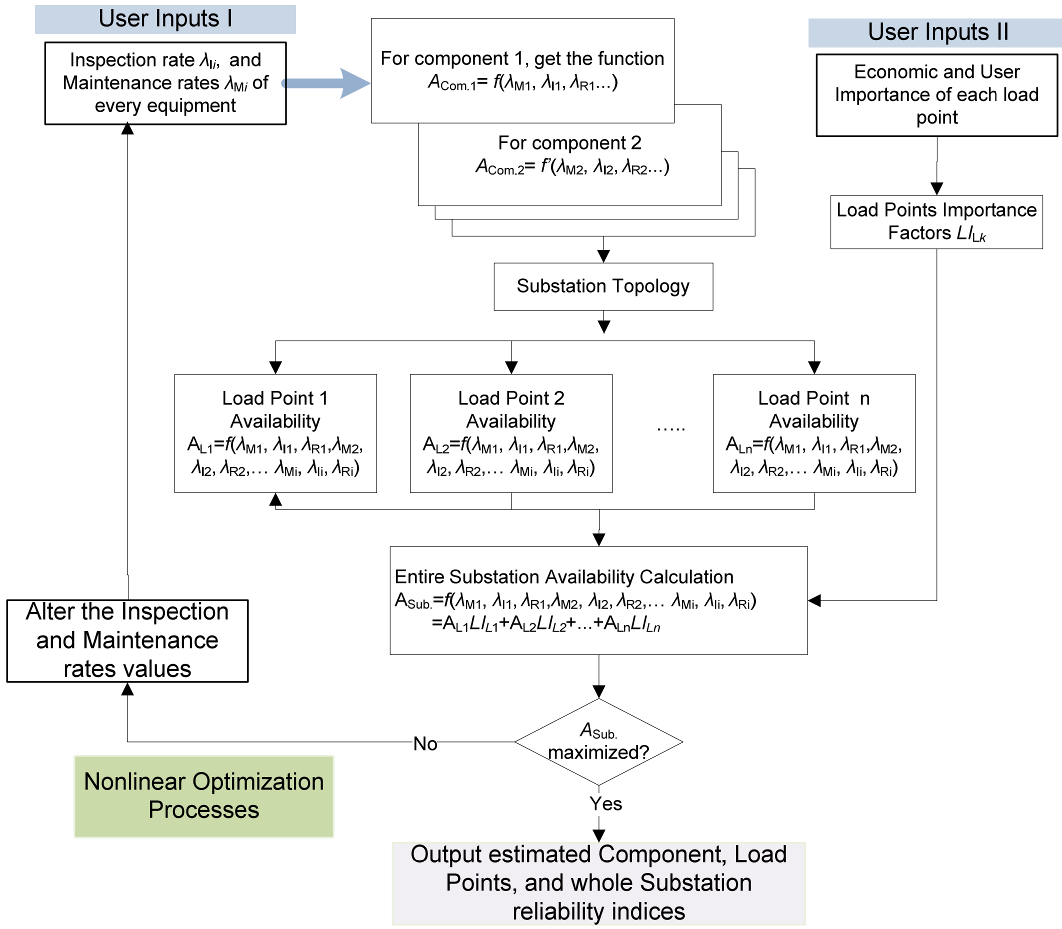


Figure 4.8 Flow Chart of Reliability Evaluation of Substations with Aging Equipment

In Figure 4.8, the user input includes the parameters for building equipment reliability Markov models, and *EI/UI* values for calculating load point importance factors. The accuracy of former input depends on whether historical reliability and maintenance data are available, and whether the method for data analysis is accurate; the accuracy of the latter depends on how well utility owners know their customers that are connected to the substation.

4.6 Modeling of Substation Economic Benefit

The economic modeling of substations is an indispensable part of asset management. The utility owner should be aware of the expected cost/benefit that will be achieved based on current maintenance decisions. Also, since the objectives of maximizing reliability and minimizing Operations & Maintenance cost are sometime on the opposite directions (generally higher reliability means higher maintenance cost, especially for substations with aging infrastructure), the utility owner needs to carefully balance the reliability improvement and the maintenance cost growth. Therefore, economic analysis plays an important role in substation maintenance optimization.

4.6.1 Equipment Economic Contribution Quantification

Usually, it is desired for utility owners to quantify the annual benefits of a load point or the entire substation, rather than individual equipment. However, since the substation economical analysis is based on the economical modeling of individual equipment (Chapter 3), it is necessary to dispense the entire substation benefits into individual equipment. Therefore, methods to quantify the economic contribution of individual equipment towards substation benefit needs be developed.

In this dissertation, the sensitivity values of equipment availability towards the load point or substation availability S_i (i is the number of equipment in a substation) are utilized to quantify equipment's contributions.

From the definition of sensitivity, S_i is defined as

$$S_i = \frac{\Delta A_{Sub.}}{\Delta A_i} \tag{4.6}$$

where, ΔA_i is the slight change in equipment availability of equipment i; ΔA_{Sub} is the corresponding substation availability changes.

S_i expresses the quantified impact of equipment availability changes, toward the substation availability variation. By comparing S_i values for all equipment within a substation, it is possible to determine which equipment is more important than others, with respect to their contribution on substation availability.

However, the sum of S_i may not be 1, therefore, S_i is normalized by (4.7)

$$S_{i\_normalized} = S_i / \sum S_i \tag{4.7}$$

The expected economic benefit of individual equipment B_i can be calculated by (4.8)

$$B_{Equ.\_i} = R_{\mathrm{Sub.}} S_{i\_normalized} \tag{4.8}$$

where $R_{\mathrm{Sub.}}$ is the annual *substation revenue*. The value of R_{Sub} can be determined, through estimating the contribution of this particular substation toward the annual utility revenue.

It should be noted that the meaning of $R_{\mathrm{Sub.}}$ is different than substation benefit $B_{\mathrm{Sub.}}$ (will be explained in Section 4.6.2). $B_{\mathrm{Sub.}}$ not only includes consideration of revenue $R_{\mathrm{Sub.}}$ that substation earns through successful serving of the load point, but also contains Operations & Maintenance and penalty costs that substation incurs when fail to serve load points. In contrast $R_{\mathrm{Sub.}}$ focuses on the rewards when substations can successfully serve the load.

4.6.2 Substation Economic Benefit Calculation

Given that the expected economic benefit $B_{\mathrm{Equ.}}$ of equipment is evaluated through equation (4.10) in Chapter 4, equipment annual benefit $B_{\mathrm{Equ.}}$ can be calculated based on the approach presented in Chapter 4, as a function of the maintenance rate λ_M and inspection rate λ_I . Besides, since *EI* and *UI* also participate in substation sensitivity values $S_{i\_normalized}$, the $B_{\mathrm{Equ.}}$ Value is also a function of *EI* and *UI*.

Therefore, similar to equation (4.5) for equipment availability, the expected equipment economic benefit can be expressed as

$$B_{\text{Equ.}} = f(\lambda_{Mi}, \lambda_{Ii}, UI_1, EI_1, UI_2, EI_2, ..., UI_m, EI_m) \tag{4.9}$$

and the substation economic benefit can be calculated by

$$B_{\text{Sub.}} = \sum B_{\text{Equ.}} = f^{'}(\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In}, UI_1, EI_1, UI_2, EI_2, ..., UI_m, EI_m) \tag{4.10}$$

Examples and cases studies of developing the reliability and economic models for substations based on above theories are presented in Chapter 6.

Figure 4.9 gives a flowchart illustrating the procedures of calculating economic benefits for substations.

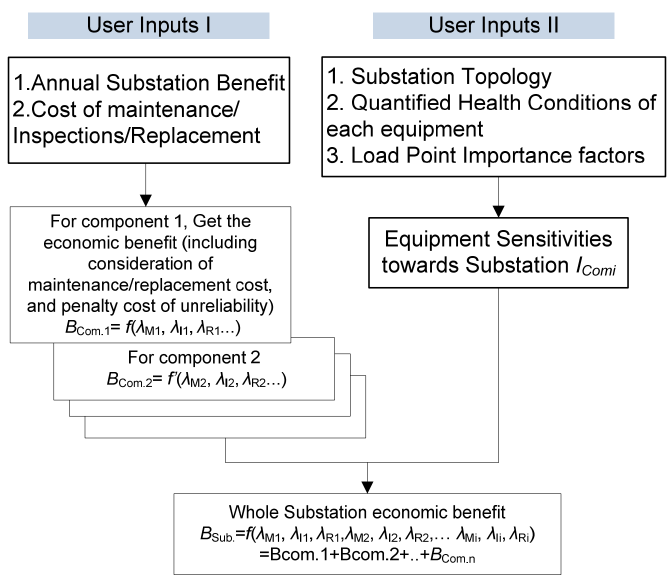


Figure 4.9 Flow Chart Diagram of Economic Benefit Modeling of Substations

Compared with previous reliability modeling for substations or systems, the approaches for substation reliability and economic modeling developed here have the following advantages:

- Provide a method to perform studies of determining the impact of maintenance schedules of aging equipment (inspections, minor & major maintenance), on the entire substation reliability.
- Incorporate detailed modeling of aging processes and maintenance on individual equipment, while still compatible with most existing reliability models. Therefore, it is flexible, and can be conveniently added to the existing system models.
- Identify critical equipment in a substation which contributes mainly to A_{Sub}, while studying the sensitivity of equipment toward $A_{\mathrm{Sub.}}$ This approach can assist asset managers identifying critical equipment, which will make the most contributions toward system availability.
- In the economic analysis of substations, the proposed method is based on the detailed economic modeling of individual equipment by SMDP, which contains cost of investment/replacement, maintenance, and outage penalty cost. Therefore the substation economic model developed in this paper is more accurate than other existing models.
- Since the method developed provides the relationships between substation reliability and economic cost while considering the maintenance of individual equipment, the models can be potentially utilized for maintenance optimization studies in substations.

4.7 Background of Maintenance Optimization

With the growing number of aging equipment in power systems and the increased loading conditions, grid owners are eager to find asset management programs in which it can effectively manage their assets and systems, while meeting the limited maintenance resources/budget constraints. Therefore, maintenance optimization has become a key aspect in asset management.

Through the analysis of power industry requirements and utility customers' surveys, following questions are of interest when maintenance related decisions are to be made [70]:

1) Which equipment should receive maintenance?
2) How much is the frequency of maintenance; what type of maintenance?
3) How to prioritize/rank the maintenance tasks for a substation?
4) For a given maintenance policy, what is the expected reliability improvement for a load point or the entire substation, and what is the corresponding maintenance cost?
5) How to dispense the limited maintenance budget to individual equipment, in order to maximize load point or entire substation reliability?
6) How to minimize the maintenance economic cost, or maximize the substation economic benefit while meeting target availability constraints?
7) From customer viewpoints, what is the expected reliability improvement? Are failure frequency / duration decreasing?

The purpose of this chapter is to classify various maintenance optimization scenarios and the corresponding solution techniques, to answer the above questions.

4.8 Optimization Scenarios

4.8.1 Scenario 1- Maximize Substation Availability with no Constraints

In this scenario, the objective of optimization is to maximize substation availability, regardless of maintenance cost.

This scenario has a potential application for critical substations maintenance decisions. Contingency analysis or Failure Mode, Effects, and Criticality Analysis (FMECA) can be utilized to identify the critical substations in which failures are extremely undesired.

Equations (4.11) and (4.12) describe this optimization scenario:

Objective:

$$\text{Maximize } A_{Sub.} = f(\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In}, EI_1, UI_1, EI_2, UI_2, ..., EI_j, UI_j ..., EI_J, UI_J) \quad (4.11)$$

Constraints:

$$\text{Lower Limits} < \lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In} < \text{Upper Limits} \quad (4.12)$$

where,

$A_{Sub.}$ is the substation availability specified as the objective function;

$\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In}$ are decision variables;

$EI_1, UI_1, EI_2, UI_2, ..., EI_m, UI_m$ are user input variables for determining the load point importance factors *LI*, as described in Chapter 4.

Here, for the purpose of generality, the maintenance rates for all equipment within a substation are listed as decision variables. In practice, however, some equipment may not need maintenance, or the maintenance schedules of some equipment maybe fixed, due to mandatory regulation requirements. In these cases, the mathematical equations given above can be modified accordingly.

The following examples are developed to represent the above situations.

1) Case I- Partial Maintenance

In this case, only a portion of substation equipment will receive maintenance, and the corresponding maintenance rates are decision variables that need to be optimized. Other equipment either have fixed maintenance rates, or receive no maintenance. For example, in a substation, the major maintenance rates for transformers should be optimized, since transformer maintenance is costly and should be avoided if unnecessary.

Meanwhile, when the number of decision variables are less than 2 or 3, the optimization process and the maximum availability point can be visualized, which is an advantage for methodology illustration.

2) Case II- Single Type Maintenance

In this case, all equipment will receive maintenance. However, only one type of maintenance needs to be determined (for example, only the major maintenance rates). Other maintenance related parameters, such as inspection rates or replacement rates, are pre-determined.

The purpose of this case is to provide a base line in order to compare it with the case of multi-type maintenance optimization.

3) Case III- Multi-type Maintenance (or Full Maintenance)

In this case, all maintenance related parameters for all equipment will be optimized. The purpose of this scenario is to examine the necessity of doing comprehensive maintenance optimizations among all equipment.

For example, both inspection rates and major maintenance rates for all equipment in the substation will be determined.

The studies to illustrate above three scenarios are presented in Chapter 6.

4.8.2 Scenario 2- Maximize Substation Benefit under Target Availability

The *target availability* is defined as the availability that the substation must maintain. Usually this value is determined by some mandatory organizations (such as NERC or local regulation organizations). Equations (4.13) and (4.14) describe this optimization scenario (maximizing the substation benefit as an example):

Objective:

$$\text{Maximize } B_{Sub.} = f^{'}(\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In}, EI_1, UI_1, EI_2, UI_2, ..., EI_j, UI_j ..., EI_J, UI_J) \quad (4.13)$$

Constraints:

$$\text{Lower Limits} < \lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In} < \text{Upper Limits} \quad (4.14)$$

$A_{Sub.}$ > target availability value

This scenario applies widely in the electric power industry. As from utilities' perspective, they would like to maximize benefits (or minimize operation and maintenance cost); but from society or customers' perspective, certain target availability constraints still need to be satisfied.

4.8.3 Scenario 3- Maximize Substation Availability under Limited Budget

Equations (4.15) and (4.16) describe this optimization scenario:

Objective:

$$\text{Maximize } A_{Sub.} = f(\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In}, EI_1, UI_1, EI_2, UI_2, ..., EI_j, UI_j ..., EI_J, UI_J) \quad (4.15)$$

Constraints:

$$\text{Lower Limits} < \lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In} < \text{Upper Limits} \quad (4.16)$$

$C_{\text{Sub.}}$ <Maximum Budget;

This scenario has applications in which the budget is limited. The optimization process for this scenario can determine how to allocate maintenance resources to all equipment (or a portion of equipment in a substation that will receive maintenance), in order to maximize the entire substation reliability.

In this scenario, the relationship between the maintenance cost and the corresponding equipment reliability improvement should be quantified. Explicit relationship between maintenance cost and the associate equipment reliability needs to be established, which is another challenge due to insufficient maintenance history records. The authors in [19] made the following assumption on this relationship, in Markov modeling of equipment reliability:

1) If maintenance cost increases/decreases, the probability of transition to a better condition state after maintenance (such as M_3 -> D_1 or D_2) increases/decreases, respectively.
2) If maintenance cost increases/decreases, the time spent in maintenance state decreases

However, since in this dissertation the equipment economic benefit is modeled (Chapter 3) instead of cost, the relationship between equipment economic benefit and maintenance rate, as well as substation benefit $B_{\text{Sub.}}$ is developed explicitly.

The following equations express Scenario 3.

Objective:

$$\text{Maximize } A_{Sub.} = f(\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In}, EI_1, UI_1, EI_2, UI_2, ..., EI_j, UI_j ..., EI_J, UI_J) \tag{4.17}$$

Constraints:

$$\text{Lower Limits} < \lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In} < \text{Upper Limits}$$

$B_{Sub.}$ <Budget limit value (4.18)

Comparison of equations (4.17) and (4.18) with equations (4.15) and (4.16) indicates that only $C_{\mathrm{Sub.}}$ in (4.16) is changed to $B_{\mathrm{Sub.}}$ However, this change will not jeopardize the applicability of the proposed method, since intuitively the method presented in Chapter 3 can be used to model either cost or benefit. The case study of this scenario in Chapter 6 will follow equations (4.17) and (4.18).

Beyond these three scenarios, there are other potential applications that can be developed when reliability and economic models of the substation are available. However, in the interest of time and space, they are not presented in this dissertation.

4.9 Optimization Methodologies

The above three optimization scenarios have some common characteristics:

1) Multi-decision Variables

   Considering the cases in Scenario 1, the number of decision variables is typically large. Generally if a substation has N equipment, and each equipment has M maintenance related decision variables, the number of total variables to be optimized in the above scenario is $N \times M$.

2) Unknown Characteristics

   Because of the complexity of the system, it is difficult to determine the characteristics of $A_{Sub.}$ and $B_{Sub.}$. For optimization purpose, the characteristic of objective function is desired in order to select appropriate optimization solution techniques; for example, whether $A_{\mathrm{Sub.}}$ is a linear function of maintenance rates, or whether local minimum/maximum maintenance rates exist. Also, it is difficult to visualize the problem, when the number of decision variables is large.

4.9.1 Overview of Global Optimization Techniques

To solve the above optimization problems, several techniques are available, such as Stochastic -based algorithms (i.e. Simulated Annealing), Evolutionary algorithms (e.g., Genetic Algorithm), Swarm-based optimization algorithms (e.g., Particle Swarm Optimization, and Ant Colony Optimization). Following is a brief description of each algorithm:

- *Simulated Annealing* (SA) was first applied by Kirkpatrick [86]. SA is often used in discrete search spaces. In some cases, SA is more effective than exhaustive enumeration method. However, SA is unsuitable for the optimization problem described in previous section, since our decision variables (inspection and maintenance rates) are continuous.
- *Genetic algorithm* (GA) is an example of evolutionary algorithms inspired by biology evolutionary, such as inheritance, mutation and crossover. It combines the function evaluation with the randomized and exchanged information among the solution, to arrive at a global optimal. Fraser developed a series of papers to artificially simulate nature selection, in which GA is inherited [87].
- *Ant colony optimization* (ACO) is a member of ant colony algorithms family, in swarm intelligence methods. It was initially developed by Marco Dorigo in 1992 [88]. In ACO, the simulation agents (Artificial ants) locate optimal solutions by moving through a searching space of all possible solutions. Each agent (ant) will record history position and solutions, for itself and other agents to locate better solutions. ACO is appropriate in problems to find optimal paths to goals, given the all paths exists (discrete number of search space). However, for the

optimization problems in this dissertation, only the search space is available, and decision variables are continuous not discrete. Therefore, it is not applied in this dissertation.

- *Particle swarm optimization* (PSO) is an algorithm inspired by social behavior of bird flocking or fish schooling, first developed by Eberhart and Kennedy in 1995 [89]. PSO is a global optimization algorithm for problems in which the best solution is represented by an n-dimensional space. Particles move among the search space with initially defined position and velocities; the position of the particle with best current fitness value is shared by other particles, based on which the velocities will be changed. PSO is suitable for continuous variables, and generally faster than other global optimization methods [90]. In this dissertation, PSO is applied to solve the optimization problems.

4.9.2 Particle Swarm Optimization (PSO)

In PSO, each particle represents a potential solution, and has a position in the problem space, represented by a position vector $\vec{x}_i$. Particles also have velocity vector $\vec{v}_i$ to represent the speed parameter of moves through the problem solving space. At each time step, there is a function f_i used to evaluate the fitness of $\vec{x}_i$. Each particle keeps track of its own best position $\vec{x}_{i,Sbest}$, and the best position found? so far $\vec{x}_{i,Gbest}$ is shared by all particles [91].

At each time step, a new velocity for particle is updated by (4.19)

$$\vec{v}_i(k+1) = w\vec{v}_i(k) + c_1\phi_1[\vec{x}_{i,Sbest}(k) - \vec{x}_i(k)] + c_2\phi_2[\vec{x}_{i,Gbest}(k) - \vec{x}_i(k)], i = 1,2,...,N \quad (4.19)$$

where c_1 and c_2 are positive constants representing the weight of the acceleration, that guide each particle toward the individual best $\vec{x}_{i,Sbest}$ and swarm best position $\vec{x}_{i,Gbest}$; ϕ_1

and ϕ_2 are uniformly distributed random numbers in [0,1]; w is a positive inertia weight to provide better control between exploration and exploitation; N is the number of particles in the swarm; $\vec{v}_i$ is limited to the range [$-\vec{v}_{\max}$, $\vec{v}_{\max}$] [91].

The first term in (4.19) performs a global search by exploring a new search space; the last two terms enable each particle to perform a local search around its individual best position $\vec{x}_{i,Sbest}$, and the swarm best position $\vec{x}_{i,Gbest}$. Based on the updated velocity, each particle changes its position according to (4.20) [91].

$$\vec{x}_i(k+1) = \vec{x}_i(k) + \vec{v}_i(k+1), i = 1,..., N \qquad (4.20)$$

Compared with other evolutionary computation algorithms such as GA algorithm, PSO enables a fast and efficient search for the optimal solution. In GA, chromosomes share information with each other, so the whole population moves like one group towards an optimal area. However, in PSO only $\vec{x}_{i,Sbest}$ gives out the information to others, and it is a one-way information sharing mechanism. Therefore, compared with GA, all particles tend to converge to the best solution quickly, even in the local version in most cases. Because in standard GA, the next generation is generated based on crossover and mutations, where the position of the individual who has highest fitness value are not shared and directly utilized.

4.9.3 Solution of Maintenance Optimization Problem by PSO

In this dissertation, depending on the scenarios, substation availability function A_{Sub} (in Scenarios 1 and 3) and benefit B_{Sub} (for Scenario 2) are selected as fitness function; maintenance/inspection rates $\lambda_{M1}, \lambda_{I1}, \lambda_{M2}, \lambda_{I2}, ..., \lambda_{Mn}, \lambda_{In}$ are decision variables.

The initial values is chosen to be the middle point of the searching space according to (4.21)

$$\vec{x}_0 = mean[\text{Lower Limits of } \vec{\lambda}_M \text{ and } \vec{\lambda}_I, \text{Upper Limits of } \vec{\lambda}_M \text{ and } \vec{\lambda}_I] \tag{4.21}$$

The objective of PSO is to search for the optimal estimates of maintenance/inspection rates.

Also, for Scenarios 2 and 3, the target availability and minimum economic benefit values are applied as inequality constraints in the PSO implementations.

In summary, Figure 4.10 is a flowchart illustrating the procedures described above for maintenance optimization for substations.

In Figure 4.10, the dashed rectangle includes the processes of optimizations, in which PSO is applied as solution techniques. Following the flowchart, users need to input optimization scenarios (i.e., objective functions, constraints, stop criteria, decision variables, and etc.); after the optimization process is completed, the optimal maintenance rates, as well as the corresponding $A_{Sub.}$ and $B_{Sub.}$ values are presented.

Figure 4.10 will assist asset managers make maintenance schedule decisions, while meeting reliability requirement or budget constraints.

