RELIABILITY MODELING AND EVALUATION IN AGING POWER SYSTEMS

A Thesis

by

HAG-KWEN KIM

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

August 2009

Major Subject: Electrical Engineering

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ABSTRACT

Reliability Modeling and Evaluation in Aging Power

Systems. (August 2009)

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Chair of Advisory Committee: Dr. Chanan Singh

Renewal process has been often employed as a mathematical model of the failure and repair cycle of components in power system reliability assessment. This implies that after repair, the component is assumed to be restored to be in as good as new condition in terms of reliability perspective. However, some of the components may enter an aging stage as the system grows older. This thesis describes how aging characteristics of a system may impact the calculation of commonly used quantitative reliability indices such as Loss of Load Expectation (LOLE), Loss of Load Duration (LOLD), and Expected Energy Not Supplied (EENS).

To build the history of working and failure states of a system, Stochastic Point Process modeling based on Sequential Monte Carlo simulation is introduced. Power Law Process is modeled as the failure rate function of aging components. Power system reliability analysis can be made at the generation capacity level where transmission constraints may be included. The simulation technique is applied to the Single Area IEEE Reliability Test System (RTS) and the results are evaluated and compared.

The results show that reliability indices become increased as the age of the system grows.

ACKNOWLEDGEMENTS

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1. INTRODUCTION

In power systems, effective reliability analysis and assessment are essential factors in operation, and planning [1]-[2] in the long term. Such analysis enables to supply continuous electric power for time-varying loads by predicting future system behaviors and making maintenance plans [3]-[5] at an appropriate time. A number of power system equipments, such as generators, transmission/distribution lines, or transformers have been increasingly getting older. According to U.S. National Academy of Engineering [6]-[8], North American electricity infrastructure has more than 200,000 miles of transmission lines and 950,000 MW of generating capacity with about 3,500 utilities. So it is called first world grid because of its size and complexity. However, it also received a grade of D because of aging or poor maintenance policies by American society of Civil Engineers (ASCE). In many electric utilities, maintenance planning and investment do not adequately cover growing load demand and aging of existing components. Low reliability due to aging not only declines a competitive advantage, or valuation in the energy utilities market, but also needs greater operation and maintenance costs. In the light of current situation, it is more important than ever to evaluate the aging of equipment quantitatively and incorporate this into the estimation of future reliability of the system. An acceptable level of reliability needs be achieved at the minimum possible cost. There exists trade off between reliability and costs. So, system performance optimization can be more effectively implemented by cost-reliability

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This thesis follows the style of *IEEE Transactions on Reliability.*

analysis based on multi-objectives optimization technique [9]-[10].

In general, equipment has three patterns over time, shown by Figure 1. The graph is called bathtub curve because of its looks. In the first stage, which is called infant mortality or burn in, failure rate is decreasing over time. So up times tend to become greater, i.e., reliability growth. In the second stage which is called useful life, failure rate is constant. There is no trend, indicating a renewal process. In the final stage, which is called wear out, failure rate is increasing. So time between failures becomes smaller, showing aging trend.

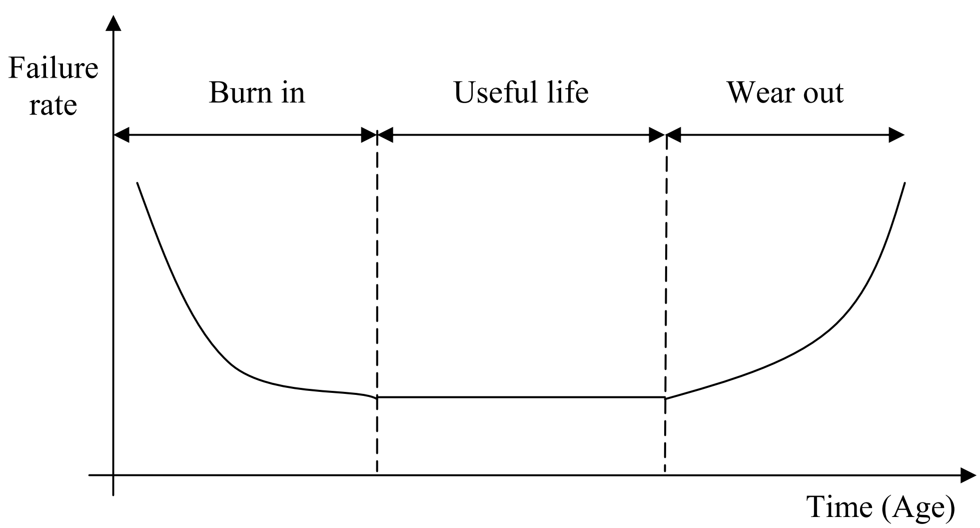

Figure 1: Failure Rate Curve of General Equipment over Time

There are three types of trends: zero, positive and negative trend [11]-[13]. If inter-arrival times have no patterns, i.e., neither improvement nor deterioration, the process has zero trends. However, if failure rate is increasing over time, the process has positive trend and indicates aging. When it is a decreasing function over time, the process has negative trend, showing reliability growth. In general, electromechanical equipment of power systems has positive trend as the age of components increases. Although reference [11] analyzed the trend in generating units, the mechanism of incorporating aging in power system reliability evaluation has not received considerable attention [14]. This thesis examines the issues related to incorporating aging effects in reliability evaluation of repairable power systems in details and introduces some methods using Monte Carlo Simulation. Reliability analysis is carried out in Hierarchal level 1 and Hierarchal level 2 [15]-[16]. The single area RTS [17]-[18] is used to illustrate application of proposed techniques.

2. PROBLEM FORMULATION

For purposes of reliability modeling, the repairable component of a system can be modeled as a Stochastic Point Process [19]. Figure 2 shows a sample path of Stochastic Point Process, $\{N(t), t \geq 0\}$ where N(t) is the number of events occurred during time t. Index x is inter-arrival time, and t is arrival time, i.e., time event occurred, illustrated by equations (1), (2), (3), and (4).

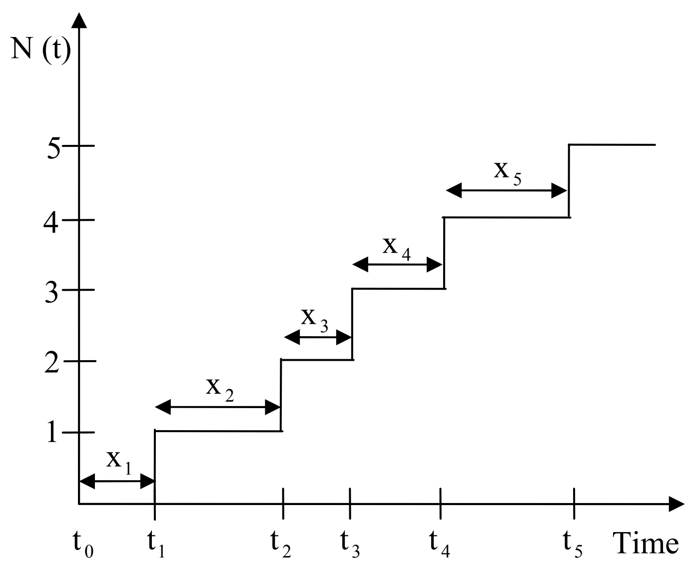

Figure 2: A Sample Path of Stochastic Point Process

$$t_0 = 0 \tag{1}$$

$$t_k = x_1 + x_2 + x_3 + ... + x_k \tag{2}$$

$$t_k = x_k + t_{k-1}, \ k \geq 1 \tag{3}$$

The expected value of N (t) can be represented by:

$$\Lambda(t) = E[N(t)] \tag{4}$$

The derivative of $\Lambda(t)$ is called the rate function or intensity function $\lambda(t)$ of the process and in reliability analysis represents the failure or repair rate depending upon whether up times or repair times are being modeled. In a Homogeneous Poisson Process (HPP) [20], $\lambda(t)$ is constant and equal to λ. The HPP is basically a renewal process with exponentially distributed inter-failure times. Reference [21] describes comprehensive models when the up times in a renewal process are non-exponentially distributed. A Non-Homogeneous Poisson Process (NHPP) [20] is, however, more general and can handle trends, aging or reliability growth, with proper specification of intensity rate function $\lambda(t)$.

The preliminary step of modeling and simulation is to detect the presence of aging in components. This is carried out by trend analysis [11]. The aim of trend analysis is to predict future's trend, or pattern of measurement, based on statistical, historical data. There are a number of quantitative trend test techniques [11], [22]. In this thesis, Mann's nonparametric test [11] is described. Statistic variable M is based on standard normal distribution with mean 0 and variance 1, shown in Figure 3 and described by equations (5)-(8).

$$M = \frac{T_n - E(T_n) \pm 0.5}{\sqrt{V(T_n)}} \tag{5}$$

$$E(T_n) = \frac{n(n-1)}{4} \tag{6}$$

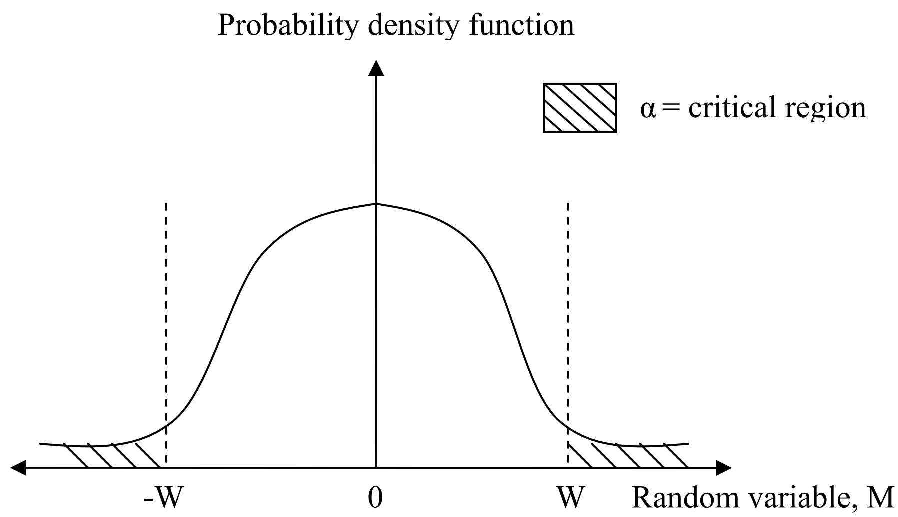

Figure 3: Probability Density Function of Random Variable M

$$V(T_n) = \frac{n(n-1)(2n+5)}{72} \tag{7}$$

$$\frac{1}{\sqrt{2\pi}} \int_{-w}^{w} e^{-\frac{u^2}{2}} du = 1 - \alpha \tag{8}$$

Where T_n : the number of a case that ith value is less than kth value for order i< k in the sequence of data.

