Reliability Evaluation of Generation System with Multi-state Generating Units using Monte Carlo Simulation Technique

BY

MD. ATAUR RAHMAN KHAN

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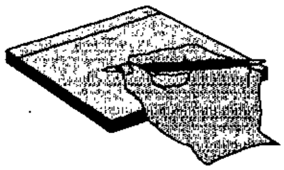
ABSTRACT

The reliability assessment of generation systems now a days has drawn prime interest in the area of power system planning, designing and evaluation of reliability. As the demand of the modern society is to have electrical energy as economically as possible with a specified degree of reliability, therefore, there is a significant need to assess the reliability of generation systems. There are two basic techniques available in the literature for reliability evaluation of generation systems: the analytical approach and the simulation approach. Most of the techniques available in the literature for assessing the reliability of generation systems are based on analytical methods. The simulation approach estimates reliability indices by simulating the actual behaviour of the system.

A new methodology has been developed in this thesis for inclusion of multi-state failures of generating units in sequential Monte Carlo simulation procedures. The developed approach for accommodating multi-state failures is first applied to solve the state space diagram of such failures and the results are compared with those obtained by using analytical technique. The results show very close comparison. Finally the new algorithm is included in sequential Monte Carlo simulation procedures and applied to evaluate the IEEE-RTS with multi-state generating units. The results are also compared with that obtained by using analytical techniques. They compare favourably indicating the effectiveness of the new approach.



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ABBREVIATIONS

IEEE	:	Institution of Electrical and Electronic Engineers.
DNS	:	Demand Not Served.
ENS	:	Energy Not Served.
FOR	:	Forced Outage Rate.
IFC	:	Incremental Fuel Cost.
IHRC	:	Incremental Heat Rate Curve.
LDC	:	Load Duration Curve.
MCs	:	Monte Carlo simulation.
PDF	:	Probability Density Function.
RTS	:	Reliability Test System.
HLI	:	Hierarchical Level I.
YENS	:	Yearly Energy Not Served.
CEA	:	Canadian Electric Association.
TTF	:	Time To Failure.
TTR	:	Time To Repair.
MTTF	:	Mean Time To Failure.
MTTR	:	Mean Time To Repair.
DOI	:	Duration Of Interruption.
NOI	:	Number Of Interruption.
YDOI	:	Yearly Duration Of Interruption.
LOEE	:	Loss Of Energy Expectation.
LOLE	:	Loss Of Load Expectation.
FOI	:	Frequency Of Interruption.
LCY	:	Load Curtailment per Year.
EIR	:	Energy Index Reliability.
EENSPI	:	Expected Energy Not Served Per Interruption.
EID	:	Expected Interruption Duration.
ELCI	:	Expected Load Curtailment per Interruption.
TTTR	:	Time To Transition.
TNOI	:	Total No Of Interruption

NOTATIONS

$\overline{Q}$	:	Unavailability (failure probability)
α	:	Coefficient of Variation.
U_i	:	Uniformly distributed random. number of the i-th unit.
F(x)	:	Cumulative probability distribution function.
S_i	:	State for the i-th component.
T_i	:	Sample duration for the i-th component.
P_j	:	Conditional Probability for j-th component.
x_i	:	i-th sample of interest.
C(h)	:	Generation cost during the h-th hour.
IFC_i	:	Incremental Fuel Cost of the i-th unit during the h-th hour.
NT	:	Total number of Thermal units.
$P_i(h)$	:	Power output of the i-th unit during the h-th hour.
$YENS_i$	:	Yearly Energy Not Served during the i-th year.
$YDOI_i$	:	Yearly Duration of Interruption during the i-th year.
C_i	:	The loss of load for system state i.
P_i	:	Probability of system state i.
$ENSPI_i$	:	Energy Not Served Per Interruption During i-th Year.
DOI_i	:	Duration of Interruption during i-th year.
$LOLE_G$	:	Loss Of Load Expectation Generation only.
$LOLE_T$	:	Loss Of Load Expectation Transmission only.
TTF_i	:	Time To Failure of the i-th unit.
TTR_i	:	Time To Repair of the i-th unit.
TTT_{ij}	:	Time To Transition from state i to j.
TR_{ij}	:	Transition rate from state i to j.
λ_i	:	Failure rate of the i-th unit.
μ_i	:	Repair rate of the i-th unit.

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Chapter-One

Introduction

1.1 General

The primary objective of the techniques and criteria used for planning, designing and operating power systems is to supply electrical energy to the customers as economically as possible and with an acceptable degree of reliability and quality. Reliability assessment are therefore an integral part of power system studies in order to assist decisions regarding how much should be expended on the system in order to improve or maintain the quality, adequacy and reliability of the system. With the ever growing technical advancement and tremendous industrial automation during the past few decades, electricity has become an integral part and vital life line of present-day society. The failure of electricity can often cause effects that range from inconvenience and irritation to a severe impact on society and on its environment. Almost every function of present-day halts when the supply of electricity halts. A high degree of reliability of electricity is of utmost concern to the electricity supply industries. So, reliability is, and always has been, one of the major factors in the planning, design, operation and maintenance of the electric power systems. According to Bagowsky, "Reliability is the probability of a device performing its purpose adequately for the period of time intended under the operation conditions encountered" [1].

Modern society, because of its pattern of social and working habits, has come to expect that the supply should be continuously available on demand [2]. This is not possible due to random system failures which are generally outside the control of power system engineers. The probability of customers being disconnected, however, can be reduced by increased investment during either the planning phase, operating phase or both. Increased investment is necessary to achieve increased reliability or even to maintain reliability at current and accepted levels. Over-investment can lead to excessive operating costs although the system may be very reliable. On the other hand, under investment leads to the opposite situation. It is evident that the economic and reliability constraints can be competitive, and this can lead to difficult managerial decisions at both the planning and operating phases. The system planner has to work within various uncertainties and complex scenarios in order to evaluate a power system for its past performance or to predict its future performance.

Past performance assessment is valuable because it :

a) identifies weak areas needing modifications

b) establishes chronological trends in reliability performance

c) establishes existing reliability indices, which serves as a guide for acceptable values in future reliability assessments.

d) enables previous predictions to be compared with actual operating experience.

e) monitors the response to system design changes.

Assessment of future system performance is valuable because it predicts the following:

a) how the system is expected to behave in the future.

b) the benefits of alternative system designs, reinforcements and expansion plans.

c) the effects of alternative operational and maintenance policies.

d) the related reliability cost/benefit/worth of the alternatives associated with b and c.

1.2 Overview of generating system reliability

In a generating system, the total system generation is examined to determine its adequacy to meet the total system load requirement. This activity is usually termed "generating capacity reliability evaluation". The system model at this level is shown in Figure 1.1.

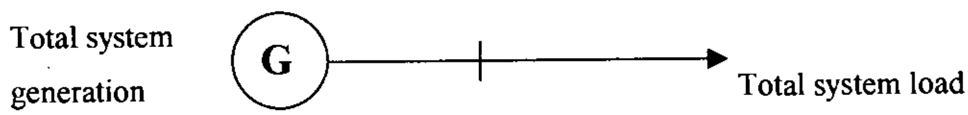


Figure 1.1:Hierarchical level 1(HL1) model.

The transmission system and its ability to move the generated energy to the consumer load points is ignored in generating system adequacy assessment. The basic concern is to estimate the generating capacity required to satisfy the system demand and to have sufficient capacity to perform corrective and preventive maintenance on the generating facilities. The basic technique, used in the past, to determine the capacity requirement was the percentage reserve method. In this approach the required reserve is a fixed percentage of either the installed capacity or predicted load. This and other criteria, such as a reserve equal to one or more of the largest units, have now been largely replaced by probabilistic methods which respond to and reflect the actual factors that influence the reliability of the system.

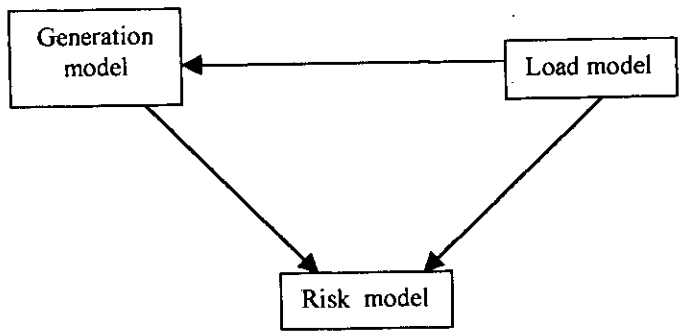


Figure 1.2: Conceptual tasks for HLI evaluation.

The basic modeling approach for an HLI study is shown in Figure 1.2. Analytical methods and Monte Carlo simulation utilize different techniques to assess generation and load models. The essential concept shown in Figure 1.2 is basically the same for both techniques.

A power system consists of three basic functional zones: Generation, Transmission and Distribution. The functional zones can be combined for the purpose of reliability evaluation as illustrated in the hierarchical levels shown in Figure 1.3. The generation system is defined as HLI. Generation system reliability performance is measured in terms of the amount of unreliability created by events in the bulk power system. Unreliability denotes the inability to provide the required electricity to all ultimate customers supplied by the bulk power system [3]. It involves the system failure events which consists of loss of load and system collapse arising from wide spread outages. In this thesis power system reliability evaluation is carried out at HLI, i.e. generation system.

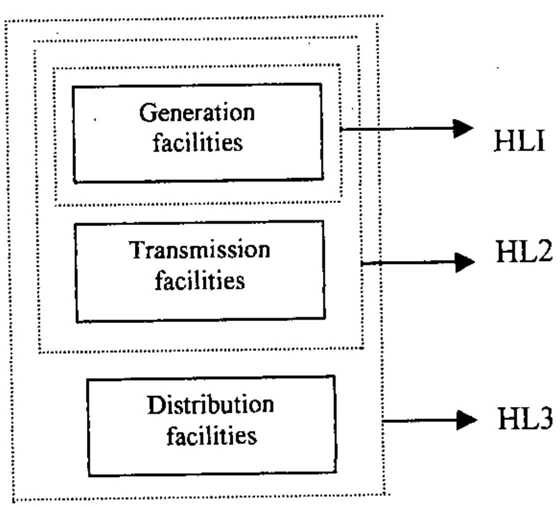


Figure 1.3: Hierarchical levels

1.3 Historical background

The determination of the required amount of system generating capacity to ensure an adequate supply is an important aspect of power system planning and operation. The total problem can be divided into two conceptually different areas designated as static and operation capacity requirement. The static capacity area relates to the long term evaluation of this overall system requirement. The static requirement can be considered as the installed capacity that must be planned and constructed in advance of the system requirements [4].

A practice that has developed over many years is to measure the adequacy of both the planned and installed capacity in terms of a percentage reserve. An important objection to the use of percentage reserve criterion is the tendency to compare the relative adequacy of capacity requirements provided for totally different systems on the basis of peak loads experienced over the same time period for each system. The percent reserve criterion also attaches no penalty to a unit because of size unless this quantity exceeds the total capacity reserve. The criteria and techniques first used in practical applications, however, were all deterministically based. Typical criteria for deterministically based analysis are:

a) Planning generating capacity–installed capacity equals the expected maximum demand plus a fixed percentage of the expected maximum demand.
b) Operating capacity – spinning capacity equal expected load demand plus a reserve equal to one or more largest units;
c) Planning network capacity – constructing a minimum number of circuits to a load group, the minimum number being dependent on the maximum demand of the group [4].

Although these and other similar criteria have been developed in order to account for randomly occurring failures, they are inherently deterministic. The essential weakness of deterministic criteria is that they do not respond nor reflect the probabilistic or stochastic nature of system behavior, of customer demands or of component failures. The need for probabilistic evaluation of system behavior has been recognized [5-9] since at least 1930s. Interest in the application of probability methods to the evaluation of capacity requirements become evident about 1933. Lyman [5] suggested that probability be applied to generating capacity and other reserve problems as early as 1933. About the same time smith [6] made similar suggestions in a 1933 McGraw prize paper, submitted to the Edison Electric Institute.

The first significant set of papers that added impetus to the application of probability theory to reliability assessments appeared in 1947. A recognized major contribution was made by Calabrese [10]. Calabrese, belived that the method of probability should find a more extensive use than til then in the solution of reserve problems. The Calabrese method forms the basis of the loss of load approach and the loss of energy approach which is still the most widely used probabilistic technique in the reliability evaluation of generating capacity. Both of these methods concern the evaluation of expectation using basic probability methods.

Others made similar contributions [11-13] at the same time. Lyman [11], presented a short-cut method of computing probability of outage of any given magnitude while Seelye [12] determined by computation the interval in years between outages of variation magnitudes. Loane and Watchron [13], were also intervals of multiple outages, in connection with the use of hydro storage. These techniques are summarized in [14].

Another significant approach is the frequency and duration method. One of the most significant developments in this area was the application of recursive techniques published in a series of five papers by Ringlee, Wood et.al. [15-19].

These papers present reliability calculation methods for the generation system that incorporates the frequency and duration of unit outage. This method leads to calculate generation reliability measures which are the availability, frequency of occupance and mean duration of reserve states. Also the paper [15-19] presents a probabilistic model of power system loads and generation reserve margins which may be used to calculate the availabilities. Billinton and Singh [20] in 1971 extended the techniques to develop frequency and duration approach to interconnected system reliability evaluation. Also Ayoub and Patton [21] calculated the frequency and duration of load loss events as measures of generating system reliability.

Most analytical techniques are based on Calabrese approach in which the generation model represented by a capacity outage probability table. This is constructed using a state enumeration method [4]. However, alternative methods for evaluating the models also exists. Another new method is the cumulant method to obtain the capacity outage probability by using Fourier transforms and Gram-Charlier expansion was introduced by N.S Rau and K.F. Schenk [22] in 1979. This technique has been widely used for adequacy assessment, production costing and maintenance scheduling. Considerable error can occur including negative probabilities, under certain circumstances in using this method. Another alternative approach based on first Fourier transforms was proposed by R.N. Allan, et.al. [23]. This technique although computationally slower than the cumulant method does not exhibit the error problems.