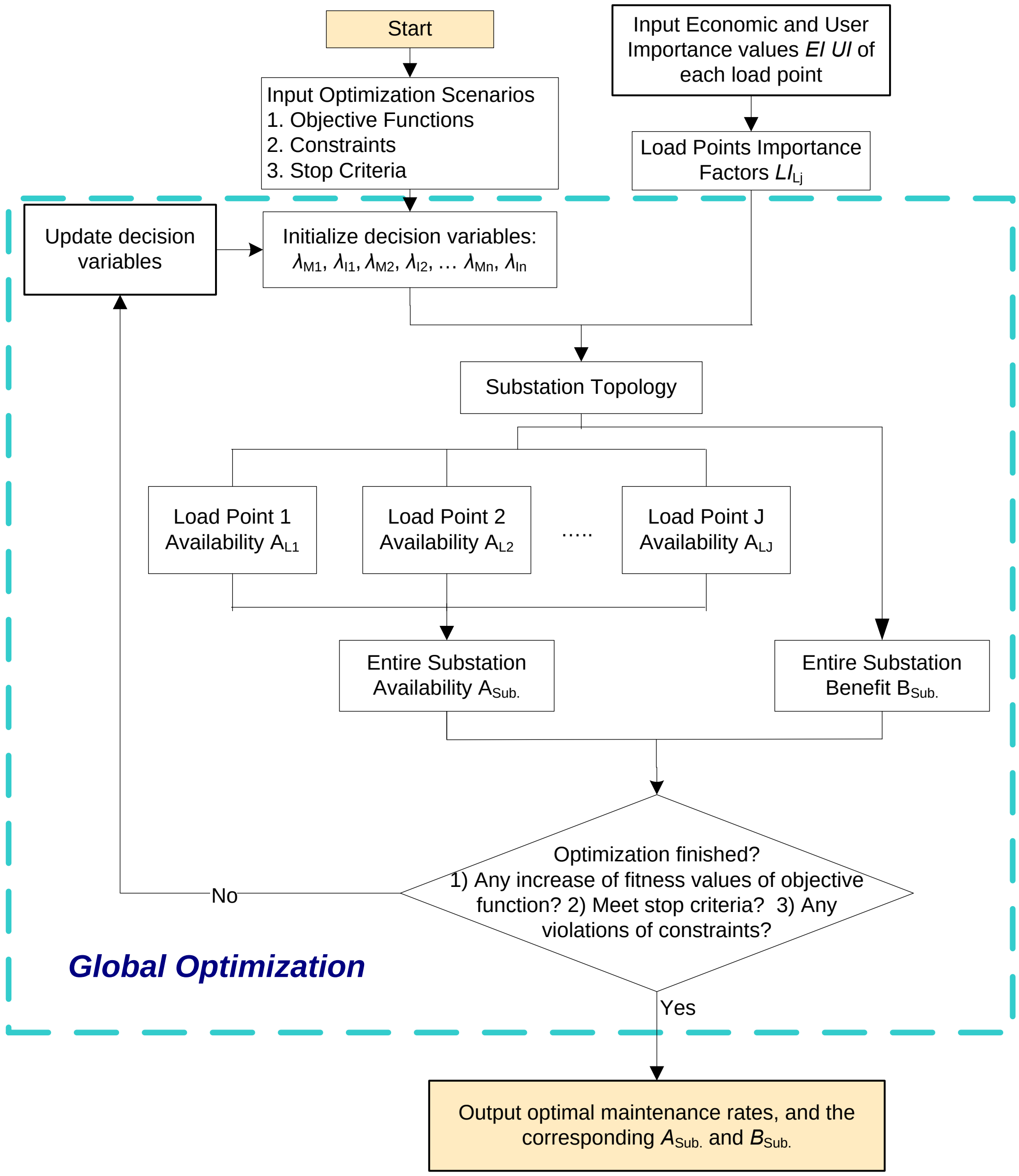


Figure 4.10 Flow Chart of Maintenance Optimization for Substation

Appendix: List of Assumptions– System Reliability Modeling

1. Equipment failures are statistically independent

2. Only first and second-order cut-set are considered

   It is assumed that the third and higher order cut-sets can be neglected. This is because the probability of having three or more equipment failure simultaneously is rare in substations, therefore it is reasonable to only consider first and second order cut-sets, as shown in Figure 4.7.

3. It is assumed that sub-transmission lines have no outages, or the availability values are 100%.
4. All switching devices operate successfully when required (availability is 100%) It is assumed that there is no switch delay in substations, for illustrating simplicity. Switching devices can be opened whenever possible to isolate a fault. Therefore, switch related states are not included in equipment modeling.
5. In Figure 4.6, it is assumed that all transformers and circuit breakers are the same types, follow the same operation condition, and utilize the same maintenance actions; future maintenance decisions for all transformers and circuit breakers are also the same.
6. In Figure 4.6, it is assumed that transition times among all states follow exponential distributions. Therefore, conventional Markov models for equipment reliability modeling are used (continuous-time Markov chains).

The models developed in this chapter are valuable to assist evaluation of the impact of equipment maintenance toward system reliability and cost. Detailed case studies will be presented in Chapter 6.

CHAPTER 5 UNCERTAINTY QUANTIFICATION AND PARALLEL SIMULATION

In this Chapter, a general approach for a fuzzy Markov model is proposed. This approach incorporates parameter uncertainties and probabilities in aging equipment models and existing reliability models for substations. The proposed method can also be used for determining the optimal maintenance rates that maximizes specific reliability indices.

Also, this chapter describes a new method for reliability evaluation using parallel Monte-Carlo Simulation (MCS) for both equipment and simple systems.

5.1 Fuzzy Set Theory

5.1.1 Fuzzy Set and Fuzzy Membership Function

A classical *set A* is a collection of distinct objects to separate the elements *x* of a given universe *U* into two groups: those belonging (members) and those not belonging (nonmembers) [32]. Zadeh introduced fuzzy sets as an extension and generalization of the basic concepts of crisp sets [31]. A *fuzzy set* ***A*** in the universe of discourse *U* is defined as a set of ordered pairs

$$A = \{(x, \mu(x)) \mid x \in U, \text{and } 0 \le \mu(x) \le 1\} \tag{5.1}$$

In equation (5.1), $\mu(x)$ is the *membership function* (abbreviated as MF hereafter) of fuzzy set ***A***, and the value of $\mu(x)$ is the *grade* (also called the *degree* or *confidence level*) of membership *x* in ***A***, which indicates the degree that *x* belongs to ***A***.

An *alpha-cut* (*α-cut*) of a fuzzy set ***A*** is a crisp set *A* that contains all the elements of the universe *U* that have an MF value in ***A*** that is greater than or equal to *α*, which is expressed in Equation (5.2),

$$A_\alpha = \{x \in U \mid \mu(x) \geq \alpha, \alpha \in (0,1]\} \tag{5.2}$$

When the confidence level equals zero, the interval of the MF is called the *support* of this MF.

5.1.2 Fuzzy extension principle

The fuzzy extension principle is a mathematical tool for generalizing the crisp mathematics concepts to the fuzzy set framework and extending the crisp, point-to-point mapping into mappings of fuzzy sets.

Consider an operation * which is valid with real numbers such that $c=a*b$; its extension to fuzzy numbers is achieved by [32],

$$\mu(c) = \min\{\mu(a), \mu(b)\}, c=a*b \tag{5.3}$$

This means if a pair (a, b) maps into a number c, c receives a degree equal to the minimum of a and b degrees; furthermore, if two pairs, (a_1, b_1) and (a_2, b_2), map into the same c, then the maximum of the possible membership grades that would be given to c is chosen as the grade of c.

The extension principle can be easily linked with *α*-cut concepts, to calculate the interval at a confidence level. For the interval at a confidence level *α*, there will only be elements c mapped from pairs (a, b), where a and b belong to that interval of confidence at level *α*. Therefore, the extremes of an interval of confidence at a certain level *α* must be searched among all possible combinations of values (a, b) which belong to intervals of the same degree [32].

5.2 Fuzzy Markov Processes (FMP)

5.2.1 Markov Processes for Aging Equipment

In most reliability studies, equipment is usually categorized using two-state models: fully success or fully failure [9]. Figure 5.1 gives a state-space diagram of a general Markov process for modeling of aging equipment [7], [59], [11].

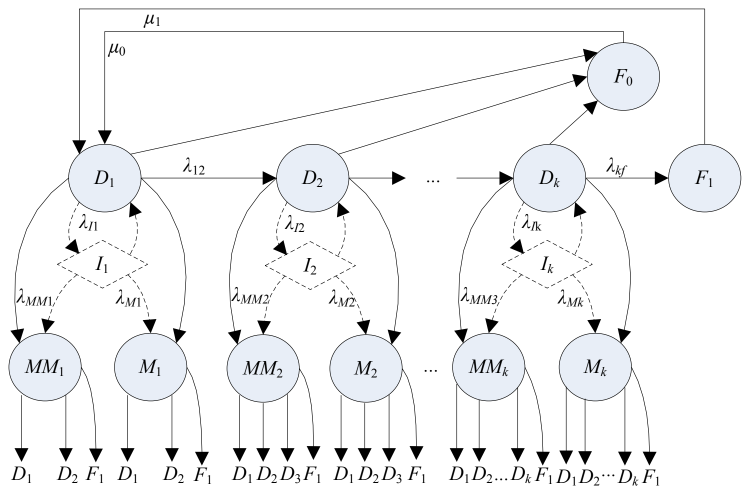


Figure 5.1 State-Space Diagram of Aging Equipment with Maintenance and Inspection

In Figure 5.1, the operable state is separated into k series deterioration stages, which is represented by D_1, D_2 to D_k. Inspection (I) was taken before making major (MM) or minor(M) maintenance. Detailed descriptions of each state are available in Section 3.4.2. The transition rate of going from one deterioration state to the next deterioration state is represented by $\lambda_{i,i+1}$ [7],[59],[11].

The deterioration rate from the last operable deteriorate state, D_k, to deterioration failure, F_1, is λ_{kf}. At each stage i, equipment can transit to maintenance state M_i with a particular maintenance rate for that stage denoted by λ_{Mi}. Another maintenance state can be added to represent another type of maintenance, for example, major maintenance in Figure 5.1 is labeled by MM_i with the rate of λ_{MMi}. From maintenance states, equipment returns to either better or worse operable states, or even transits into failure states, depending on the historical maintenance probabilities collected from data. Also, this Markov model can be easily extended to include inspection states, by adding I_1, I_2, to I_k states for each stage of deterioration. The inspection rate at each stage is denoted by λ_{Ii}. The states and the transitions with dashed lines in Figure 5.1 are used for representing the addition of inspections. The detailed modeling can be found in [95].

The commonly used reliability indices include availability, A, frequency of failure, f, and expected duration between failures, r .The definitions are available in Section 3.1.

However, in the fuzzy Markov model presented in Figure 5.1, it is not easy to derive explicit reliability indices equations as a function of maintenance, when the number of states increases. Therefore, during the calculation of reliability indices, state reduction was conducted to transform the multi-state Markov model into an equivalent binary-state model.

Following is a brief procedure for calculating the reliability indices. The detailed procedure as well as examples can be found in [95].

Step 1: Develop a semi-Markov model for equipment, and determine the corresponding transition rates and probability matrices;

Step 2: Compute the steady-state probabilities using the transition rates and probability matrices;

Step 3: Calculate the reliability indices (A, f, and r) for the equivalent binary-state Markov model, which is obtained from the original multi-state semi-Markov model.

Fuzzy Markov processes (FMP) are proposed to incorporate the uncertainties associated with transition rates or probabilities. The uncertainty levels are represented by the confidence level value of fuzzy MFs. After the calculation, reliability indices and their possibility distributions can be obtained.

Figure 5.2 illustrates the relationship between inputs and outputs of FMP for equipment.

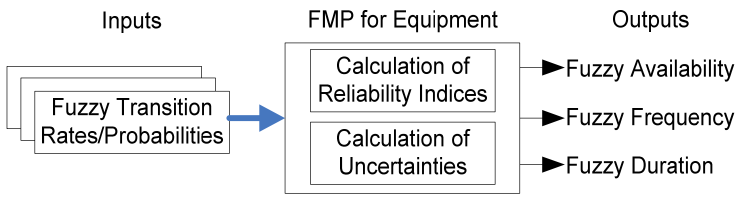


Figure 5.2 The Diagram of Fuzzy Markov Processes

5.2.2 Membership Functions Generation

One of the primary difficulties faced in applying fuzzy sets theory is the rational assignment of membership values.

One approach to determine fuzzy MFs is by a survey of experienced engineers. For example, the intervals corresponding to α-cut values of 0 and 1 for trapezoid MF are the intervals under worst conditions (support) and perfect conditions for given equipment, respectively.

MFs can also integrate condition monitoring data. In practice, there are instruments or equipment available for monitoring equipment operation or deterioration conditions. The output from these instruments represents the degree of system failure rates or deterioration rates. There are also experienced maintenance engineers or experts who can provide subjective information on the degree of confidence for deterioration rates or ranges. The most widely used fuzzy MFs are triangular, trapezoid, and symmetrical Gaussian MFs.

5.2.3 Calculation of Fuzzy Indices by Fuzzy Extension Principles

Previous researches suggested several methods of including uncertainties in Markov models where fuzzy arithmetic is applied for calculations [43]-[45]. However, the methods proposed in these papers are only applicable to small systems with a limited number of states in Markov models. This is due to the intensive calculation of fuzzy MFs for every element in the transition rates/probabilities matrix.

Theoretically, any Markov model can be solved analytically; and the reliability indices can be expressed as a function of several parameters which can be represented by fuzzy MFs while including uncertainties, such as $A= f(\lambda_{l1},\lambda_{l2},\ldots)$. Then, through this relationship, the output fuzzy reliability indices can be derived by fuzzy arithmetic.

However, this method is not applicable in practice since: 1) it is hard to solve the stochastic transition equations analytically and 2) even if it is possible to obtain the equations, it is not easy to extend the equations initially developed for crisp calculation into fuzzy calculations, as one needs to rearrange the variables to ensure that each variable will not be directly or indirectly subtracted or divided by itself [32].

In this dissertation, two fuzzy extension principle-based algorithms are proposed to extend the crisp calculation of Markov processes into fuzzy Markov processes.

Approach 1): Extension principle of nonlinear optimization

Given a Markov model with a fuzzy transition rate of A_λ, at a confidence level of α, and the extremes of the transition rates as $[\lambda_\alpha^-, \lambda_\alpha^+]$, the extremes of the steady-state probabilities at state k, $[P_{k,\alpha}^-, P_{k,\alpha}^+]$ can be calculated by [32]:

$$P_{k,\alpha}^- = \min\{P_k(\lambda) \mid \forall \lambda : \lambda_\alpha^- \le \lambda \le \lambda_\alpha^+\} \tag{5.4}$$

$$P_{k,\alpha}^+ = \max\{P_k(\lambda) \mid \forall \lambda : \lambda_\alpha^- \le \lambda \le \lambda_\alpha^+\} \tag{5.5}$$

Equations (5.4) and (5.5) imply that the left (or right) bound of the steady-state probability of state k should be found from the minimum (or maximum) $P_k(\lambda)$ of all possible λ values in the interval of [$\lambda_\alpha^-, \lambda_\alpha^+$] at the confidence level of α.

In addition to the steady-state probabilities, other reliability indices can be calculated from P_k, and the extremes of these indices are obtained from the lower and upper bound indices where λ is in interval [$\lambda_\alpha^-, \lambda_\alpha^+$].

Similarly, for two transition rates with fuzzy inputs, such as $A_{\lambda 1}$ and $A_{\lambda 2}$, the steady-state probability of state k should be searched from all combinations of λ_1 and λ_2 in the extremes corresponding to confidence level α. Equations (5.6) and (5.7) calculate the extremes with two fuzzy inputs,

$$P_{k,\alpha}^- = \min\{P_k(\lambda) \mid \forall\lambda : \lambda_{1,\alpha}^- \le \lambda_1 \le \lambda_{1,\alpha}^+, \lambda_{2,\alpha}^- \le \lambda_2 \le \lambda_{2,\alpha}^+\} \tag{5.6}$$

$$P_{k,\alpha}^+ = \max\{P_k(\lambda) \mid \forall\lambda : \lambda_{1,\alpha}^- \le \lambda_1 \le \lambda_{1,\alpha}^+, \lambda_{2,\alpha}^- \le \lambda_2 \le \lambda_{2,\alpha}^+\} \tag{5.7}$$

where [$\lambda_{1,\alpha}^-, \lambda_{1,\alpha}^+$] and [$\lambda_{2,\alpha}^-, \lambda_{2,\alpha}^+$] are the extremes of λ_1 and λ_2, at a confidence level of α.

In summary, in a fuzzy Markov process at a confidence-level of α, the extremes of the reliability indices are computed by the following optimization:

Objective functions:

For the left extreme, minimize the reliability index to be calculated, which is a function of steady-state probabilities $P_1, P_2, \ldots, P_n$. Take the availability A for instance, the objective function for the left extreme is

$$A^- = \min\{f(P_1, P_2, \ldots, P_n, \boldsymbol{\lambda})\} \tag{5.8}$$

Similarly, maximize the reliability indices for the right extreme. For example, the right extreme for availability A is

$$A^{+} = \max\{f(P_1, P_2, ..., P_n, \boldsymbol{\lambda})\} \tag{5.9}$$

Constraints:

$$(\mathbf{M} - \mathbf{I})\mathbf{P} = 0; \sum \mathbf{P} = 1 \tag{5.10}$$

$$\boldsymbol{\lambda}_{\alpha}^{-} \leq \boldsymbol{\lambda} \leq \boldsymbol{\lambda}_{\alpha}^{+} \tag{5.11}$$

Where **P** is the vector of steady-state probabilities; **M** is the transpose of the transition matrix, and [$\lambda_{\alpha}^{-}, \lambda_{\alpha}^{+}$] are the vectors of extremes of the intervals of transition rates with confidence level α; ***I*** is the identity matrix.

Random variables:

Steady-state probabilities vector **P**; Transition-rates vector **λ**.

Approach 1 eliminates the matrix inversion step during calculation of the steady-state probabilities, by adding the Markov equation as a constraint in the optimization, as indicated in Equation (5.10). Therefore, this approach has a merit of solving large scale Markov model for equipment as it avoids matrix inversion process which decreases the complexity.

However, approach 1 increases the computation burden and complexity because of the increased number of random variables during the optimization. Moreover, the extension of this approach to system level calculation of reliability indices is not an easy task; since the number of random variables is significantly increased (each equipment will have its own steady state probabilities). Therefore, approach 1 was modified, in order to come up with a more practical solution.

Approach 2): A modified optimization method

For many cases where Markov model for equipment is not very large, current computers can efficiently perform the matrix inversion task, since it takes less computational time compared with non-linear optimization approach. Therefore approach 1 can be modified, by including the equality constraints of Markov equations into the objective functions, in order to improve the computational efficiency.

The modified approach is formulated as follows:

Objective function:

Minimize the reliability index (e.g., availability) as a function of transition rates vector $\boldsymbol{\lambda}$, minimizing $A(\boldsymbol{\lambda})$. The left and right extremes for the availability index A are

$$A^{-} = \min\{f^{'}(\boldsymbol{\lambda})\} \tag{5.12}$$

$$A^{+} = \max\{f^{'}(\boldsymbol{\lambda})\} \tag{5.13}$$

Constraints:

$$\boldsymbol{\lambda}_{\alpha}^{-} \leq \boldsymbol{\lambda} \leq \boldsymbol{\lambda}_{\alpha}^{+} \tag{5.14}$$

Random Variables:

Transition rates vector $\boldsymbol{\lambda}$.

In this approach, Markov equations are integrated into the objective functions, and the number of random variables is reduced.

Compared to approach 1, approach 2 has the same accuracy but requires less computation time. The major difference between the two approaches is the inclusion of random variables. In approach 1, random variables are steady state probabilities $P_1, P_2, \ldots, P_n$ of the equipment model, and the transition rates $\boldsymbol{\lambda}$. On the other hand, in approach 2 the random variables are just the transition rates $\boldsymbol{\lambda}$. Because of the decreased number of random variables, approach 2 has less execution time. Moreover, it can be easily integrated into system level calculation of fuzzy reliability indices.

Figure 5.3 is a flowchart of the fuzzy Markov processes, and the steps required to calculate fuzzy reliability indices by the extension principle.

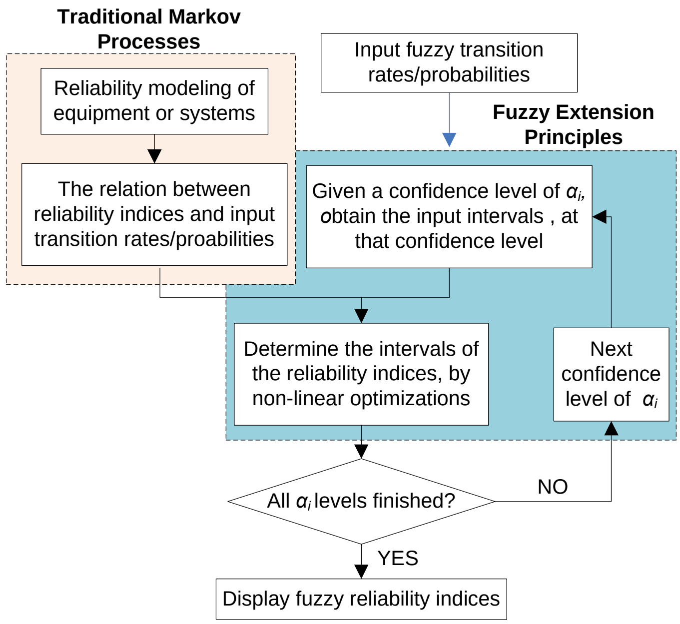


Figure 5.3 Flowchart of the Calculation Procedure of Fuzzy Markov Processes

In Figure 5.3, an optimization technique is required for determining the minimum and maximum values of objective functions. The nonlinear constraints optimization function from MATLAB Optimization Toolbox is used in this dissertation to solve optimization problems.

5.3 Fuzzy Markov Decision Processes (FMDP)

Similar to using fuzzy Markov processes to calculate fuzzy availability values for equipment, the fuzzy extension principle can be applied in calculating fuzzy economic benefit for equipment, by fuzzy Markov decision processes (FMDP).

Figure 5.4 gives the flowchart for calculating fuzzy economic benefit of equipment by fuzzy Markov decision processes, based on the existing equipment economic cost model developed in Chapter 4.

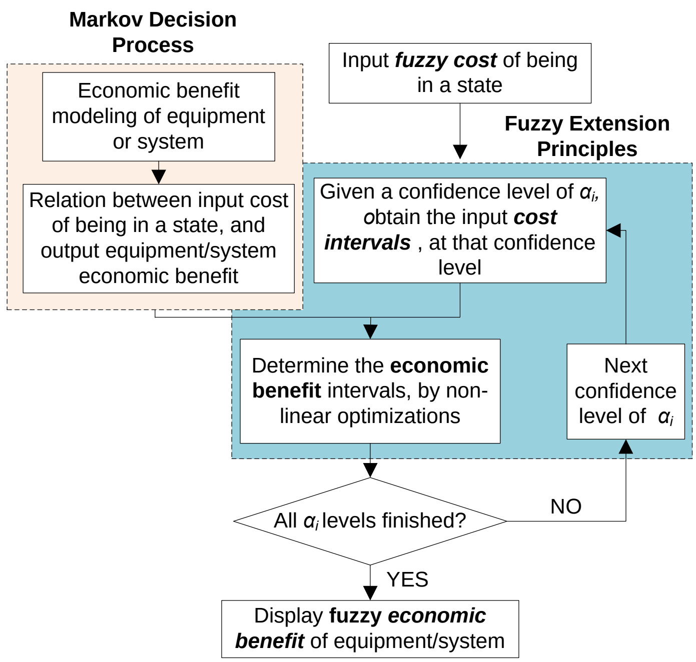


Figure 5.4 Flowchart of Fuzzy Markov Decision Process

5.4 Reliability Evaluation through Simulation

In station reliability evaluation studies, there are mainly two methods applied: Analytical methods and MCS methods.

Analytical methods, such as Markov Processes are frequently utilized for reliability modeling of aging equipment and small substations, in which operations, maintenances, and failures can be incorporated[7][59][9][95]. The advantages of analytical method include high accuracy and fast computation time; the disadvantage is limitation of number of states to be considered, and the lack of providing more reliability information. Moreover, in some situations, transitions between some states do not have Markovian characteristics (the transition to the next state only depend on current state), therefore cannot be modeled by regular Markov Processes [68].

Compared with analytical methods, MCS methods are powerful tools to handle more conditions related to reliability evaluation (such as impacting of severe weather) of a system, and are capable of providing more comprehensive results than analytical methods (such as the probability distribution of the reliability indices). Consequently, MCS are broadly applied for reliability evaluations in transmission [98], distribution [70], substations [20] and renewable energy systems [99].

In addition to the high computation burden, several other limitations also exist when applying MCS in reliability evaluation of aging equipment or substations:

1) Most studies use a binary-state model to represent the component in a system, in order to simplify the model and increase the convergence speed. Because of lack of modeling states other than operations and failures, those models mask the impact of deterioration of equipment, maintenances or other conditions which are common in operation of aging equipment or substations.

2) Algorithms are designed to be executed on a single processor, where the computation capacity and memory is limited. Consequently, the size or scale of studies using MCS for reliability evaluation is limited, and the speed of execution is relatively slow.

3) Few simulation approaches incorporate cost into consideration, which on the other hand is critical and desired by asset managers to compare different strategies and make decisions.

Also, with the fast development of computer technologies, parallel computers and supercomputers are available which provide an environment of fast computing with large memory. It enables the possibility to utilize the large memories and fast computing facilities of parallel computers to perform reliability evaluation by simulation. Several pioneer studies have been taken to use parallel computers in reliability studies [100] and evaluating the "Reliability Test System" by distributed computers [101]. In these applications, traditional MCS algorithms with binary-state component models were parallelized; the scale down strategies and their efficiencies were examined. However, simulating multi-state Markov process was not studied, and the application for system reliability evaluation with detailed equipment modeling was not included.

This chapter will focus on MCS, and how to apply parallel computing techniques for fast and efficient simulation.

5.5 Parallel Monte-Carlo Simulation

5.5.1 Sequential Multi-State Monte-Carlo Simulation

There are two approaches for MCS: state sampling and sequential sampling [21] [98]. In state sampling, the system states are randomly sampled based on the probability distributions of the component states. In sequential sampling, the chronological behavior of the system is simulated by sampling sequences of system operating states.

In reliability evaluations of substations where faults of aging equipment account for a large portion of outages, sequential sampling outperforms state sampling, because equipment are frequently modeled with multi-states, and the time-to transitions among states may belong to different distributions [21].

For example, given a machine that are modeled by three states: operations (abbreviated by UP), failures (DN) and maintenance (M), the randomly transitions among those states can be modeled by a Markov Process, assuming it meets the Markovian characteristics [14]. The stochastic process of this model can be visualized by a set of continuously connected rectangles, where the color of the blocks represents the states, and the length of the rectangles stands for the duration of time being in this state, where it is named as *reliability history chart* for this machine. The reliability history chart visualizes the stochastic transitions among the state with different hold times, and can be adopted for reliability evaluation. Figure 5.5 gives a reliability history chart of a three-state machine.