If $T_n > E(T_n)$, the sign of value 5 is negative. If $T_n < E(T_n)$, it is positive and if $T_n = E(T_n)$, the value disappears. Using statistical hypothesis test, it is possible to detect and analyze the presence of trend by a given significance level α [23]-[25].

Let

H_0 (Null Hypothesis): No significant trend

H_1 (Alternate Hypothesis): Significant trend

Significance level α represents the error of rejecting H_0 when H_0 is assumed to be true. So if M is in critical region, H_0 is rejected and there exists significant trend. Basically M is function about T_n. So if M is positive, the data shows reliability growth. If it is negative, the data shows aging trend. On the other hand, if M is outside critical region, H_0 is accepted, i.e., this is renewal process. α is usually set to 5 %, 1%, or 0.1%.

Repair actions about aging are taken in repairable systems. When a component fails and is repaired, the condition of the component can fall into the following three categories [22].

1. The component may be as good as new after repair. This is called perfect repair and is what is commonly assumed in power system reliability modeling and analysis. This can be modeled by a renewal process whose inter-failure times are independently and identically distributed. Further when these inter-failure times are exponentially distributed, the process becomes a HPP and the intensity function is constant.
2. The component may be only as good as it was immediately before failure. This is called minimal repair and can be represented by a NHPP.
3. The component may be in between 1 and 2. This is called general or imperfect

repair and can also be modeled by a NHPP.

A general model for dealing with aging in repairable systems can be formulated by using the concept of virtual age [26]-[29]. Virtual age, also called effective age means the component's present condition, is not actual age. So it is supposed to represent the age in terms of the reliability perspectives as compared with the calendar age, i.e., actual age. In Type I Kijima Model, for example, the virtual age at n^{th} repair is given by (9).

$$V_n = V_{n-1} + qx_n = q(x_1 + x_2 + ... + x_n) = qt_n, \ 0 \le q \le 1, \text{ for } n = 1,2,3,... \qquad (9)$$

where q is the repair adjustment factor, x is the inter-failure time, and t is the arrival time. For a renewal process q is zero, that is, after every repair the virtual age is set to zero indicating the component is as good as new after repair or it does not age from one inter-failure interval to the next. It is important to note that in this case, the component may age from the beginning of the inter-failure time to the end but repair is assumed to restore the component to as good as new state so that there is no aging over the long run. For a NHPP, q can be assumed to be one, i.e., the virtual age is equal to the real age experienced by the component, meaning after the repair the component is only as good as before the failure, i.e., the component is aging. When the minimal repair is modeled as in NHPP, the failure rate continues to change after repair as if the component is continuing to operate incessantly. Other repair strategies can be represented by different values of q to model different repair actions.

As is shown later, modeling technology can handle imperfect repair with q other than 1 or 0. If q can be estimated, by expert opinion or available data or a combination, then general repair can be handled. In case, such an estimate can not be obtained, the results obtained by 0 and 1 can be interpreted as lower and upper bounds.

It should be noted that since in the aging components, the failure rate is continuously varying (generally increasing) with time, this introduces a correlation of the failure rate with the load which is also changing. Such correlation is not causal but only coincidental as the load changes and the failure rate steadily increases with time. However, at least conceptually, the use of an average probability of aging components is likely to cause error because of this correlation. It appears that in such cases the use of Sequential Monte Carlo simulation [30]-[34] will be the most reasonable choice.

3. RELIABILITY MODELING USING SEQUENTIAL MONTE CARLO SIMULATION

There are two main approaches to analyze system reliability: Analytical method and Monte Carlo simulation [11], [35]. As an analytical method, state enumeration or min cuts method is often used. In state space approach, from all possible states of components of a system, the system state space is constructed and then reliability indices are calculated by examining these states. However, for large systems, much time and effort are required to carry out the process and sometimes this becomes impractical. For complex systems consisting of independent components, min cut method is quite effective. Monte Carlo simulation randomly mimics the system history (working and failure) using probability distribution function. The idea is that a state having a higher probability of occurrence is more likely to be simulated over time. This is flexible for complicated operations such as load uncertainty or weather effects, being based on probabilistic laws. Expected reliability indices can be calculated regardless of the number of buses in the power system, compared with analytical method. There are two methods for Monte Carlo: random sampling and sequential method. In the random sampling method, the state of each component is sampled and system state is non-chronologically determined. In sequential Monte Carlo, however, system state is sequentially determined, based on distribution function of each component state residence time. So, this method requires more calculation time than random sampling. However, sequential method is appropriate for both independent and dependent events.

Therefore, on this thesis Sequential Monte Carlo simulation is used to build reliability models and carry out assessment.

A general algorithm, for any type of distribution of component state residence times, can be described in the following steps:

It is assumed that the k^{th} transition has just taken place at time t_k and the time to next transition of component i is x_i. Then the vector of times to component transitions is given by $\{x_i\}$ and the simulation proceeds in the following steps.

Step 1. The time to next system transition is given by the minimum value of the component transition times, shown by (10).

$$x = \min\{x_i\} \tag{10}$$

If this x corresponds to x_p, which is the p^{th} component, and then next transition occurs by the change of state of this component.

Step 2. The simulation time is now updated by (11).

$$t_{k+1} = t_k + x \tag{11}$$

where x is given by (10).

Step 3. The residual times to component transitions are calculated by (12).

$$x_i^r = x_i - x \tag{12}$$

Where x_i^r is residual time to transition of component i.

Step 4. The residual time for component p causing system transition becomes zero and time to its next transition x_p is determined by using a random number.

Step 5. The time x_i is set as shown in (13).

$$\begin{aligned} x_i &= x_i^r, \; i \neq p \\ &= x_p, \; i = p \end{aligned} \tag{13}$$

Step 6. In the interval t_k to t_{k+1}, the status of component stays fixed and the following steps are performed for measurements of reliability indices.

(a) The load for each bus is updated to the current hour.

(b) If no bus has loss of load, the simulation proceeds to the next hour, otherwise state evaluation module is called.

(c) If after remedial action all loads are satisfied, then simulation proceeds to next hour. Otherwise, this is counted as loss of load hour for those buses and the system.

(d) Steps (a) – (c) are performed until t_{k+1}

Step 7. The statistics are updated as described by step 6 and the process moves to step 2. The simulation process is continued until convergence criterion is satisfied.

4. SAMPLING TIME TO NEXT TRANSITION

4.1. Transition Time for Non-aging Model

Probability distribution of renewal process [19], [21], is independently, identically repeated during every cycle. Figure 4 shows the failure rate curves for different distributions. Each vertical dotted line indicates the moment of repair. So its duration is one cycle. As the term 'renewal' implies, failure rate after repair gets renewed, whether it increases or not during its working period. So renewal process has a zero trend over sequential cycles. If the inter-failure time in renewal process is exponentially distributed, it is a HPP. On the other hand, for an aging component, it has a positive trend over sequential cycles. Up time tends to become smaller as the age of a component grows.

The time to next transition is sampled by using inverse transform method [36], described by (14), (15). Time x is interval-time, Z is a uniform random variable with an interval on (0, 1], and function F is a probability distribution function.

$$Z = \Pr(x \leq Z) = F(x) \tag{14}$$

$$x = F^{-1}(Z) \tag{15}$$

Renewal process has several kinds of probability distribution functions. Here we briefly introduce commonly used four probability distribution functions.

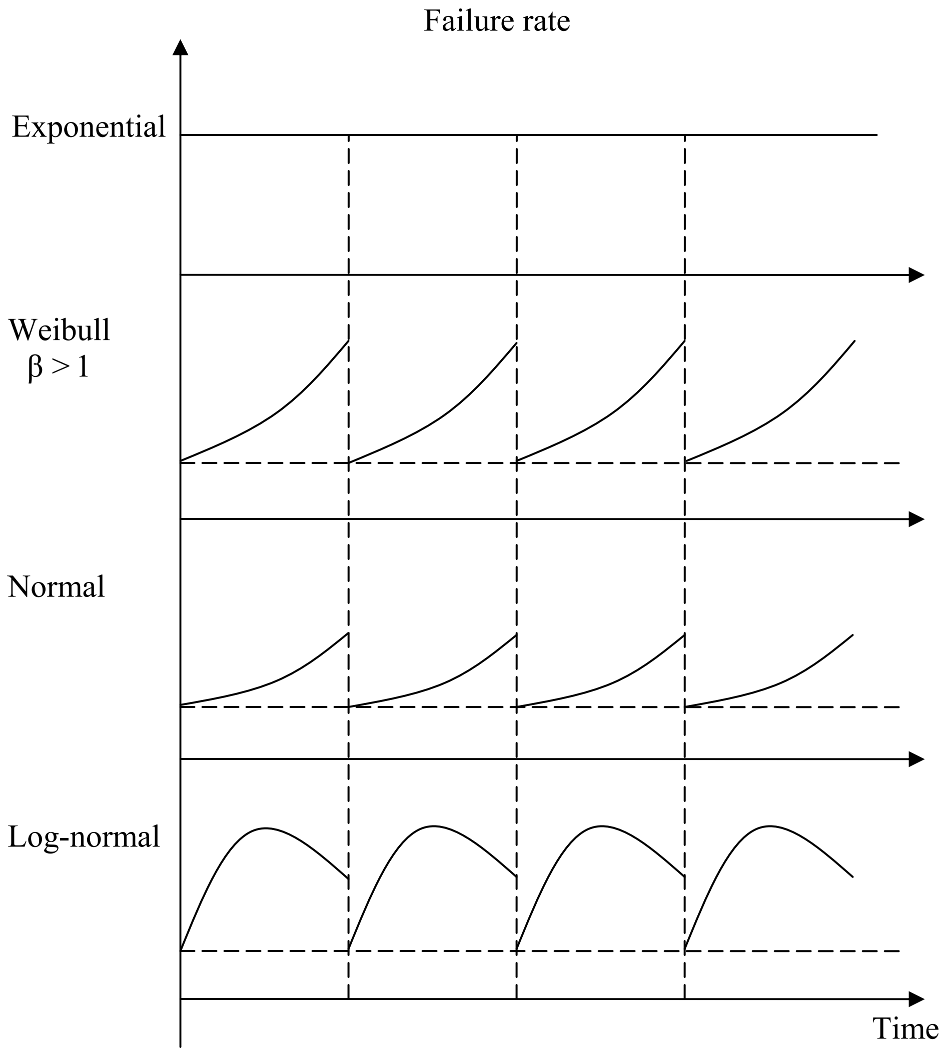

Figure 4: Failure Rate Comparison for Different Probability Distributions

(1) Exponential

In a stochastic point process, if N (t) is given by a Poisson distribution, the interval-time is exponentially distributed. Intensity rate of a component is constant. Equation (16) shows probability distribution of time x. Then time x is given by simple function (17). The mean value of time x is a reciprocal of intensity ρ, shown by (18).