Another important technique was proposed by K.F. Schenk [24]. The method consists of obtaining the frequency distribution of equivalent loads by convolving the generating units in a merit order of loading. The convolution process is achieved by appropriately shifting and combining the statistical moments of hourly loads and machine outages. Quantitative reliability evaluation using probability methods began with the evaluation of system adequacy at hierarchical level I.

An alternative approach is simulation, generally known as Monte Carlo simulation. There has been a tendency in North America to use the former and in Europe and south America to use the latter. Due to the recent development of computing power simulation techniques are gaining popularity in North America as well.

An early example of simulation approach is found in [25]. This paper presents a new model for forced outages for use in a general system simulation program. Monte Carlo methods were applied to the model to simulate random occurrences of unit forced outages, random variations in daily peak load and others. This work has a significance of calculating the dispersion of actual performance about the average performance or about the effects of error in estimation of outage rates. In a most recent paper [26] it was proposed that load and generation should not be treated independently but should be considered in a co-related manner. It was found that simulation was appealing for this application. Other pioneers of simulation include ENEL (Italy) and EDF (France). Papers from these organizations, including [27], [28] and others appear in many CIGRE publications and in various European conference proceedings.

One of the most recent publications by Billinton and Ghajar [29] illustrated an overall approach in generating system adequacy evaluation using Monte Carlo simulation technique and this is widely used now-a-days. This approach is based on random simulation. Another paper [30] depicted a Monte Carlo simulation method used for generating capacity adequacy assessment. Monte Carlo simulation can be divided into two categories; non sequential (or random) and sequential. Reference [31] shows the use of a direct simulation method for considering a vast number of random contingencies. Both random and sequential Monte Carlo approaches have also been applied in 1975 [32]. The sequential approach was used in planning studies of mixed hydro thermal generating systems. Reference [38] presents a recent application of the Monte Carlo simulation to the IEEE-RTS [33]. Reference [34] describes some of the basic modeling concepts based on hybrid approach of the Monte Carlo simulation and enumeration technique. In reference [35] and [36] a new computational tool has been described where the reliability evaluation methodology is based on Monte Carlo sampling with a variance reduction scheme. This latter technique allows the incorporation of analytical methods. Most of these papers have described the application of random and sequential simulation to the generation system only [32].

The techniques based on analytical approach for assessing the composite systems is relatively straight forward in concept but it is usually restricted to the evaluation of expected values only and sometimes to a limited range of system parameters. The merits of having planning and operational decisions based on expected values is questionable. As stated earlier that Hoffman, et. al [25] at first in 1959 pointed out the necessity of the likely range of the reliability indices. This can only be assessed from a knowledge of the probability distributions that is wrapped around the expected value and this is hardly achievable by using the analytical approach. Simulation approach estimates the reliability indices by simulating the actual behavior of the system. Ubeda and Allan [37] summarized the basic characteristics of sequential simulation and applied for reliability evaluation of composite systems. In the random simulation approach each sample of system states is randomly selected from the appropriate distributions quite independently from previous and subsequent sample.

In sequential simulation however, each sample of system states are related to the previous system states. Therefore the evaluation of the system behavior is modelled enabling a greater range of reliability indices to be evaluated including frequency and duration of states.

The main emphasis of this thesis work is to develop a new approach for taking into account multi-state or derated state outages of generating units in sequential Monte Carlo simulation technique to evaluate reliability indices of generating system. Although the state space transition diagrams for multi states generating units are possible to appreciate from detail data collection schems they can only be utilized in random or non sequential and not in sequential simulation. The available technique for generation system reliability evaluation using sequential simulation considers only binary state units. Many utilities are now appreciating multi-state representation of generation units for system adequacy analysis. In this research the developed approach for accommodating multi-state failures is first applied to solve the state space diagram of such failures and the results are compared with those obtained by using analytical technique. The results show very close comparision. Finally, the new algorithm is included in sequential Monte Carlo simulation procedures and applied to evaluate the IEEE–RTS [33] with multi-state generating units. The results are also compared with that obtained by using analytical techniques.

After some initial runs it was decided to simulate the IEEE–RTS for 3000 years. At the end of each year the yearly values of reliability indices are stored. At the end of the simulation the expected values are calculated. The results of such a study can be of great importance to the system planner and operators during design and operation phase of power a system.

1.4 Thesis organization:

This thesis consists of six chapters. As an introduction, chapter 1 draws an overview of the generating system reliability and the historical background of the reliability assessment of power systems. In chapter 2, a concise idea is given on the Monte Carlo simulation for evaluating power system reliability. Chapter 3 deals with the modeling of generating system. Discussion in chapter 3 is directed towards the description of generating system and load models that are used in this research. Chapter 4 describes the new approach for modeling of multi-state generating unit which is used in this research for evaluating IEEE–RTS. Different reliability indices have been estimated and the numerical results are shown in chapter 5. In chapter 6 observations, discussions and conclusions are presented on the basis of the results of chapter 5. Recommendations for further research are also provided in chapter 6.

Chapter-two

Monte Carlo simulation for evaluating power system reliability

2.1 Introduction

The Monte Carlo Method is the general designation for stochastic simulation using random numbers. Monte Carlo simulation methods, however, estimate the indices by simulating the actual process and random behaviour of the system [39]. This method can be used to solve not only stochastic but also deterministic problems. Application of Monte Carlo techniques can be found in many fields such as complex mathematical calculations, stochastic process simulation, medical statistics, engineering system analysis and reliability evaluation. This chapter describes Monte Carlo methods applied to power system reliability evaluation. The basic concepts of Monte Carlo method are presented and discussed from a reliability evaluation point of view.

Monte Carlo simulation approach simulates the basic intervals of the simulated period in chronological order [40-41]. In sequential simulation a large amount of computing time is generally needed. With the advent of new powerful computing machine, this drawback has been greatly reduced during the last few years. The concepts of Monte Carlo simulation used in this research work are based on :

(1) The multiplicative congruent method for generating pseudo-random numbers.

(2) The inverse transform method for converting these to the relevant probability distribution.

(3) The sequential simulation approach in order to represent the time dependent process and to obtain density estimates associated with each of the indices.

2.2 Main Feature of Monte Carlo Methods in Reliability Evaluation

A fundamental parameter in reliability evaluation is the mathematical expectation of a given reliability index. Salient feature of the Monte Carlo method for reliability evaluation therefore can be discussed from an expectation point of view.

Let $\bar{Q}$ be the unreliability (failure probability) of a system and x_i be a zero-one indicator variable which states that

$x_i = 0$ if the system is in the up state.

$x_i = 1$ if the system is in the down state.

The estimate of the system unavailability is given by

$$\bar{Q}=\frac{1}{N}\sum_{i=1}^{N}x_i \quad \ldots\ldots(2.1)$$

Where N is the number of system state samples. The unbiased sample variance is

$$V(x)=\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{Q})^2 \quad \ldots\ldots(2.2)$$

When the sample size is large enough, equation 2.2 can be approximated by

$$V(x)=\frac{1}{N}\sum_{i}^{N}(x_i-\bar{Q})^2 \quad \ldots\ldots(2.3)$$

Because x_i is a zero-one variable, it follows that

$$\sum_{i=1}^{N}x_i^2=\sum_{i=1}^{N}x_i \quad \ldots\ldots(2.4)$$

Substituting equation 2.1 and 2.4 into equation 2.3 yields

$$V(x)=\frac{1}{N}\sum_{i=1}^{N}x_i^2-\frac{1}{N}\sum_{i=1}^{N}2x_i\bar{Q}+\frac{1}{N}\sum_{i=1}^{N}\bar{Q}^2=\bar{Q}-\bar{Q}^2 \quad \ldots\ldots(2.5)$$

Equation (2.1) gives only an estimate of the system unavailability. The uncertainty around the estimate can be measured by the variance of the expectation estimate:

$$V(\bar{Q})=\frac{1}{N}V(x)=\frac{1}{N}(\bar{Q}-\bar{Q}^2) \quad \ldots\ldots(2.6)$$

The accuracy level of Monte Carlo simulation can be expressed by the coefficient of variation, which is defined as

$$\alpha=\sqrt{V\bar{Q}\Big/\bar{Q}} \quad \ldots\ldots(2.7)$$

substitution of equation (2.6) into equation (2.7) gives

$$\alpha=\sqrt{\frac{1-\bar{Q}}{N\bar{Q}}} \quad \ldots\ldots(2.8)$$

$$N = \frac{1-\bar{Q}}{\alpha^2 \bar{Q}} \quad \text{....................(2.9)}$$

This equation indicates two important points:

(a) For a desired accuracy level α, the required number of samples N depends on the system unavailability but is independent of the size of the system. Monte Carlo methods are therefore suited to large-scale system reliability evaluation. This is an important advantage of Monte Carlo methods compared to analytical enumeration techniques for reliability evaluation.

(b) The unavailability (failure probability) in practical system reliability evaluation is usually much smaller than 1.0 . Therefore equation 2.9 can be expresses as :

$$N \approx \frac{1}{\alpha^2 \bar{Q}} \quad \text{...........(2.10)}$$

This means that the number of samples N is approximately inversely proportional to the unavailability of the system. In other words, in the case of a very reliable system, a large number of samples is required to satisfy the given accuracy level.

2.3 Random number generation

Random numbers are essential in all simulation techniques. A uniform random number is a variable having values uniformly distributed in the interval (0,1).True uniformly distributed random numbers are random variables with the probability density function (pdf):

$$\begin{cases} f(u)=1 & 0 \le u \le 1 \\ \quad =0 & elsewhere \end{cases}$$

The corresponding pdf is shown in Figure 2.1

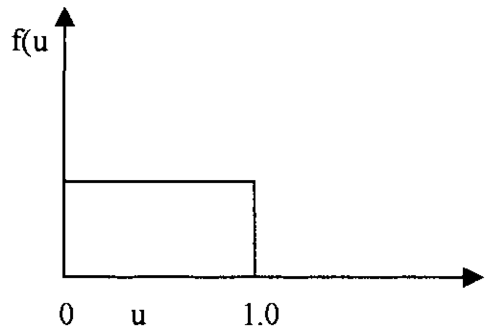


Figure 2.1: pdf of uniformly distributed random number.

Random numbers are created by a digital computer using the deterministic algorithms known as random number generators .As the numbers generated by a random number generator follow the mathematical rules of the algorithm, they are not the true random numbers and instead are called pseudo-random numbers. The basic requirements of the generator are that the random numbers should possess the following characteristics:

- randomness and uniform distribution
- a large period before the sequence repeats
- reproducibility so that the same sequence can be repeated.
- computational efficiency in their creation.

The most commonly used present-day method for generating pseudo-random numbers is one that produces a sequence of numbers according to recursive formula based on calculating the residues modulo of an integer of a linear transformation. Although these process are completely deterministic, it can be shown [42] that the numbers generated by the sequence appear to be uniformly distributed and statistically independent. The congruential methods, first proposed by Lehmer [43] are based on a fundamental congruence relationship from which a new number X_{i+1} in a sequence is calculated from the previous value X_i using the expression:

$$X_{i+1}=(AX_i+C)(\text{mod } B) \qquad (2.11)$$

Where the multiplier A, the modulus B and the increment C are all non-negative integers. If C>0 then the generator is called a mixed-congruential generator and if C=0 it is called a multiplicative generator. The modulo notation (mod B) means that:

$$X_{i+1}=AX_i+C-BK_i \qquad (2.12)$$

Where $K_i=(AX_i+C)/B$ denotes the largest positive integer in $(AX_i+C)/B$. After deducing the sequence of random numbers X_i, a uniformly distributed random number U_i in the range (0,1) is found from the relation:

$$U_i=X_i/B \qquad (2.13)$$

The process is started by choosing a value X_o known as the seed. The sequence is then produced automatically. However the sequence will repeat itself after a number of steps which can be shown [44] to be equal to a value not greater than B. The routines used in these studies to produce random numbers use a multiplicative generator and the constant A and B are chosen to give optimal statistical properties [45]. The multiplier and the modulus values used in these studies are:

$$A=16807$$

$$B=2^{31}-1$$

After a sequence of random numbers has been created, they can be tested for independence and randomness using one of the standard statistical tests such as Chi-squard or Kolmogorov-Smirnov goodness-of-fit tests [46].

2.4 Random variates generation

The procedure for generating uniformly distributed random variates can be generally categorized into three techniques:

(1) Inverse transform method,

(2) Comparison method,

(3) Acceptance-rejection method.

Inverse transform method is most frequently used. The exponential and normal distributions are the most important ones in reliability evaluation. The procedure for generating random variates using the inverse transform method is as follows:

Step1: Generate a uniformly distributed random number sequence U between [0,1].

Step 2: Calculate the random variate which has the cumulative probability distribution function F(x) by $X=F^{-1}(U)$

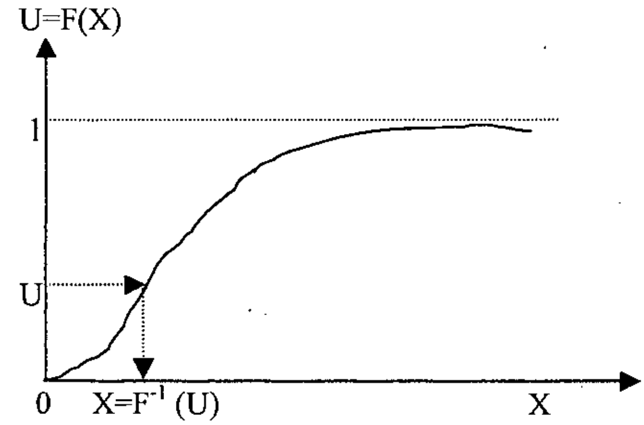


Figure 2.2: Explanation of the inverse transform method.