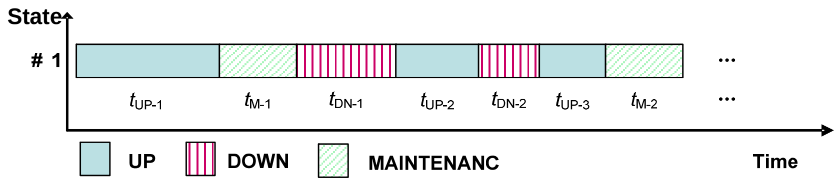


Figure 5.5 Equipment Reliability History Chart through Simulation

In Figure 5.5, the blue rectangle means currently the state resides in operation state, and the lengths of the rectangle $t_{UP\text{-}i}$ (i=1,2,…) are the holding times of being in this operation states, before it makes a transition to another state. The destination of the transitions and the holding time is random and determined by the probabilistic characteristics among those states; the hold time sets ($\{t_{UP\text{-}i}\}$, $\{t_{DOWN\text{-}j}\}$, and $\{t_{M\text{-}k}\}$) have specific probability distribution that can be determined by analysis of historical reliability data.

Given a reliability history chart, the reliability indices, such as availability A(percentage of time staying in operation state), frequency of failure f (average number of arriving the failure state in per unit time) and expected duration between failures r can be calculated from above reliability history chart, by following equations.

$$A = \frac{\sum t_{UP-i}}{\sum t_{UP-i} + \sum t_{DOWN-j} + \sum t_{M-k}} \tag{5.15}$$

$$f = \frac{N_{UP-DN}}{\sum t_{UP-i} + \sum t_{DN-j} + \sum t_{M-k}} \tag{5.16}$$

$$r = \frac{\sum t_{DN-j}}{N_{UP-DN}} \tag{5.17}$$

In above equations, $N_{UP\text{-}DN}$ is the total number of transitions to failure state.

Clearly, the reliability history chart shown in Figure 5.5 can be generated by sequential MCS [21]. Any update of this history chart (such as addition of a new state) will result in a new set of reliability indices. The final reliability indices are the mean values of all the sets. For example, if the total availability values calculated during the simulation is $\{A_i\}$, where A_i is the availability value computed after the ith iteration, the estimated availability from the simulation is

$$A = E[A_i] = \frac{1}{N}\sum A_i \tag{5.18}$$

where N is the total number of iterations.

For the purpose of checking the convergence and terminating the iteration process, there are several different types of stop criteria, such as maximum number of iteration, maximum execution time, or coefficient of variance. Among these criteria, coefficient of variance is widely utilized in MCS for reliability evaluation [21].

The coefficient of variation (CV) is a normalized measure of dispersion of a probability distribution. It is defined as the ratio of the standard deviation σ to the mean μ. The CV values of the availability sets during simulation is

$$CV = \frac{\sqrt{\sum (A_i - E[A_i])^2 / N}}{E[A_i]} \tag{5.19}$$

The above simulation process and stop criteria enable generation of reliability history chart and calculation of reliability indices for equipment. However, in practice, recording reliability history chart and the calculating of reliability indices and stop criteria after addition of new state to the history chart is both time and memory consuming. Thus, the simulation process is modified, to separate the reliability history chart into different periods, where calculation of reliability indices and checking for stop criteria are only activated at the end of each period. Then the original reliability history chart is discarded, and only reliability related data (such as total simulation time in this period, total transition to failure states, and total duration of being in failure state) is recorded. This modification reduces computation of stop criteria and the requirement of memory, therefore improves the computation efficiency.

Figure 5.6 gives a modified reliability history chart generated by this modified sequential MCS.

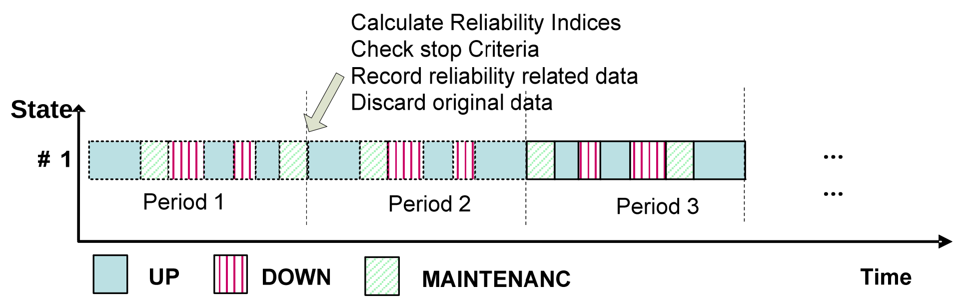


Figure 5.6 Modified Reliability History Chart of Equipment

5.5.2 Parallel Computing

Parallel computers and supercomputers are developed as a technique to solve the limitation of memory latency in computation capacity. Currently there are several different types of parallel computers available. Based on the configurations of memory, the architecture of parallel computers can be separated to share memory, distributed memory and hybrid architecture. Distribution memory architecture is frequently utilized for parallel computers and supercomputers.

The programming model adopted in the applications is master-slave model with communications among different processors. For the communications, several message passing techniques are available, where Message Passing Interface (MPI) is widely utilized, as it supports both shared memory architecture and distributed memory architecture.

The program in parallel programming is to maximize the utilization of processors and minimize the communications among different processors, in which the tasks of scaling down a sequential code to parallel code is the primary work. In the programming, the dispatching of jobs for each processor and communications among those processors are the key factors to achieve high performance in parallel computing.

In this dissertation, the OnDemand (Rocks-131) Cluster in San Diego Supercomputer Center (SDSC) is utilized [102]. The cluster has 32 nodes with each node of two processors. Each node has 8G memory. The Star-P is utilized [103] during programming because it enables reusing existing MATLAB models and codes, and the jobs of task dispatching and communications is coordinated by the Star-P server environment running on supercomputers.

5.5.3 Parallel Sequential Monte-Carlo Simulation for Equipment

Theoretically, the sequential MCS discussed in Section 5.5.1 is capable of modeling equipment with any number of state. In practice, the requirement of memory to record reliability related data and the computation and dependency on computation to check the stop criteria cannot always be met when running on single processor environment.

But the generation of reliability history chart in Figure 5.5 is not possible to be directly scaled for parallel computing, because of the nature that in sequential simulation the determination of every state depends on its previous state.

However, since reliability indices are calculated as the mean value of the total indices in the simulation, and they are steady-state measures, the selection of initial state at every period in Figure 5.6 will not have explicit influence on the results, as long as the number of state in a period are not too short. This hypothesis will be verified during case studies.

With this hypothesis, the generation of reliability history chart for each period is independent of other periods. The character of independency indicates that the generation process can be separated into different periods and simulated independently, which is a typical example of task parallel application. For this task parallel application, the task (reliability history generation in each period) can be dispatched to a worker processor, and overall tasks coordination can be assigned to a master processor.

Based on the above description, Figure 5.7 shows the reliability history chart generation by parallel computers, with CPU 1,2,3 as workers, and CPU 0 as master.

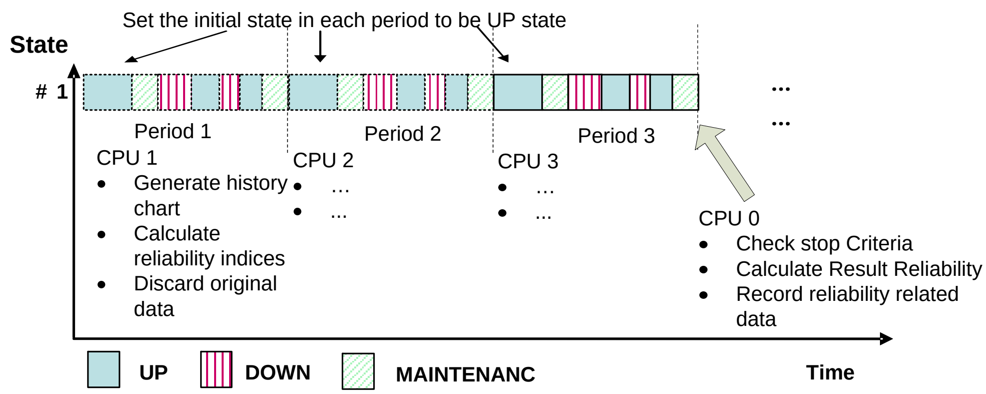


Figure 5.7 Generating Reliability History Chart through Parallel Computing

Figure 5.8 is the flowchart of using parallel sequential MCS for reliability evaluation of equipment.

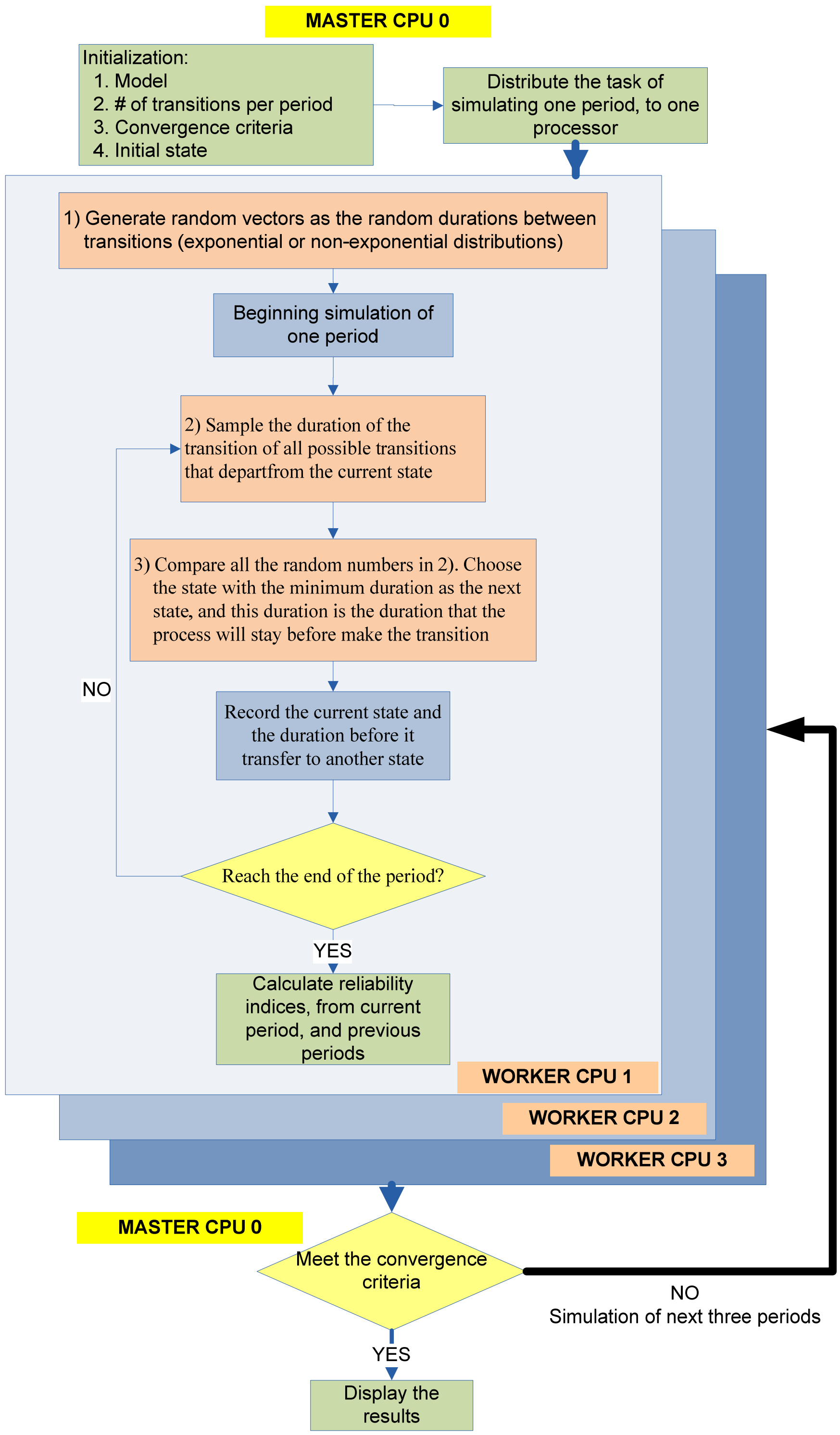


Figure 5.8 Flow Chart of Parallel Sequential MCS for Reliability Evaluation

5.5.4 Parallel Monte-Carlo Simulation for System

In a system where different components are interconnected, the components are operated either independently or dependently (for example, protection control).

In this dissertation, it is assumed that the components are operated independently, for the purpose of simplicity. Also, the impact of power flow is neglected, and it is assumed that every component operates under or equal to the rated power.

Because of this independency assumption, there are two strategies available for parallel simulation. First, the simulation of reliability history diagram of each component in the system can be dispatched to different processors and simulated simultaneously; or, similar to the parallel simulation of equipment, the simulation can be separated into different periods, and the generation of reliability history of each period is executed on a processor.

Comparing these two strategies, the latter strategy can also simulate the interdependent operation among components, because even in a period, the condition of a component will have impact on the transition of another component, the communication during the simulation in this period is within the same processor.

Here, the latter strategy is used in this dissertation. Figure 5.9 shows the parallel simulation of system with independent operation components.

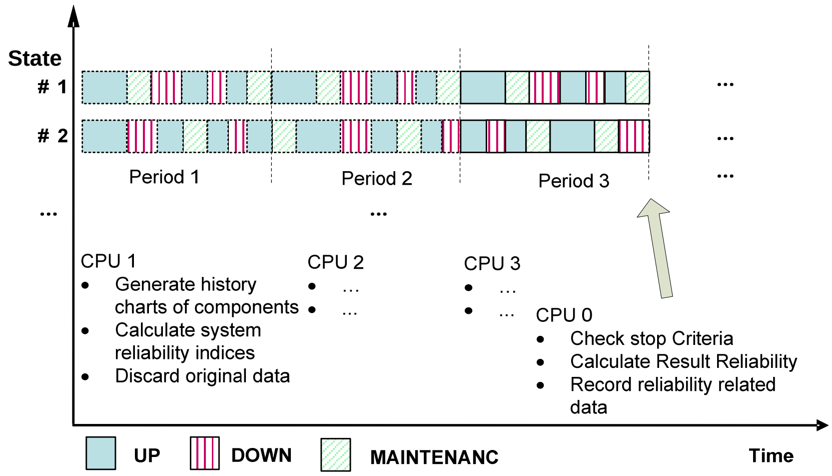


Figure 5.9 Parallel Sequential MCS for System Reliability Evaluation

This chapter describes a fuzzy Markov process and fuzzy Markov decision process based approaches, to facilitate calculating fuzzy reliability indices and costs. The approaches developed here mitigate the limitation of having uncertain parameter, which are common in reliability engineering.

Also, the parallel MCS algorithms developed in this chapter effectively apply the parallel computing resource to reduce the execution time, which are valuable to be extended to system level reliability evaluations.

CHAPTER 6
CASE STUDIES

Previous chapters have presented the algorithms developed for reliability / economic modeling, as well as the maintenance optimization for equipment / substation.

In this chapter, case studies of applying above theories are presented for illustration purposes. Sensitivities studies are also performed to study the impact of varying input variables toward equipment or substation reliability / economic assessment, and the optimal maintenance rates for equipment or substation.

6.1 Reliability Modeling with Maintenance for Aging Equipment

The purpose of studies in this section is to demonstrate how semi-Markov processes (SMP) are utilized for equipment reliability modeling with aging processes and maintenance.

6.1.1 Semi-Markov Processes

In previous work [58] [92], optimal maintenance policy evaluation techniques for power equipment have been studied using minor or major maintenance [15-17].

However, these works ignored the existence that utility usually performed inspection before make maintenance related decision. Natti analyzed inspection's impact on circuit breaker failure probability, failure cost, maintenance cost; a method to determine the optimal inspection rate for lowest cost at various stages was developed [93]. In that method, continuous-time Markov model is used for representing aging and maintenance and the transition time among all states are assumed to follow exponential distributions, which might not be true in practice.

This paper includes inspection into equipment modeling by using SMP on reliability modeling of circuit breaker.

Anders's research on air blast breakers [94] indicates that the time to failure rate of power breakers varies according to different distributions. At "infant mortality" period, time to failure follows Weibull distributions, and the failure rate decreases when the time increases. Then the equipment enters normal life period, in which the time to failure follows exponential distribution. In "wear out" period, the failure rate increases, because the equipment goes into irreversible deterioration.

In the model developed in this case, equipment is represented by a series of deteriorating, maintenance, and failed states. It is assumed that equipment can fail due to either deterioration (F_1) or random failure (F_0). According to the degree of deterioration, the workable states could be categorized into k discrete deterioration states: D_1, D_2 to D_k. After k deterioration states, if there is no preventive maintenance, equipment reaches deterioration failure F_1. Before preventive maintenance, inspections will be performed, in order to determine whether maintenance is not necessary (action **I**), or performing minor maintenance (action **II**), or carrying out major maintenance (action **III**). The inspection state is labeled as I_1 to I_k accordingly. The maintenance states are labeled as M_1 to M_k, for minor maintenance, and MM_1 to MM_k for major maintenance. After maintenances, equipment returns either to the current state or to better or worse D-state, depending on probabilities.

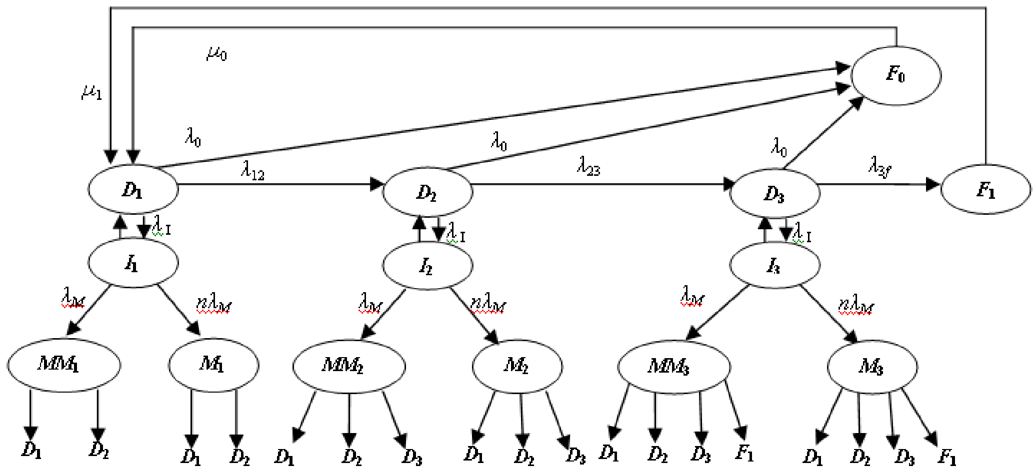


Figure 6.1 gives the state-space diagram of this model when k=3.

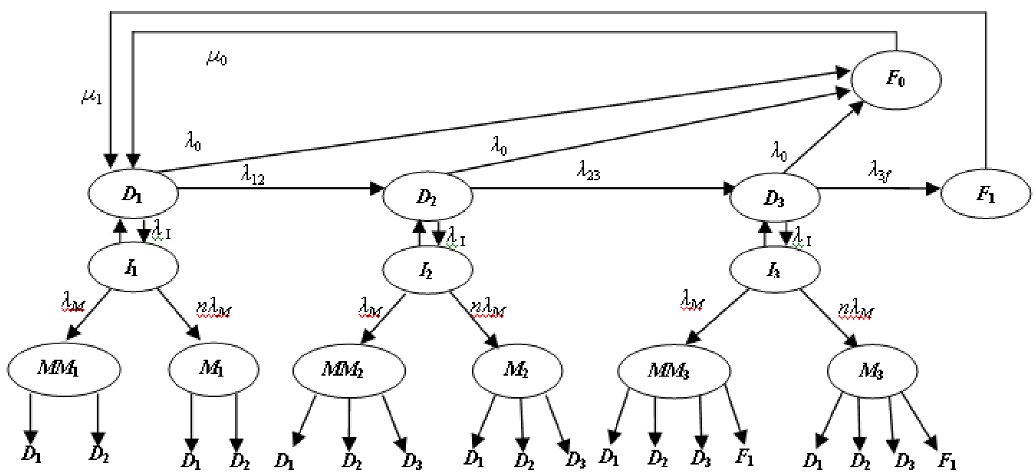


Figure 6.1 State-Space Diagram with Three Successful States

The following estimations on the transition probabilities associated with maintenance were made, based on historical data and relevant experience [7].

$P_{I\text{-}MM1} = 0$; $P_{I\text{-}M1} = 0$;
$P_{I\text{-}MM2} = 0$; $P_{I\text{-}M} = 1$;
$P_{I\text{-}MM3} = .9$; $P_{I\text{-}M3} = .1$;

Probabilities of going to D states after maintenance:

$P_{MM1\text{-}D1} = 1$; $P_{MM1\text{-}D2} = 0$; $P_{MM1\text{-}D3} = 0$;
$P_{MM2\text{-}D1} = .9$; $P_{MM2\text{-}D2} = .09$; $P_{MM2\text{-}D3} = .01$;
$P_{MM3\text{-}D1} = .9$; $P_{MM3\text{-}D2} = .09$; $P_{MM3\text{-}D3} = .01$; $P_{MM3\text{-}F1} = 0$;
$P_{M1\text{-}D1} = .99$; $P_{M1\text{-}D2} = .01$; $P_{M1\text{-}D3} = 0$;
$P_{M2\text{-}D1} = .3$; $P_{M2\text{-}D2} = .6$; $P_{M2\text{-}D3} = .1$;

$P_{M3\text{-}D1} = 0$; $P_{M3\text{-}D2} = .3$; $P_{M3\text{-}D3} = .6$; $P_{M3\text{-}F1} = .1$

In this case, the probability of transition from one state to itself is zero. Therefore it is an irreversible Semi-Markov Chain, and the steady-state probability π_i^e exists, which can be found through (6.1) and (6.2).

$$\sum_{i \in S} \pi_i^e = 1 \tag{6.1}$$

$$\Pi^e P = \Pi^e \tag{6.2}$$

where Π^e is the vector of steady state probabilities of the transition probability matrix P.

The final steady state probability should take into account of sojourn time, which is calculated by (6.3).

$$A_{Equ.} = \sum_{i=1,2,3} \pi_{D_i} \qquad \pi_i = \frac{\pi_i^e t_i}{\sum_{i \in S} \pi_i^e t_i} \tag{6.3}$$

where t_i is the sojourn time of state i; π_i is the steady state probability of being in a state i.

The sum of the steady-state probabilities of D_1 D_2 D_3 gives *equipment availability* (in some cases, inspection state can also be categorized into success, such as on-line monitoring, or visual/external inspections). Since in above calculation, inspection rate λ_{I} is a variable, the availability will be an expression in terms of the λ_{I}. Take the derivative of the availability with respect to λ_I, and set it equal to zero to solve for optimal λ_I that maximizes equipment availability.

Sojourn time is the time that the process stays in a state before it makes a transition to another state. As for the Markov model in this case, the times to transition from current state to other state follow exponential distributions (i.e., the times to transition from D_1 to D_2, I_1 or F_0 state all belongs to exponential distribution,), the sojourn time of each state can be calculated and listed in Table 6.1.

TABLE 6.1 SOJOURN TIME OF ALL STATE

State	Sojourn Time	State	Sojourn Time
D_1	$1/(\lambda_{0}+\lambda_{12}+\lambda_{i})$	MM_2	$1/\mu_{mm}$
D_2	$1/(\lambda_{0}+\lambda_{23}+\lambda_{i})$	MM_3	$1/\mu_{mm}$
D_3	$1/(\lambda_{0}+\lambda_{3f}+\lambda_{i})$	M_1	$1/\mu_m$
I_1	$1/\mu_i$	M_2	$1/\mu_m$
I_2	$1/\mu_i$	M_3	$1/\mu_m$
I_3	$1/\mu_i$	F_0	$1/\mu_0$
MM_1	$1/\mu_{mm}$	F_1	$1/\mu_1$

Table 6.2 is the deterioration, failure and repair rates utilized in this model.

TABLE 6.2 DETERIORATIONS, FAILURES AND REPAIR RATES

Parameters	Rates(times/day)	Parameters	Rate(times/day)
λ_0	1/10000	μ_{mm}	1/5
λ_{12}	1/1095	μ_m	1/1
λ_{23}	1/1277.5	μ_i	1/(1/24)
λ_{3f}	1/730	μ_1	1/40.15
μ_0	1/7		

By solving the SMP equations of (3.9) and (3.11) in Chapter 3, the relation between equipment availability and the λ_I can be expressed in (6.4).

$$A_{Equ.} = \frac{8.39+\lambda_I \bullet 5.66\times10^3+\lambda_I^2 \bullet 9.03\times10^5}{8.49+\lambda_I \bullet 5.69\times10^3+\lambda_I^2 \bullet 9.07\times10^5+\lambda_I^3 \bullet 3.76\times10^4} \tag{6.4}$$

And, Figure 6.2 gives the curve of (6.4).