$$F(x) = 1 - e^{-\rho x} \tag{16}$$

$$x = \frac{-\ln(Z)}{\rho} \tag{17}$$

$$E(x) = \frac{1}{\rho} \tag{18}$$

(2) Weibull

Weibull distribution is characterized by probability distribution function shown by (19). Similar to the previous case, interval-time x is taken by (20) using (15). The expected value is given by (21). When β is equal to one, it is exactly the same as exponential.

$$F(x) = 1 - e^{-(x\rho^{\frac{1}{\beta}})^{\beta}} \tag{19}$$

$$x = \left(\frac{-\ln(Z)}{\rho}\right)^{\frac{1}{\beta}} \tag{20}$$

$$E(x) = \frac{\Gamma(1+\frac{1}{\beta})}{\lambda^{\frac{1}{\beta}}} = \frac{\frac{1}{\beta}\Gamma(\frac{1}{\beta})}{\lambda^{\frac{1}{\beta}}} \tag{21}$$

where $\Gamma(\bullet)$ is a gamma function, described by (22).

$$\Gamma(z) = \int_0^{\infty} t^{z-1} e^{-t} dt \tag{22}$$

(3) Normal

Normal distribution is given by (23).

$$F(x) = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{x - m}{\sigma\sqrt{2}}\right)\right] \tag{23}$$

where m is mean value of x, σ is standard deviation of x, and erf indicates error function, described by (24). Similarly, time x is given by (25), using inverse transform method.

$$\mathrm{erf}(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-t^2} dt \tag{24}$$

$$x = m + \sigma\sqrt{2}\,\mathrm{erf}^{-1}(2Z-1) \tag{25}$$

(4) Log-Normal

In general, Log-normal distribution, given by (26), is used more for repair time modeling than the failure time. Time x and its mean value are given in (27), (28).

$$F(x) = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{\ln(x) - m}{\sigma\sqrt{2}}\right)\right] \tag{26}$$

$$x = e^{m+\sigma\sqrt{2}\,\mathrm{erf}^{-1}(2Z-1)} \tag{27}$$

$$E(x) = e^{m+\frac{\sigma^2}{2}} \tag{28}$$

4.2. Transition Time for Aging Model

It should be evident that the aging is associated with time to failure and the time to repair distribution may have nothing to do with aging. So the time to repair can be modeled as a non-aging renewal process.

NHPP is introduced as a model for the aging failures. Specially, Power Law Process (PLP) [12], [20], [37]-[39] is used for this model and is described by (29)-(32). As shape parameter β varies, three types of trend are generated. If β is one, it is a zero trend. If β is greater than one, the process has an aging trend. If β is less than one, it has a negative trend, i.e., reliability growth. PLP is actually based on Weibull distribution because of failure rate function given by (29). However, as we can see from the comparison of Figure 4 and Figure 5, they are different immediately after first repair. Expected value of N(t) during time t is given by (30) and probability of k events during time Δt is given by (31). Equation (32) is expanded by substituting (30) in (31).

$$\lambda(t) = \lambda\beta t^{\beta-1} \tag{29}$$

$$\Lambda(t) = E[N(t)] = \int_0^t \lambda(u)du = \lambda t^{\beta} \tag{30}$$

$$\Pr(N(\Delta t) = k) = \frac{\{\Lambda(\Delta t)\}^k e^{-\Lambda(\Delta t)}}{k!} \tag{31}$$

$$\Pr(N(\Delta t) = k) = \frac{\lambda^k (\Delta t)^{\beta k} e^{-\lambda(\Delta t)^{\beta}}}{k!} \tag{32}$$

Just as in Figure 4, vertical dotted lines in Figure 5 represent the repair actions. Failure rate is, however, not renewing, instead is the same as immediately before failure, which is called as good as old. This is minimal repair, while the repair action of Weibull renewal distribution from Figure 4 is perfect - after repair, it is as good as new. In practice, however, a component of a system may be having a general repair, which is between perfect repair and minimal repair.

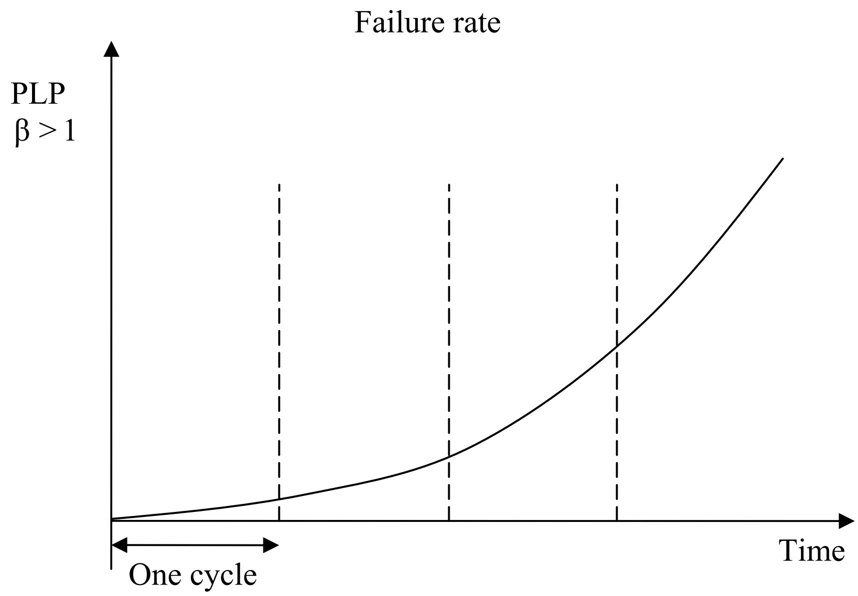

Figure 5: Failure Rate Variation with Time of PLP Model

There are several techniques [40]-[42] that can be used to sample the NHPP and here three are proposed below and studied in this thesis.

(a) Interval by Interval Method (IIM)

This method is based on interval time probability distribution function. Supposing that a failure just occurred at t_k, the probability distribution for the interval time τ is given by (33), using (30)-(32).

$$F_{t_{k+1}}(x) = 1 - \exp[-\int_0^x \lambda(qt_k + \tau)d\tau]$$
$$= 1 - \exp[-\lambda\{(qt_k + x)^\beta - (qt_k)^\beta\}] \quad (33)$$

where parameter q is repair adjustment factor discussed in Section 2. If q is zero, it is exponential distribution function. In this thesis, it is assumed that q is one, i.e., minimal repair.

Then, Equation (34) is given using (14).

$$Z = F_{t_{k+1}}(x) = 1 - \exp[-\lambda\{(qt_k + x)^\beta - (qt_k)^\beta\}] \quad (34)$$

Since 1-Z has the same probability distribution as Z, (34) can be rewritten as (35).

$$Z = F_{t_{k+1}}(x) = \exp[-\lambda\{(qt_k + x)^\beta - (qt_k)^\beta\}] \quad (35)$$

Which gives following (36)-(38):

$$t_{k+1} = \{(qt_k)^\beta - \frac{\ln Z}{\lambda}\}^{\frac{1}{\beta}} - (q-1)t_k, \text{ for } k \geq 0 \quad (36)$$

$$x_k = (\frac{-\ln Z}{\lambda})^{\frac{1}{\beta}}, \text{ for } k = 1 \quad (37)$$

$$x_k = [\{q(\sum_{i=1}^{k-1} x_i)\}^\beta - \frac{\ln Z}{\lambda}]^{\frac{1}{\beta}} - q(\sum_{i=1}^{k-1} x_i), \text{ for } k > 1 \quad (38)$$

By substituting q equal to one in (37)-(38), (39)-(40) is developed.

$$x_k = (-\frac{\ln Z}{\lambda})^{\frac{1}{\beta}}, \text{ for } k = 1 \quad (39)$$

$$x_k = \{(\sum_{i=1}^{k-1} x_i)^{\beta} - \frac{\ln Z}{\lambda}\}^{\frac{1}{\beta}} - \sum_{i=1}^{k-1} x_i, \text{ for } k > 1 \quad (40)$$

Using (39) and (40), the failure times can be sampled by drawing random numbers Z. And the repair action is taken as minimal repair.

(b) Time Scale Transformation (TST)

This method is based on the result that arrival times $t_1, t_2, t_3 ...$ are the points in a NHPP with the cumulative rate function $\Lambda(t)$ if and only if arrival times $t_1', t_2', t_3' ...$ are the points in a HPP with intensity rate one [42], where

$$qt_k = \Lambda^{-1}(t_k') \quad (41)$$

From (41), (42)-(45) are given.

$$t_k' = \Lambda(qt_k) = \int_0^{qt_k} \lambda(t)dt = \int_0^{qt_k} \lambda\beta t^{\beta-1}dt = \lambda(qt_k)^{\beta} \quad (42)$$

$$t_k = \frac{1}{q}(\frac{t_k'}{\lambda})^{\frac{1}{\beta}} \quad (43)$$

$$x_k = (\frac{x_k'}{\lambda})^{\frac{1}{\beta}}, \text{ for } k = 1 \quad (44)$$

$$x_k = -\sum_{i=1}^{k\_1} x_i + \frac{1}{q}(\frac{\sum_{i=1}^{k} x_i'}{\lambda})^{\frac{1}{\beta}}, \text{ for } k > 1 \quad (45)$$

It may be inefficient to apply this method to complicated intensity functions, since it requires numerical calculation of inverse function, as shown by (41). However, in the case of PLP, the calculation is easily expanded, described by (42). Time x_k' is inter-arrival time by HPP with rate one, and time x_k is inter-arrival time by NHPP. x_k' is calculated by (17), and then inter-arrival time for aging model, x_k is obtained by (44), (45). This calculation is a little bit complicated than method (a), since it can be taken only after calculation of a HPP

(c) Thinning Algorithm (TA)