Example: Given the following probability density function:

$$f(x)=\begin{cases}2x & 0\leq x\leq 1\\ 0 & \textit{Otherwise}\end{cases}$$

The cumulative probability distribution function is

$$F(x)=\int_0^x 2x\,dx = \begin{matrix} x^2 & 0\leq x\leq 1 \\ =0 & x>1\end{matrix}$$

The random variate which follows this cumulative probability distribution function is obtained using

$$X=F^{-1}(U)=\sqrt{U}(0\leq U\leq 1)$$

Where U is a uniformly distributed random number sequence between [0,1].

2.4.1 Generating exponentially distributed random variate

An exponentially distributed random variate has the probability density function $f(x)=\lambda e^{-\lambda X}$

Its cumulative probability distribution function is $F(x)=1-e^{-\lambda X}$

By using inverse transform method:

$$U=F(x)=1-e^{-\lambda X}$$

so that $X = F^{-1}(U) = -\frac{1}{\lambda}\ln(1-U)$

Since (1-U) distributes uniformly in the same way as U in the interval (0,1).

$$X = -\frac{1}{\lambda}\ln U$$

where U is an uniformly distributed random number sequence and X follows an exponential distribution.

2.5 Simulation approaches in reliability evaluation

2.5.1 State sampling approach

A system state depends on the combination of all component states and each component state can be determined by sampling the probability that the component appears in that state. The behavior of each component can be described by a uniform distribution between [0,1]. Assume that each component has two states of failure and success and that component failure and success are independent events. Let S_i be the state of the i-th component and PF_i denotes its failure probability. A random number U_i distributed uniformly between [0,1] for the i-th component.

$$S_i = \begin{cases} 0 \; success & if \; 0 \geq PF_i \\ 1 \; failure & if \; 0 \leq U_i \prec PF_i \end{cases}$$

The state of the system containing m components is expressed by the vector S, $S=(S_1,\ldots\ldots\ldots,S_i,\ldots\ldots\ldots\ldots,S_m)$

Assuming that each system state has the probability P(S) and the reliability index function F(S), the mathematical expectation of the index function of all system states is given by:

$$E(F) = \sum_{S \varepsilon G} F(s)P(s)$$

Where G is the set of system state.

$$E(F) = \sum_{S\varepsilon G} F(s)\frac{n(s)}{N}$$

Where N is the number of sample of n(S) in the number of occurrences of state S.

Advantages:

a) Sampling is relatively simple. It is only necessary to generate uniformly distributed random numbers between [0,1]

b) Required basic reliability data are relatively few. Only the component state probabilities are required.

c) State sampling not only applies to component failure events but also can be easily generalized to sample states of other parameters in power system reliability evaluation such as load, hydrological and weather states, etc.

Disadvantage:

It cannot be used to calculate the actual frequency index.

2.5.2 State duration sampling approach

The state duration sampling approach is based on sampling the probability distribution of the component state duration. In this approach, chronological component state transition processes for all components are first simulated by sampling. The chronological system state transition process is then created by combination of the chronological component state transition processes. In a two state component representation, these are the operating and repair state duration distribution functions and are usually assumed to be exponential. The state duration sampling approach can be summed up in the following steps:

Step 1: Specify the initial state of each component. Generally, it is assumed that all components are initially in the success or up state.

Step 2: Sample the duration of each component residing in its present state. For example, given an exponential distribution, the sampling value of the state duration is

$$T_i = -\frac{1}{\lambda_i} \ln U_i$$

Where U_i is a uniformly distributed random number between [0,1] corresponding to the i-th component; if the present state is the upstate, λ_i is the failure rate of the i-th component; if the present state is the down state, λ_i is the repair rate of the i-th component.

Step 3: Repeat step2 in the given time span(yr), and record sampling values of each state duration for all components. Chronological component state transition process in the given time span for each component can be obtained and have the forms shown in Figure 2.3.

Step 4: The chronological system state transition process can be obtained by combining the chronological component state transition processes of all components. The chronological system state transition process for the two components is shown in Figure 2.4.

Step 5: Conduct system analysis for each different system state to obtain the reliability index F(S) to calculate expectation of the index function E(F).

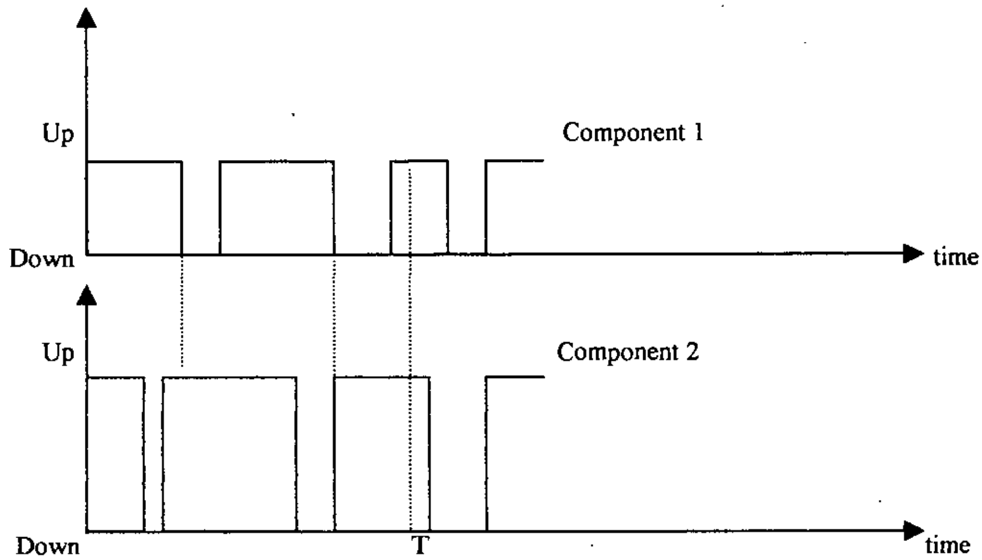


Figure 2.3 Chronological component state transition process

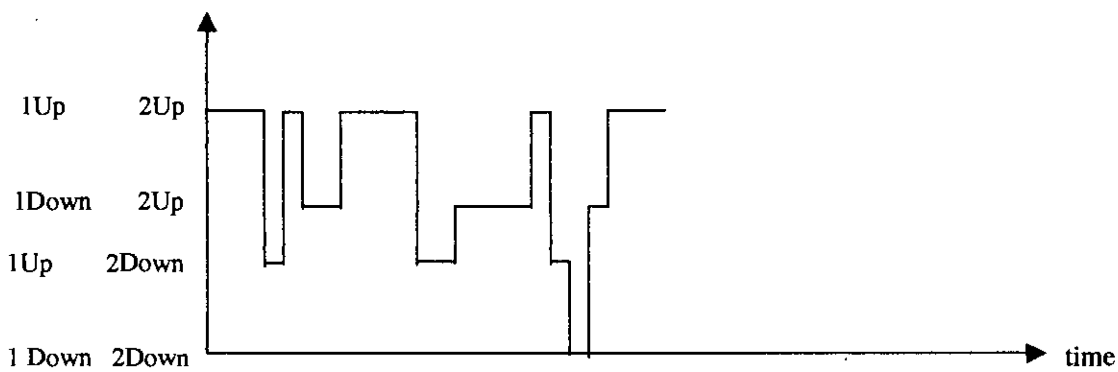


Figure 2.4 Chronological system state transition process

Advantages:

a) Easily calculates the actual frequency index.

b) Any state duration distribution can be easily considered.

c) The statistical probability distributions of the reliability indices can be calculated in addition to their expected values.

Disadvantages:

a) Compared to the state sampling approach, it requires more computing time and storage because it is necessary to generate a random variate following a given distribution for each component and store information on chronological component and store information on chronological component state transition processes of all components in a long time span.

b) This approach requires parameters associated with all component state duration distributions. Even under a simple exponential assumption, these are all transition rates between states of each component. For a multi-state component representation, it might be quite difficult to provide all these data in an actual system application.

2.5.3 System state transition sampling approach

This approach focuses on state transition of the whole system instead of component states or component state transition process. Suppose that the present system state is $S^{(k)}$ and the transition rate of each component relating to $S^{(k)}$ is λ_i (i =1,---,m). Transition of the system state depends randomly on the state duration of the component which departs earliest from its present state, i.e. the duration T of the system state $S^{(k)}$ is a random variable which can be expressed by $T = \min \{T_i\}$.

Since state duration of each component T_i follows an exponential distribution with parameter λ_i, the random variable T also follows an exponential distribution with the Parameter

$$\lambda = \sum_{i=1}^{m} \lambda_i$$

i.e, T has the probability density function

$$f(t) = \sum_{i=1}^{m} \lambda_i \exp\left(- \sum_{i=1}^{m} \lambda_i t \right)$$

Assume the system state $S^{(k)}$ starts at instant 0 and the transition of the system state from $S^{(k)}$ to $S^{(k+1)}$ takes place at instant t_0. The probability that this transition is caused by departure of the j-th component from its present state is the following conditional probability:

$$P_j = P(T_j = t_o / T = t_0) = \lambda_j \Big/ \sum_{i=1}^{m} \lambda_i$$

State transition of any component in the system may lead to system state transition. Consequently, starting from state S(k), the system containing m components has m possible reached states. The probability that the system reaches one of these possible states is expressed by the above equation:

$$\sum_{j=1}^{m} P_j = 1$$

Therefore, the next system state can be determined by the following simple sampling. The probabilities of m possible reached states are successively placed in the interval [0,1] as shown in Figure 2.5

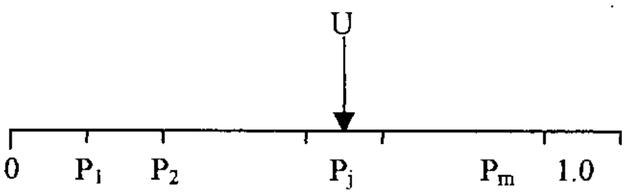


Figure 2.5:Explanation of system state transition sampling.

Now a uniformly distributed random number U between [0,1] is generated. If U falls into the segment corresponding to P_j, this means that transition of the j-th component leads to the next state. A long system state transition sequence can be obtained by a number of samples and the reliability of each system state can be evaluated.

Advantages:

a) It can be used to calculate the exact frequency index without the need to sample the distribution function and storing chronological information as in the state duration sampling approach.

b) In the state sampling approach, m random numbers are required to obtain a system state for an m-component system. This approach requires only a random number to produce a system state.

Disadvantage:

It only applies to exponentially distributed component state durations.

2.6 Sample mean and variance

The majority of the reliability indices represent the mean value of some magnitudes of interest such as energy not supplied, duration of inadequacy, load not supplied, frequency of interruption, etc. The magnitudes of interest can be accumulated based either on a yearly basis or on an interruption basis as 'observation'. The estimates most commonly evaluated are the various moments of simulation samples such as expected (mean) values and variances (or standard deviations). Sometimes higher order moments are also calculated in order to obtain measure of either skewness or of kurtosis.

The expected value E(x) and sample variance V(x) of the observations can be found from

$$E(x) = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$V(x) = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - E(x))^2$$

Where N : number of samples of interest

x_i : i-th sample of interest

It is important to note that E(x) is not the true mean value rather only a estimate of the exact value, since the value of N must tend to infinity before a true value can be obtained. Even then, the value that would be given would be the exact value associated with the model of the system being used, and not necessarily of the system itself. Also the variance of the sampling distribution, i.e. V(E(x)), is different from V(x).

2.7 Confidence interval

As mentioned earlier, the mean and variance given by the equations do not represent the true values. They only represent the sample mean and variance. So it is important to establish the precision and uncertainty associated with the estimated value of the parameter of interest. Usually it is preferable to express this precision in the form of an interval estimate. This estimate is constructed in such a way that the planner has a certain confidence that the interval does contain the unknown parameter. The interval estimate is then called a confidence interval.

Let a system be simulated for a certain period of time and the results are stored accordingly. Now if the same system simulation is repeated again with a different set of seeds for the random number generators, then generally speaking the results will differ from the previous values. If the experiment is repeated many times, the results still can vary from a minimum to a maximum value. A very simple example can be the values obtained for the yearly energy not served (YENS) index in different years when the system is simulated for a number of years. Therefore, an apparent question can be asked to the system planner. How confidence can the planner be about the values of the reliability indices?. This can only be answered by building a confidence interval around the value. The confidence interval depends on various factors such as sample variance, number of simulation etc. and mathematical formulation is given in the next section.

2.7.1 Mathematical Representation

Let x be a random variable having true mean and standard deviation given by μ and σ respectively, both are unknown. If the random variable has N values obtain from N independent observations, then the sample mean E(x) and standard deviation S(x) can be estimated from the following equations:

$$E(x) = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$V(x) = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - E(x))^2$$

Where N: number of samples of interest

x_i : i-th sample of interest.

If N is sufficiently large, then the central limit theorem [47] establishes that the distribution of E(x) tends to a normal distribution with mean μ and standard deviation $\sigma/\sqrt{N}$. Therefore the random variable Z given by:

$$Z = \frac{E(x) - \mu}{\sigma / \sqrt{N}} \quad \text{..................(2.14)}$$

is approximately normally distributed with a mean of zero and a variance of unity i.e. N(0,1).

If σ is replaced with its sample estimate S(x) , then the random variable:

$$t = \frac{E(x) - \mu}{s(x) / \sqrt{N}} \quad \text{..................(2.15)}$$

has a sampling distribution which is somewhat more spread out than the standard normal distribution. It can be shown [47] that the random variable t, called the Student t-distribution. s(x) is calculated from sample size N, so it has (N-1) degree of freedom. Like the standard normal distribution this distribution is symmetric with mean zero.