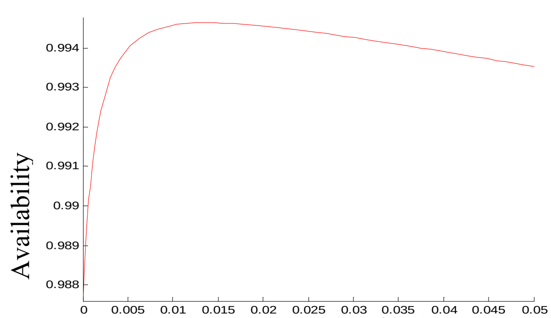


Figure 6.2 Curve of the Equation (6.4)

6.1.2 Sensitivity Study of Inspection, Maintenance on Equipment Availability

1) *Optimal inspection rate for maximum availability*

It is assumed that major and minor maintenance rates are constant and minor maintenance rates is three times of major maintenance rate (λ_{MM}). By varying inspection λ_I, the corresponding long time availability is calculated. The availability versus λ_I is shown in Figure 6.3.

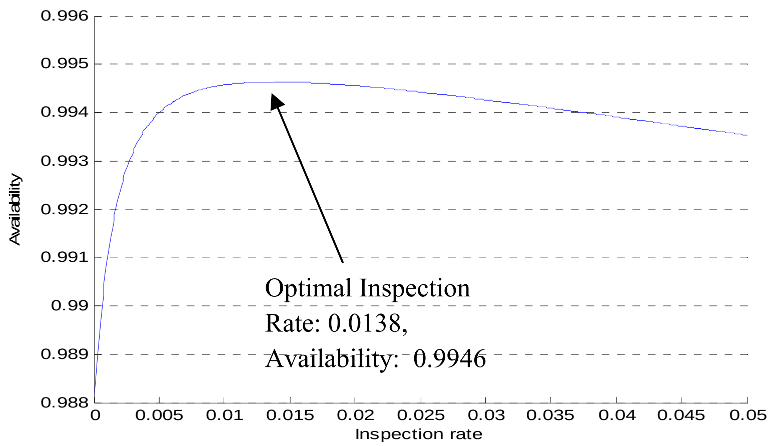


Figure 6.3 Optimal Inspection Rate for Maximum Availability

Comparison of Figure 6.2 and Figure 6.3 shows that two curves are completed overlapped. This comparison validate that the relationship between availability and inspection can be determined by either equation derivation, or numerical trail methods.

From Figure 6.3, the optimal λ_I is 0.0138 times per day (around 72 days per inspection), and the corresponding availability is 0.9946.

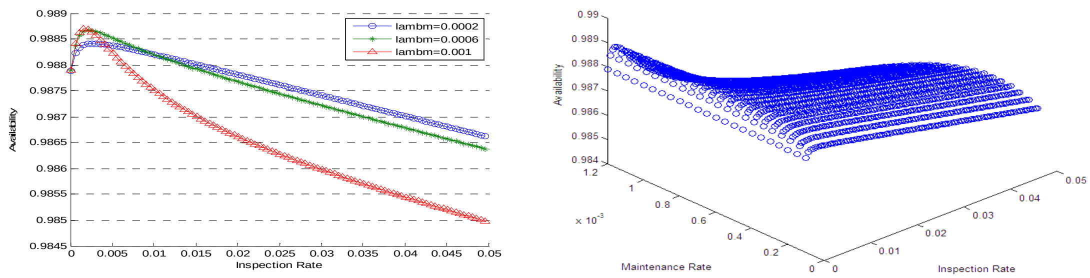
Following observations are found to explain the optimal λ_I:

i) When λ_I is too low, potential faults of the equipment may not be discovered, hence higher probability of having failures, or lower availability;

ii) On the other hand, too much inspection will let equipment undergo unnecessary inspections procedures, which also decreases equipment availability.

2) *Availability vs. inspection & maintenance rate*

Moreover, the impact of major and minor maintenance rates can be determined together with the λ_I. Figure 6.4 shows the availability versus λ_I under various λ_{MM}.



(a) (b)

Figure 6.4 Relationships of Availability and Inspection/Maintenance Rates

(a) Availability versus Inspection Rates under Different Maintenance rates
(b) Availability versus Inspection Rate and Maintenance Rates

3) *Availability vs. inspection duration*

In order to study the impact of inspection duration towards equipment availability, the inspection duration is varied. The corresponding availability is presented in Figure 6.5.

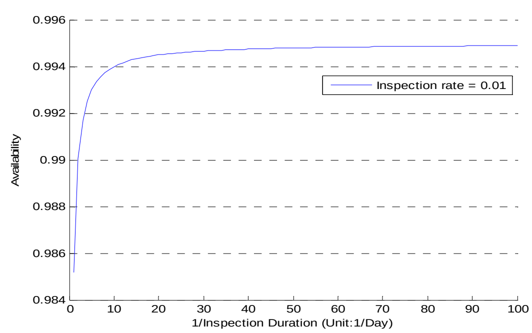


Figure 6.5 Availability versus Inspection Duration for Equipment

From Figure 6.5, initially availability increases when inspection duration decreases. But after it increases till 30 times per day, the availability approaches a constant value. The reason lies that the shortening of inspection duration will improve the efficiency to discover potential equipment failures. But inspections alone cannot improve equipment conditions. In order to improve the availability, the equipment needs to undergo fewer failures, or shorter maintenance durations.

In addition, this result is compared with other modeling methods in our previous research studies. Figure 6.6 is the comparison of different methods with the same experiment data.

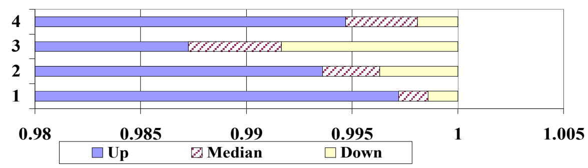


Figure 6.6 Comparison of Availability by Various Methods
1) Markov Processes with one Maintenance [15]; 2) SMP with one Maintenance[16]; 3) SMP with two Types of Maintenance [17]; 4) SMP with two Types of Maintenance and Inspection.

From Figure 6.6, apparently the introduction of inspection improves equipment availability. The reason is that by including inspection, the deterioration condition, or potential random failure could be detected earlier, therefore necessary policy can be implied at the right time. This model is also more realistic with real problems.

Above examples and sensitivity studies validate the advantages of using SMP:

1) Compared with discrete-Markov processes and continuous-time Markov processes, SMP are more general. SMP are more appropriate and accurate to model aging processes and maintenance.
2) Similar to maintenance, inspection is indispensable in aging equipment modeling. The inspection may significantly affect equipment availability, if the frequency is not properly determined.

6.2 Economic Modeling with Maintenance for Aging Equipment

This section illustrates how semi-Markov decision processes (SMDP) can be applied, to calculate the expect benefit of equipment, and determine optimal maintenance policy that achieve the maximum equipment benefit.

6.2.1 Semi-Markov Decision Processes

The rewards are assigned according to transitions from a state to another. The values are based on levels of deterioration, maintenance, and equipment outages. The higher deterioration state results in lower reward value. The rewards from deterioration states to maintenance states are the incurred cost of maintenance and the cost associated with equipment outages. The longer the component is out of service, either from maintenance or repair or failure, the lower rewards is has.

Therefore, rewards matrix among states can be established from historical data, similar to transition probability matrix *P*. With the steady-state probability matrix obtained from *P*, the expected rewards value at each state can be calculated. Table 6.3 gives the expected rewards values for each state. Note that positive values indicate the reward earned, and negative values indicate the cost incurred.

TABLE 6.3 EXPECTED REWARD OF EACH STATE

State	Reward R_i (\$/day)	State	Reward R_i (\$/day)
D_1	12000	MM_2	-14400
D_2	9000	MM_3	-14400
D_3	6000	M_1	-1200
I_1	-200	M_2	-1200
I_2	-200	M_3	-1200
I_3	-200	F_0	-10000
MM_1	-14400	F_1	-144000

where $\boldsymbol{R_i}$ is the reward value of being in state *i*.

The optimal λ_I that maximizes equipment availability calculated above will be used, to determine optimal maintenance policy that minimizes equipment cost.

Using policy improvement algorithm, the optimal policy is found after only 2 iterations, the optimal policy is [III II II], presented in Table 6.4.

TABLE 6.4 GAIN VALUES OF ALL ITERATIONS

Iteration #	Policy (d)	Benefit g($/day)
1	[I I I]	150.9
2	[III II II]	170.9

This means perform major maintenance (action III) at the first deterioration stages, and then perform minor maintenances at other two deterioration stages. This policy will theoretically allow equipment to operate at minimum cost, while still providing maximum availability.

In this study benefit value is used as a numeric indication. One can also use maintenance cost as indication, by simply negating the values in Table 6.3, and choose the optimal policy with minimized cost.

6.2.2 Sensitivity Study of Inspection and Maintenance on Equipment Benefit

Similar to the reliability modeling of equipment, the relationship between the equipment economic benefit and the λ_I/λ_{MM} can be studied by varying the inspection/ maintenance rates. Figure 6.7, Figure 6.8 and Figure 6.9 present these relations, by varying the λ_I, λ_{MM}, or both, respectively.

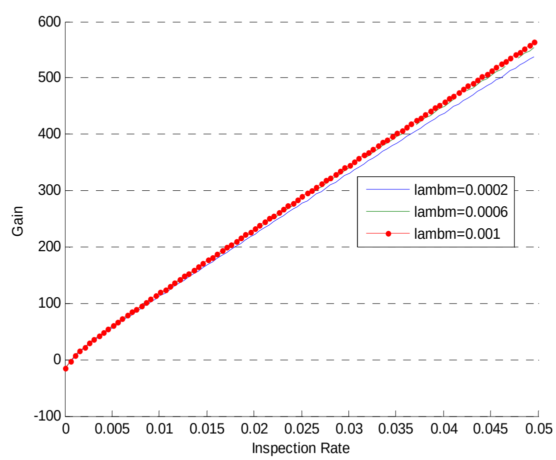


Figure 6.7 Gain versus Maintenance Rates under Inspection various Rates

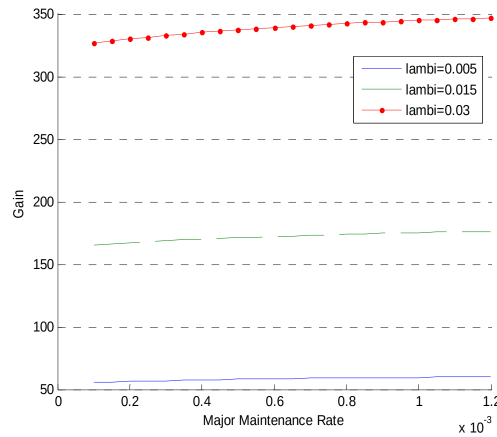


Figure 6.8 Gain versus Inspection Rates under various Maintenance Rates

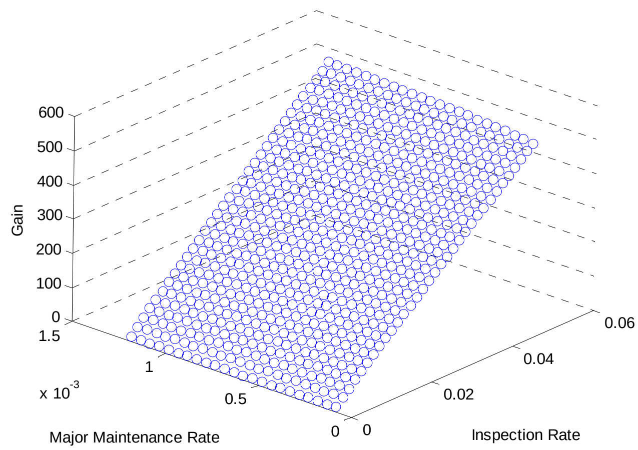


Figure 6.9 Gains versus Major Maintenance Rates and Inspection Rates

By studying the relationships presented in Figure 6.7, Figure 6.8 and Figure 6.9, the utility owners can find in which range, the economic benefit of equipment is sensitive to λ_I or λ_{MM}.

6.2.3 Maintenance Optimization for Equipment

Maximizing equipment availability is just one objective of maintenance optimization. In fact, asset manager usually make operation and maintenance decisions by balancing reliability improvement and the corresponding maintenance cost.

Under this situation, three optimization cases are considered:

1) *Maximize equipment benefit while meeting target availability*

The mathematical formulation of this optimization problem is given as:

Objective: Maximize B_{Equ} (6.5)

Constraints: $A_{Equ.}$ > Target Availability;

A measure that determines how effective a policy is can be calculated by examining how much gain value is achieved by this policy. If two policies have the same availability, the policy with higher gain value is a better policy.

Using the same equipment parameters, assuming that availability of .9945 is acceptable, will give the range of λ_I between 0.0086 and 0.0223. The policy with minimized cost or maximized benefit will then be chosen, as shown in Figure 6.10.

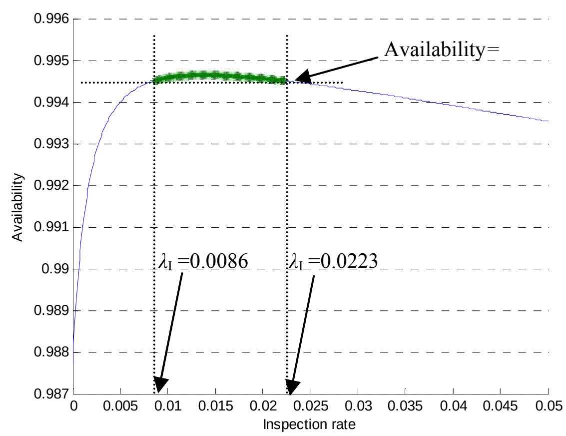


Figure 6.10 Inspection Rates that the Corresponding Availability is greater than Target Availability

Now the SMDP can be run for the range of acceptable rates, to find the least cost and the corresponding policy. The best policy is still [III II II], but now the λ_I which could result in maximized gain value is 0.0223. The corresponding availability now is 0.9945.

2) *Most cost-effective inspection/ maintenance for equipment*

Another parameter facilitates utilities to make maintenance related decisions is cost-effective factor. *Cost-effective* factor means how much availability can be achieved by per unit investment. Obviously the maintenance policy with higher cost-effective factor is more favorable.

Since in this dissertation equipment benefit other than cost is focused, another parameter *benefit-effective* factor is defined instead. *Benefit-effective* means how much benefit can be achieved in terms of one unit of availability.

Equation (6.6) gives the definition of benefit-effect factor

$$benefit - effective = \frac{B_{Equ.}}{A_{Equ.}} \tag{6.6}$$

Equation (6.7) gives the mathematical formulation of this optimization problem:

$$\begin{array}{ll} \text{Objective:} & \text{maximize } \textit{Benefit-effect} \text{ factor} \text{ ;} \\ \text{Constraints:} & A_{Equ.} > \text{Target Availability} \\ & B_{Equ.} > \text{Lower limit} \end{array} \tag{6.7}$$

Figure 6.11 gives the benefit-effect factor values under various λ_I.

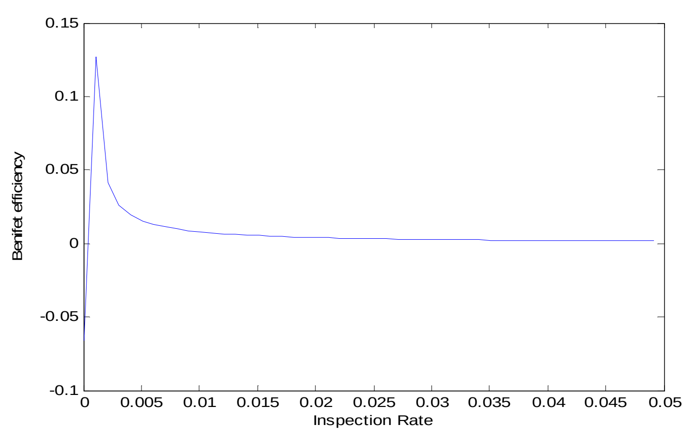


Figure 6.11 Benefit Effect Values at various Inspection Rates

Figure 6.11 shows that in this example, increasing the λ_I will greatly increase the benefit, around λ_I value of 0.002 times / day. However after 0.01 times/day, the benefit efficiency does not change too much.

6.3 Reliability Modeling with Maintenance for Substation

The purpose of this section is to illustrate how to calculate the load point and entire substation availability, and perform sensitivity studies of varying λ_I/λ_{MM}. It should be noted that here only availability is calculated. However, proposed methods can also be extended to calculate failure frequency /duration indices. Some assumption restrictions are applied, which are listed at the bottom of this chapter.

6.3.1 Load Point Availability

Calculation of entire substation availability is based on the load point availability. An example illustrating load point availability calculating procedures is given in Section 4.5.2. Here a more complicated substation is studied, in order to validate the effectiveness of the proposed method.

Figure 6.12 is the diagram of this substation.

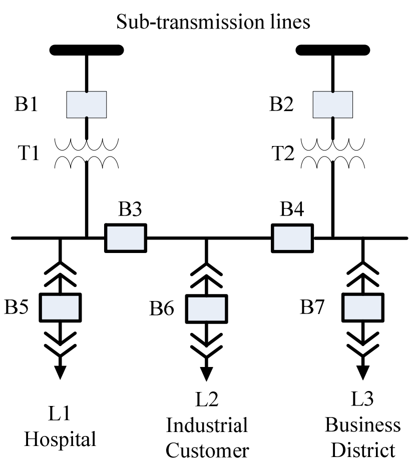


Figure 6.12 Topology of a Sectionalized Substation Modified from a Utility

Assume the sub-transmission lines are 100% reliable. The objective is to calculate load point 1 availability A_{L1}.

According to minimum cut-set theory, the 1st and 2nd order cut-set for load point are displayed in Figure 6.13, and the equations for calculating A_{L1} is presented in (6.8).

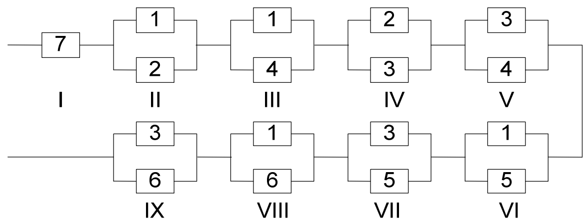


Figure 6.13 First and Second Order Cut-sets for Load Point 1

$$\begin{aligned}
U_{L1} &= U(\mathrm{I}) + U(\mathrm{II}) + \ldots + U(\mathrm{IX}) \\
&\quad - U(\mathrm{I} \cap \mathrm{II}) - U(\mathrm{I} \cap \mathrm{III}) - \ldots - U(\mathrm{I} \cap \mathrm{IX}) \\
&\quad - U(\mathrm{II} \cap \mathrm{III}) - U(\mathrm{II} \cap \mathrm{IV}) - \ldots - U(\mathrm{II} \cap \mathrm{IX}) \\
&\quad \ldots \\
&\quad - U(\mathrm{VII} \cap \mathrm{VIII}) - U(\mathrm{VII} \cap \mathrm{IX}) \\
&\quad - U(\mathrm{VIII} \cap \mathrm{IX}) \\
A_{L1} &= 1 - U_{L1}
\end{aligned} \tag{6.8}$$

Here the third and further higher orders of cut-sets are neglected, as the probability of having three or more equipment failures simultaneously are extremely small, comparing with first and second order cut-sets.

Given the reliability related data for all equipment as provided in the Appendix I, equipment availability A_{Equ} and unavailability $U_{\mathrm{Equ}} = 1 - A_{\mathrm{Equ}}$ can be calculated. Then by equation (6.8), the load point availability A_{L1}can be determined.

A_{L1} will be a function of λ_{MM} of equipment that are related with L1 (for example, since B6 and B7 are not related with L1, A_{L1} has no connection with λ_{MM} of B6 and B7, as presented in (6.8)).

The plot of A_{L1} verses λ_{MM} of T1 and T2 are presented in Figure 6.14, giving the pre-defined λ_{MM} for B1, B2, …, B7, listed in Table 6.5 .

TABLE 6.5 PREDETERMINED INSPECTION AND MAINTENANCE RATES FOR EQUIPMENT

Equipment	**B1**	**B2**	**T1**	**T2**	**B3**	**B4**	**B5**	**B6**	**B7**
λ_I (1/day)	0.0351	0.0371	0.0381	0.0391	0.0401	0.0411	0.0421	0.0431	0.0441
λ_{MM} (1/day)	0.0006	0.0008	-	-	0.0011	0.0012	0.0013	0.0014	0.0015

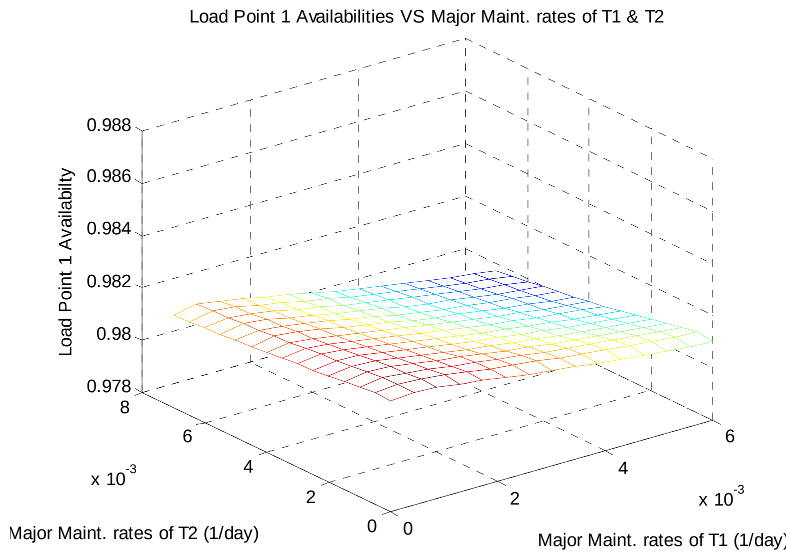


Figure 6.14 Impacting of λ_{MM} of T1 and T2 towards the Load Point 1 Availability

Figure 6.14 shows that A_{L1} has non-linear and complex relationship with the λ_{MM} for T1 and T3, due to the complex models for equipment and substation.

Similarly, it is also reasonable to assume that A_{L1} has non-linear relationship with λ_I and λ_{MM} of other equipment. Therefore, during the maintenance optimization process, nonlinear and global optimization techniques are required to solve the problem.

6.3.2 Load Point Importance Quantification

In the proposed reliability models for entire substation, the Economic Importance values *EI* and User Importance values *UI* are needed to be provided, for calculation of Load Point Importance *LI*.

In order to study the sensitivity of these input values, as well as their impact towards the substation availability, different *EI* and *UI* values are designed, for the purpose of comparison.

TABLE 6.6 INPUT ECONOMIC IMPORTANCE AND USER IMPORTANCE VALUES

Set	Load Point No.	Economic Importance EI_i	User Importance UI_i	Pre- Load Point Importance LI_i	Load Point Importance LI_i
I	L1	0.1	0.55	0.055	0.25
	L2	0.6	0.1	0.06	0.2727
	L3	0.3	0.35	0.105	0.4773
II	L1	0.75	0.5	0.375	0.8152
	L2	0.05	0.1	0.005	0.0109
	L3	0.2	0.4	0.08	0.1739
III	L1	0.1	0.7	0.07	0.2917
	L2	0.8	0.2	0.16	0.6667
	L3	0.1	0.1	0.01	0.0417

In Set I, Business customers have the hightest *LI* values, since from the utility perspective business customers have higher revenue contribution, compared with other load points. Similarly, in sets II and III, the Hospital and Industry customer will have the highest *LI* values, respectively. The purpose of assigning different importance values is to examine their impact towards the entire substation availability.

6.3.3 Sensitivity Study of Inspection and Maintenance on Substation Availability

1) *Impact of major maintenance rates of T1 and T2 toward substation availability*

Similar to the case of studying the impact of λ_{MM} of equipment towards load point, the substation availability also varies under different equipment λ_{MM} values.

Figure 6.15 shows the plot of the entire substation availability versus the variation of λ_{MM} for T_1 and T_2. Here, the load point importance sets III was selected, and λ_I or λ_{MM} for other equipment are pre-defined, according to Table 6.15 and Table 6.16 in the Appendix I.

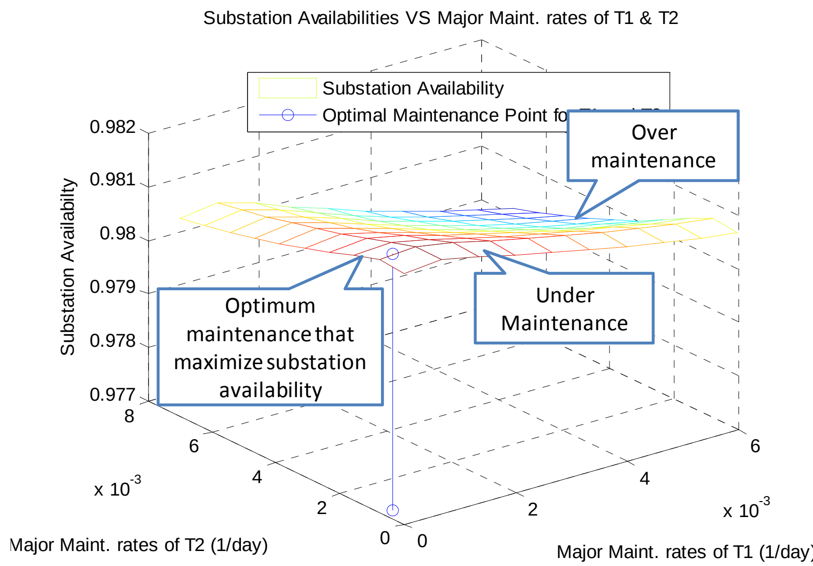


Figure 6.15 Impacting of λ_{MM} of T1 and T2 towards Substation Availability

Figure 6.15 demonstrates that the shape of the surface is similar to the load point availability, because the calculation of substation availability is the weighted sum of load points availability, therefore this linear relationship between substation availability and load points availability are similar.