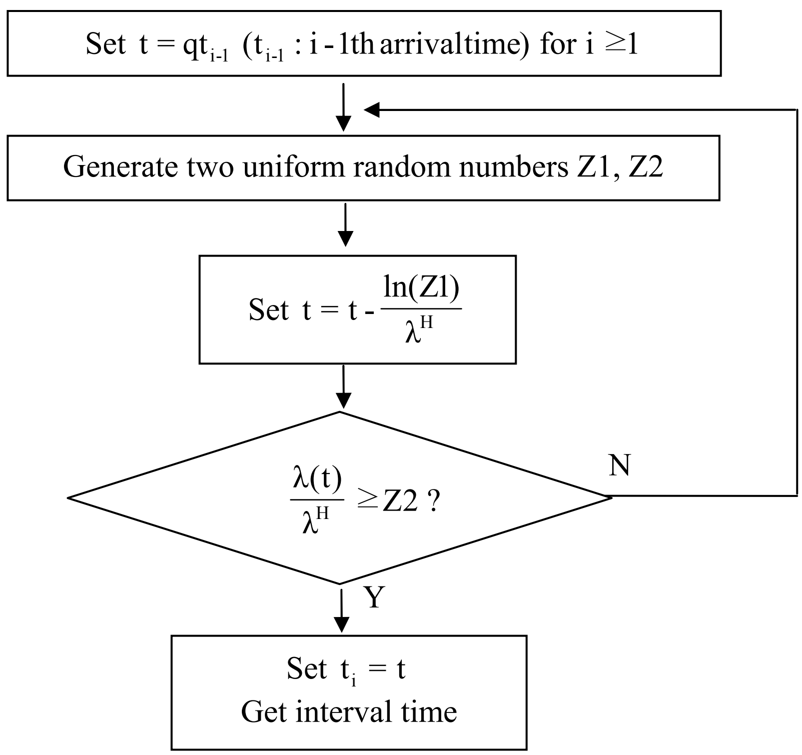

Figure 6: Flowchart for Thinning Algorithm

Figure 6 illustrates the total procedure for this approach. Parameter q is repair factor, which is set to one on this simulation. From occurred arrival time with $\lambda^H = \max_{t \in [0,T]} (\lambda(t))$, thinning out, or removing process is made with probability $1 - \lambda(t)/\lambda^H$. As $\lambda(t)$ increases, 1 $\lambda(t)/\lambda^H$ becomes smaller and then, thinning out process occurs less. On the other hand, as $\lambda(t)$ is getting decreased, the thinning out process occurs more often and interval times are increasing. Contrary to method (a) and (b), this method does not need numerical inverse integral calculation of intensity function. Besides, Log-linear rate function, or Exponential Polynomial rate function method [43]-[44] is employed for specific intensity rate function.

5. SIMULATION METHODOLOGY

5.1. System Reliability Indices

There are a number of indices in power system reliability evaluation. In this thesis, LOLE, LOLP, LOLD, LOLF, and EENS [45]-[48] are calculated and compared. The expected value of loss of load hours during simulation time is LOLE [h]. Then, LOLP [%] is calculated as LOLE divided by 8736 hours, since one year from RTS system data is 52 weeks. LOLD [h] is given by LOLE divided by number of the load loss event. Finally, LOLF [#/h] is taken from a ratio of LOLP to LOLD.

The indices are calculated and compared in hierarchical level 1 and hierarchical level 2. Loss of load is evaluated by difference between generating capacity and load in hierarchical level 1, while it is calculated by linear programming optimization based on DC power flow in hierarchical 2. To handle degree of aging, parameter β in a PLP model and aging adjustment factor q in repair actions are controlled. By variations of these variables, reliability indices are changed and compared over time.

5.2. Criterion for Convergence

Monte Carlo simulation is based on probabilistic laws, not deterministic law. So, a criterion for convergence of estimated values needs to be used. As a convergence criterion, coefficient of variation [49] is applied. For different indices, the corresponding convergence rates may be different. Let,

I_i Reliability index from simulation result for year *i*

N_Y Number of years of simulated data available

SD_I Standard deviation of the estimate I_i

Then, estimate of the expected value of the index I_i is given by (46), averaging the index and standard deviation of the estimate is shown by (47).

$$\bar{I} = \frac{1}{N_Y} \sum_{i=1}^{N_Y} I_i \tag{46}$$

$$SD_I = \sqrt{\frac{SD_2}{N_Y}} \tag{47}$$

where

$$SD_2 = \frac{1}{N_Y} \sum_{i=1}^{N_Y} (I_i - \bar{I})^2 \tag{48}$$

$$COV = \frac{SD_I}{\bar{I}} \tag{49}$$

Note SD_I, the standard deviation of the estimate, $\hat{I}$, varies as $1/\sqrt{N_y}$ and will approach zero as N_y goes to infinity. Convergence rate become faster as mean value of estimate $\hat{I}$ is getting bigger, from (49). The Coefficient of Variation (COV) is used as the convergence criterion of the Sequential Monte Carlo Simulation. So the simulation is iterated until COV is lower than preset tolerance level. Usually, the value is set to 5 % or 2.5 %. If tolerance level is higher, accuracy of the estimate is lower. Its value is set to 5 % in the thesis. The number of samples N_Y is independent of system size. So Monte

Carlo is efficient for simulation of large and complex systems.

5.3. DC Power Flow and Linear Programming

Major part of power system consists of three divisions [15]-[16]: generation, transmission and distribution, shown by Figure 7. In general, electric utilities have some of three divisions for the purpose of system planning, operation, or analysis. Reliability indices can be evaluated in each hierarchical level and provide planners or operators with alternate planning or operating techniques [1]. In this thesis, reliability modeling and analysis is based on generation capacity and transmission system [48], [50]-[51] which are hierarchical level 1 and 2. Composite power system reliability assessment deals with transmission constraints as well as generation capacity. In this level 2, reliability is the ability to supply generated energy to meet pool load points without violating transmission constraints. So if transmission line flow exceeds its limits, load loss event occurs even though generation capacity meets load. As transmission system is incorporated in generation capacity reliability, AC or DC power flow needs to be used for determining the system status [51]-[53].

To save computation time and effort to solve the power balance equation, this paper has selected DC power flow approach. This has been a commonly used analytical technique despite approximate solution.

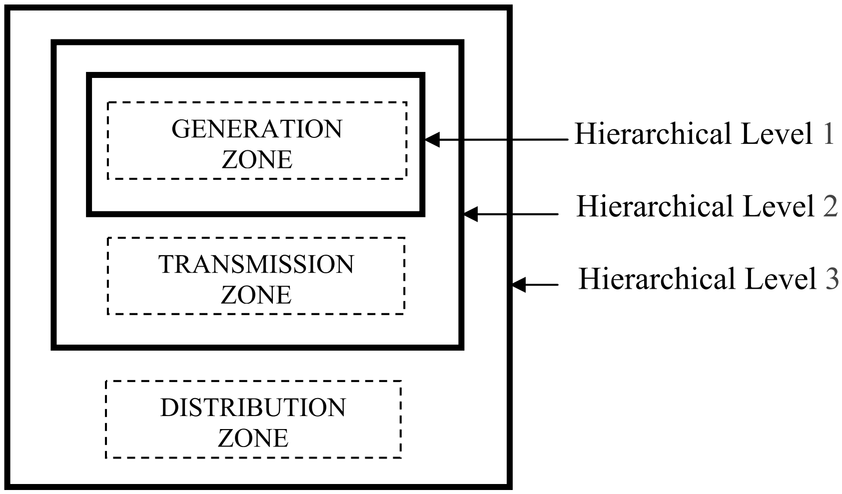

Figure 7: Three Zones of Power Systems

DC power flow equation is derived by ignoring reactive power-voltage equation in the Fast decoupled method. The following assumptions are made:

1. Each bus voltage magnitude is one per unit.
2. No line losses. Only imaginary part of Y matrix is considered.

So that power flow in bus i is given by (50).

$$P_i = \sum_j -B_{ij}\theta_{ij}, \text{ for bus i} \tag{50}$$

Matrix form is given by (51).

$$P = -B\theta \tag{51}$$

where P_i is real power flow at bus i, matrix B is an imaginary part of Y matrix, θ_{ij} is the difference between angles from bus i to j.

For generation capacity reliability evaluation, load curtailment is calculated just by difference between total capacity and total load. Such studies are done for generation planning. However, in case of composite system reliability studies, it is required to check if flows of all the lines are within the limits. This case is more meaningful, when effect of transmission needs to be studied. In DC power flow, total generation dispatched should be the same as the total load because of no line losses. To handle generation and load for each bus, there can be many combinations. So, to solve this problem, minimization model based on linear programming is introduced. This approach is to minimize the total load curtailment, meeting the power balance of DC power flow and related constraints. Equations (52)-(56) describe this formulation.

$$\text{Load curtailment} = \text{Min} \sum_{i}^{N} C_i \quad (52)$$

Subject to

$$B\theta = P_G - P_D + C \quad (53)$$

$$P_G \le P_G^{max} \quad (54)$$

$$0 \le C \le P_D \quad (55)$$

$$|P_{line}| \le P_{line}^{max} \quad (56)$$

where N is the number of buses

C is the vector of load curtailments

P_G is the vector of generation

P_G^{max} is the vector of upper limits of generation

P_D is the vector of load

P_{line} is the vector of line real power flows

P_{line}^{max} is the vector of upper limits of flows

In above equations, B, P_G^{max}, P_{line}^{max}, and P_D are knowns, and θ, P_G, and, C are unknowns and, P_{line} is the function of θ calculated by (51). So above equations are based on standard linear programming model. MATLAB software provides functions related linear programming optimization. Function linprog is applied to solve the problem.

5.4. Control of Parameter of Aging Model for Different Degrees of Aging

For performing the fair comparison of both non-aging and aging situations, the given component is assumed to have the same reliability level at the beginning. So, aging will start after the first cycle of the process. Then Mean Time to First Failure (MTTFF) of PLP should be the same as $1/\lambda e$. And Mean up time during only the first cycle of PLP is the same as that of Weibull distribution, shown by Figure 4 and Figure 5. Using these facts, following equations are derived. The reliability or survivor function, i.e., the probability of not failing by time t can be obtained from (32) by setting k to zero, shown by (57).

$$R(t) = e^{-\lambda t^{\beta}} \tag{57}$$

The MTTFF can be obtained by integrating the reliability function from zero to infinity [11] and given by (58).

$$\text{MTTFF} = \int_0^{\infty} e^{-\lambda t^{\beta}} = \frac{\frac{1}{\beta}\Gamma(\frac{1}{\beta})}{\lambda^{\frac{1}{\beta}}} = \frac{1}{\lambda_e} \tag{58}$$

Where $\Gamma(\bullet)$ is a gamma function. λ is a function about β, which gives (59). Equation (61) is developed by using the property of a gamma function (60).

$$\lambda = \lambda_e{}^{\beta}[\Gamma(1+\frac{1}{\beta})]^{\beta} \tag{59}$$

$$\Gamma(z+1) = z\Gamma(z) \tag{60}$$

$$\lambda = \lambda_e{}^{\beta}(\frac{1}{\beta})^{\beta}\,\Gamma(\frac{1}{\beta})^{\beta} \tag{61}$$

Where $\lambda_e = \lambda$ when β is one. Parameter λ should be updated for different β in aging model to satisfy this property.