The integral of the t-distribution from $-\infty$ to a value T is the probability that the random variable t is less than or equal to T. Suppose the value of T is chosen so that the result of the integration is equal to $(1-\alpha/2)$ where $\alpha/2$ is some constant less than 1. let this value of T be denoted as $t_{\alpha/2}$. The probability that t is greater than $t_{\alpha/2}$ is then $\alpha/2$. As the t-distribution is symm-etric about its mean, so the probability that t is less than $-t_{\alpha/2}$ is also $\alpha/2$. Consequently, the probability that t lies between $-t_{\alpha/2}$ and $t_{\alpha/2}$ is $(1-\alpha)$

$$\Pr ob\left[-t_{\alpha/2} \le t \le t_{\alpha/2}\right] = 1 - \alpha \quad \text{..................(2.16)}$$

With the help of equation (2.15) the probability statement can be rewritten interms of the sample mean as :.

$$\Pr ob\left[E(x) - t_{\alpha/2}\frac{s(x)}{\sqrt{N}} \le \mu \le E(x) + t_{\alpha/2}\frac{s(x)}{\sqrt{N}}\right] = 1 - \alpha \quad \text{............(2.17)}$$

The value of $t_{\alpha/2}$ from t-distribution depends on the degrees of freedom, sometimes equation (2.17) becomes-

$$\Pr ob\left[E(x)-(t_{\alpha/2;N-1})\frac{s(x)}{\sqrt{N}} \leq \mu \leq E(x)+(t_{\alpha/2,N-1})\frac{s(x)}{\sqrt{N}}\right] = 1-\alpha \quad \ldots(2.18)$$

Where (N-1): designates the degree of freedom of the t-distribution.

The constant (1-α), usually expressed as a percentage, is the confidence level and the interval:

$$E(x) \pm (t_{\alpha/2,N-1})\frac{s(x)}{\sqrt{N}} \quad \ldots\ldots\ldots\ldots(2.19)$$

is the confidence interval for the true mean value μ. From a statistical point of view, equation (2.18) can be interpreted as:

'if for each simulation it is claimed that the mean value lies within the confidence interval, then in the long run 100(1-α) percent of these claims would be true'. The value $t_{\alpha/2,N-1}$ can be obtained from the standard statistical table given for the student t-distribution.

Chapter-three

Modelling of generating system

3.1 Introduction

Generating system adequacy assessment (HLI) is used to evaluate the availability of the system generating capacity to satisfy the total system load. This assessment can be conducted using either an analytical technique or the Monte Carlo method. Monte Carlo simulation is considered as the evaluation technique in this thesis. The simulation approach can be preferred for the following considerations:

(a) Time dependent or chronological issues are considered in simulation approach.

(b) Non exponential component state duration distributions can be considered.

(c) Distributions of reliability indices can be obtained in simulation approach.

In order to assess the generating system reliability (Hierarchical Level-I) accurately, the multi-state generating unit outages must be modelled to represent the generation system inadequacies. The models associated with multi-state generating units for considering in sequential simulation domain are developed in this thesis. These are described in detail in chapter 4. Although the IEEE-RTS is used for numerical evaluation, the hydro units of this system are modelled as energy abundant units and treated similar to thermal units. Accept the detail models of multi-state generating units, all other issues of generation system modelling are given in the following sections of this chapter.

3.2 Generating system

In order to carry out a meaningful reliability assessment of a power system it is necessary to appreciate the behaviour of all its components. The generating system is one of the major parts of a power system and usually comprises thermal and hydro generating plants. Thermal plants consists of the boilers, turbines, alternators and other auxiliary elements. All these components can be modelled separately but in power system reliability analysis these are generally grouped into generating units and represented by their availability models. Hydro units are modelled without considering any energy limitation.

Often a thermal unit is represented by a two-state model for reliability evaluation purposes. Now-a-days utilities are much more concerned about representing a generating unit by a more realistic model such as a multi-state representation. The Canadian Electric Association (CEA) defines as many as eleven possible states for generating units in some cases [48]. The model described in this research can take into account any multi-state representations in addition to usual binary state representation.

Thermal generating units are classified into four types :

1. THA-Base generation.
2. THB-Economic generation.
3. THC-Expensive generation.
4. THD-Peaking generation.

3.3 Availability Model

As far as forced outages and repairs are concerned, both thermal & hydro generating units are represented by the same model. This assumes that [51] :

a) The time between forced outages and the outage duration are independent.

b) A forced outage of any unit causes the loss of total or partial generating capacity depending on whether it is a binary or a multi-state unit.

c) The time to failure (TTF) is sampled from the corresponding underlying distribution using the mean time to failure (MTTF). A random value of TTF is sampled every time the failed unit is repaired and restored to service.

d) The outage duration is also assumed to be distributed obeying any underlying probability distribution having themean value given by the mean time to repair (MTTR). A random value of TTR is sampled every time a component fails.

e) The repair is under taken as soon as any element fails, repair time is independent of any other repairs or failures and repair is always successful and restores the component to as-good-as-new.

3.4 Load Model

Sequential simulation evaluates system performance hour by hour chronologically. In order to measure system adequacy during any hour it is necessary to know the system demand during that hour. Therefore all load models are represented by a Chronological hourly load.

Now a chronological hourly load can be described in many ways, e.g. determining load levels for each hour from a yearly chronological load curve. But, the most common form of representation is that described in the IEEE-RTS where monthly peaks are given as a fraction of the system peak, daily and hourly peaks are shown as a fraction of the monthly and daily peaks respectively. A load model of this kind represents actual variations of the system load over the year. Now the system inadequacies calculated on the basis of such a load model are commonly known as 'annual inadequacies' [49]. Sometimes system performance is also evaluated assuming a single load level (usually system peak load) throughout the year. In that case, the system evaluation is known as an 'annualized basis'.

Specified load levels used for any study represent the forecasted level for the period under consideration. Therefore, a degree of uncertainty can possibly remain within the forecasted load levels. The actual system load therefore may differ from the specified level for number of reasons. The uncertainty can be realized in the form of a probability distribution.

3.5 Load forecast uncertainty

It is extremely difficult to obtain sufficient historical data to determine the distribution describing the load forecast uncertainty. Published data [49], however, has suggested that the uncertainty can be reasonably described by a normal distribution. Uncertainty of the load can be simulated by multiplying the specified load by an uncertainty factor. This actually represents the deviation from the specified load level. This uncertainty factor is sampled from a normal distribution, N(0,1), with mean value of unity and standard deviation specified as input data. As the standard deviation (uncertainty level) increases, system unreliability also increases [49]. For a standard deviation equal to zero no uncertainty is considered. In these studies, the standard deviation for load forecast uncertainty is assumed to be zero, although the algorithm and program used is able to accommodate any non-zero value.

3.6 Operating and Dispatch policies

In a mixed hydro thermal generating system different operating policies can be followed. The principle for operating an energy limited system is to use the available energy in the best possible way during the period in which it is available. The operating policies determine what thermal generation and what hydro plants and units should be committed.

An operating policy can be based on either a pure safety policy where only system reliability is of interest or a mixed economy-safety policy when reliability as well as running cost are considered [50]. The mixed economy-safety policy is applied as an economic dispatch where the cost of generation is reduced. The available hydro generation is used not only to reduced the loss of load but also to substitute thermal generation on economic grounds. In this research work hydro units are considered without any energy limitation and therefore they are loaded as base loaded unit.

3.7 Production Cost

Thermal units are associated with incremental fuel costs and these vary over a wide range depending on the type of the fuel used. The incremental fuel cost associated with a thermal unit usually represents the average behaviour of the corresponding heat rate curve.

In reliability assessment, it is the number of units, their capacities and their failure and repair pdf which account for the system reliability rather than the order in which the units are loaded. However, in cost analysis the loading order is also important. For the economic operation of the system, the schedule for the commitment of the units in order of their increasing average incremental cost called economic commitment schedule or merit order of loading is used. The most economical generating unit is the one with the lowest incremental cost among all the available units and this generating unit is loaded first. Next in line will be the generating unit with again the lowest incremental cost among the remaining available units. After each hour of simulation, the total production cost during that hour is calculated using:

$$C(h) = \sum_{i=1}^{NT} IFC_i P_i(h) \cdots\cdots\cdots\cdots\cdots (3.1)$$

Where $C(h)$ = Generation cost during the h-th hour.

IFC_i = Incremental fuel cost of the i-th thermal unit.

$P_i(h)$ = Power output of the i-th unit during the h-th hour.

NT = Total number of thermal units.

It is worth mentioning that in general the IFC of equation (3.1) is not a constant quantity rather it is a function of the output power of the unit. If the functional relation is known, then it can be accommodated easily during the simulation procedure. However this average representation is often used in reliability evaluation procedure to calculate the system production cost.

3.8 Quantitative measurement of inadequacies

Historically, the evaluation of the planning criteria in power system has led to the development of reliability indices which are responsive to the basic planning parameters. Although the underlying objective of reliability criteria is to provide a basis for balancing cost and reliability, primarily these reliability indices are used as a consistent basis for planning. One potential advantage of quantitative reliability measure is their ability to serve as an absolute basis for determining an adequate level of system reliability.

As simulation progresses, interruptions are encountered due to the inability of the system to meet the demand. These inadequacies are caused by the generation system. The evolution of supply deficiencies requires the collection of three basic quantities :

- Energy not supplied per interruption, ENSPI.
- Duration of interruption, DOI.
- Number of interruption, NOI.

Deficiencies are also grouped by simulated years in order to obtain annual reliability indices.

$$YENS_i = \sum_{j=1}^{YNOI_i} ENSPI_j \cdots\cdots\cdots(3.2)$$

$$YENS_i = \sum_{j=1}^{YNOI_i} DOI_j \cdots\cdots\cdots\cdots(3.3)$$

To produce annual indices basic quantities are stored such that :

where $YENS_i$: yearly energy not served during the i-th year.

$YDOI_i$: yearly duration of interruption during the i-th year.

$YNOI_i$: Total number of interruptions during the i-th year.

Equation (3.2) and (3.3) represents quantities that are used to produced global annual indices. Similarly, quantities for generation only and transmission-only annual indices can be stored.

Bulk power system reliability indices are mainly grouped into three categories :

(a) Annual based

(b) Interruption based

(c) Load point based

3.9 System Annual indices

The most commonly used annual indices are :

(1) Loss of energy expectation (LOEE)

(2) Loss of load expectation (LOLE)

(3) Frequency of interruption (FOI)

(4) Load curtailment per year (LCY)

(5) Energy index of reliability (EIR)

LOEE (Mwh/yr)

$$LOEE = \sum_{i \in S} 8760 C_i P_i$$

where P_i is the probability of system state i and s is the set of all system states associated with loss of load and C_i is the loss of load for system state i.

The LOEE index is the expected energy not supplied by the generating system due to the load demand exceeding the available generating capacity.

The LOEE incorporates the severity of deficiencies in addition to the number of occasions and their duration and therefore the impact of energy shortfalls as well as their likelihood is evaluated. It is hence believed that this index will be used more widely in the future, particularly for situation in which alternate energy replacement sources are being considered.

LOLE (days/yr or hr/yr)

$$LOLE = \sum_{i \in S} P_i T$$

where P_i is the probability of system state i and s is the set of all system states associated with loss of load The LOLE is the average number of days or hours in a given period (usually one year) in which the daily peak load or hourly load is expected to exceed the available generating capacity.

It should be noted that the LOLE index in days/yr or in hr/yr has quite different meanings. When it is in days/yr, P_i depends on a comparison between the daily peak load and the available generating capacity. When it is in hr/yr, P_i depends on a comparison between the hourly load and the available generating capacity. The LOLE index does not indicate the severity of the deficiency nor the frequency nor the duration of loss of load. Despite these shortcomings, it is at present the most widely used probabilistic criterion in generating capacity planning studies.

Frequency of interruption (FOI)

$$FOI = \frac{1}{NY} \sum_{i=1}^{NY} YNOI_i \ \text{int}/yr$$

where NY : Total number of simulation year.

Load curtailment per year (LCY)

$$LCY = \frac{1}{NY} \sum_{i=1}^{NY} \left(\frac{YENS_i}{YDOI_i} \right) Mw/yr$$

where NY : Total number of simulation year.

Energy index reliability (EIR)

The complementary value of energy not supplied i.e. energy actually supplied, can be divided by the total energy demand to give a normalized index known as the energy index reliability (EIR). This index can be used to compare the adequacy of systems that differ considerably in size.

3.10 Interruption indices

Interruption indices give inadequacies associated with individual load curtailment. Annual indices give the average behaviour of the system over a year whereas interruption indices measure system performance on an interruption basis. These indices calculate the likely severity as well as the duration of interruptions. Interruption indices calculated in these studies are:

(a) Expected energy not served per interruption (EENSPI)

(b) Expected interruption duration(EID)

(c) Expected load curtailment per interruption (ELCI)

These are calculated using:

$$EENSPI = \frac{1}{TNOI} \sum_{i=1}^{TNOI} ENSPI_i \; Mwh/\text{int}$$

$$EID = \frac{1}{TNOI} \sum_{i=1}^{TNOI} DOI_i \; hr/\text{int}$$

$$ELCI = \frac{1}{TNOI} \sum_{i=1}^{TNOI} \left(\frac{ENSPI_i}{DOI_i} \right) Mw/\text{int}$$

TNOI: total number of interruptions during the entire simulation span.

Chapter-four

New approach for multi-state generating unit modelling

4.1 Introduction

This chapter describes a new approach for taking into account multi-state or derated-state outage of generating units in sequential Monte Carlo simulation technique to evaluate reliability indices of generating systems. The available technique for generation system reliability evaluation using sequential simulation considers only binary state units. Many utilities are now appreciating multi-state representation of generation units for system adequacy analysis. In this chapter developed approach for accommodating multi-state failures is first applied to solve the state space diagram of such failures and the results are compared with those obtained by using analytical technique. The result shows very close comparison.

This chapter also presents the main theme or objective of this thesis along with the methodology used and a functional block diagram to clarify that methodology. If the times to failure and repair distributions can be assumed to follow any of the most common probability distributions, this methodology can be readily applied to evaluate the reliability of the power systems. In this thesis generating unit state residence times are assured to follow exponential distribution.