Also, Figure 6.15 illustrates that both under-maintenance and over-maintenance can jeopardize the substation availability. Over-maintenance will increase the maintenance related outage time, thus decrease the substation availability; similarly, under-maintenance will result in increased risk of failures.

2) *Impact of inspection rates of T1 and T2 toward substation availability*

To study the impact of increasing the λ_I, and mimic the action of continuous condition-monitoring actions, the λ_I for T1 and T2 are increased, and the corresponding substation availability is plotted in Figure 6.16.

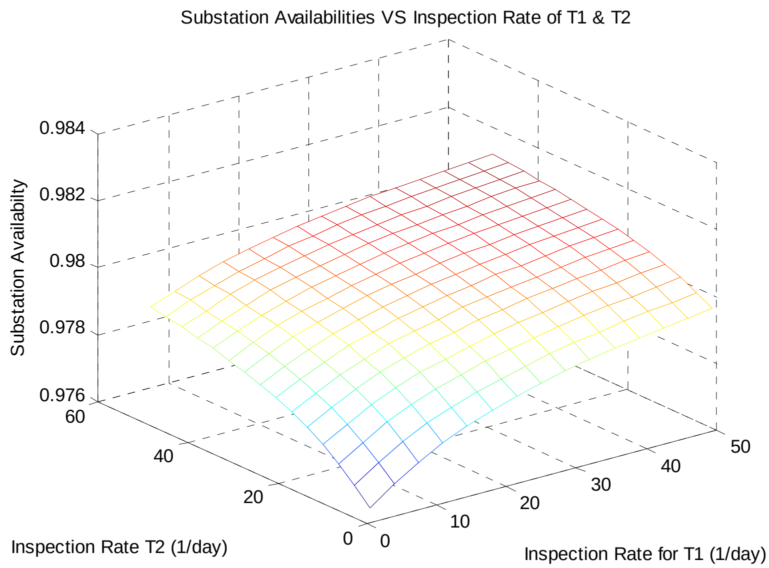


Figure 6.16 Impact of λ_I of T1 and T2 towards Substation Availability

As in this study, inspection states are treaded as "success" during state reduction, and does not account for outages (such as condition-monitoring instrument's operation will not results in equipment outages), increasing λ_I will increase $A_{Sub.}$, but too much inspections will not have signification contributions towards availability improvement, as the availability will approach to a saturation point after continuously increasing of equipment inspections rates.

3) *Sensitivity of user input UI and EI values toward the entire substation availability*

The user input importance values *UI* and economic importance values *EI* for determining the load point importance also impacts $A_{Sub.}$. Table 6.7 gives the comparison of the relationships between $A_{Sub.}$ and λ_{MM} / λ_I for T_1 and T_2, under various sets of inputs for *UI* and *EI* values in Table 6.6.

TABLE 6.7 IMPACT OF USER INPUT *UI* AND *EI* VALUES TOWARD ENTIRE SUBSTATION AVAILABILITY

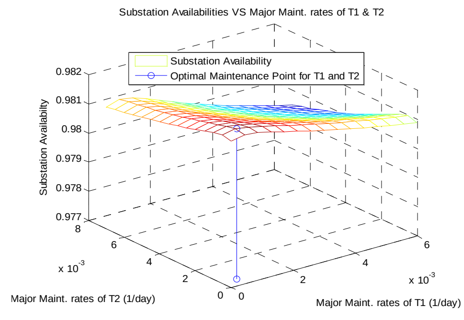
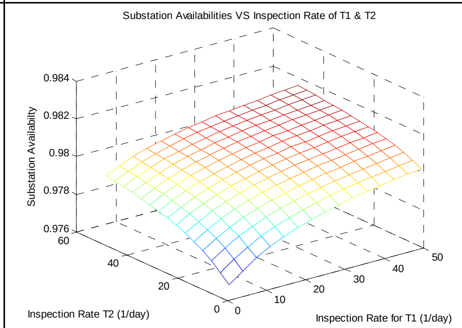
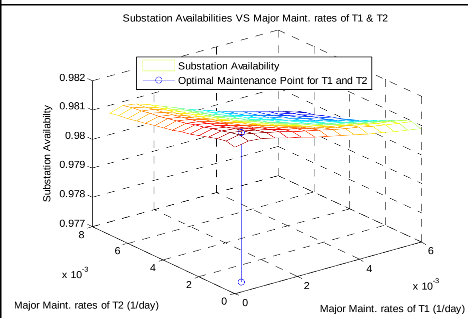
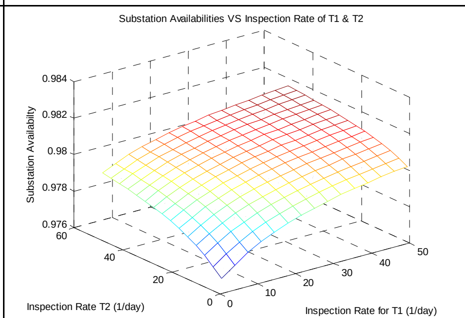
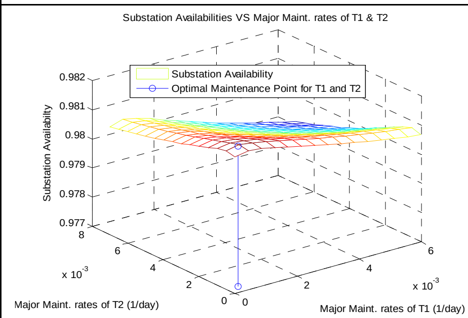
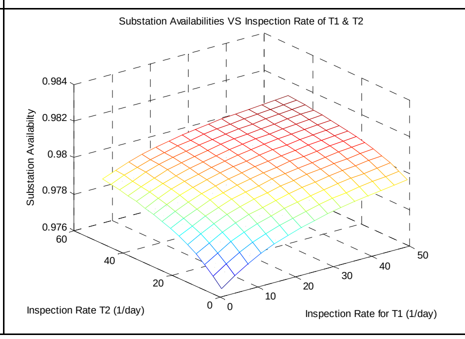
***UI* and *EI* value sets**	**Impact of maintenance of T1 and T2**	**Impact of inspection of T1 and T2**
I		
II		
III (Reference)		

Table 6.7 indicates that varying of *UI* and *EI* values has slight impact on the shapes of A_{Sub}. This is true because A_{Sub} is the weighted sum of A_{LP}, and they have linear relationships among each other. Therefore, in this case the different combination of *UI* and *EI* values only impact the values of the A_{Sub}, but not the shape.

6.4 Economic Modeling with Maintenance for Substations

6.4.1 Quantify Equipment's Contribution toward Substation Availability

According to the definition of sensitivity in Chapter 4, one can plot the sensitivity of varying equipment availability towards substation availability. Figure 6.17 plots the sensitivity of all equipment toward substation level availability, under the input *UI* and *EI* values Set III.

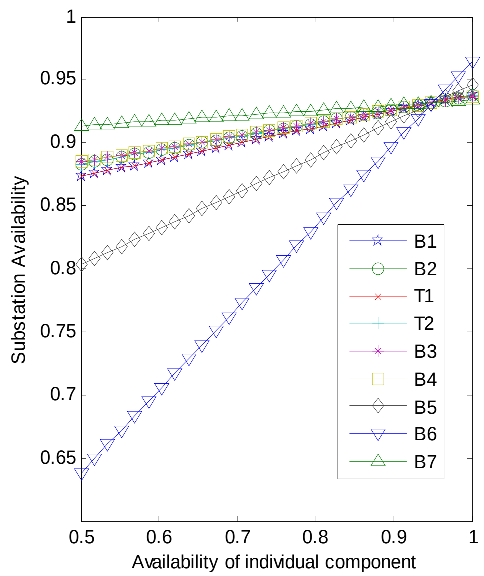


Figure 6.17 Sensitivity Study of Equipment Availability toward Entire Substation Availability

From Figure 6.17, it can be observed that there is a linear relationship between A_{Equ} and A_{Sub} for all substation equipment.

From (6.8) used to calculate load point availability, and (4.6) in Section 4.6.1 used to calculate sensitivity, the fixed sensitivity values is explainable, because both functions of (6.8) and (4.6) are linear.

However, it should be noted that this is only the approximation, as in equation (7.8), the third and higher orders cut-sets are neglected. Therefore, the sensitivity values are reasonable approximation only, but not the exact true value.

In Figure 6.17, the sensitivity values (slope values) will be utilized as the equipment's economic contribution toward substation. Figure 6.18 compares the differences among equipment's sensitivity toward various load points and entire substation.

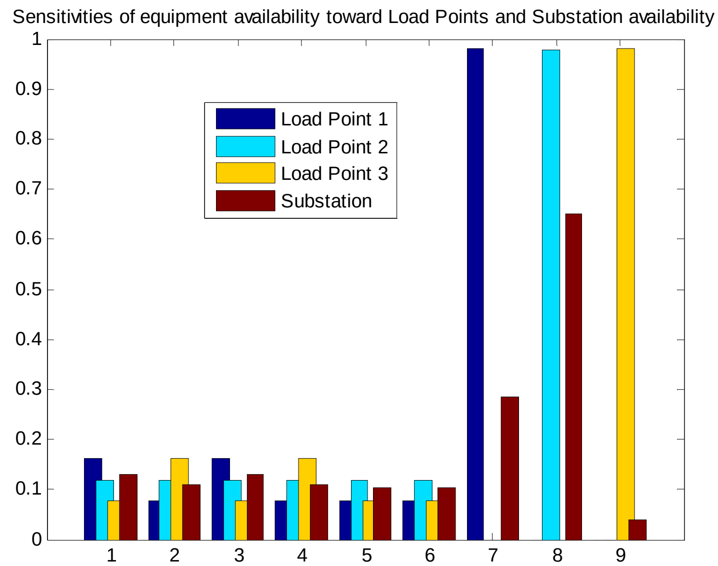


Figure 6.18 Sensitivity of Equipment Availability toward Load Points and Entire Substation Availability, under the Load Point Importance Set Value III

In Figure 6.18, it should be noted that there are some "missing" bars. Actually they are not missing; just the values of the bars are zeros. For example, since equipment 7 (B5) has no connection with L2 and L3, the sensitivity values are zero. Therefore, the corresponding bars are missing in Figure 6.18, and the economic contribution of equipment B5 toward the substation is zero.

6.4.2 Expected Substation Benefit and Optimal Maintenance Policy

After the economic contribution of all equipment toward substation is determined, the substation benefit can be attributed to individual equipment, based on the economic contribution of equipment toward the entire substation, in order to determine the optimal maintenance policies, as well as the corresponding expected benefit.

For example, the percentages of equipment's economic contribution toward the entire substation benefit are presented in Figure 6.19, under Set III input *UI* and *EI* values.

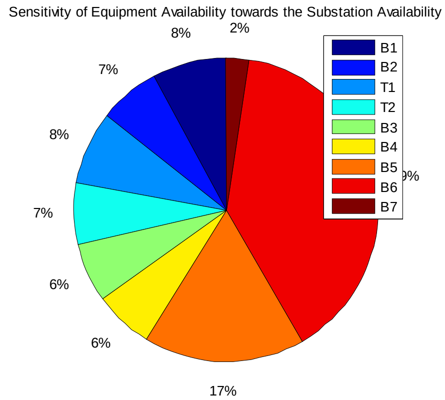


Figure 6.19 Percentage of Economic Contribution of Equipment toward Substation Benefit, under *UI* and *EI* sets III Values

Under the condition of the λ_{MM} for T1 and T2 [$\lambda_{MM\_T1,}$ λ_{MM_T2}] that can achieve maximum substation availability in the case in Section 6.1, and the expected cost/benefit of being in every state listed in Table 6.17 in Appendix I, the corresponding optimal maintenance policies, and the associated equipment / substation expected benefit can be calculated, as presented in Table 6.8.

In Table 6.8, breaker B7 has the highest expected benefit value. The result matches equipment sensitivity analysis results in Figure 6.19: Equipment B6 has the highest sensitivity, hence the highest economic contribution toward the entire substation.

TABLE 6.8 OPTIMAL MAINTENANCE POLICIES FOR ALL EQUIPMENT UNDER MAXIMUM SUBSTATION AVAILABILITY

Equipment	Optimal Maintenance Policy	Expected Benefit ($/day)
B1	[III III III]	26.4458318469804
B2	[III III III]	22.2884937705962
T1	[III II II]	18.2341219347696
T2	[III II II]	14.1658378121240
B3	[III III III]	24.0777869539366
B4	[III III III]	24.8718477981986
B5	[III III III]	87.8006442397341
B6	[III III III]	221.257521231025
B7	[III III III]	2.44254023358495
Total	-	**151.1020**

Notes: **I** Doing Nothing; **II** Doing Minor Maintenance; **III** Doing Major Maintenance

It should be noted that, the Expected Benefit values in Table 6.8 might be negative in some cases. The negative values do not mean operating the equipment will generate negative benefits; they are just internal mathematic calculation results.

6.4.3 Sensitivity Study of Inspection and Maintenance on Substation Benefit

Similar to the sensitivity studies of load points and substation availability, the relationship between expected substation benefit and equipment λ_{MM} for T1 and T2 are visualized in Figure 6.20.

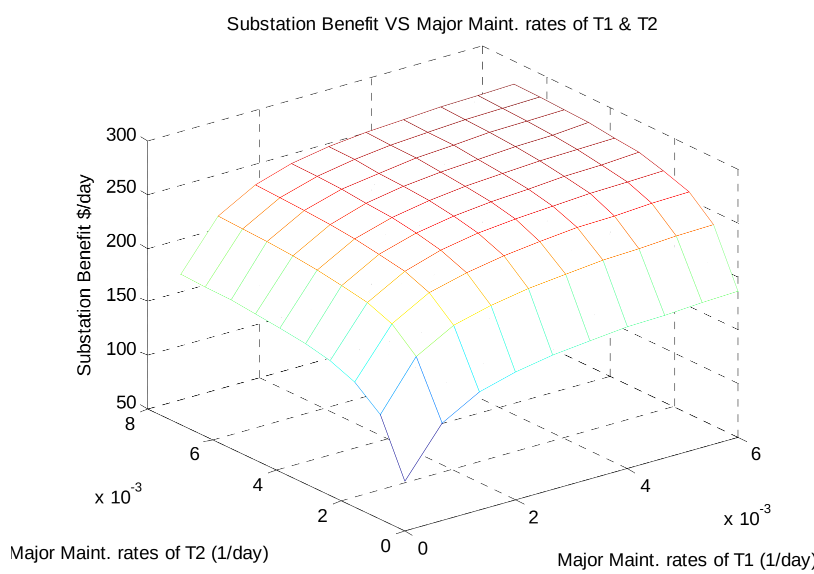


Figure 6.20 Impact of Inspection Rates of T1 and T2 towards Substation Benefit

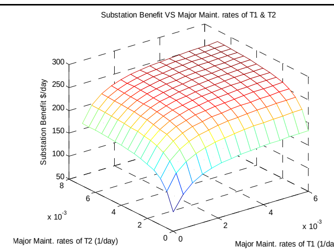
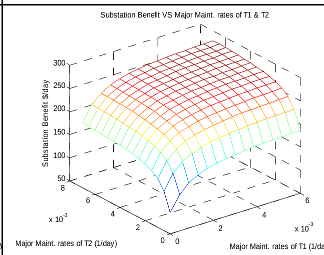
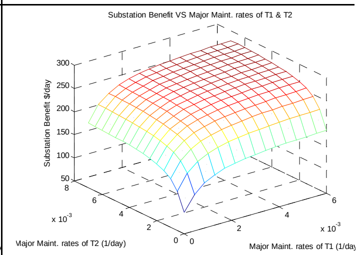
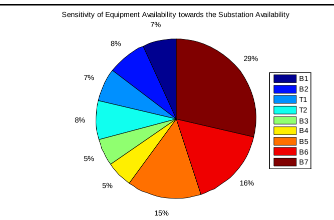
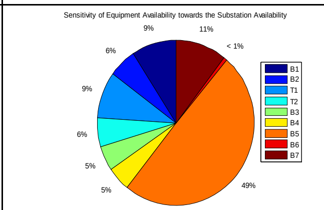
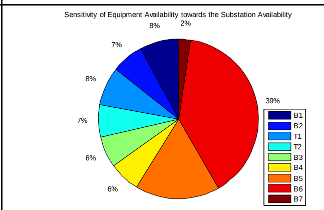
In the maintenance range displayed in Figure 6.20, the increased maintenance will increases the expected substation benefit. However, decision of optimal maintenance can not merely depend on this diagram, as the region of high expects substation benefit might not meet the target availability constraints.

6.4.4 Sensitivity Study of *UI* and *EI*

As described before, the changes of *UI* and *EI* values will impact the quantified values of equipment importance. Moreover, the variation of *UI* and *EI* values will affect substation benefit values, and the sensitivity of these needs to be examined.

Table 6.9 gives the equipment importance values under various *UI* and *EI* inputs, as well as the corresponding substation benefit, with regards to λ_{MM} of T1 and T2.

TABLE 6.9 SENSITIVITY STUDIES OF VARYING INPUT *UI* AND *EI* VALUES TOWARD SUBSTATION BENEFITS

***UI* and *EI* value sets**	**I**	**II**	**III (Reference)**
Relationship between B_{Sub} and λ_M of T1 and T2			
Equipment importance diagram			

Results given in Table 6.9 illustrate that variation of *UI* and *EI* values will have obviously impact on equipment importance values, especially for B5, B6 and B7. However, the variation of *UI* and *EI* does not change the shape of substation benefit and λ_{MM} values of T1 and T2. The reasons of insignificant change are caused by the small changes of T1 and T2 importance values, under different *UI* and *EI* value sets.

6.5 Substation Optimization

6.5.1 Scenario 1 - Maximize Substation Availability without Constraints

Case 1: *Two decision variables*

It is difficult to visualize the “optimal” λ_{MM} value points, when the number of decision variables is larger than 2 or 3. Therefore, Case 1 is designed to have only two decision variable, for the purpose of visualization.

Figure 6.15 gives a visualized optimal maintenance point, for the λ_{MM} of T1 and T2 that achieved the maximum substation availability.

Similarly, the optimal λ_{MM} values also depend on the *UI* and *EI* values. Table 6.10 summarizes comparison of optimal λ_{MM} under different *UI* and *EI* values sets, and the corresponding maximum $\boldsymbol{A}_{\textbf{Sub}}$.

TABLE 6.10 OPTIMIZE MAJOR MAINTENANCE RATES FOR TRANSFORMERS TO MAXIMIZE SUBSTATION AVAILABILITY (TWO DECISION VARIABLES)

***UI* and *EI* Values**	**Set I**		**Set III**	
Maximum Substation Availability A_{Sub}	0.981595920011630		0.981791265908509	
	λ_{MM} (1/day)	**A_{Equ}**	**λ_{MM}(1/day)**	**A_{Equ}**
T1	0.000397317827373400	0.985487169910991	0.000363993747514243	0.985485490993851
T2	0.000400919973687954	0.986052223692927	0.000315241936080604	0.986031869571058

Case 2: *Nine decision variables*

Table 6.11 presents the optimal λ_{MM} of all equipment, in order to maximize substation availability. At this time, the number of decision variables is 9.

TABLE 6.11 OPTIMIZE MAJOR MAINTENANCE RATES FOR ALL EQUIPMENT (NINE DECISION VARIABLES)

***UI* and *EI* Values**	**Set I**		**Set III**	
Maximum Substation Availability	0.982881807839729		0.983704096578446	
Optimal Maintenance Rates and Equipment Availability	**λ_{MM} (1/day)**	**A_{Equ}**	**λ_{MM} (1/day)**	**A_{Equ}**
B1	0.00143147837310296	0.985449407746721	0.000149067716997437	0.988548372705735
B2	2.82493762634654e-06	0.987587575250540	0.000356560928018366	0.988587553511713
T1	0.000822899296741583	0.984394553087483	0.000845349866932766	0.984300756897922
T2	0.000505324947236865	0.985920000797705	0.000550456035047019	0.985820984631886
B3	0.00340538537606497	0.976509952014162	0.00315557571702210	0.977489074904800
B4	0.00590326812140218	0.967889770238115	2.68098012576060e-05	0.986708441550209
B5	0.000573140740828589	0.985648070828731	0.000503453515953773	0.985693461850127
B6	0.000620665567803540	**0.985341504912132**	0.000577876325192394	**0.985385273653368**
B7	0.000520944743298776	0.985115132240230	0.000462538285992490	0.985118706433782

Detailed results in Table 6.11 indicate that equipment availability value after optimization also matches the equipment important changes. For example, from Table 6.6, for B6 the equipment importance value under *UI EI* Set I is smaller than in Set III; this importance is reflected by the increased equipment availability values presented in Table 6.11(highlighted in bold font). Similar results can be observed for other equipment.

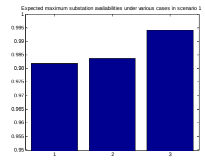
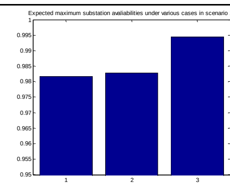
Therefore, when the equipment importance value increases, the λ_{MM} of that specific equipment also changes, in order to achieve higher equipment availability.

Case 3: Eighteen-decision variables

TABLE 6.12 OPTIMIZE BOTH INSPECTION AND MAJOR MAINTENANCE RATES, FOR ALL EQUIPMENT (EIGHTEEN DECISION VARIABLES)

***UI* and *EI* Values**	**Set I**			**Set III**		
Maximum Substation Availability:	0.994404888817886			0.994106462578223		
Optimal Maintenance Rates and Equipment Availability	**λ_I(times/day)**	**λ_{MM} (times/day)**	**A_{Equ}**	**λ_I(times/day)**	**λ_{MM} (times/day)**	**A_{Equ}**
B1	47.4835576386203	0.00398039810980066	0.988488579124940	12.0113062168274	0.000696825384624991	0.991992000690080
B2	31.4964459621610	5.14263647322899e-05	0.994720778828201	48.1841349371802	0.00584632816005944	0.983843744395615
T1	47.8814271896449	0.000157587919219030	0.994918865645791	31.0432255962951	0.000116856605403501	0.993261238096784
T2	17.5924118783646	0.000283836806850715	0.991861502954502	49.8330692601080	0.000868888771306483	0.994821365432778
B3	41.1144021561305	0.00507594045232106	0.984243032322999	31.9575584946783	0.00237554230467015	0.990277575875726
B4	14.7415352083341	0.00268672744174929	0.984599471512063	16.7795971157950	0.00149237110374575	0.990073747580481
B5	48.7907382623306	0.000358329945939991	**0.995216723750046**	43.5063107480181	4.48905711047012e-05	**0.994437157896343**
B6	48.4658548856219	0.000485294610756504	**0.995117281734455**	48.9250660065671	0.000542981421981095	**0.995135650903358**
B7	49.7081806790924	0.000431102450131183	**0.995095198331627**	34.9927125772247	0.00152738177511183	**0.992361986152629**

TABLE 6.13 COMPARISONS OF MAXIMUM SUBSTATION AVAILABILITIES OF DIFFERENT CASES, UNDER VARIOUS *UI* AND *EI* VALUE SETS

***UI* and *EI* Values**	**Set I**	**Set III**
Comparisons of maximum substation availabilities of different cases		

By summarizing above results, one can make the following conclusions:

1) When the number of decision variables increases (from 2, 9 to 18), the maximum availability that can be achieved is also increased. This observation indicates that mandatory pre-determined λ_{MM} might not effectively increase entire substation availability. From system point of view, the maintenance of all equipment should be optimized, to further improve substation availability.

2) PSO techniques is an effective method to solve maintenance optimization problems, because a) it is a global optimization tool; b) the computing time is much less, compared with traditional evolution -based tools, and the speed can be further reduced by applying parallel computing techniques.

6.5.2 Scenario 2 - Maximize Substation Benefit under Availability Constraint

For the purpose of visualization, this dissertation only considers two decision variables: the λ_{MM} for T1 and T2. There are two steps in the optimization process:

Step 1): Determine the search space of λ_{MM} that the corresponding A_{Sub} is higher than target availability. Figure 6.21 gives λ_{MM} values spaces that the corresponding $A_{Sub} > 0.98$.

In Figure 6.21, the blue layer represents the target availability with $A_{Sub.}$ value of 0.98. Only the λ_{MM} values that can achieve the availability above this layer qualify the narrowed search space for the maximum substation benefit decision.