6. CASE STUDIES

6. 1. Effect of Parameter β in a PLP Model on Consecutive Up Times

The Single Area of the 24 bus IEEE RTS [17]-[18] is shown by Figure 8. This system has been used for reference network to test and compare methodology for system reliability evaluation. It consists of two subsystems by voltage level: the north subsystem is at 230kV, and south subsystem at 138kV. It has 10 generator buses, 33 transmission lines, 5 transformers, and 17 load buses. There are 32 generating units so that total capacity is 3405 MW. Load varies with every hour with Peak load 2850 MW. MATLAB is used for system modeling and simulation.

Before considering the issue of aging, let us examine the non-aging model. Generating unit 27 is located at bus 13 from RTS generating bus data [17]-[18]. Based on generating unit reliability data, Table 1 describes generator capacities, failure, and repair rates. If Mean Time to Failure (MTTF) or Mean Time to Repair (MTTR) of different distributions used in renewal process is the same, it should be the same even after each failure or repair, because of renewal property. To take the identical mean up time to failure, mean value of Exponential, Weibull, Normal, and Log-normal distributions is set to the same value, for example $1/\lambda_e = 950$, where λ_e indicates failure rate of unit 27 from Table 1 when the inter failure time is exponential.

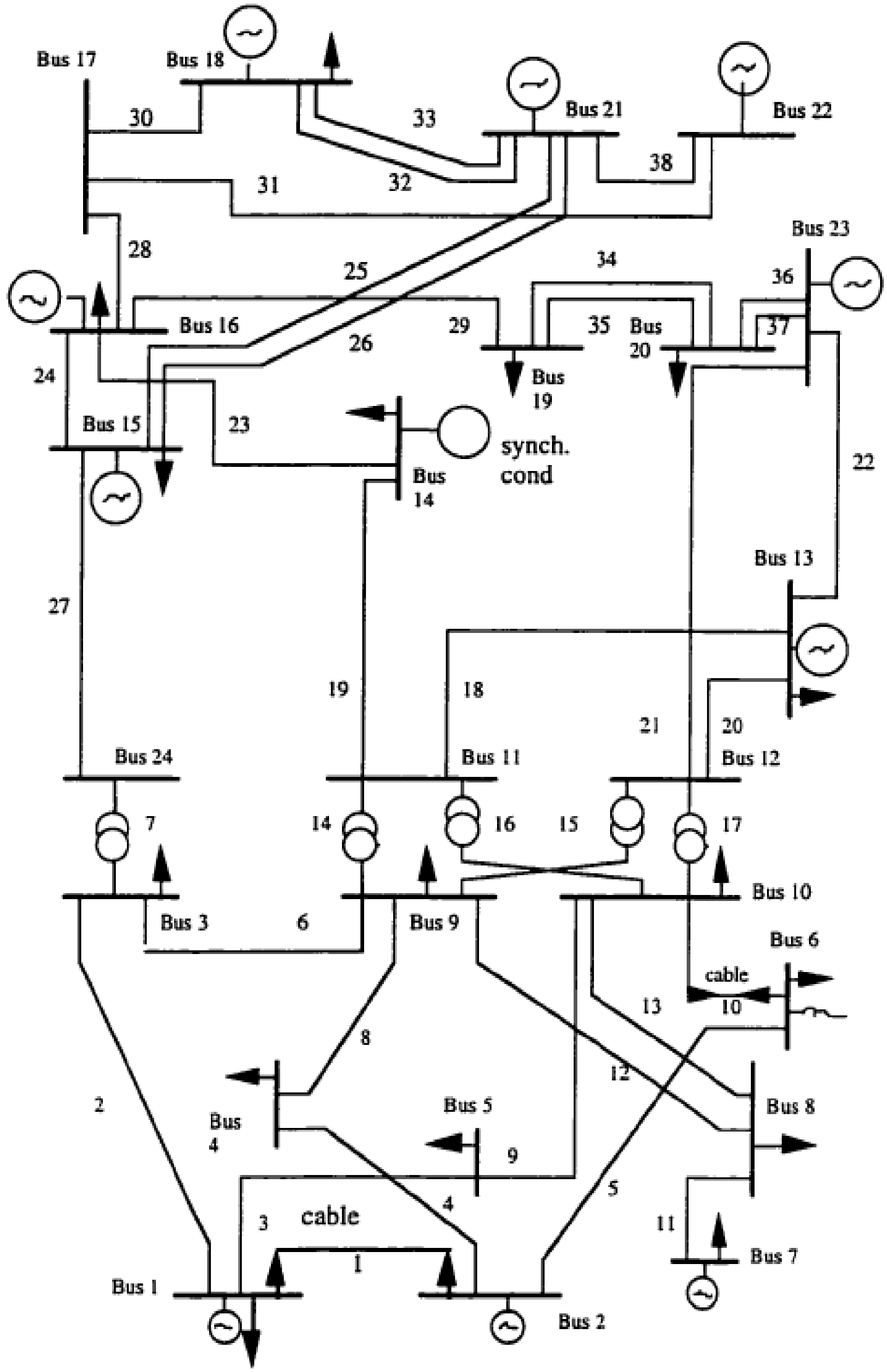

Figure 8: The Single Area RTS

Table 1: Reliability Data of Generating Units

Generators	Capacity [MW]	Failure Rate [#/h]	Repair Rate [#/h]
1-5	12	1/2940	1/60
6-9	20	1/450	1/50
10-15	50	1/1980	1/20
16-19	76	1/1960	1/40
20-22	100	1/1200	1/50
23-26	155	1/960	1/40
27-29	197	1/950	1/50
30	350	1/1150	1/100
31-32	400	1/1100	1/150

To get the same mean time to failure, parameter values for four distributions are set by (62)-(67). In Exponential, mean value is simply set to reciprocal of intensity rate. In Weibull, β is input data. λ should be changed for different input β to get the same MTTF. In the case of Normal or Log-normal, standard deviation of the variable is input data. It is assumed that standard deviation is one. If we use high standard deviation, simulation will need a more time to satisfy convergence criterion.

Exponential $$\frac{1}{\lambda_e} = 950 \tag{62}$$

Weibull $$\frac{\frac{1}{\beta}\Gamma(\frac{1}{\beta})}{\lambda^{\frac{1}{\beta}}} = \frac{1}{\lambda_e} \tag{63}$$

$$\lambda = {\lambda_e}^{\beta}(\frac{1}{\beta})^{\beta}\Gamma(\frac{1}{\beta})^{\beta} \tag{64}$$

Normal $$m = \frac{1}{\lambda_e} \tag{65}$$

Log-normal

$$\frac{1}{\lambda_e} = e^{m+\frac{1}{2}} \tag{66}$$

$$m = \ln(\frac{1}{\lambda_e}) - \frac{1}{2} \tag{67}$$

Table 2, Table 3, Table 4, and Table 5 describe the mean values of up to 10 consecutive up times of unit 27 for different probability distributions. Until simulation gets 10 up times of the generator 27, it is continued. Then, to get desirable 10 mean up times of the component, convergence criterion described in Section 5 is employed with COV which is set to 5%. This value is used for all reliability indices in this thesis. As you see from the Tables, mean up time of each distribution is still maintained as the age of component 27 grows. Also, mean up times for different distributions have approximately the same value, since mean up times for 4 different distributions are set to be equal. Small differences between them are caused by randomness.

Table 2: Unit 27 Mean Up Times Using Exponential

1st	2nd	3rd	4th	5th
951.211	950.266	951.311	949.561	950.918
6th	7th	8th	9th	10th
951.751	948.991	952.534	950.505	950.232

Table 3: Unit 27 Mean Up Times Using Weibull ($\beta = 2$)

1st	2nd	3rd	4th	5th
952.241	950.322	953.030	950.212	951.876
6th	7th	8th	9th	10th
950.312	952.287	951.112	950.199	951.819

Table 4: Unit 27 Mean Up Times Using Normal

1st	2nd	3rd	4th	5th
949.900	950.800	951.300	949.800	950.900
6th	7th	8th	9th	10th
950.700	949.900	951.200	950.600	951.100

Table 5: Unit 27 Mean Up Times Using Log-normal

1st	2nd	3rd	4th	5th
953.387	950.221	950.435	951.436	953.466
6th	7th	8th	9th	10th
949.452	953.322	950.599	951.646	952.426

Next, let us examine impact of beta in a PLP model, one of aging models, on mean up times. In a PLP, parameter β determines the shape of rate function. To show how β affects mean up times, the following case is considered first. The results are described in Table 6. Interval by Interval method, one of non-homogeneous poison process simulation techniques is used for this simulation. Up to 10 consecutive mean up times of generator 27 are estimated from simulation. For 10 mean up times, when β is equal to one, interval times are exponentially distributed. As expected, all the values are almost identical and equal to reciprocal of failure rate of generator 27. On the other hand, if β is greater than one, mean up times are getting decreased as age of a component grows, showing positive aging trend. Mean time to failure of the component is decreased by 24.42 % in 10 mean up times. However, MTTFF of unit 27 is still very close to mean up times of exponential distribution even a case of β greater than one. This is based on assumption that aging may start after one cycle, discussed in Section 5.

Table 6: Unit 27 Mean Up Times with Variations of β

β	10 Mean up times				
1.0	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
	948.11	951.89	953.08	950.76	952.05
	6^{th}	7^{th}	8^{th}	9^{th}	10^{th}
	952.05	950.12	949.13	950.64	951.92
1.1	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}
	952.09	873.71	817.64	771.07	755.13
	6^{th}	7^{th}	8^{th}	9^{th}	10^{th}
	749.03	741.86	732.75	727.03	719.55

6. 2. Generation Capacity Reliability Evaluation

As we discussed in Section 5, power system consists of three hierarchical levels: Generation, Transmission, and Distribution. In this thesis, HL 1 and HL 2 are used for evaluation of power system reliability. Figure 9 shows the flowchart of Generation system (HL 1) reliability assessment. System failure, i.e., loss of load is detected and calculated by the difference between generation capacity and load.