4.2 Multi-state generating unit modelling

One of the important issues in the quantitative adequacy assessment of generating systems is the need to improve representations of the availability models for generating units. This includes the need to recognize derated states for generating units. Using an equivalent or de-rating adjusted forced outage rate for generating units instead of a multi-state model can lead to pessimistic results [52]. Many utilities are now using multi-state representations for system adequacy analysis. The Canadian Electric Association (CEA) defines as many as eleven possible states for generating units in some cases [53]. Therefore, it is important to include these types of partial outages in simulation procedures. Before going to the details of new approach it is worth recollecting how the sequential simulation proceeds incase of a system having two states generating units only.

Two- state generating unit

The state space diagram of a two-state generating unit is shown in Figure 4.1. At the beginning of the simulation, an initial state of the component is assumed, i.e state 1.Then the time-to-failure (TTF) or state residence time of the i-th unit is sampled by using equation (4.1).

$$TTF_i = -\frac{1}{\lambda_i}\ln(U_i)\cdots\cdots\cdots(4.1)$$

Where λ_i is the failure rate of the i-th unit.

U_i is the uniformly distributed random number for failure process of the i-th unit.

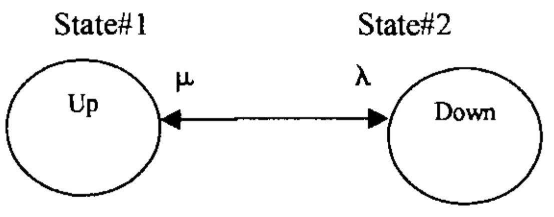


Figure 4.1: State space diagram of a typical two state unit.

After this value of TTF has elapsed, the component moves from state 1 to State 2. The time-to-repair (TTR) or state residence time in state 2 is then sampled using equation (4.2).

$$TTR_i = -\frac{1}{\mu_i}\ln(\overline{U_i})\cdots\cdots\cdots(4.2)$$

Where μ_i is the repair rate of the i-th unit.

$\overline{U_i}$ is a uniformly distributed random number for repair process of i-th unit.

After this value of TTR has elapsed, the unit transits to state 1 again and the cycle is repeated for the entire period of the simulation time.

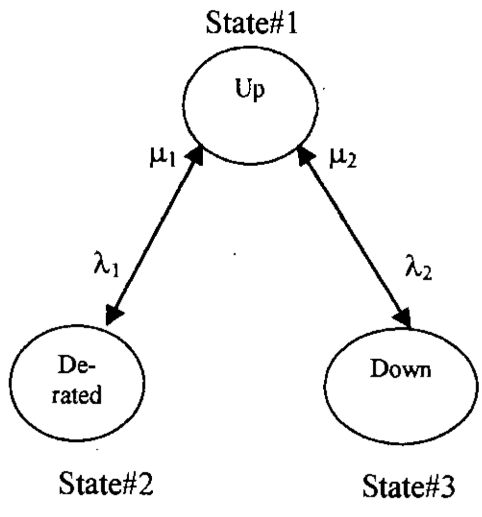


Figure 4.2 : State space diagram of a derated State unit.

On the other hand with multi-state generating units, several departure transition can emanate from a state as depicted in Figure 4.2. For example, in Figure 4.2, after finishing the state residence time in state 1, the component can transit to state 2 or state 3. Therefore it is difficult to predict the next transition. In order to overcome this difficulty of knowing which transition occurs, a predetermined operating cycle is considered in Reference [54]. However, this may not reflect correctly the stochastic nature of state transition of a generating unit. In order to represent accurately the sampling process in sequential simulation, a new approach for generating units having multi-state failures is presented in this chapter.

4.3 New approach for Multi-state unit

Using appropriate underlying probability distribution for each possible transition the time-to-transition (TTTs) are calculated using the following equation:

$$TTT_{ij} = -\frac{1}{TR_{ij}} \ln\left(U_{ij}\right) \cdots\cdots (4.3)$$

Where j encompasses all the states of the component that can be reached directly from state i.

TR_{ij} is the transition rate from state i to j.

U_{ij} is a uniformly distributed random number

From the state space diagram, the total number of possible transitions are determined for each state together with the correct transition rate for each transition. After calculating all the

TTTs, the lowest value of TTT is identified. This lowest value will be the state residence of this state. After elapsing the time the component will go to the next state.

If the load is greater than the total generation, there will be an interruption in the current hour. Now this interruption will be updated for that hour, otherwise, it will go to the next hour. This simulation steps are repeated hour by hour for a period of simulated time long enough to include most of the events. This approach is applicable to any state space diagram. This technique is applied in this research to accommodate multi-state generating unit outages in order to determine the transition that will take place and the current state residence time. Once the current state of the generating unit is known, then the capacity available from the unit is also known.

4.4 Calculation of limiting state probabilities using new approach

To verify the applicability, the new approach is applied to determine the limiting state probabilities of various states of a number of state space diagram for multi-state generating units shown in Figures 4.2-4.4. All these state space diagrams are selected arbitrarily in order to show the effectiveness, stability and raggedness of the algorithm. Some of the transitions included in these diagrams may not exit in reality. However, they are used just to appreciate stochastic nature of transitions in case of multi-state generating unit. Limiting state probabilities are also calculated for all these state space diagrams using analytical technique by solving the stochastic transitional probability matrix [55]. The results are shown in Tables 4.1-4.3 together with the results obtained from analytical solution. In these tables P's denote limiting state probabilities of corresponding states. For each state space diagram three sets of transition rates are used ranging from a reliable to a less reliable unit.

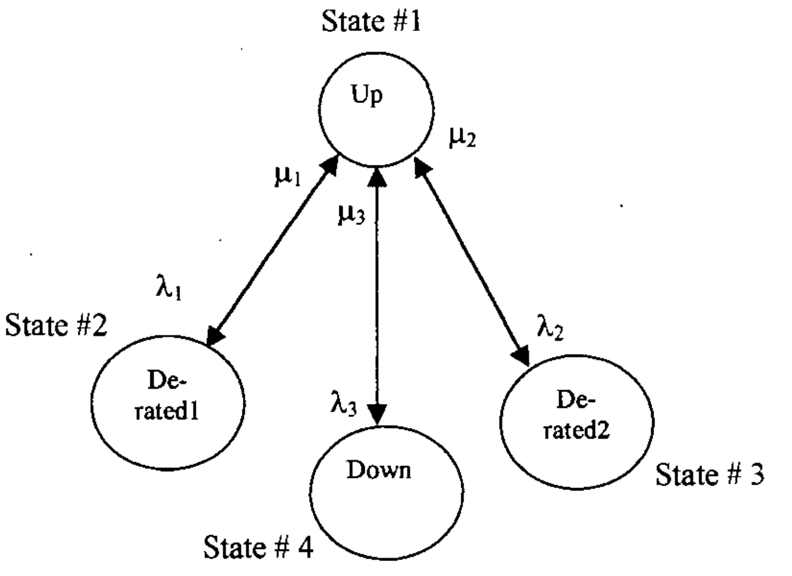


Figure 4.3: State-space diagram of a unit with two derated state.

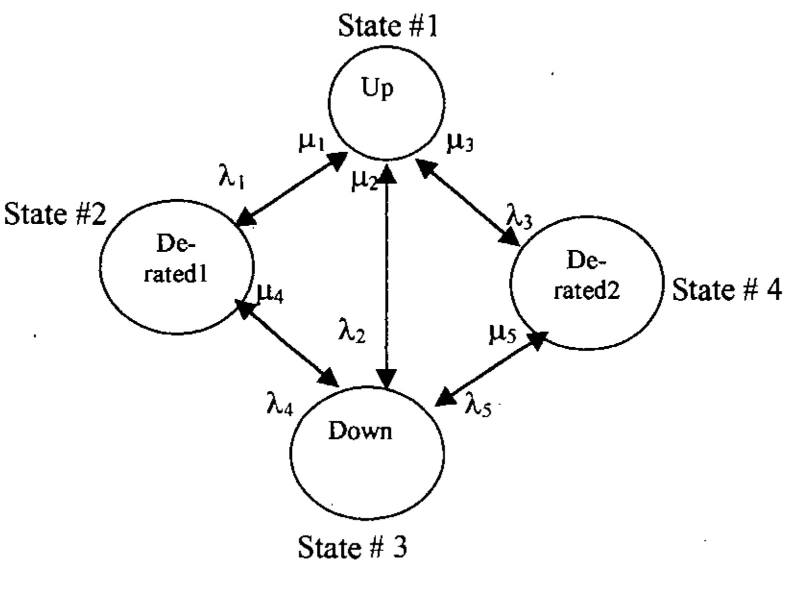


Figure 4.4: Unit with two derated states having more transitions.

Table 4.1: Limiting state probabilities for Figure 4.2

Transition rates	Analytical result	Simulation result
λ_1=8 tr./yr λ_2=5 tr./yr. μ_1=300 tr./yr. μ_2=300 tr./yr	P_1=0.958466 P_2=0.025559 P_3=0.015974	P_1=0.957897 P_2=0.026002 P_3=0.016100
λ_1=7 tr./yr λ_2=4 tr./yr μ_1=300tr/yr μ_2=300tr/yr	P_1=0.964630 P_2=0.022508 P_3=0.012861	P_1=0.964104 P_2=0.022932 P_3=0.012962
λ_1=6 tr./yr λ_2=3 tr./yr μ_1=300 tr./yr μ_2=300 tr./yr	P_1=0.970873 P_2=0.019417 P_3=0.009708	P_1=0.970264 P_2=0.019831 P_3=0.009903

Table 4.2: Limiting state probabilities for figure-4.3

Transition rates	Analytical result	Simulation result
λ_1=10 tr./yr λ_2=15 tr./yr λ_3=12 tr./yr μ_1=300 tr./yr μ_2=300 tr./yr μ_3=150 tr./yr	P_1=0.859599 P_2=0.028653 P_3=0.042980 P_4=0.068768	P_1=0.858771 P_2=0.028889 P_3=0.043535 P_4=0.068805
λ_1=8 tr./yr λ_2=6 tr./yr λ_3=4 tr./yr μ_1=300tr/yr μ_2=300tr/yr μ_3=150 tr./yr	P_1=0.931677 P_2=0.024845 P_3=0.018634 P_4=0.024845	P_1=0.931206 P_2=0.025274 P_3=0.018812 P_4=0.024707
λ_1=7tr/yr λ_2=5 tr./yr λ_3=3 tr./yr μ_1=300 tr./yr μ_2=300 tr./yr μ_3=150 tr./yr	P_1=0.943396 P_2=0.022013 P_3=0.015723 P_4=0.018868	P_1=0.942824 P_2=0.022410 P_3=0.015877 P_4=0.018889

Table 4.3: Limiting state probabilities for figure-4.4

Transition rates	Analytical result	Simulation result
λ_1=15 tr./yr λ_2=12 tr./yr λ_3=10tr/yr λ_4=5 tr./yr λ_5=8 tr./yr μ_1=150 tr./yr μ_2=250 tr./yr μ_3=300 tr./yr μ_4=120 tr./yr μ_5=175 tr./yr	P_1=0.843973 P_2=0.097193 P_3=0.020044 P_4=0.038790	P_1=0.842277 P_2=0.098903 P_3=0.020006 P_4=0.038814
λ_1=14 tr./yr λ_2=11 tr./yr λ_3=9 tr./yr λ_4=3 tr./yr λ_5=7 tr./yr μ_1=140tr/yr μ_2=240tr/yr μ_3=260 tr./yr μ_4=115 tr./yr μ_5=155 tr./yr	P_1=0.843017 P_2=0.098656 P_3=0.019303 P_4=0.039622	P_1=0.841537 P_2=0.099728 P_3=0.019226 P_4=0.039510
λ_1= 13tr/yr λ_2=7 tr./yr. λ_3=6 tr./yr λ_4=2 tr./yr λ_5=4 tr./yr μ_1=125 tr./yr μ_2=225 tr./yr μ_3=255 tr./yr μ_4=110 tr./yr μ_5=145 tr./yr	P_1=0.860054 P_2=0.099457 P_3=0.013184 P_4=0.027305	P_1=0.859093 P_2=0.100664 P_3=0.013162 P_4=0.027181

The results obtained from these solutions confirm the applicability of the new approach for sequential simulation. The limiting state probabilities calculated using the new methodology and shown in Tables 4.1-4.3 clearly indicate close conformity with those obtained using analytical techniques which are also shown in Tables 4.1-4.3. These results clearly indicate that the new methodology is acceptable and can be applied for evaluating reliability of generation system.

4.5 Sequential simulation procedure

In sequential simulation procedures used in this research work only the generation system is considered and reliability evaluation is carried out using the following steps:

(1) At the beginning of the simulation all necessary system data are read. These include:

(a) data about the thermal generating units. These include the number of states of the unit, capacity of each state, transition rate between states, capacity multiplier, incremental fuel cost, loading order position etc.

(b) Load model data.

(c) Monte carlo simulation related data such as type of underlying probability distribution, seed for the random number generators etc.

(2) Initialization of all component states.

(3) For every simulated hour the availability of all system elements, such as generating units are checked.

(4) Times-to-fail or repair are produced by sampling the exponential probability distribution.

(5) If multi-state generating unit exists, then the new approach described in section 4.3 is used.

(6) Components and their operations are represented by mathematical models

(7) Combined operation of the power system is then assessed.

(8) System deficiencies, if there are any, are recorded in magnitude and frequency in various formats. Each deficiency is stored as an independent sample. These deficiencies are also grouped by simulated years.

(9) Reliability indices are obtained from the above records together with their frequency distributions.

(10) The simulation steps are repeated hour by hour for a period of simulated time long enough to include most of the events of interest.