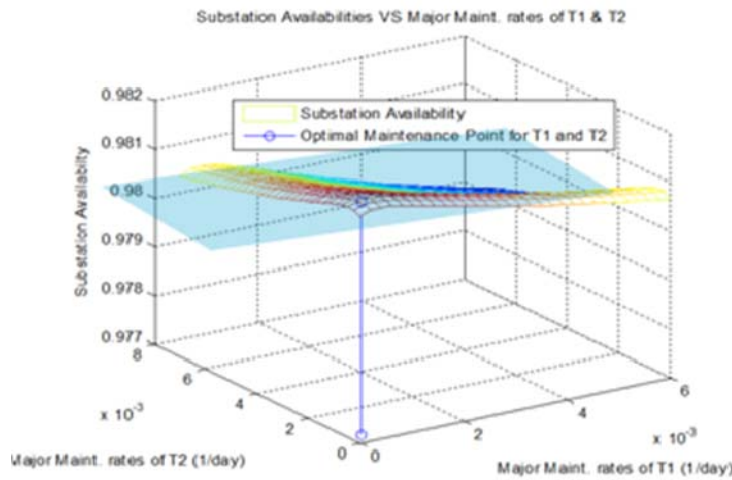


Figure 6.21 Substation Availability and the Layer of Target Availability

Figure 6.22 gives the space of λ_{MM} of T1 and T2 selected from Step 1).

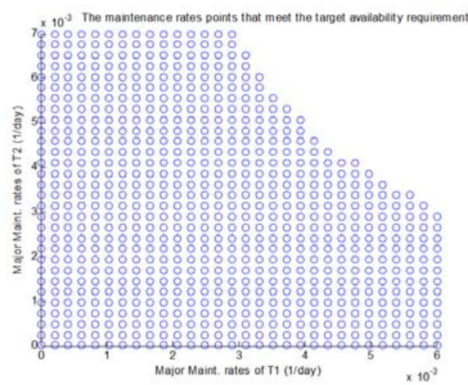
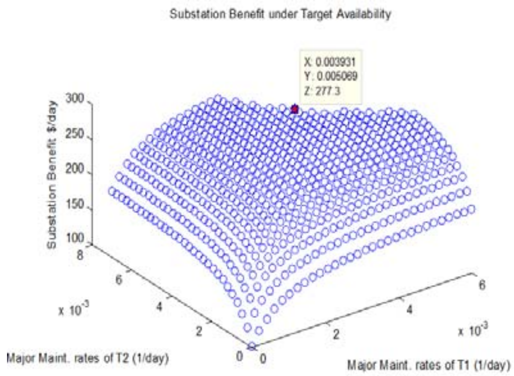
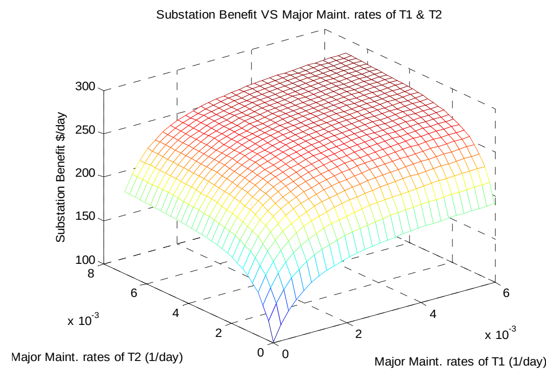


Figure 6.22 Space of λ_{MM} of T1 and T2 that the Corresponding A_{Sub}>=0.98

Step 2):

After the decision variable space that meets the target availability is determined, the maximum substation benefit can be calculated. The result is presented in Figure 6.23 (a). Also, the original surface of substation benefit without target availability limitations is also presented in Figure 6.23 (b).





(a) (b)

Figure 6.23 Comparisons of Maximum Substation Benefit Values, with and without Target Availability Constraints
(a) With Target Availability Constraints; (b) Without Target Availability Constraints

6.5.3 Scenario 3 - Maximize Substation Availability under Benefit Constraint

Similar to Scenario 2, the object of Scenario 3 is to determine the maximum substation availability, under substation benefit constraint (such as the substation benefit must be higher than a pre-defined value).

The reason of use benefit other than cost as constraint is because the equipment economic modeling developed in Chapter 4 is based on calculating expected benefit values. However, the algorithm designed here is also eligible to solve similar problems under cost constraint. In that situation, the economic model to estimate the substation cost (including inspection / maintenance / replacement cost, and penalty cost due to outages) should be established.

Step 1):

Determine the search space of λ_{MM} that the corresponding $B_{Sub.}$ is higher than \$250/day. This is similar to use a virtual plane that B_{Sub}= \$250/day, to cut the surface in Figure 6.20; only the λ_{MM} that the corresponding B_{Sub} values are above this plane qualifies the constraint. Then the original search space can be narrowed to Figure 6.24.

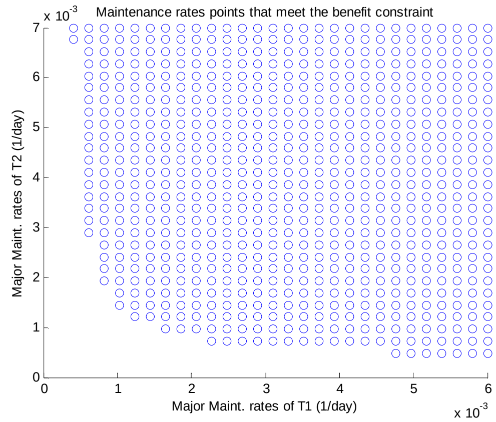
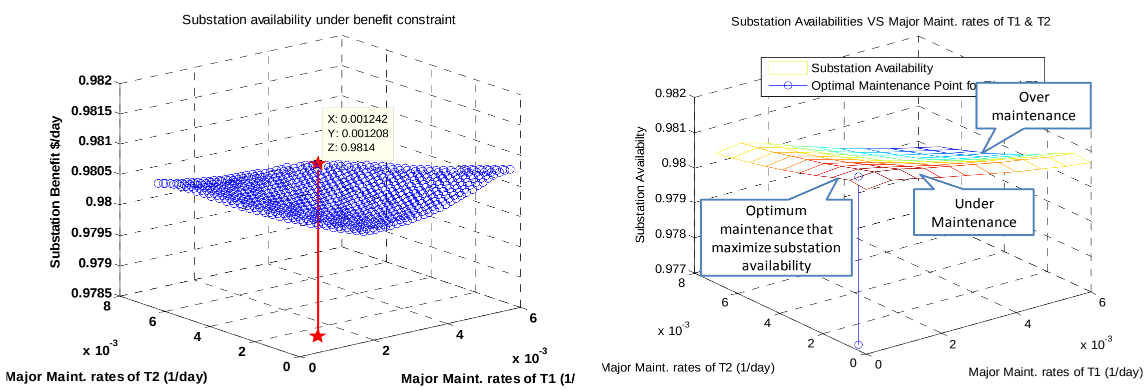


Figure 6.24 Space of λ_{MM} of T1 and T2, that Meet the Substation Benefit Constraint of B_{Sub}>=\$225/day

Step 2):

After the search space is narrowed, the maximum substation availability can be determined, from searching all possible λ_{MM} values in Figure 6.24. The optimal λ_{MM} that corresponding to the maximum substation availability can be determined, which are presented in Figure 6.25 (a). Figure 6.25 (b) is the original optimal λ_{MM} that maximize substation availability without constraint, for comparison purposes.



(a) (b)

Figure 6.25 (a) Optimal major maintenance rates of T1 and T2 that maximize substation availability, while meeting substation benefit constraint; (b) Original maintenance rates, without substation benefit constraint

The case studies in Scenarios 1, 2 and 3 only give fundamental applications of maintenance optimization in a substation. In practice, more objectives or more constraints may be added:

1) Add other reliability indices in constraints, such as minimize failure frequency or outage durations.
2) Prolong the lives of specific equipment, such as high value transformers.
3) Minimize the life cycle cost of specific equipment, such as transformers.

For these conditions, appropriate equality or inequality equations should be added or modified, to the mathematic equations in (4.15)-(4.18) in Chapter 4. Usually the added constraints or increased decision variables increases the complexity of optimization problems. Even though generally the regular PSO can solve these problems, modified structure or parallel PSO may be considered, to solve large scale optimization problems.

6.6 Case Studies of FMP and FMDP

In order to illustrate the effectiveness of the proposed method, case studies using fuzzy Markov processes for modeling of equipment and a small substation are conducted separately. Here, the results obtained from approach 2) are presented, since it takes less execution time with the same accuracy.

The uncertain maintenance rates are modeled here, assuming the maintenance data obtained from equipment or system is incomplete or inaccurate.

However, the approach can also handle modeling other parameters' uncertainties, such as failure rate or repair/replacement time, by selecting the appropriate membership function for these uncertain variables.

6.6.1 Equipment Modeling with FMP (Case A)

First, for demonstration purposes, a simple example of an 8-state Markov process (MP) with maintenance states is given. Figure 6.26 is the state-space diagram of this model. More information, including the transition rate data, can be found in [34].

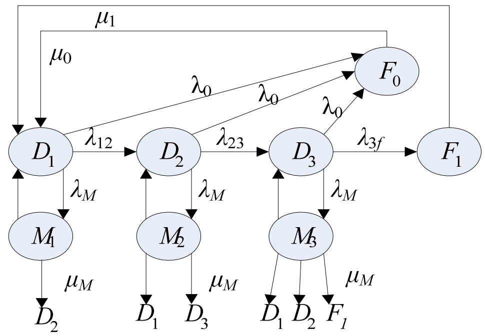


Figure 6.26 The State-Space Diagram of a Markov Process for Equipment Modeling

i) Existing fuzzy Markov processes

In order to emphasize the advantages of the proposed method over existing fuzzy Markov models, examples of how to calculate the reliability indices through existing methods are presented.

One widely used fuzzy approach is to directly replace the variables in the matrix of Markov equations with fuzzy membership functions. Even though theoretically one can always derive the corresponding fuzzy reliability indices, similar to traditional Markov models, in practice the derivation might be too difficult to be applied to large Markov models or system level reliability evaluations.

Another approach is the derivation of the reliability indices as functions of transitions rates/probabilities, and applying fuzzy arithmetic to compute the fuzzy indices [44]. For example, the relationship between A and λ_M is

$$A = \frac{1.6 \cdot (9.2\text{e}10^3 \lambda_{\text{M}} + 5.8 + 5.5\text{e}10^6 \lambda_{\text{M}}^2 + 1.6\text{e}10^9 \lambda_{\text{M}}^3)}{1.5\text{e}10^4 \lambda_{\text{M}} + 9.4 + 8.8\text{e}10^6 \lambda_{\text{M}}^2 + 2.5\text{e}10^9 \lambda_{\text{M}}^3 + 2.5\text{e}10^9 \lambda_{\text{M}}^4} \tag{6.9}$$

However, this approach requires derivation of explicit equations, which are impractical in some cases especially in system level models. Moreover, the variables in the equations have to be carefully placed, to avoid directly dividing by themselves, which will introduce errors during fuzzy calculation [32].

ii) Calculation of fuzzy reliability indices

Following the FMP procedure and given the input fuzzy maintenance rate in Figure 6.27, the fuzzy reliability indices are obtained, which are shown in Figure 6.27 (b) and Figure 6.28.

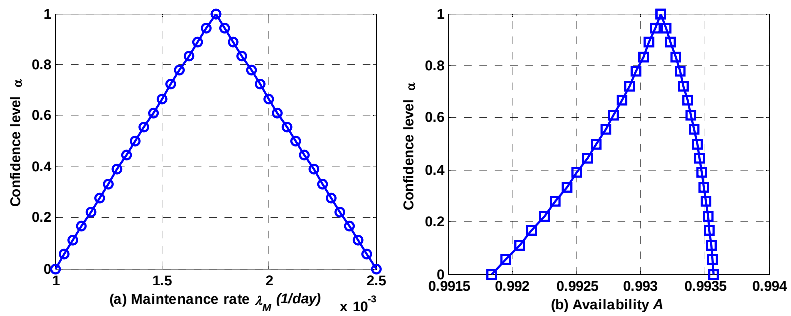


Figure 6.27 The input fuzzy maintenance rate (a) for Case A, and the output fuzzy availability indices (b)

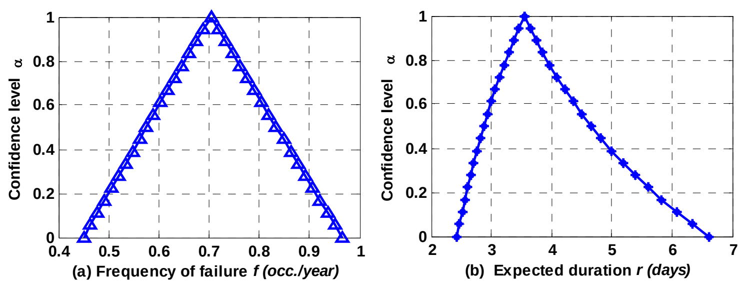


Figure 6.28 The Fuzzy Frequency of Failure (a) and Expected Failure Duration (b) Indices for Case A

In Figure 6.27 (a), the x-axis represents the possible maintenance rate values, while the y axis represents the level of confidence or possibility of a particular maintenance rate value.

In comparing existing Markov models with fuzzy calculation approach, the proposed method does not require deriving explicit equations, or complex fuzzy arithmetic calculations in Markov models. Instead the extension-principle-based fuzzy calculation is relatively simple and clear, and it still maintains the same accuracy as the existing method, at a given confidence level. Moreover, in this method, addition the number of fuzzy variables only increases the number of constraints in the non-linear optimization presented in Section 5.2.3, and will not increase the algorithm complexity.

iii) Optimal maintenance for maximum availability

Another application of this algorithm is the optimal maintenance determination using the optimization processes explained in Section 5.2.3.

In this dissertation, for the purpose of illustrating the capability of the proposed method in maintenance optimizations, case studies to determine the optimal maintenance rates that achieve the maximum availability for equipment and substations are presented. It should be noted that though in this dissertation the objective function is simply maximizing the availability of equipment or substations, and the parameters to be optimized are maintenance rates, in practice the maintenance optimizations may include other objectives functions, such as prolonging the equipment remaining life, minimizing the maintenance cost, and maximizing specific reliability indices; the parameters to be optimized in practical maintenance optimizations may also include the depth or types of maintenance at each stage. Detailed description of maintenance optimization can be found in [95], [72], [96].

For example, in this case, given the maintenance range of (0, 0.02], the maximum availability is 0.9936, with the corresponding optimal maintenance rate of 0.00271/day. This result matches well with a previous study of the same model [16], in which the crisp point of the optimal maintenance rate and the maximum availability are calculated as shown in Figure 6.29.

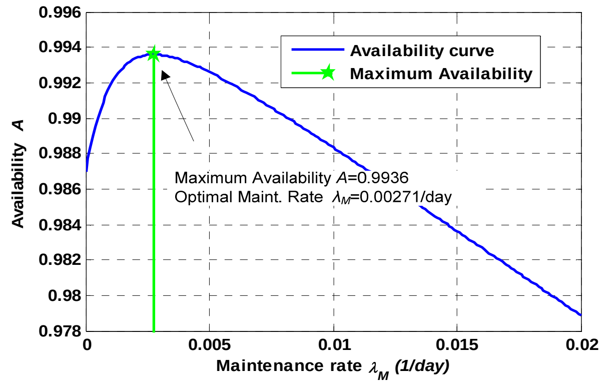


Figure 6.29 The Optimal Maintenance Rate that Maximizes Availability for Case A

6.6.2 Advanced model of equipment by FMP (Case B)

For the purpose of illustrating the capability of proposed FMP in modeling of equipment, another advanced Markov model with inspections and minor and major maintenance states is also studied, which is presented in Figure 6.1. The description of each state is available in Section 5.2.1. Detailed information about this model, as well as results using standard Markov processes, is given in [95].

i) <u>Calculation of fuzz reliability indices</u>

It is assumed that both inspection rates and major maintenance rates of equipment are not known precisely, or in other words uncertain. These rates are assumed to be modeled by two fuzzy MFs in which the inspection rates are modeled by a triangular MF, and the major maintenance rates are modeled by trapezoid MF. Figure 6.30 shows the plots for the input fuzzy inspection rate and fuzzy major maintenance rate.

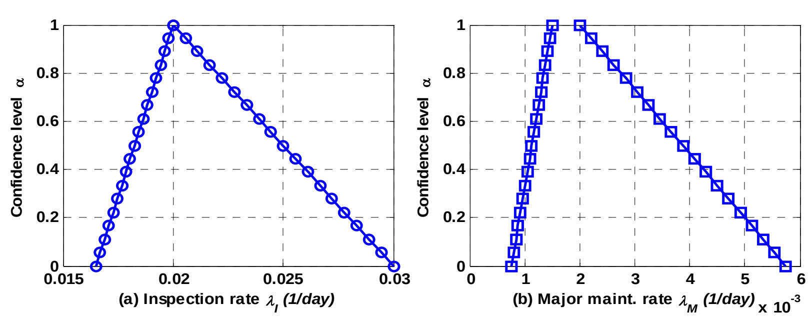


Figure 6.30 Input Fuzzy Inspection Rate (a) and Fuzzy Major Maintenance Rate (b) for Case B

Assume that equipment can be operable during inspections. Except operable (D_i) and inspection states (I_i), all other states are considered as failure states. Figure 6.31(a) and (b) show the corresponding output fuzzy availability and failure frequency.

ii) Optimal maintenance and inspection rates

In this case, given the range of inspection rates as (0, 0.05), and the range of major maintenance rates as (0, 0.00012), the maximum availability is 0.9887; and the corresponding optimal inspection and major maintenance rate values are 0.001026 and 0.001602. This result also matches well with the previous study in [95], which is presented in Figure 6.32.

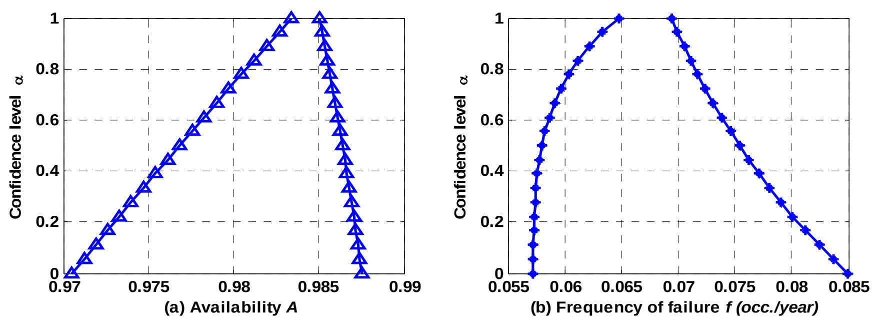


Figure 6.31 The Output Fuzzy Availability (a) and Fuzzy Frequency of Failure (b) for Case B

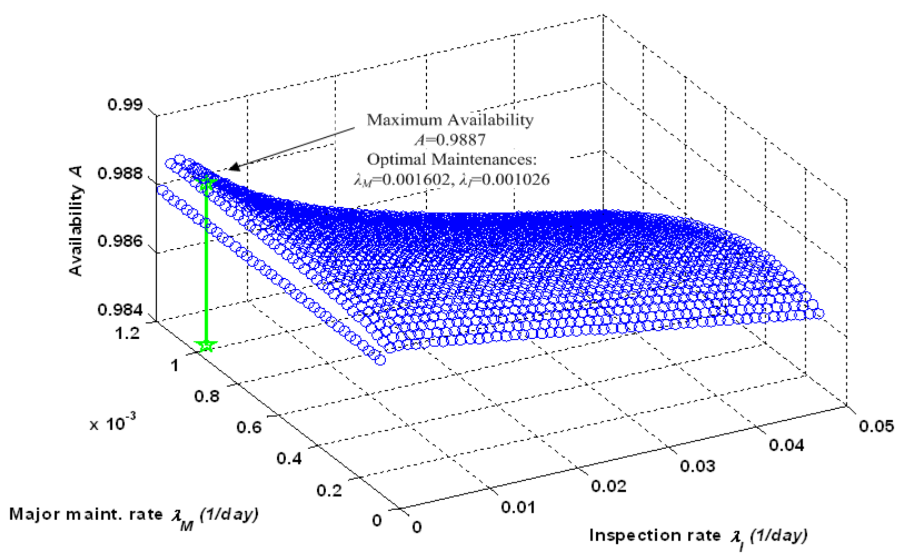


Figure 6.32 The Optimal Maintenance and Inspection Rates that Maximize the Availability for Case B

6.6.3 Modeling of substation with FMP (Case C)

In addition to modeling of equipment, FMP can be extended for station/substation reliability evaluation, in which each component is represented by a detailed Markov model.

For example, for a simple substation with five components, shown in Figure 4.6, assume the availability of transmission lines is 100%. For simplicity, all the circuit breakers (CB) (labeled as 1, 2, 5) and transformers (TF) (labeled as 3,4) are assumed to be identical with the same operation and deterioration conditions; each component is modeled by a 11-state Markov process shown in Figure 6.1, in which inspection states are ignored. The minor maintenance rate is three times the major maintenance rate. It is assumed that the cut-sets of third order and higher can be neglected.

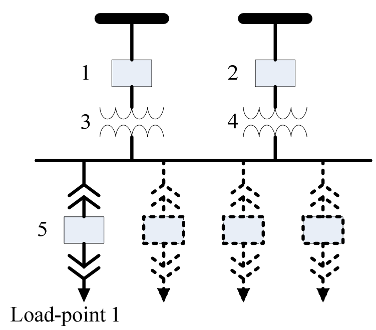


Figure 6.33 Topology of a Five-Component Substation in Case C

Given a triangular fuzzy maintenance rate for transformers and a symmetrical Gaussian fuzzy maintenance rate for circuit breakers, the corresponding fuzzy availability for load point 1 can be calculated. The fuzzy inputs, as well as the fuzzy outputs, are presented in Figure 6.34 and Figure 6.35.

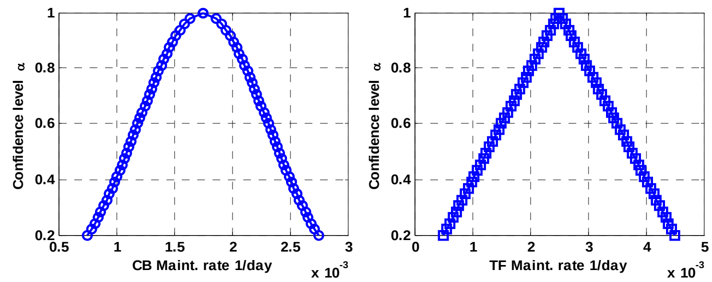


Figure 6.34 The Input Fuzzy Maintenance Rate for Circuit Breakers (a) and Transformers (b) for Case C

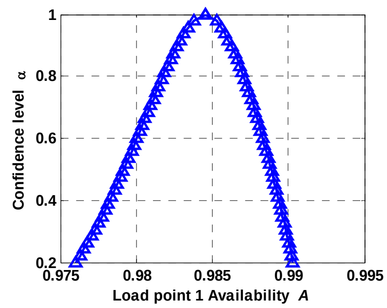


Figure 6.35 The Output Fuzzy Availability at Load-Point 1 for Case C

Moreover, the optimal maintenance rates of circuit breakers and transformers that maximize the availability of load-point 1, can be calculated, which is also in accordance with previous models shown in Figure 6.36 [96].

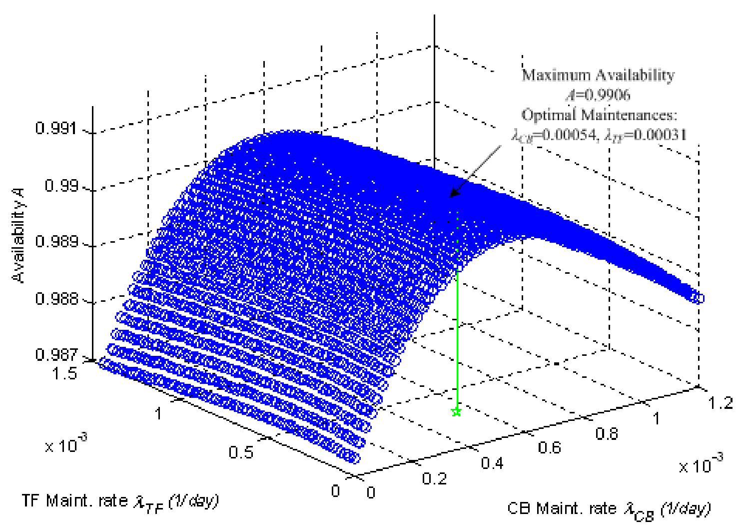


Figure 6.36 The Optimal Maintenance Rates for Circuit Breakers and Transformers that Maximize Load Point 1 Availability for Case C

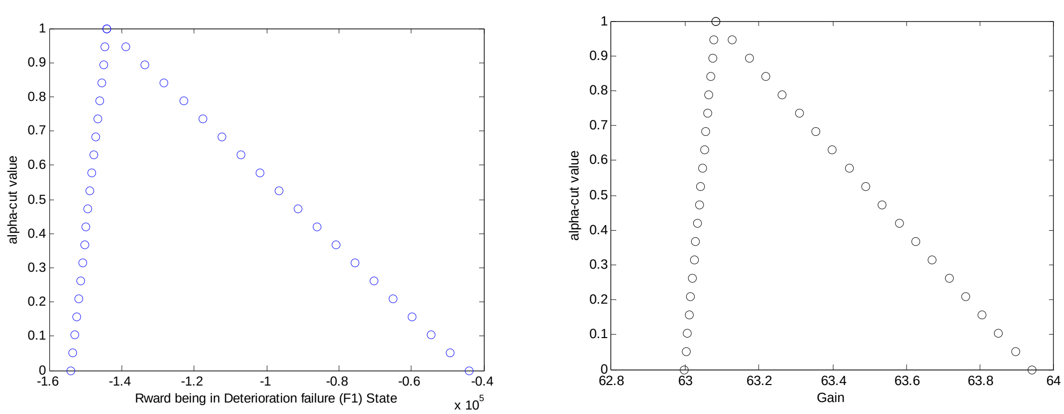
The above three cases also validate the following advantages of the proposed method over existing Markov processes with fuzzy calculations:

1) The proposed method is more compatible with current reliability models than existing fuzzy methods. It still uses the current reliability models to set objective functions for calculating the left and right extremes of availability index;

2) The proposed method can be extended to calculate system-level reliability indices including uncertainties. Traditional fuzzy arithmetic methods rely on explicit reliability indices equations, and usually it is difficult to get these equations for system-level studies. However, the proposed method in this dissertation does not have that requirement.