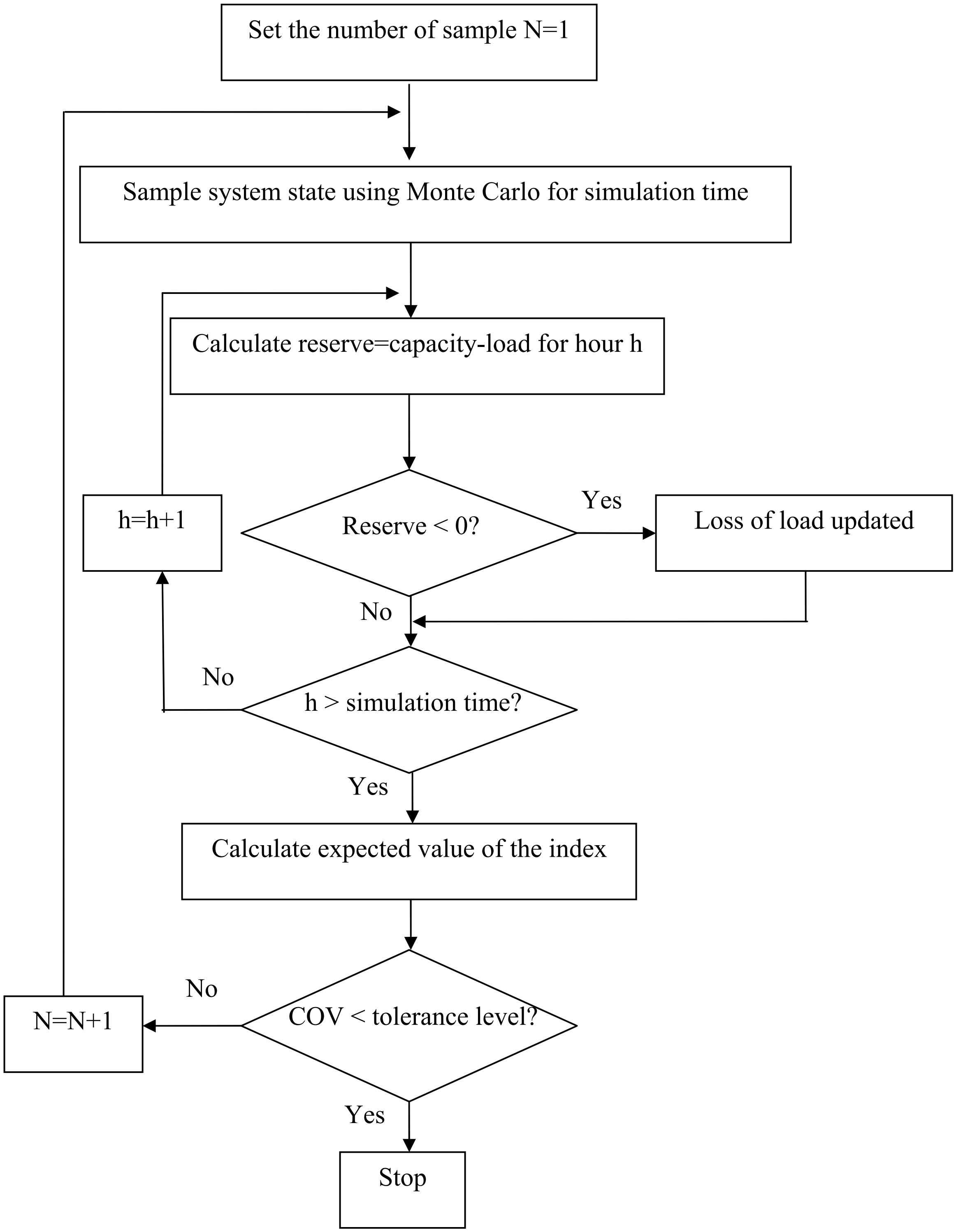

Figure 9: Flowchart of Generation System Reliability Assessment

Table 7 shows reliability indices for different renewal distributions. Simulation time is set to one year. The indices are almost the same, since MTTF or MTTR is set to equivalent value using (62)-(67).

Table 7: Indices Comparison for Three Different Renewal Distributions

Non-Aging Models	LOLE [h]	LOLP [%]	LOLD [h]	LOLF [#/h]	EENS [MWh]
Exponential	9.171	0.105	2.384	4.40×10^{-4}	1123.716
Weibull	9.147	0.104	2.199	4.76×10^{-4}	1099.765
Normal	9.211	0.105	2.405	4.38×10^{-4}	1125.522
Log-Normal	9.253	0.105	2.332	4.54×10^{-4}	1130.991

Where LOLP is expressed as percent, LOLE and LOLD are in hours, LOLF is per hour, and EENS is in MWh. The three different NHPP methods are also implemented as an alternative for non-aging model by setting β equal to one. As shown in Table 8, the results have similar values, compared with Table 7. The differences attributed to randomness of estimation.

Table 8: Indices Comparison for Three NHPP Simulation Methods

Aging Model (β =1.0)					
Method	LOLE [h]	LOLP [%]	LOLD [h]	LOLF [#/h]	EENS [MWh]
IIM	9.45	0.108	2.377	4.55×10^{-4}	1095.567
TST	9.20	0.105	2.540	4.14×10^{-4}	1132.547
TA	9.10	0.104	2.346	4.44×10^{-4}	1098.291

Next, it is assumed that generators 23-26 and 30 from table 1 have positive aging trend. The remaining components are exponentially distributed. Unit 23 is located at bus 15, unit 24 at bus 16, and unit 25, 26, and 30 at bus 23. Three simulation methods are implemented for generating interval times: Interval-by-Interval Method (IIM), Time Scale Transformation (TST) and Thinning Algorithm (TA) and the results are shown in Table 9 for $\beta = 1.3$. It is assumed that aging adjustment factor q is one, i.e., minimal repair. The results by the three methods have similar values. As parameter β is increased greater than one, reliability indices tend to grow. From table 9, required simulation duration of three sampling methods of a NHPP is also compared. IIM is based on probability distribution of interval times. The kth interval time is directly taken from k-1th interval time in (39)-(40). So this method shows the best performance in terms of time requirements, shown by Table 9. TST is based on inverse integrated rate function. The kth interval time of a NHPP is taken from k-1th interval time of a NHPP and kth interval time of a HPP with rate one in (44)-(45). On the other hand, TA does not use integrated rate function, instead, being based on thinning out process and calculation of $\lambda(t)$. Each interval time of a NHPP is taken only after thinning out arrival times of a HPP with the highest rate. For aging PLP model, failure rate steadily increases. So in this case, the thinning out process occurs less as time passes. In other words, in the increasing failure rate condition from Figure 6, more ‘Yes’ answers occur over time. So this method requires more time than the previous ones. In conclusion, it appears the most efficient simulation method is IIM, considering computer time and storage requirements.

Table 9: Reliability Indices with Aging Components

Some components are in Wear-Out stage (β =1.3)				
Indices	LOLE [h]	LOLF [#/h]	EENS [MWh]	Simulation time [m]
IIM	41.149	1.05×10^{-3}	5890.765	20
TST	43.084	1.04×10^{-3}	5842.243	26
TA	43.211	1.03×10^{-3}	5942.011	39

From results of Table 7-9, it can be seen that if some of components begin to have positive aging trend, load loss event will occur more frequently than before. The degree depends on the value of β , i.e., the degree of aging. These results indicate that it is important that the effect of aging, if present, be included in reliability evaluation otherwise the computed reliability may be optimistic. It is evident that the indices are sensitive to the value of β. The value of β to be used in a planning study will depend on the age of the component at the beginning of the study year and needs to be estimated from the field data. Table 10 and Table11 show the variation of reliability indices, LOLE and EENS, as β varies from 1.0 to 1.8. As you see from the Tables, indices are increased, β becomes to grow.

Table 10: LOLE Variations for Different Parameter β

LOLE [h]					
β	1.0	1.2	1.4	1.6	1.8
IIM	9.451	24.343	63.670	141.184	238.914
TST	9.204	22.055	63.511	137.205	243.122
TA	9.107	24.282	62.599	139.977	238.833

Table 11: EENS Variations for Different Parameter β

EENS [MWh]					
β	1.0	1.2	1.4	1.6	1.8
IIM	1095.567	3431.206	9531.999	22659.550	46315.685
TST	1132.547	3288.471	9632.433	23168.273	45603.909
TA	1098.291	3298.719	9598.238	22317.299	45466.661

Now, to examine the degree of aging for different components on system reliability, following two cases shown in Table 12 are proposed. It is assumed that the remaining generators are exponentially distributed. In general, for system planning, long operation time is required. So simulation process is measured for five years.

Table 12: Description for Case 1 and 2

Case	Applications
1	16-19, 30 are aging
2	23-26, 30 are aging

Figure 10 and Figure 11 show the LOLE variations with different β during five years in the two cases, respectively. This index is calculated only during each one year interval and is not accumulated. In the case of $\beta = 1$, LOLE is almost the same over time for both cases and the value is also equal to the results from the Table 10. This is because that failure rate of PLP is constant in case of $\beta = 1$.

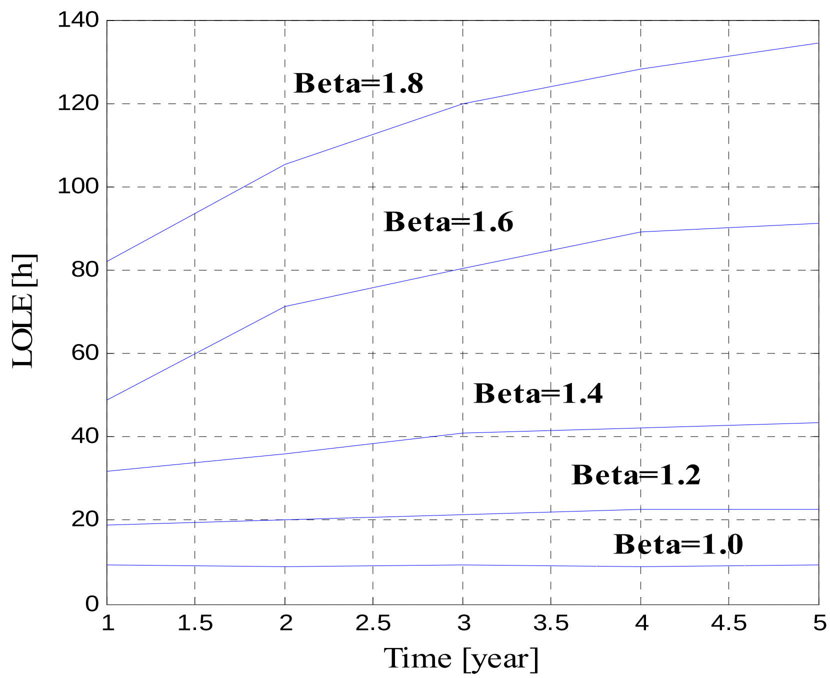

Figure 10: LOLE Change for Different β in Case 1

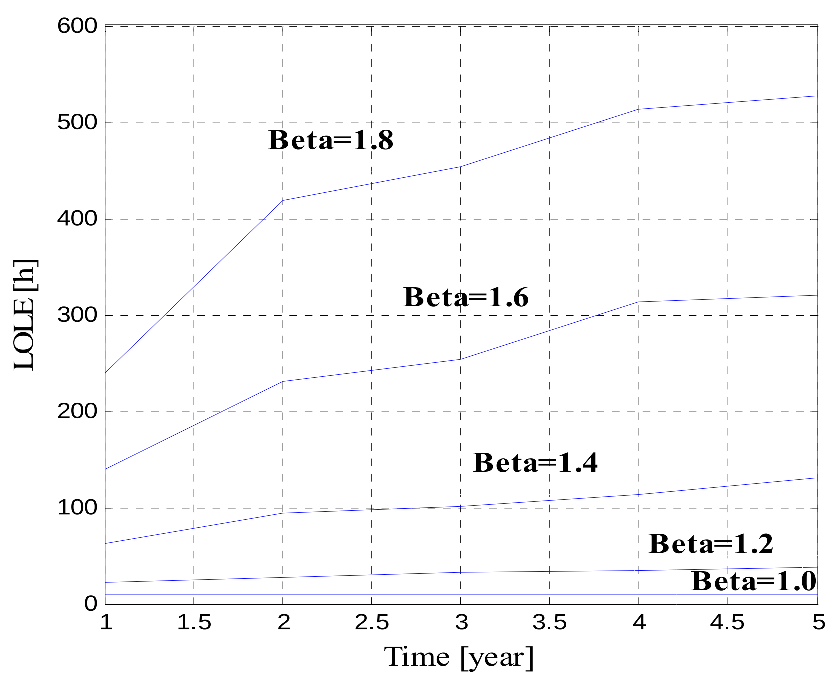

Figure 11: LOLE Change for Different β in Case 2

In case 1, the total capacity of aging generators is equal to 815 MW, constituting 26.6% from the total generator capacity of 3055 MW. In case 2, the aging capacity is 605 MW, constituting 19.9% of the total capacity. So, aging capacity of case 1 is bigger than that of case 2 and failure rates of case 1 are higher than those of case 2. From these facts, it should be evident that LOLE of case 1 increases faster, as β increases, or as the age of the system grows.