4.6 Simulation Methodology

The system operation is simulated over a long period of time, which is subdivided into reference periods of one year. Each year is divided into basic time intervals during which state of the system is assumed to be constant. The present model works on an hourly basis which means that changes in the system are assumed to occur only at the beginning of an hour. The detailed procedure is described in the next section. The simulation procedures can be programmed using any high level programming language. FORTRAN77 is used to implement the simulation procedures in this research.

4.7 Schematic diagram of sequential simulation methodology

A brief schematic diagram depicting the methodology is given in Figure 4.5

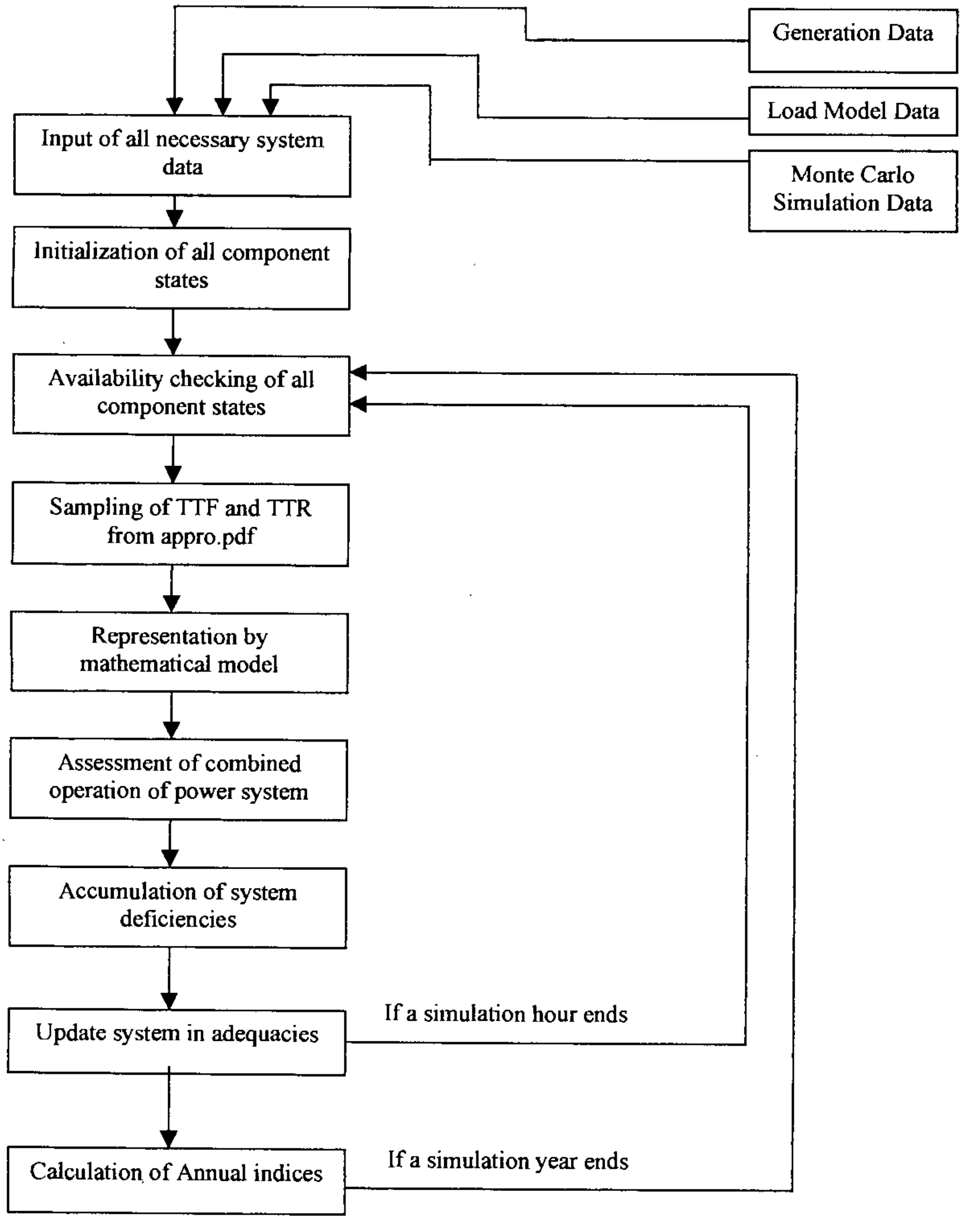
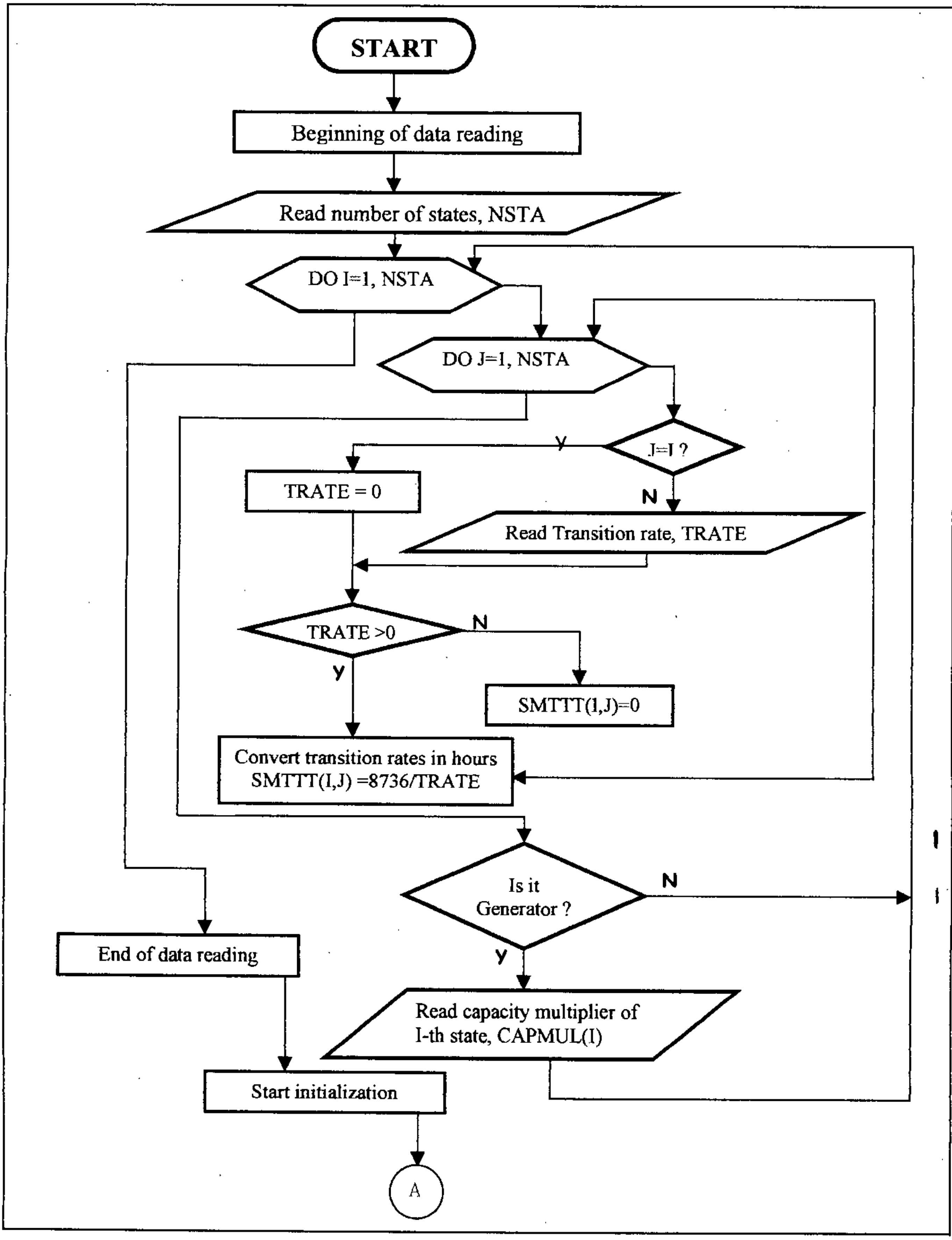
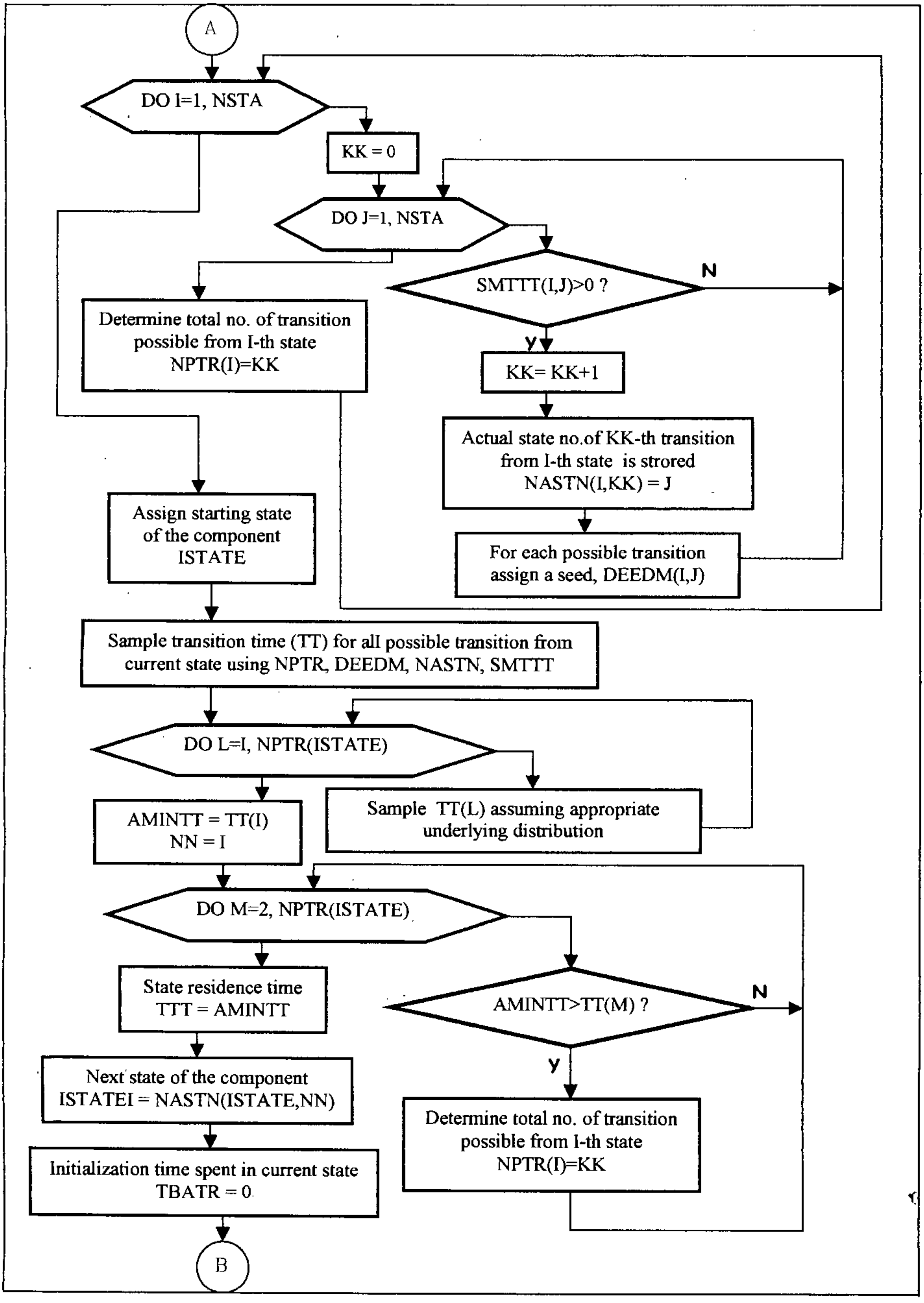


Figure 4.5 : Schematic diagram of simulation methodology

4.8 Flow chart for the multi-state problems




A
DO I=1, NSTA
KK = 0
DO J=1, NSTA
SMTTT(I,J)>0 ?
N
Y
Determine total no. of transition possible from I-th state NPTR(I)=KK
KK= KK+1
Actual state no.of KK-th transition from I-th state is strored NASTN(I,KK) = J
Assign starting state of the component ISTATE
For each possible transition assign a seed, DEEDM(I,J)
Sample transition time (TT) for all possible transition from current state using NPTR, DEEDM, NASTN, SMTTT
DO L=I, NPTR(ISTATE)
AMINTT = TT(I)
NN = I
Sample TT(L) assuming appropriate underlying distribution
DO M=2, NPTR(ISTATE)
State residence time TTT = AMINTT
AMINTT>TT(M) ?
N
Y
Next state of the component ISTATEI = NASTN(ISTATE,NN)
Determine total no. of transition possible from I-th state NPTR(I)=KK
Initialization time spent in current state TBATR = 0
B