6.6.4 Equipment Economic Cost Modeling through FMDP

Following is a simple case study to illustrate the FMDP. In the Markov decision model utilized to calculate expected economic benefit for equipment in Figure 3.18, assume that the cost of being in deterioration failure state (F_1) is not known precisely, i.e., uncertain. A triangular fuzzy reward membership function is used to model this uncertain cost, and fuzzy Markov decision processes will be used to calculate the fuzzy economic benefit value for equipment. Figure 6.37 (a) gives the input fuzzy reward of state F_1, and Figure 6.37 (b) provides the corresponding output fuzzy economic benefit value.



(a) (b)

Figure 6.37 Input Fuzzy Reward of State F1 (a), and the Output Fuzzy Economic Benefit Value of Equipment (b)

Similar to fuzzy maintenance rate described in Figure 8.5, a fuzzy cost is a combination of range of possible cost values and the associated existing possibility of being at each value point. For example, in Figure 6.27, the *x*-axis is the possible economic benefit value points, and *y*-axis is the corresponding possibility of having that value.

Comparison of Figure 6.37 (a) and (b) shows that there is little shape changes. This is true as the relationship between input the parameter associated with reward value of being in F_1 and the output parameter associated with economic benefit B_{Equ}. is approximately linear, which is similar to the relationship between λ_{I} and $B_{\mathrm{Equ.}}$, as plotted in Figure 6.7.

However, it should be noted that although there are unapparent changes of the shape in output fuzzy benefit values, the optimal policy may change under various fuzzy cost input. Thus is because under each possible R_{F1} values, the MDP will determine an optimal policy for that specific R_{F1} value only.

Similarly, as the relationship between B_{Equ} and B_{Sub} have been established by (4.8) and (4.10), above algorithm can be extended to calculate substation level economic benefit by applying fuzzy extension principles on these two equations. Due to limitations of space, the process is not presented in this dissertation.

6.7 Sensitivity Studies of Fuzzy Maintenance Rates

In practice, determining the type of appropriate fuzzy membership functions is important. In this dissertation, the impact of varying fuzzy membership functions towards the calculation of reliability indices is studied, including varying membership function types, parameters, and comparison of uncertainties associated with different membership functions, in order to deal with vagueness and imprecision associated with input data.

6.7.1 Relationship between FMP and Traditional Markov Process

Following is an example describing the comparison of FMP with MP. The gradual reduction in the range of the input fuzzy maintenance rate in Figure 6.27 for Case A decreases the range of the output fuzzy availability. Figure 6.38 shows the impact of reducing the fuzzy maintenance rate range on the fuzzy availability. Also, the fuzzy Markov process is an extension of traditional Markov process by including the fuzzy calculations.

Theoretically, the traditional MP can be treated as a special case of FMP, where the input and output supports equal zero. The Calculation of fuzzy reliability indices is also based on the traditional Markov processes.

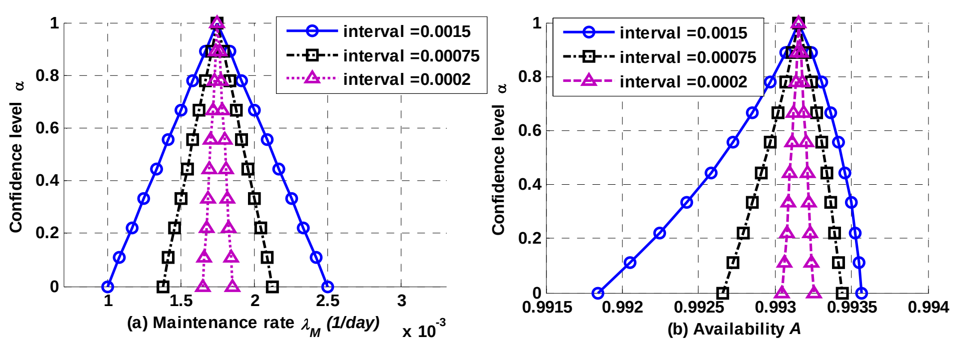


Figure 6.38 Reduction in the Input Fuzzy Values and the Corresponding Outputs
(a) Input fuzzy maintenance rates for Case A; (b) Output fuzzy availability for Case A.

The major difference between fuzzy Markov processes and traditional Markov processes is the introduction of fuzzy transition rates/probabilities, and the fuzzy reliability indices. The fuzzy transition rates/probabilities are capable of modeling and quantifying the uncertainties in data, and the fuzzy reliability indices will provide the possibility or confidence level of results associated with reliability indices.

6.7.2 Effects of Various Membership Functions

In order to compare various MFs and their impact on reliability indices, several conditions should be met in order to make the comparison reasonable, e.g., under the same centroid or entropy values.

Centroid x^* is a measure of the center point in a fuzzy MF $\mu(x)$ as defined in Equation (6.10),

$$x^* = \sum_i^N [x_i \cdot \mu(x_i)] \Big/ \sum_i^N \mu(x_i) \tag{6.10}$$

where, N is the total number of discrete points in $\mu(x)$.

This parameter is one of the frequently used defuzzification indices, which can be interpreted as the most possible crisp value of a MF.

Besides the centroid, there are other defuzzification methods available, such as bisector of area and mean of maximum [97].

Entropy Y is a measure of the uncertainty of a fuzzy MF $\mu(x)$. It describes how much ambiguity or uncertainty a MF contains. Generally, the larger the support of a MF, the higher entropy value it has. Equation (6.11) gives a widely used *linear entropy* measure.

$$Y = \frac{2}{N}\left[\sum_{i=1}^{N} \min\left(\mu(x_i), 1-\mu(x_i)\right)\right] \tag{6.11}$$

The linear entropy gives a quantitative parameter for the amount of uncertainty of a fuzzy MF. For example, if Y_A and Y_B are the entropy values of two triangular fuzzy MFs, μ_A and μ_B, and $Y_A > Y_B$, then fuzzy MF μ_A contains more uncertainty information than μ_B.

i) <u>Effects of MF type</u>

In order to analyze the impact of varying fuzzy MF types on the results, Case A is used as a base case. A trapezoidal fuzzy MF and a symmetric Gaussian MF are used as replacements for the original triangular MF in Figure 6.27. In order to make the studies comparable, the centroid and linear entropy of the new input fuzzy MF are the same as the original triangular MF in Figure 6.27 (centroid x^*=0.00175, linear entropy Y=0.1954). The trapezoid and symmetric Gaussian input MFs and the corresponding fuzzy availability, frequency, and duration are shown in Figure 6.39 and Figure 6.40.

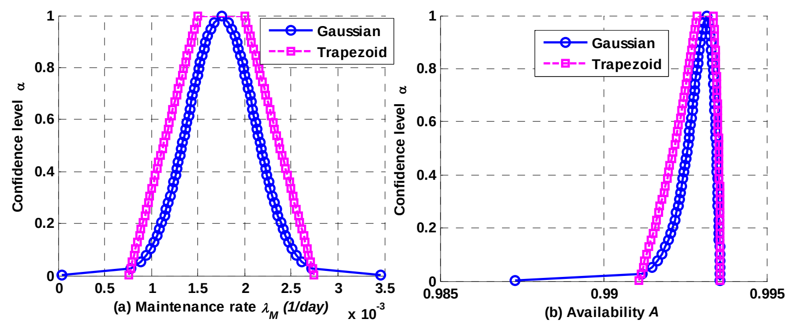


Figure 6.39 (a) The Input Trapezoid and Symmetrical Gaussian Membership Functions for Case A; (b) The output fuzzy availability for Case A

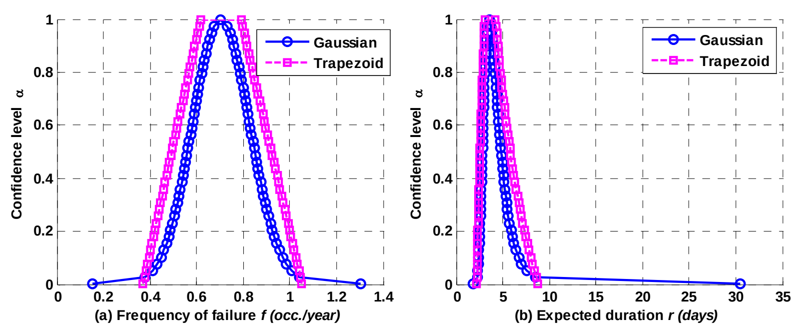


Figure 6.40 (a) The Output Fuzzy Frequency; (b) The output fuzzy durations

Table 6.14 gives the comparison of the centroid and linear entropy values of these input MFs. As entropy is a measure of uncertainty, Table 6.14 also indicates that the FMP merely transfers the uncertainties from the input MF to the output fuzzy reliability indices. The FMP alone does not generate any uncertainty, and the traditional Markov processes can be treated as a special fuzzy MP, where the uncertainty equals zero (or the entropy is zero).

TABLE 6.14 MEMBERSHIP FUNCTIONS

Membership Function Type	Input Fuzzy Maintenance Rates		Output Fuzzy Availabilities		Output Fuzzy Frequencies		Output Fuzzy Durations	
	Centroid	Entropy	Centroid	Entropy	Centroid	Entropy	Centroid	Entropy
Triangular	0.00175	0.1953	0.99309	0.24515	0.70420	0.24515	3.68061	0.24515
Trapezoid	0.00175	0.1940	0.99295	0.24515	0.70558	0.24515	3.97211	0.24515
Symmetrical Gaussian	0.00175	0.1942	0.99307	0.2451	0.70441	0.2451	3.72742	0.2451

ii) <u>Shifting input fuzzy MFs</u>

Another issue of interest to engineers is to determine the range in which the output fuzzy reliability indices will be sensitive to the input fuzzy maintenance rates. This can be addressed by shifting the input fuzzy MF in a given range and comparing the shapes of the output fuzzy reliability indices.

For example, in Case A, given a symmetrical Gaussian MF with a centroid value of 0.00175 and shift it to the values of 0.00215, 0.00255, 0.00295, the corresponding fuzzy availability, frequency, and durations are calculated. The fuzzy maintenance inputs, as well as the outputs, are presented in Figure 6.41.

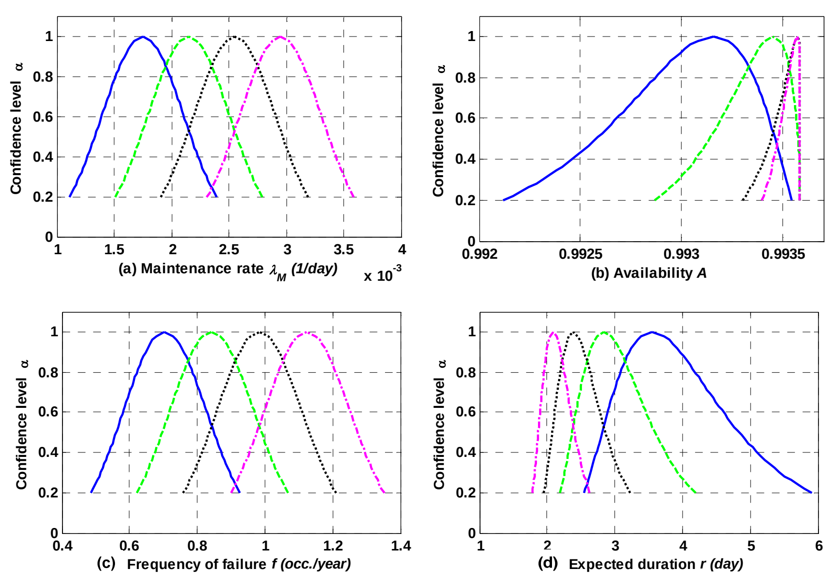


Figure 6.41 (a) Shifting of Input Fuzzy Maintenance Rates in Case A; (b) The Corresponding Fuzzy Availability Changes; (c) The Corresponding Fuzzy Frequency of Failure in Case A; (d) The Corresponding Fuzzy Expected Duration
— Centroid=0.00175; --- Centroid = 0.00215; … Centroid = 0.00255; -.- Centroid =0.00295

By comparing the change in shape of fuzzy reliability indices, one can observe in which range the FMP model is more sensitive to the fuzzy input MFs. For example, the fuzzy availability indices are more sensitive when the centroid range of fuzzy input is (0.00175, 0.00215) rather than the range of (0.00255, 0.00295).

Similarly, from Figure 6.41(c), the fuzzy frequency of failure indices has no distinct sensitivity among the ranges. In Figure 6.41 (d), the fuzzy expected duration of failure indices are more sensitive when the centroid range of fuzzy input is (0.00255, 0.00295) rather than the range of (0.00175, 0. 00215). The variations are caused by the nonlinear characteristics of the Markov model among different reliability indices.

Furthermore, the intuitive relationship between fuzzy reliability indices and the input boundaries are shown in Figure 6.42.

Given the maintenance rates with uncertainties represented by an interval, the corresponding availability interval can be calculated. However, the information on how much uncertainty exists at each possible availability value within the interval is still unknown. This is indicated in Figure 6.42 (b). In contrast, the utilization of fuzzy availability MF can be used to meet the shortcoming of quantified uncertain information, which is presented in Figure 6.42 (a).

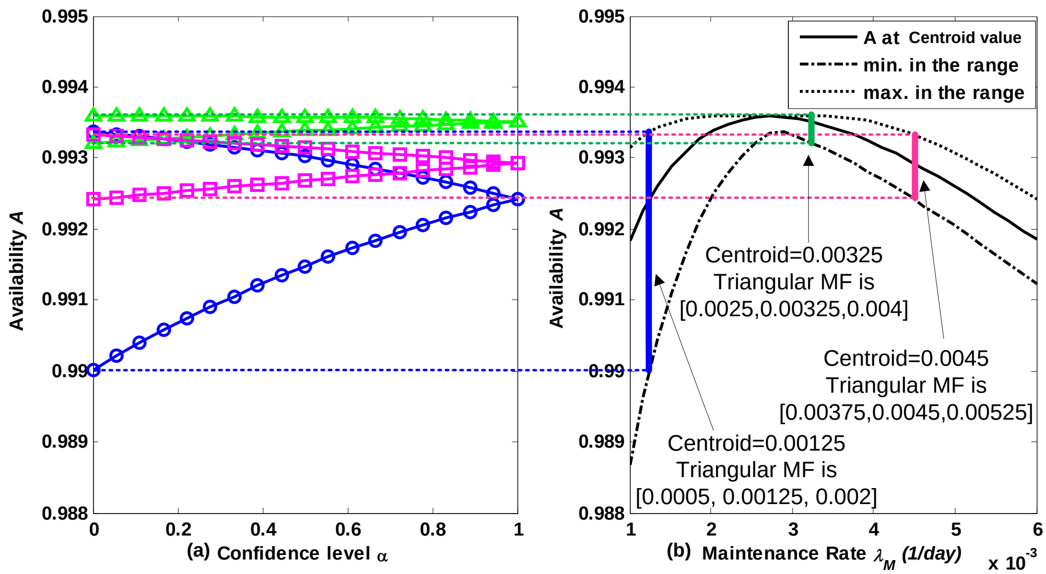


Figure 6.42 The Relationship of Fuzzy Reliability Results and Reliability Intervals

6.8 Summary of FMP and FMDP

A fuzzy Markov model incorporating uncertain transition rates/probabilities is developed in which the extension principle is used for calculating reliability indices. Examples of how FMP can be applied in modeling aging equipment and substations are given where the fuzzy reliability indices are calculated and illustrated. Sensitivity studies are also performed to determine the impact of varying input fuzzy MFs.

Results obtained from case studies and the sensitivity analyses validate the advantages of including fuzzy set theory in reliability evaluations: The fuzzy reliability indices not only calculate the boundaries of the indices but also provide quantified information for the degree of possibility or confidence in reliability indices.

Compared with traditional MP and fuzzy Markov models in previous research, the algorithm developed in this dissertation has the following advantages:

1. The algorithm provides a general approach for solving Markov models with uncertain transition rates/probabilities. This method is compatible with current Markov models

for modeling aging equipment or substations, and can be treated as an extension to the traditional Markov processes;

2. The fuzzy reliability indices calculated in this dissertation provide more valuable information than crisp reliability indices, where the quantitative information of how much uncertainty is associated with every parameter value can be incorporated;
3. The method is also capable of determining optimal maintenance to maximize/minimize reliability indices.

6.9 Case Studies of Parallel Monte-Carlo Simulation

6.9.1 Validation of Sequential Multi-State MCS for Equipment

An analytical method, such as Markov Processes is selected as reference, to validate the correctness of sequential MCS for reliability evaluation of equipment with multi-state.

Figure 6.43 is a Markov Process for equipment with operation (UP), maintenance (M) and failure (DN) states.

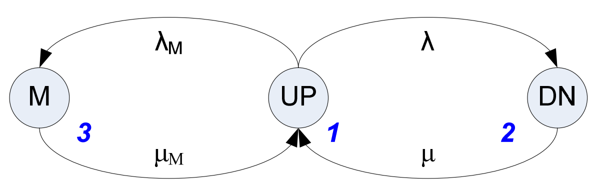


Figure 6.43 State-Space Diagram of a Three-state Markov Process

In Figure 6.43, the transition times for all transitions are assumed to be exponentially distributed. Calculation of availability A, frequency of failure f, and expected duration between failures r from analytical approaches are available from [9]. The values of the parameters of this model are chosen to be λ=1/1095 failures/yr, μ=1/40 replacement/yr, λ_M=1/365 maintenance/yr, μ_M=1/10 repair/yr. In this model, repair and maintenance are modeled separately, where repaired process is embedded into failure (DN) state.

Following the procedures described in Section 5.5.1, the reliability history chart is generated by sequential MCS, and the reliability indices as well as the probability distributions of reliability indices are presented in Figure 6.44, and Figure 6.45. The analytical results are also plotted in these figures as a reference.

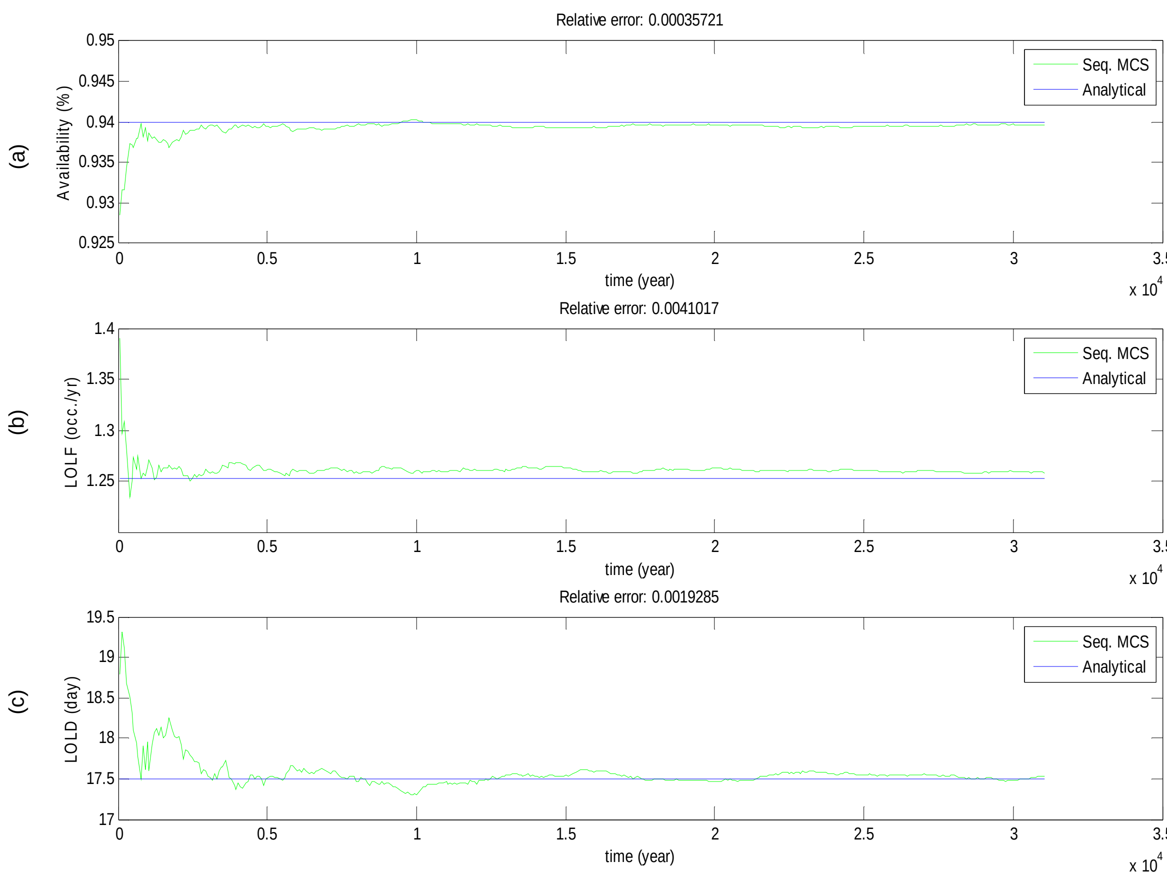


Figure 6.44 Simulation Results of the Reliability Indices of a Three-state Equipment.
(a) Availability A ; (b) Frequency of failure f ; (c) Duration between failures r

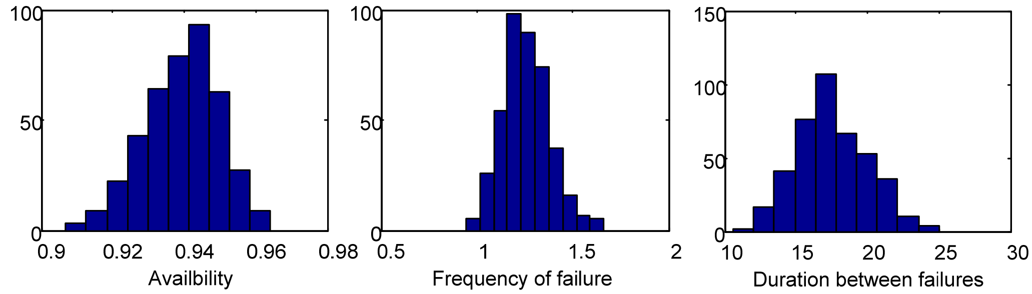


Figure 6.45 The Probability Distributions of the Reliability Indices of a Three-state Equipment

From Figure 6.44 to Figure 6.45, it can be observed that the sequential MCS provide very close results, compared with the results acquired by analytical method (the relative error for A, f and r are 0.0357%, 0.41%, 0.193%, respectively).

Firstly, Figure 6.44 validates the correctness of the hypothesis that the selection of initial state in every period doesn't have explicit impact on the final result. The sensitivity study of the impact of the selection of the length of a period is omitted in this dissertation.

Moreover, this result clearly validates the correctness and accuracy of the modified sequential MCS in equipment reliability evaluation.

However, it should be emphasized that, for equipment and small system reliability evaluations, analytical method such as Markov Processes would be the first choice. The simulation of equipment with multi-states provides a foundation for studying large scale system reliability evaluation, where impact of equipment toward the system reliability needs to be studied.

6.9.2 Validation of Parallel MCS for equipment

The same model in Figure 6.43 is scaled and executed on 4 nodes on the Rock-131 supercomputers in SDSC [102]. In order to examine the improvement of the computation efficiency, the maximum iterations number of 2,000,000 (number periods is

10,000, transitions within each period is 200) is selected as the stop criteria, rather than the coefficient of variance.

Figure 6.46 and Figure 6.47 show the results of parallel simulation. The results are compared with both the results from single processor simulation, and the results from analytical method.