Now, let us think about effect of variation of repair adjustment factor q in HL 1. A study is carried out to observe the variation of the repair adjustment factor q. This factor was varied from 0 to 1 and all the three methods were tested. The results obtained by all the three methods were very close, so only the results by the best choice, IIM method are shown in Figure 12. As we can see from the figure, the effect of q is not linear. It first increases fast and then more gradually.

Of course the effect of q also is dependent on the value of β. For example for β equal to 1, the value of q will not have any effects on reliability since the component is not aging and so the failure rate at the beginning and end of an interval is equal. As the value of β increases, the effect of the choice of q will have more significant effect. And for the case that q is equal to one, index LOLE is all the same regardless of β, since failure rate after each cycle is the same, showing renewal process. The difference in reliability indices for different values of q can be quite significant.

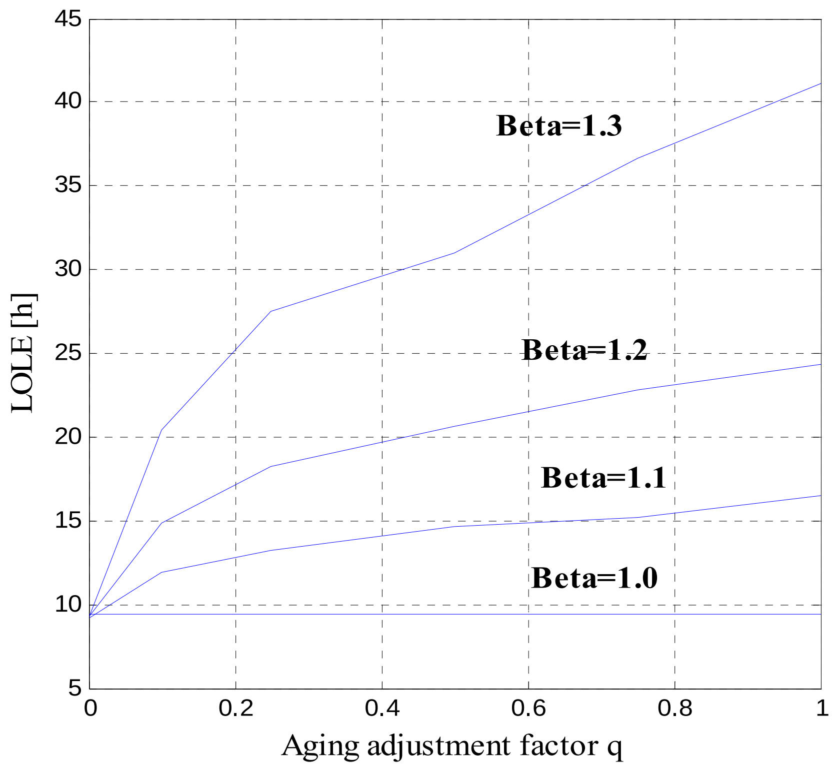

Figure 12: LOLE for Different q with Different β in HL 1

6. 3. Composite System Reliability Evaluation

Figure 13 shows the total flowchart of composite system reliability assessment. By linear programming, optimized value of load curtailment is calculated during simulation time of one year. One year consists of 364 days which are 52 weeks. Expected load curtailments value during one year is EENS [MWh/year] according to convergence criterion. Number of the event is counted every time load curtailment occurs.

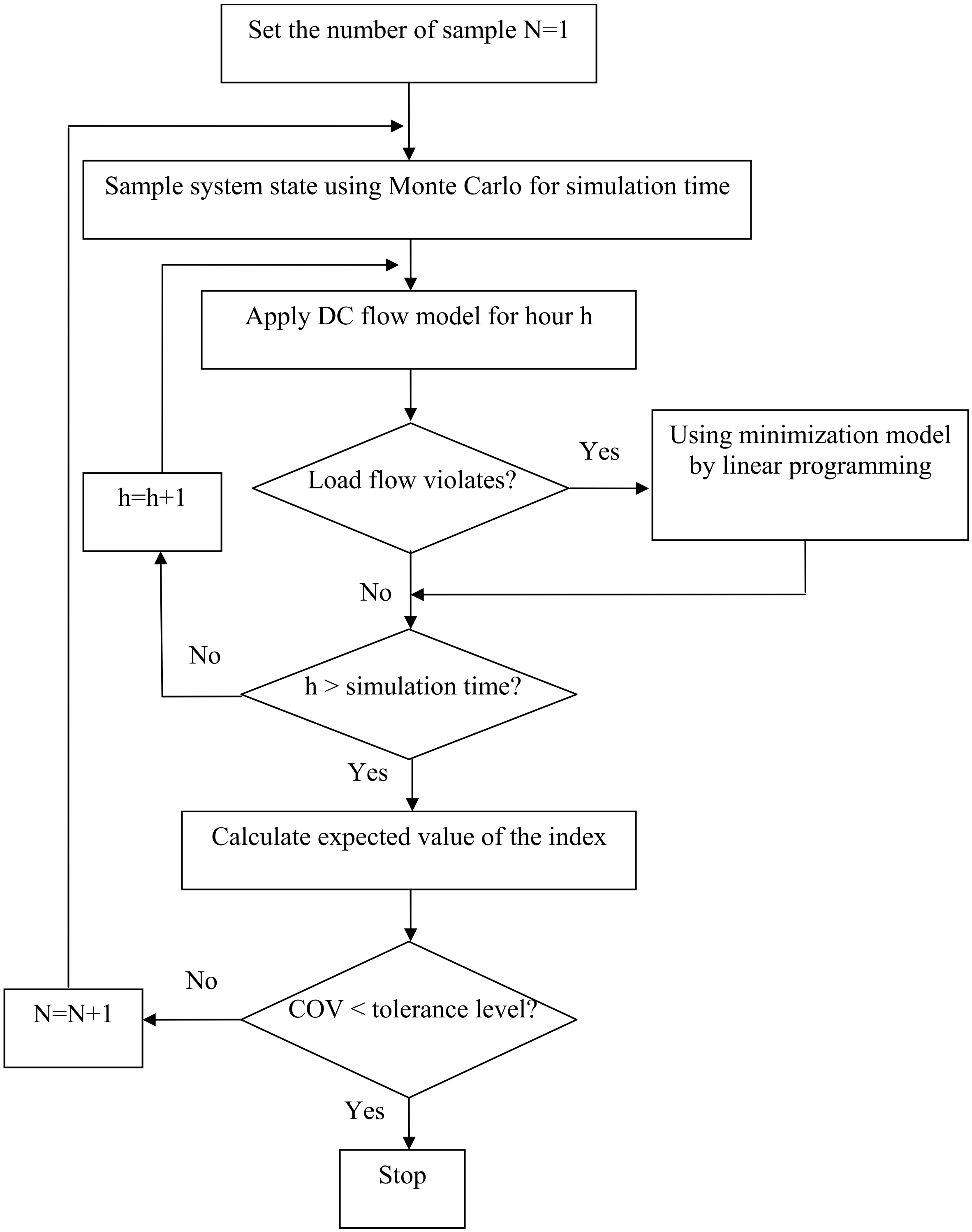

Figure 13: Flowchart of Composite System Reliability Assessment

To go through aging effects on composite system reliability evaluation in detail, following cases are proposed in table 13. For case 3, transmission constraints are not considered. Reliability assessment is performed only by generation capacity. On the other hand, case 4 includes transmission system constraints. In this case, linear optimization technique based on DC flow is used, illustrated in Section 5. For the two cases, reliability indices are compared with variation of degree of aging. As non-aging model, HPP is applied. For aging model, Interval by Interval method is used for simulation by taking a PLP model. To handle aging effects, parameter β in a PLP function is properly controlled, ranging from 1.0 to 1.8.

Table 13: Description of Case 3 and 4

Case	Description
3	HL 1 (generation system)
4	HL 2 (composite system)

Table 14 describes location of generating units and their capacities for each bus. It is assumed that aging buses are 13, 18, and 21, consisting of 1391 MW, 40.85 % of total capacity 3405 MW for both case 3 and 4. Hourly load data with peak load 2850 MW are modeled from data form RTS and, bus load data is given in Table 15.

Table 14: Generator Bus Data

Bus	Units [MW]	Capacity [MW]
1	G6/G7/G16/G17	192
2	G8/G9/G18/G19	192
7	G20/G21/G22	300
13	G27/G28/G29	591
15	G1/G2/G3/G4/G5/G23	215
16	G24	155
18	G31	400
21	G32	400
22	G10/G/11/G12/G13/G14/G15	300
23	G25/G26/G30	660

Table 15: Bus Load Percent of System Load

Bus	Load percent	Bus	Load percent	Bus	Load percent
1	3.8	7	4.4	15	11.1
2	3.4	8	6.0	16	3.5
3	6.3	9	6.1	18	11.7
4	2.6	10	6.8	19	6.4
5	2.5	13	9.3	20	4.5
6	4.8	14	6.8		

In case 3, reliability indices for non-aging model are shown by Table 16 in HL 1 level. For non-aging model, all generators are modeled by exponential distribution. The indices are almost the same as that of the case that β is one in aging model, shown by Table 17. So a PLP model is an alternate for a HPP, since exponential distribution itself is a special case of Weibull distribution by setting the value $\beta = 1$. As β is increased, aging level becomes high. As a result, all related indices rise.