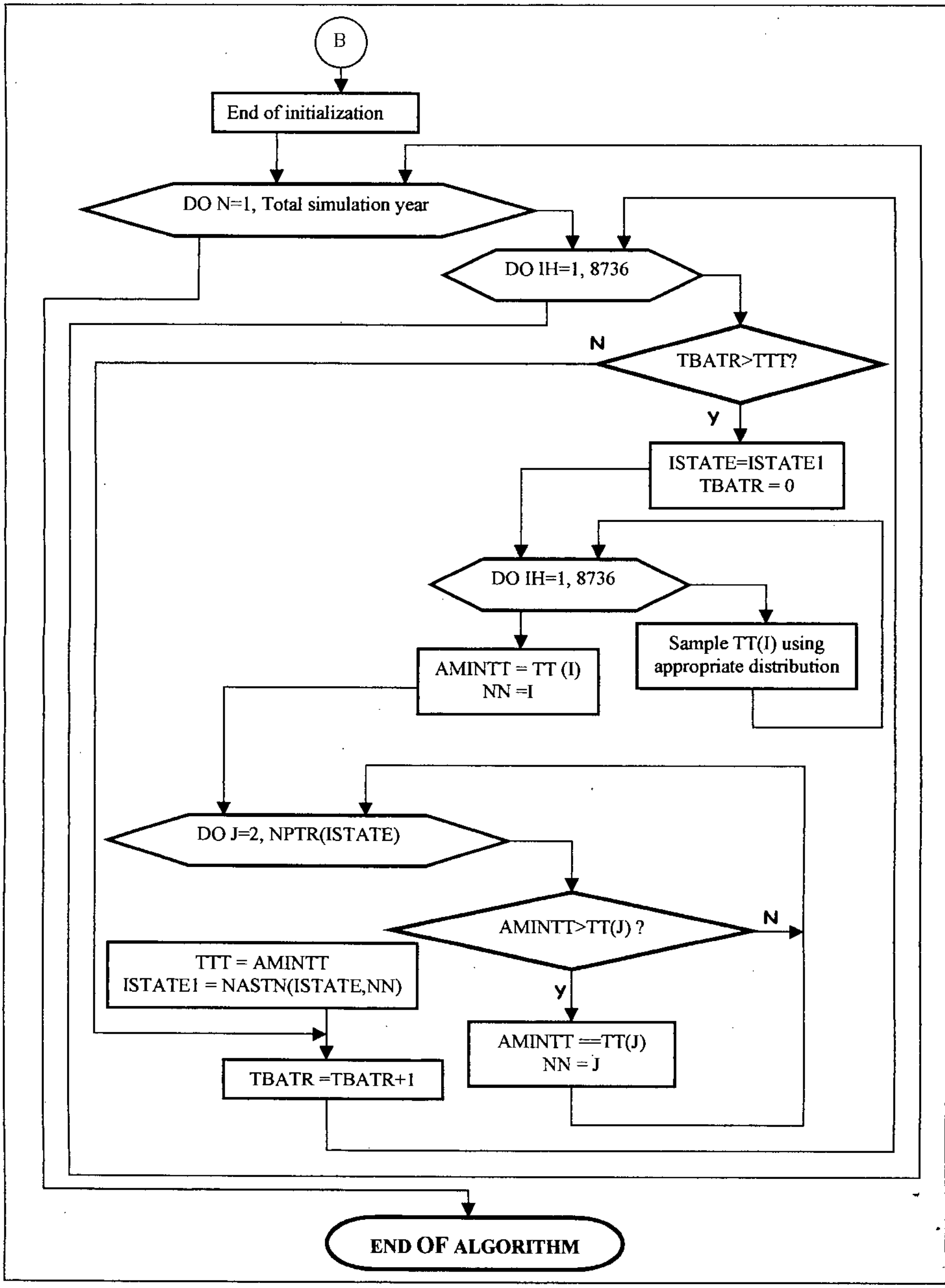


Figure 4.6 : Flow chart for the multi-state problems

Chapter-five

Numerical Evaluation

5.1 Introduction

For the simulation of generation system having multi-state generating units methodology has been developed in chapter 4. This methodology is applied to evaluate the reliability of the IEEE-RTS. In the numerical evaluation sequential Monte Carlo simulation is performed. Four different cases are considered for the IEEE-RTS generation system (namely base case, case-I, case-II and case-III) depending on the number of multi-state generating units.

The results that are presented in this chapter include the expected values of the reliability indices and their distributional parameters. Also the graphical representation of the variation of yearly energy not served per interruption (ENSPI), duration of interruption (DOI) and loss of load per interruption (LOLPI) and their histograms are presented to clarify the unreliability events associated with the IEEE-RTS.

5.2 IEEE-Reliability Test System

The IEEE Reliability Test System (RTS) was developed by the subcommittee on the application of probability methods of the IEEE power Engineering society to provide a common test system which could be used for comparing the results obtained by different evaluation methods. In this research work IEEE-RTS data have been used for computation.

5.2.1 Generation data

Generation data of IEEE-RTS used in this research are given in appendix A. The total Installed capacity of the system is 3405 MW which contains 32 generating units, ranging from 12 to 400 MW.

5.2.2 Load data

Hourly load data of IEEE-RTS are used in this research for simulating the reliability test system. The hourly peak load in percent of daily peak load and the daily peak load in percent of weekly peak load are given in appendices B and C respectively. The hourly load is found by multiplying the corresponding percent hourly load with the daily peak load.

5.3 Results for IEEE-RTS

IEEE-RTS data is considered for the evaluation of reliability by using sequential Monte Carlo simulation technique. The IEEE-RTS is evaluated at hierarchical level I. This is discussed in detail in the next section.

5.3.1 System evaluation

It is assumed in this evaluation that the underlying distribution is exponential, i.e. state residence time of all generating units are exponentially distributed. A chronological relationship of load is needed in sequential simulation and hourly load model described in [56] is utilized for this purpose. To represent multi-state failures of generating units, the 400 MW nuclear units and the 350 MW thermal unit are given more exhaustive representation. These are included in Figures 5.1 and 5.2. The 400 MW nuclear units and the 350 MW unit each have one derated state as shown in Figures 5.1 and 5.2 respectively using transition rates that are consistent with reference [57].

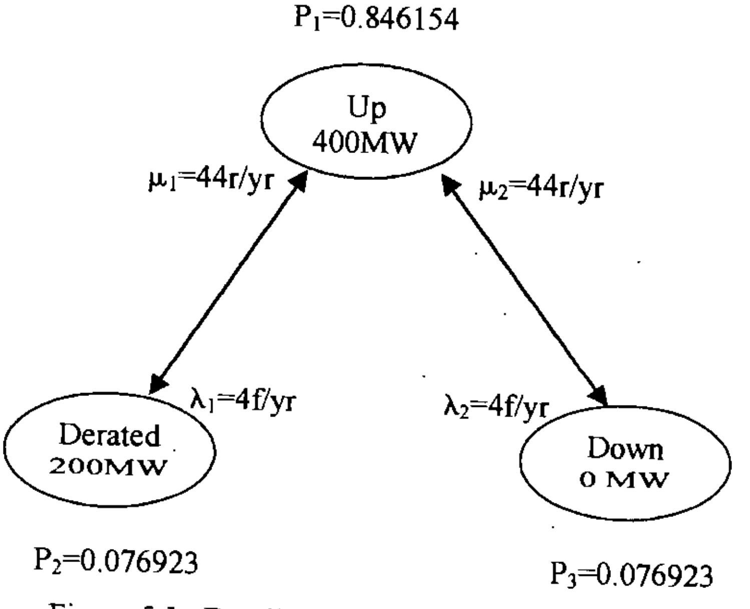


Figure 5.1 : Detail representation of 400 MW nuclear unit

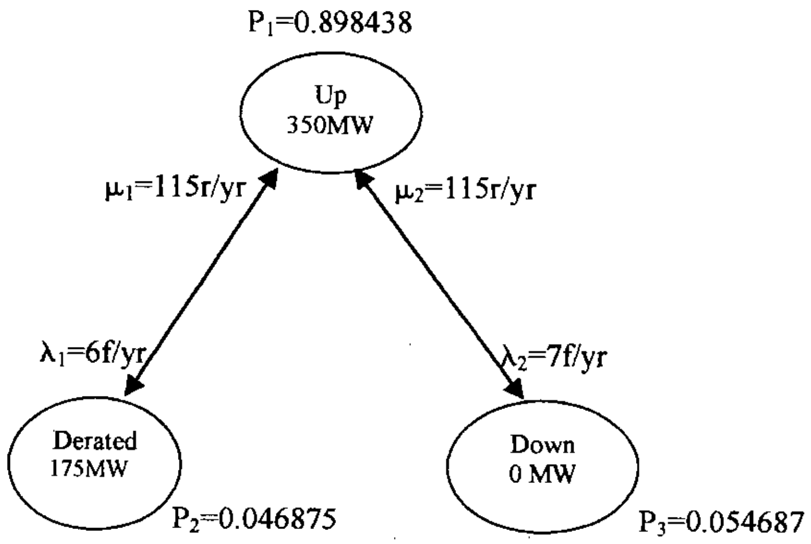


Figure 5.2 : Detail representation of 350 MW thermal unit

5.3.2 System simulation results

As the sequential simulation algorithm is well established without these multi-state failures, the new approach is included in the sequential Monte Carlo simulation procedures and then used to evaluate the reliability of IEEE-RTS system at hierarchical level I (HLI). At HLI, the generating system is assumed to be connected directly to the load, i.e. in other words, it is assumed that the transmission system of IEEE-RTS is not limited by capacities or forced outages.

After some initial runs it was decided to simulate the IEEE-RTS for 3000 years. At the end of each year the yearly values of reliability indices are stored. At the end of the simulation the expected values are calculated.

Four different cases are considered for the IEEE-RTS generation system, namely :

Base Case : Without any multi-state representation of generating unit outages i.e. all generating units are considered as binary state units.

Case-I	:	One 400 MW nuclear unit is given the multi-state representation shown in Figure 5.1.
Case-II	:	Both 400 MW nuclear units are given the same multi-state outages shown in Figure 5.1.
Case-III	:	In addition to case-II the 350MW unit is now given the multi-state failures similar to Figure 5.2.

Various annual adequacy indices and interruption indices are evaluated and some of them are shown in tables. In these studies simulation results include the following reliability indices :

Annual based indices

LOEE (MWh/yr) : Loss of energy expectation.

LOLE (hr/yr) : Loss of load expectation.

LCY (MW/yr) : Load Curtailed per year.

FOI (int/yr) : Frequency of interruption per year.

Cost of generation (M$/yr) :Average cost of generation per year.

Interruption based indices

EENSPI (MWh/int) : Expected energy not served per interruption.

EID (hr/int) : Expected interruption duration.

ELCI (MW/int) : Expected load curtailed per interruption.

The simulation results of annual and interruption based indices are shown in Tables 5.1 and 5.2. Table 5.1 shows the annual reliability indices for all four cases whereas Table 5.2 includes interruption based indices for all cases. In order to verify the developed methodology for evaluating multi-state generating units in sequential domain the IEEE-RTS is evaluated using analytical technique for the same four different cases as discussed earlier. Segmentation method [58] is used in this research as the analytical technique. For all cases the indices obtained from analytical technique are shown in Table 5.3.

Table 5.1: Annual reliability indices for all four cases

Indices	Bases Case		Case-I		Case-II		Case-III	
	Ana.	Simu.	Ana.	Simu.	Ana.	Simu.	Ana.	Simu.
LOEE (MWhr/yr)	1138.51	1105.23	941.28	952.21	744.26	730.75	650.75	647.44
LOLE (hr/yr)	9.10	9.13	7.77	7.85	6.33	6.38	5.67	5.77
LCY (MW/yr)		47.21		40.86		32.54		31.93
FOI (int/yr)		1.88		1.64		1.37		1.28
Cost of generation (M$/yr)		8.508		8.496		8.485		8.484

Table 5.2: Interruption based reliability indices for all cases

Indices	Bases Case	Case-I	Case-II	Case-III
EENSPI (MWhr/int)	586.85	582.04	533.78	504.36
EID (hr/int)	4.84	4.80	4.66	4.49
ELCI (MW/int)	82.24	80.21	75.62	74.78

Table 5.3: HL1 indices from analytical technique for four cases

Indices	Bases Case	Case-I	Case-II	Case-III
LOEE (MWhr/yr)	1138.51	941.28	744.26	650.75
LOLE (hr/yr)	9.10	7.77	6.33	5.67

Table 5.4 and 5.5 represents standard deviations of annual and interruption indices for all cases.

Table : 5.4 Standard deviations of annual reliability indices for all cases

Indices	Bases Case	Case-I	Case-II	Case-III
Standard deviation of LOEE	2667.024	2648.848	2217.284	2058.291
Standard deviation of LOLE	15.504	14.934	13.508	12.127
Standard deviation of LCY	61.206	57.739	51.708	51.134
Standard deviation of FOI	1.883	2.539	2.361	2.147
Standard deviation of cost of generation	0.140	0.139	0.141	0.141

Table :5.5 standard deviation for interruption based reliability indices for all cases

Indices	Bases Case	Case-I	Case-II	Case-III
Standard deviation of EENSPI	978.9083	1012.0527	929.0099	891.0410
Standard deviation of EID	3.7285	3.7316	3.6624	3.5197
Standard deviation of ELCI	73.9117	75.0890	69.9516	68.1648

Now the conference interval for annual and interruption indices are represented in the following section for all four cases.

Table 5.6 : Confidence intervals for annual indices

Cases	Confidence Interval (99% Confidence Level)			
	LOEE (MWhr/yr)	LOLE (hr/yr)	LCY (MW/yr)	FOI (Int/yr)
Base Case	979.60-1230.86	8.40-9.86	44.33-50.09	1.76-2.01
Case-I	827.44-1076.98	7.14-8.55	38.15-43.58	1.52- 1.76
Case-II	626.31-835.19	5.74-7.01	30.10-34.97	1.26-1.48
Case-III	550.48-744.39	5.19- 6.38	29.52-34.34	1.18-1.39

Table 5.7: Confidence intervals for interruption indices

Cases	Confidence Interval (99% Confidence Level)		
	EENSPI (MWhr/int)	EID (hr/int)	ELCI (MW/int)
Base Case	553.25-620.45	4.72-4.97	79.70-84.78
Case-I	544.77-619.31	4.66-4.93	77.45-82.98
Case-II	496.38-571.18	4.51-4.81	72.80-78.44
Case-III	467.32-541.41	4.35-4.64	71.95-77.61

Table 5.8 Expected energy generations of individual generators.