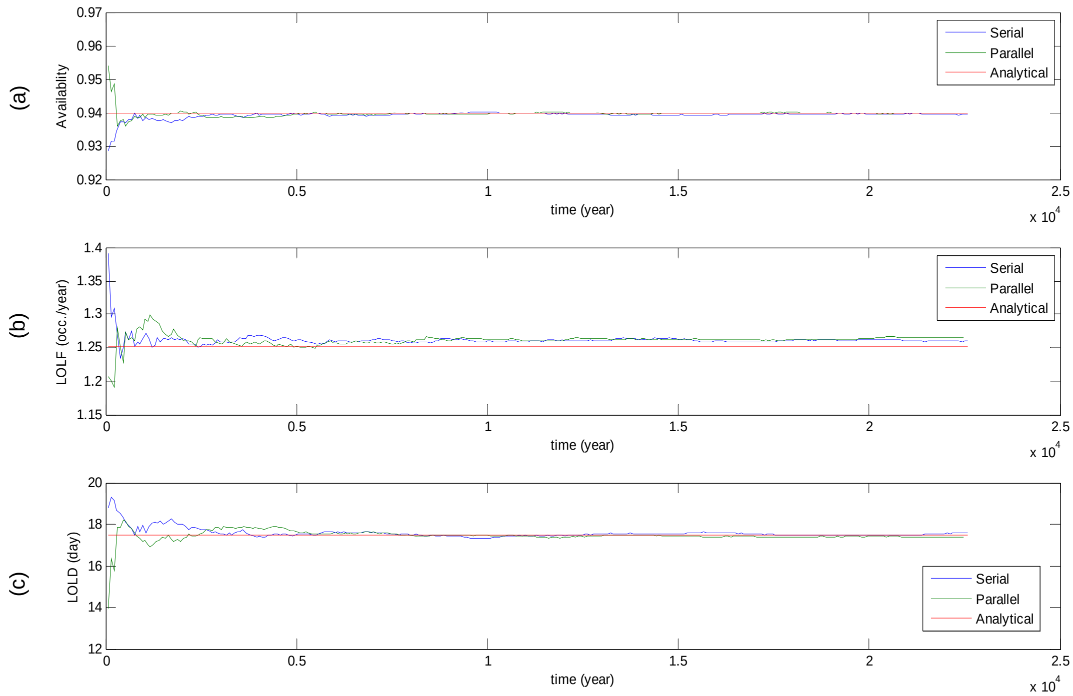


Figure 6.46 Parallel Simulation Results of the Reliability Indices of a Three-state Equipment (a) Availability A; (b) Frequency of failure f ;(c) Duration between failures r

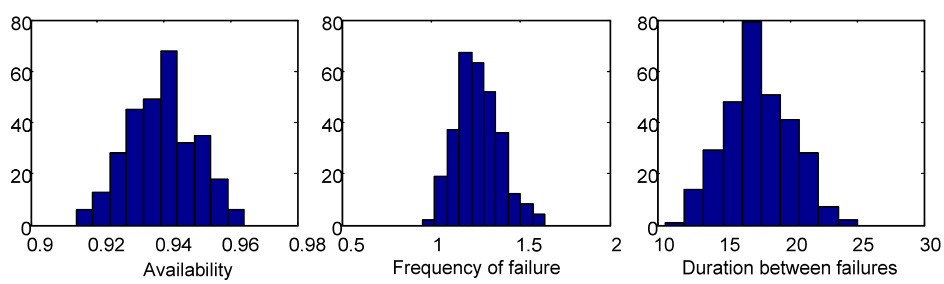


Figure 6.47 The Probability Distributions of the Reliability Indices of Three-state Equipment from Parallel Simulation

Again, the parallel simulation can achieve very close results compared with analytical method. However, the execution time is much less than using a single processor demonstrated in Case A.

It should be noted that, the difference between the values of reliability indices calculated from a single processor and parallel processors is caused by the difference between the adopted random number generated on Star-P and MATLAB. In parallel simulation program on Star-P environment, the algorithms for random number generation is different with the algorithm used by MATLAB, which result in the slight difference among reliability indices, and the probability distribution of those indices.

6.9.3 Parallel MCS for a Parallel System

A simple parallel connected system is used as a demonstration of using parallel simulation for system reliability evaluation.

Suppose in the parallel connected system, each component is modeled by a three-state Markov process in Figure 6.43. The parameters for each model are chosen as λ_1=1/1095, μ_1=1/40, λ_{M1} =1/365, μ_{M1}=1/10 ; λ_2=1/543, μ_2=1/20, λ_{M2} =1/180 , μ_{M2}= 1/5.

Following the procedure to generate reliability history chart described in Figure 5.9, the reliability indices are calculated. Figure 6.48 and Figure 6.49 are the system reliability results achieved by the parallel simulation, as well as the analytical results given as a reference.

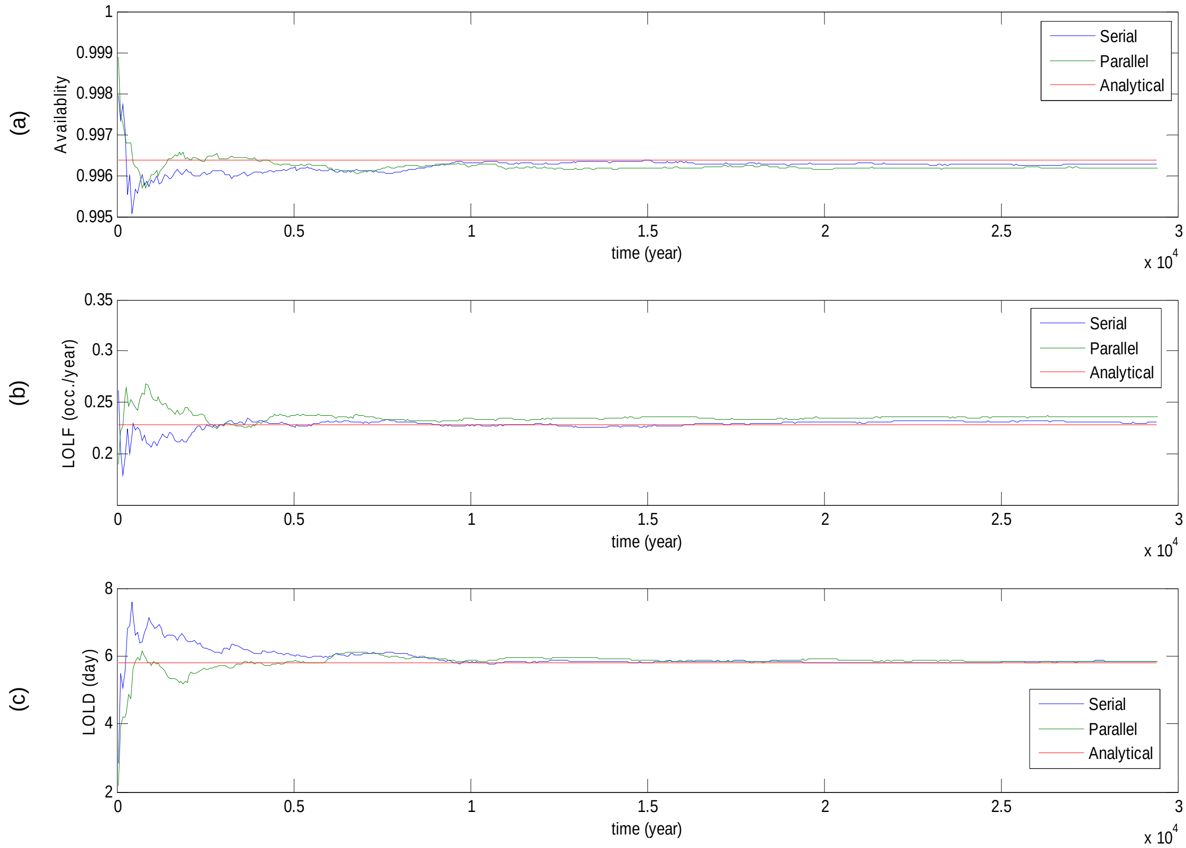


Figure 6.48 Parallel Simulation Results of the Reliability Indices of a Parallel Connected System (a) Availability A_{sys} (b) Frequency of failure *fsys* (c) Expected duration between failures *rsys*

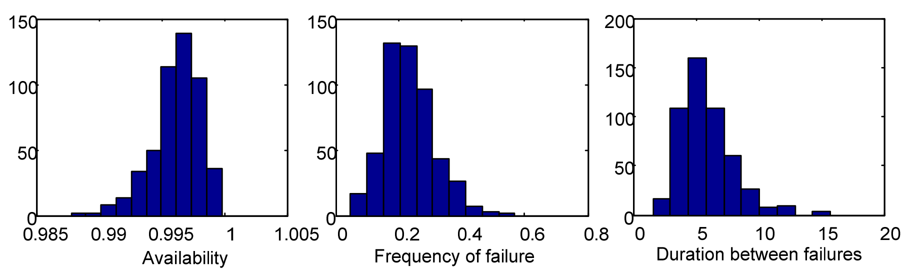


Figure 6.49 The Probability Distributions of the Reliability Indices of a Parallel Connected System

Again, Figure 6.48 and Figure 6.49 validate the accuracy of using parallel simulation method, for system level reliability studies.

6.9.4 Parallel MCS for Substation

Moreover, parallel MCS method is applied for reliability assessment of a substation, to validate the correctness of this method, and its advantages in computation efficiency.

The simple substation presented in Figure 4.6 will be studied. Equipment (transformers and circuit breakers) within this substation are modeled by a three-state model, and the algorithm will study the load point 1 availability, through parallel MCS method. For simplicity, it is assumed that the availability of sub-transmission lines is 100% (no fault).

The load point 1 availability acquired by parallel MCS method is presented in Figure 6.50. For validation purposes, the availability values calculated by analytical approaches and traditional sequential MCS method are also presented for comparison.

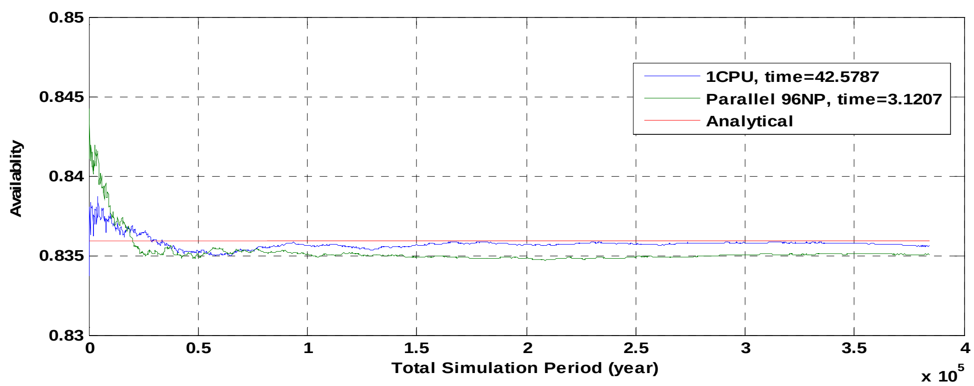


Figure 6.50 Comparison of Load Point Availability Conducted by Parallel MCS and other methods

Again, Figure 6.50 validates that the result achieved by parallel MCS method is very close to the result calculated by analytical or traditional MCS methods, while significantly reduces the execution time. Figure 6.51 provides the execution time length (unit: Second) of the parallel MCS method, when utilizing 8, 16, 32, 64 and 96 CPUs, which prove the advantages of parallel MCS in reducing execution time.

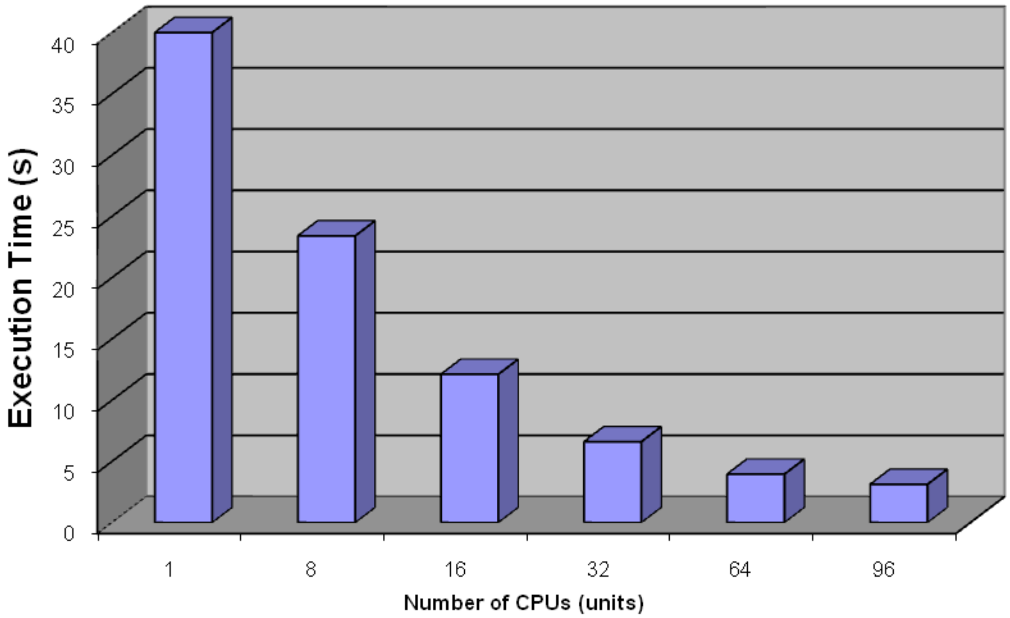


Figure 6.51 Comparison of Execution Time under different number of CPU

It should be noted that, the difference between the availability values calculated from parallel MCS, and traditional MCS is caused by the difference between the random number generation approaches adopted on Star-P and MATLAB. This is similar to the difference in results obtained in Figure 6.46 and Figure 6.48.

6.10 Summary of Parallel MCS

- Performance study of parallel computing in developing the methodology to scale down an existing algorithm and run on parallel computers is necessary. This study is preferred to be performed by rewriting the algorithm in C or FORTRAN codes, rather than high level computer languages such as Star-P, because it allows manual controls distribution of tasks to different processors and coordinate the communications among the processors. However, this dissertation aims at developing algorithms rather than scale down an existing algorithm, thus studies to examine the speedup and efficiency thing parallelizing strategy is not presented.

- Variance reduction techniques, such as *important sampling* [21] and *antithetic variates method* [59] may be necessary when the number of states increases. Because if the number of rare events sampled is insufficient, the accuracy of the reliability indices as well as the convergence speed will be reduced.
- In parallel simulation, the random number generated among different processors must be irrelevant. It is very important to assure the low relevance of the random numbers generated among the processors, to achieve high accuracy of the results. This can be achieved by selecting different seed, or utilized some toolbox for simultaneously generating random numbers among different processors.

Appendix I: Input Values

Tables 6.15 and 6.16 give the transition rates and probabilities all equipment.

TABLE 6.15 TRANSITION RATES AND REPAIR RATES OF EQUIPMENT

Failure/Repair Rates	B1(times/ day)	B2(times/ day)	T1(times/ day)	T2(times/ day)	B3(times/ day)	B4(times/ day)	B5(times/ day)	B6(times/ day)	B7(times/ day)
λ_0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
λ_{12}	0.0009	0.0009	0.0009	0.0009	0.001	0.001	0.0012	0.0013	0.0013
λ_{23}	0.0008	0.0008	0.0007	0.0007	0.0009	0.0009	0.0011	0.0011	0.0012
λ_{3f1}	0.0014	0.0014	0.001	0.001	0.0014	0.0014	0.0014	0.0014	0.0014
μ_0	0.1429	0.1429	0.0714	0.0714	0.1429	0.1429	0.1429	0.1429	0.1429
μ_1	0.025	0.025	0.0167	0.0167	0.025	0.025	0.025	0.025	0.025
μ_{MM}	0.2	0.2	0.1429	0.1429	0.2	0.2	0.2	0.2	0.2
μ_M	1	1	1	1	1	1	1	1	1
μ_I	24	24	24	24	24	24	24	24	24
K	3	3	3	3	3	3	3	3	3

TABLE 6.16 TRANSITION PROBABILITIES OF MARKOV MODELS FOR EQUIPMENT

Source State – Destination State	B1	B2	T1	T2	B3	B4	B5	B6	B7
MM1-D1	1	1	1	1	1	1	1	1	1
MM1-D2	0	0	0	0	0	0	0	0	0
MM1-D3	0	0	0	0	0	0	0	0	0
MM2-D1	0.9	0.89	0.88	0.9	0.9	0.9	0.9	0.9	0.9
MM2-D2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
MM2-D3	0.01	0.02	0.03	0.01	0.01	0.01	0.01	0.01	0.01
MM3-D1	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
MM3-D2	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
MM3-D3	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
MM3-F1	0	0	0	0	0	0	0	0	0
M1-D1	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
M1-D2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
M1-D3	0	0	0	0	0	0	0	0	0
M2-D1	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
M2-D2	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
M2-D3	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
M3-D1	0	0	0	0	0	0	0	0	0
M3-D2	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
M3-D3	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
M3-F1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Table 6.17 provides the expected cost of all equipment.

TABLE 6.17 EXPECTED COST OF BEING IN EVERY STATE OF ALL EQUIPMENT IN SUBSTATION
(Unit: $/day, the negative sign means the cost)

Source State – Destination State	B1($)	B2($)	T1($)	T2($)	B3($)	B4($)	B5($)	B6($)	B7($)
I_1	-200	-200	-500	-500	-200	-200	-200	-200	-200
I_2	-200	-200	-500	-500	-200	-200	-200	-200	-200
I_3	-200	-200	-500	-500	-200	-200	-200	-200	-200
MM_1	-14400	-14400	-36000	-36000	-14400	-14400	-14400	-14400	-14400
MM_2	-14400	-14400	-36000	-36000	-14400	-14400	-14400	-14400	-14400
MM_3	-14400	-14400	-36000	-36000	-14400	-14400	-14400	-14400	-14400
M_1	-1200	-1200	-3000	-3000	-1200	-1200	-1200	-1200	-1200
M_2	-1200	-1200	-3000	-3000	-1200	-1200	-1200	-1200	-1200
M_3	-1200	-1200	-3000	-3000	-1200	-1200	-1200	-1200	-1200
F_0	-100000	-100000	-200000	-200000	-100000	-100000	-100000	-100000	-100000
F_1	-144000	-144000	-1000000	-1000000	-144000	-144000	-144000	-144000	-144000

Appendix II: List of Assumptions

1. Assume equipment can fail due to both random and deterioration failures.
2. Assume minor and major maintenance rates is constant; minor maintenance rate is three times of major maintenance rate.
3. Assume all equipment is operated under normal power ratings.
4. Assume the random failure rate λ_0 and repair rate μ_0 are constant, in equipment reliability models

CONCLUSION AND FUTURE RESEARCH

Conclusion

In this dissertation, the approaches for studying and optimizing equipment maintenance for substations were designed. Several stochastic-based algorithms were developed for evaluating substation reliability and economic cost, and determining the optimal maintenance schedules/policies that improves substation reliability.

Following is a summary of the contributions of this dissertation.

1) Equipment Reliability Modeling including Maintenance, Aging, and Human Error

An algorithm for developing multi-state SMP-based equipment reliability models which incorporate deteriorations, inspections, maintenances, failures, human errors, and replacements was provided. Compared with our previous studies and similar researches, the algorithm has following advantages:

- It covers most frequently occurring activities related with equipment reliability, including inspection, minor and major maintenances, failures, replacement, and human errors. Compared with previous Markov models for reliability studies, it is more accurate and practical.
- It incorporates inspections that enable studying condition monitoring as well as predictive maintenance decisions in stochastic models.
- It includes human error that enables studying the sensitivity of human induced errors toward equipment reliability indices.

2) Equipment Economic Modeling based on Semi-Markov Decision Process

The economic cost models based on semi-Markov decision process provide a probabilistic approach, for computing the expected cost of equipment. The model can be used for determining optimal maintenance policies at each deterioration stage. Compared with existing economic cost models based on Markov models (a brief description of a typical model is available in Section 3.9), the SMDP-based model has the following advantages:

- It considers the possibility of having various actions at each deterioration stage, while other models do not.
- It determines the optimal maintenance policy by using policy iteration algorithm in semi-Markov decision process.
- By combining equipment reliability and economic cost model, an optimization scenario that maximizes equipment benefit while satisfying target availability constraint is developed. This scenario is valuable for making preventive maintenance decisions (maintenance rate) and predictive maintenance decision (optimal maintenance policy) together, for critical equipment.

3) Substation Reliability and Economic Cost Modeling

One of the significant contributions of this dissertation is to develop models for substation level reliability evaluation and economic analysis, based on equipment level models utilizing minimum cut sets approaches. Case studies of reliability evaluation and economic cost analysis with detailed modeling of equipment maintenance for a nine-equipment substation are conducted.

The proposed approaches have the following advantages:

- They enable studying the impact of equipment maintenance schedules of aging equipment toward reliability indices of entire substation.
- They incorporate detailed modeling of aging processes and maintenance on individual equipment, while still compatible with most existing reliability models.
- They include an algorithm to quantify the equipment's contribution toward entire substation availability, considering both topology locations and relative conditions of equipment. The algorithm can assist asset managers identifying critical equipment within a system.
- Because the proposed substation economic cost model is based on the detailed equipment models that contain investment/replacements, maintenance, and outage penalty costs, it is more accurate and practical.

4) Maintenance Optimization for Substations

A Particle Swarm Optimization-based optimization process was developed to determine the optimal maintenance rates for all equipment in a substation. Case studies of different scenarios were presented that demonstrate the process of computing optimal maintenance rates to: 1) maximize substation availability; 2) maximize substation economic benefit with target availability constraints; or 3) maximize substation availability with economic benefit constraints. The optimization process has following advantages

- It extends the concept of maintenance optimization from equipment to system level.

- The comparison results indicate that maintenance optimization should be considered globally for all equipment in a system, in order to efficiently improve overall substation availability.
- The adoption of PSO technique enables optimizing multi-decision variables with less computation time, which is an effective tool for substation maintenance optimization.
- The scenarios developed can be easily extended, to solve maintenance optimization problems with multi-constraints for practical applications.

5) Fuzzy Markov Process

A fuzzy Markov model incorporating uncertain transition rates/probabilities was developed in which the extension principle is used for calculating reliability indices. Results obtained from case studies and the sensitivity analyses validate the advantages of including fuzzy set theory in reliability evaluations: the fuzzy reliability indices not only calculate the boundaries of the indices, but also provide quantified information for the degree of possibility or confidence in reliability indices.

Compared with traditional Markov process and fuzzy Markov models in previous researches, the algorithm developed in the research has the following advantages:

- It provides a general approach for solving Markov models with uncertain transition rates/probabilities. This method is compatible with current Markov models developed for aging equipment or substations, and can be treated as an extension to the traditional Markov processes.
- The fuzzy reliability indices calculated in this paper can provide more valuable information than crisp reliability indices, where the quantitative information of

how much uncertainty is associated with every parameter value can be incorporated.

- It is capable of determining optimal maintenance to maximize/minimize reliability indices.

6) Parallel Monte-Carlo Simulation

A method to simulate the multi-state stochastic processes of equipment and system was developed, by generating the reliability history charts based on sequential MCS. A parallel Monte-Carlo simulation algorithm was developed, to separate the simulation and execute them simultaneously on different CPUs.

Compared with traditional MCS, the parallel Monte-Carlo simulation algorithm developed here has the following advantages:

- It reduces the total simulation execution time while maintain high accuracy and simulation details.
- It efficiently utilizes multi-processors and large memory resources that will be widely adopted among personal computers in next decades.
- It extends traditional sequential MCS with the capability to simulate and study the impact of equipment maintenance toward system level reliability changes.

Recommendation for Future Research

Equipment-level Maintenance Optimization

- Retirement Planning

  Optimal retirement/replacement management is an important part of asset management. Minimizing life cycle cost (LCC) is an important object adopted by many utilities, which aims reducing long term investment / maintenance costs.

Effective retirement / replacement plan will reduce failures. However, extensive studies of the impact of replacement plan toward equipment reliability and economic cost should be conducted. The equipment economic cost model developed in this dissertation can potentially be used to answer this question.

- Maintenance Delay

  In practice, maintenance may be approved but the action may be delayed, due to insufficient crews, maintenance resources, or operational reasons. However, whether the delay improves the risk of equipment or system failures are not examined. The equipment reliability model developed in this dissertation can potentially incorporate this, and study the impact of maintenance delay.

Substation-level Maintenance Optimization

- Incorporating Flexible AC Transmission System (FACTS) in Substation Reliably Evaluation

  With the further deployment of Smart Grid, FACTS has been implemented in many utilities. FACTS can provide dynamic reactive power compensation (such as Static Var Compensation-SVC), reduce transmission resistance (such as Series Compensation-SC), improve distribution reliability indices (such as Battery system), etc. Therefore, development of substation reliability and cost models, while incorporating FACTS systems are potential future researches.

- Incorporating Intermittent Generation and Stochastic Load Profiles in Maintenance Optimization

  Over-loading will increase equipment deterioration speed. Usually utilities have standard to set a maximum operation power over certain equipment (such as operate transformer should be less than 80% of its rated power). However, this deterministic limit can be violated due to stochastic load changes. Similarly, for substations that deliver intermittent power (such as substations connecting to wind farms), the characteristics of random generation will increase the difficulty in maintenance policies decisions. Therefore, how to incorporate these stochastic load changes in maintenance optimizations is another valuable research.

Fuzzy Analysis

This dissertation only studied the impact of uncertain maintenance rates toward equipment, and substation level availability. But its impact on larger systems is not conducted. A study to extend the algorithm developed in Section 5.2 to the areas of transmission or composite systems studies can be performed.

Parallel Monte Carlo Simulation

- Perform the economic cost simulation, to simulate the operation and maintenance cost for equipment or systems
- Extend the algorithm for larger scale reliability simulations, to exam its potential in reliability evaluations of practical systems, with detailed modeling of every component.

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