Table 16: Reliability Indices for Non-aging Model in HL 1

	LOLE [h]	EENS [MWh/y]	LOLD [h]	LOLF [#/h]
Non-Aging Model	9.42	1095.76	2.37	4.55×10^{-4}

Table 17: Reliability Indices for Aging Model in HL 1

	β	LOLE [h]	EENS [MWh/y]	LOLD [h]	LOLF [#/h]
Aging Model	1.0	9.35	1113.95	2.22	4.81×10^{-4}
	1.2	54.08	8018.73	5.40	11.45×10^{-4}
	1.4	185.05	33829.67	6.13	$34..54\times10^{-4}$
	1.6	455.07	95821.07	6.78	76.76×10^{-4}
	1.8	723.81	174535.44	7.31	113.28×10^{-4}

In case 4, additional line flow limits data for linear programming are required in HL 2, which include impedance and rating data of transmission. Table 18 and Table 19 show the results of composite system reliability evaluation. The indices of case 3 have greater values than those of case 1 regardless of aging effects of the components. This is because that system state that is not load curtailment in HL 1 may be determined as load curtailment event in HL 2. Similarly, as parameter β is getting increased, reliability indices tend to grow. To visualize of aging effects on system reliability, index LOLP is compared with different β in HL 1 and HL 2, shown by Figure 14 and Figure 15. System failure probability becomes higher as transmission system is included. Bigger value of β makes a system failure probability high.

Table 18: Reliability Indices for Non-aging Model in HL 2

Non-Aging Model	LOLE [h]	EENS [MWh/y]	LOLD [h]	LOLF [#/h]
	31.19	3978.09	3.47	1.02×10^{-3}

Table 19: Reliability Indices for Aging Model in HL 2

	β	LOLE [h]	EENS [MWh/y]	LOLD [h]	LOLF [#/h]
Aging Model	1.0	31.25	4101.52	3.84	0.93×10^{-3}
	1.2	140.54	24686.03	6.93	2.32×10^{-3}
	1.4	529.38	96500.03	8.08	7.49×10^{-3}
	1.6	796.65	219923.57	9.44	9.66×10^{-3}
	1.8	995.94	285900.64	9.79	11.64×10^{-3}

In closing, similarly, let us go through effect of repair adjustment factor q in HL 2. All the three methods of a NHPP simulation are tested. The results are the same, so only the results by the IIM method are shown in Figure 16.

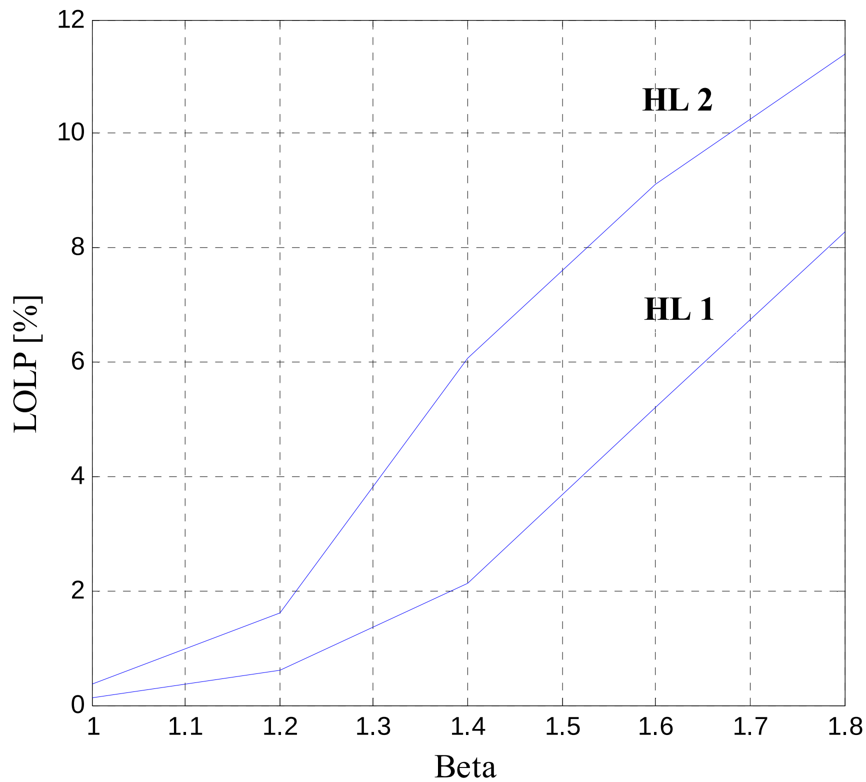

Figure 14: LOLP Comparison between HL 1 and HL 2

Like case of HL 1, the effect of q is also dependent on the value of β. For example for β equal to 1, the value of q will not have any effect, showing exponential distribution. As the value of β increases, the effect of the choice of q will have greater effect. For a case that q is equal to one, LOLE is all the same regardless of β, since failure rate after each repair is the same, renewal process. It shows that the difference in reliability level for different values of q and β may be quite significant.

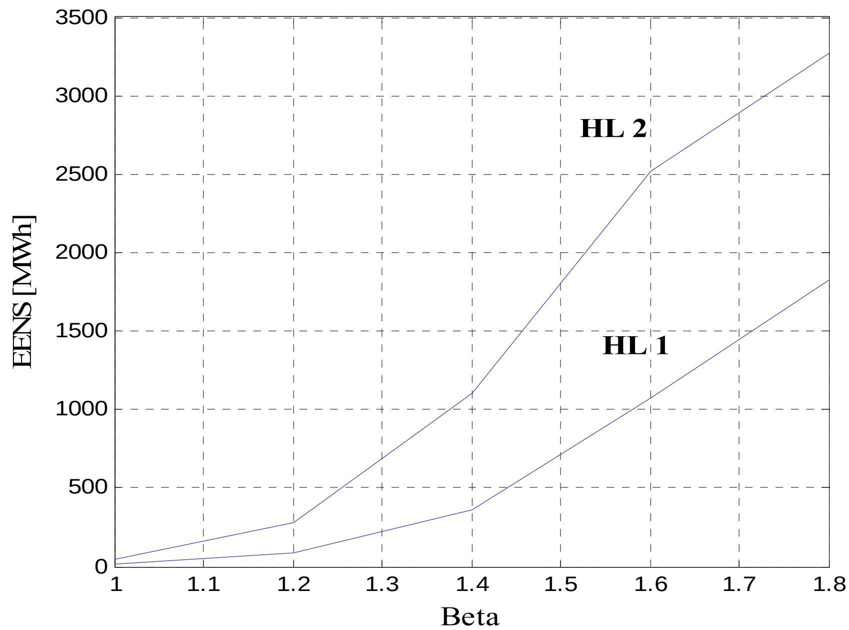

Figure 15: EENS Comparison between HL 1 and HL 2

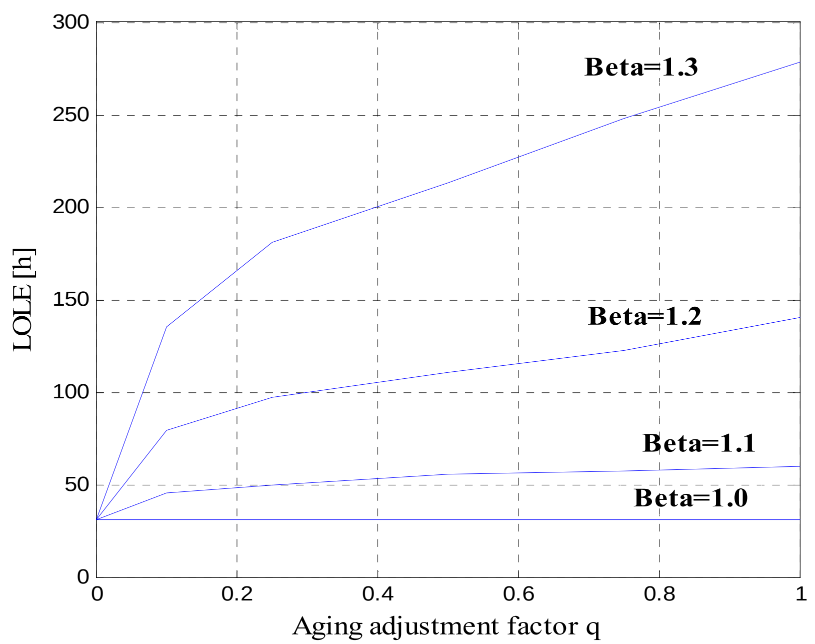

Figure 16: LOLE for Different q with Different β in HL 2

7. CONCLUSIONS

Most components of power systems around the world have been increasingly getting older. Aging of components is an important fact in power system reliability assessment. It results from a number of different reasons: deterioration, erosion, or damage of equipment. Regardless of reasons, most equipment may develop aging trend over time. As a result, aging may become the cause of load curtailments because of higher system failure probability. So it is necessary to examine aging characteristics in system reliability or in economic evaluation. Power systems with high reliability at low costs offer many benefits in competitive environment. This thesis illustrates effect of aging on composite power system reliability evaluation.

For non-aging model, Exponential, Weibull, Normal, Log-normal distributions are used to sample time to transition. These distributions are independently repeated every cycle. As special case, exponential renewal process is called a HPP. It is observed that mean up times and LOLE have almost the same values for different distributions because of this renewal property. For aging model, PLP, one of NHPP models, is introduced. This model is able to accommodate data with zero, positive, or negative aging trend by handling parameter β . Three methods, IIM, TST, and TA are applied for generating inter-arrival time sequence, based on Power Law intensity function. IIM shows best method in terms of simulation time requirements for aging model of the proposed three methods.

To observe how aging influences composite power system reliability, indices such as LOLE, LOLD, EENS etc., are calculated and compared in both cases of HL 1 and HL 2. As transmission system is considered in reliability studies, linear programming technique based on DC power flow is introduced for simulation.

Sequential Monte Carlo based on Stochastic Process is applied to Single Area IEEE RTS which is used to test and analyze reliability assessment. To find out expected value of estimates, coefficient of variation is used for testing convergence. It is observed that load curtailment event takes place more often in HL 2 due to transmission constraints. To handle aging characteristics, parameter β of PLP model is properly controlled. Three trends- zero, negative, and positive trends can be generated by setting proper value of β .As β is greater than one, or the aging of the system grows, probability and frequency of system failure become higher. Also aging adjustment factor q is handled for control of failure rate after repair actions. When q is zero, it does not show any trends indicating perfect repair. When it is one, it denotes minimal repair. General repair action is represented by setting q between zero and one. It is observed that aging grows faster, as q increases. System simulation is made during one year and five years for long term system planning in reliability analysis.

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