Sl. No.	Rated capacity(MW)	Expected energy generation of units (Mwhr/yr)			
		Base Case	Case-I	Case-II	Case-III
1	400.00	3074238.800	3093394.800	3093394.800	3093394.800
2	400.00	3069898.000	3070206.667	3086339.867	3086339.867
3	350.00	2791683.653	2791929.139	2791854.216	2799657.076
4	197.00	1503351.703	1506700.961	1510415.418	1511974.331
5	197.00	1311530.313	1313119.469	1316029.111	1316675.633
6	197.00	1103268.215	1101086.131	1099911.813	1098922.368
7	155.00	710874.083	709297.179	707791.106	707042.239
8	155.00	558802.973	557288.326	556133.558	555387.353
9	155.00	429833.714	426010.797	423107.057	421702.898
10	155.00	302908.469	299913.297	296997.790	295971.290
11	100.00	134772.244	133172.790	131660.160	131063.087
12	100.00	97351.185	95779.389	93955.793	93168.754
13	100.00	68750.369	66730.403	64634.204	63705.603
14	76.00	38039.497	36450.664	34917.011	34200.306
15	76.00	27267.966	25882.975	24461.271	23898.304
16	76.00	19030.371	17916.558	16718.502	16348.551
17	76.00	12982.806	12038.288	11105.263	10804.840
18	12.00	1622.451	1494.076	1363.903	1322.377
19	12.00	1520.702	1398.509	1268.619	1229.250
20	12.00	1432.219	1309.958	1188.226	1148.899
21	12.00	1332.544	1218.543	1104.039	1065.816
22	12.00	1255.551	1142.990	1030.471	996.029
23	20.00	1761.253	1597.583	1424.261	1376.230
24	20.00	1580.787	1431.028	1278.880	1234.016
25	20.00	1422.966	1296.303	1147.127	1101.648
26	20.00	1280.044	1151.417	1023.057	978.807
27	50.00	2886.695	2588.388	2279.068	2172.571
28	50.00	2113.795	1874.990	1631.618	1553.190
29	50.00	1541.499	1348.780	1161.629	1099.702
30	50.00	1102.378	952.736	814.425	763.038
31	50.00	779.951	673.138	560.568	521.036
32	50.00	547.811	470.954	385.854	352.088

5.3.3 Results presented in Graphical Form

Variation of the values of various reliability indices are presented in this section in the form of graphs (histogram) in order to show the trend of these indices as the simulation progresses. These results are also presented for four different cases i.e.

- Case : Base
- Case I : 1 multi-state unit.
- Case II : 2 multi-state units.
- Case III : 3 multi-state units.

These frequency histograms are shown in Figures 5.3-5.14.

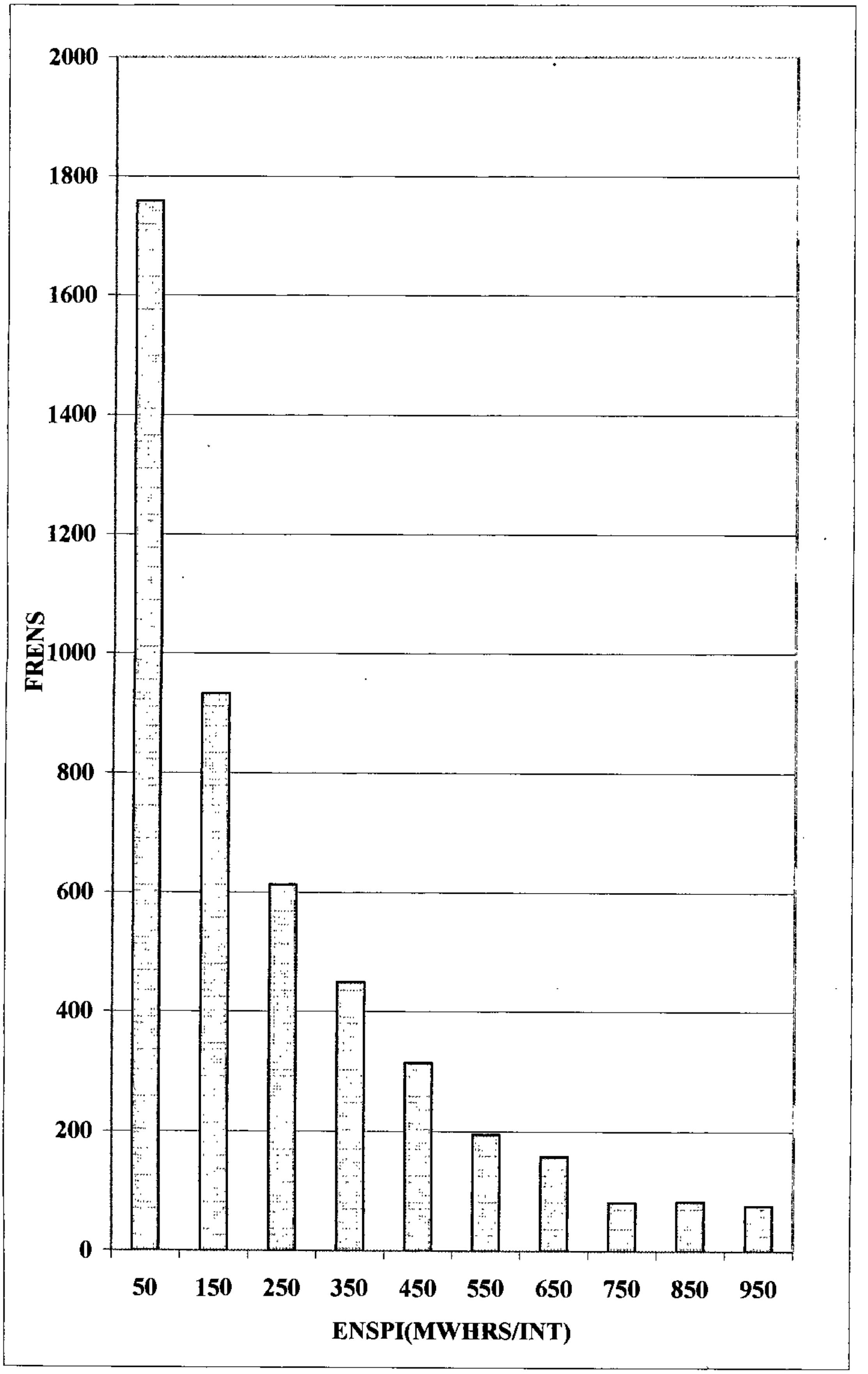


Figure 5.3 : Histogram of ENSPI for Base Case

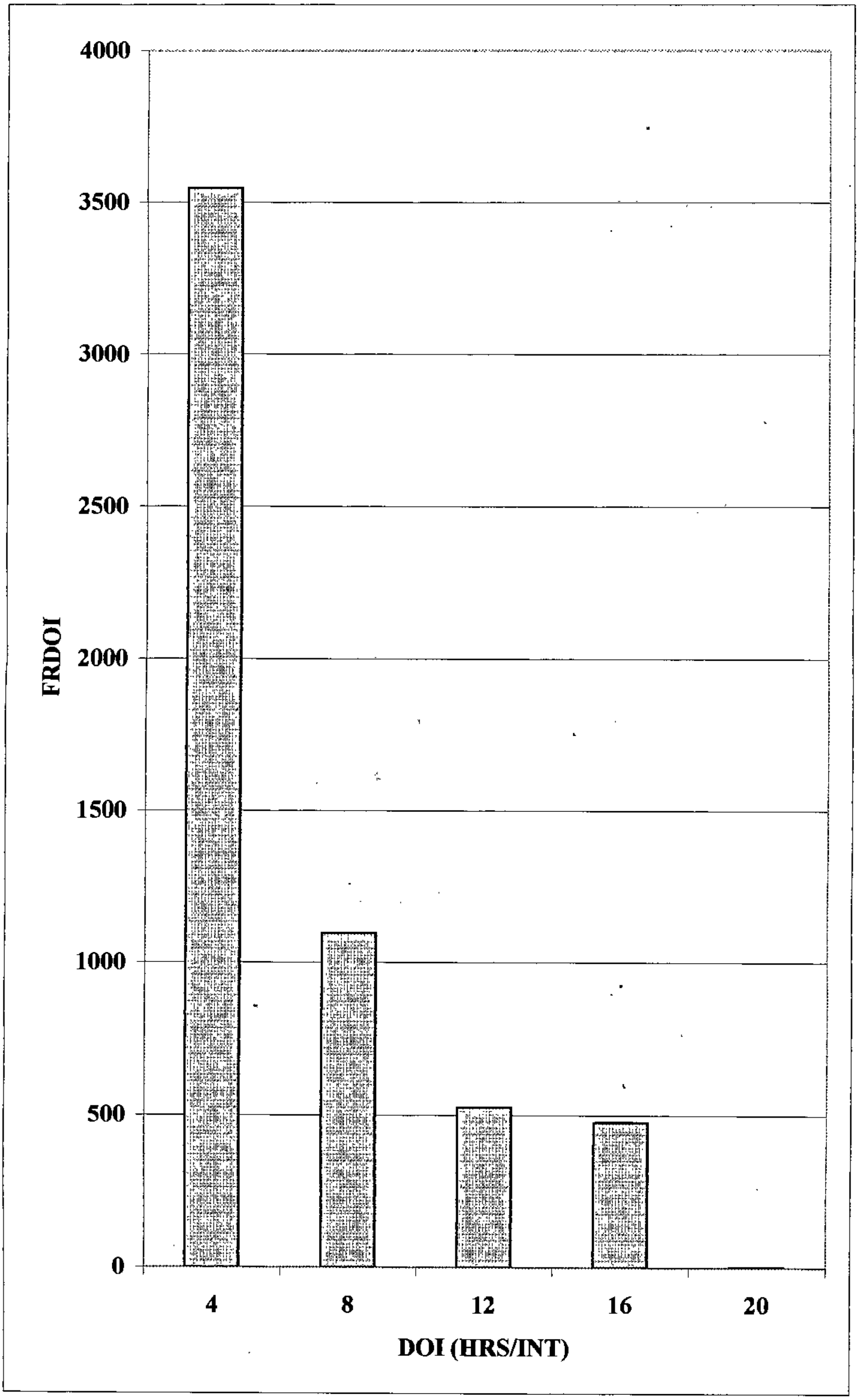


Figure 5.4 : Histogram of DOI for Base Case

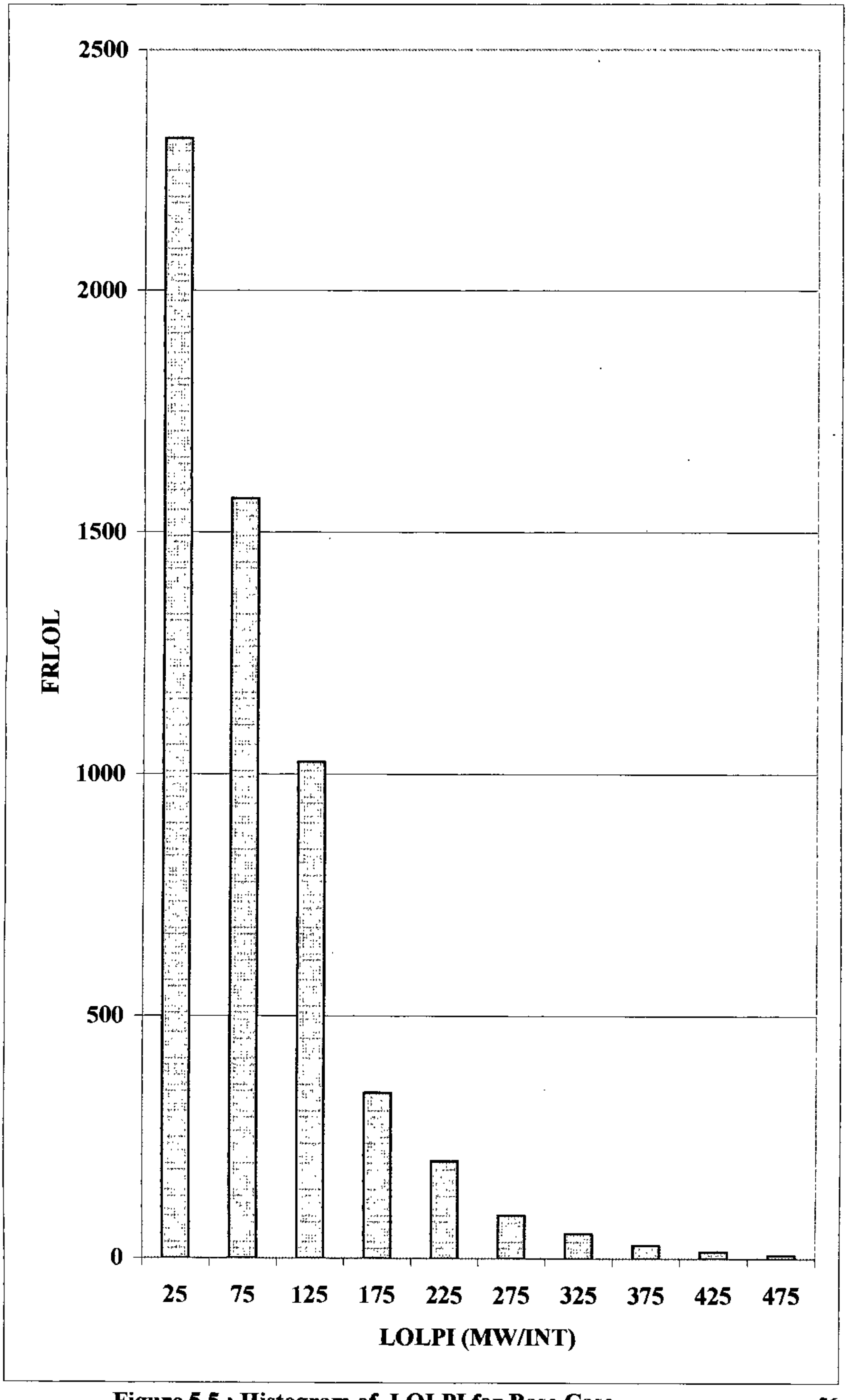


Figure 5.5 : Histogram of LOLPI for Base Case

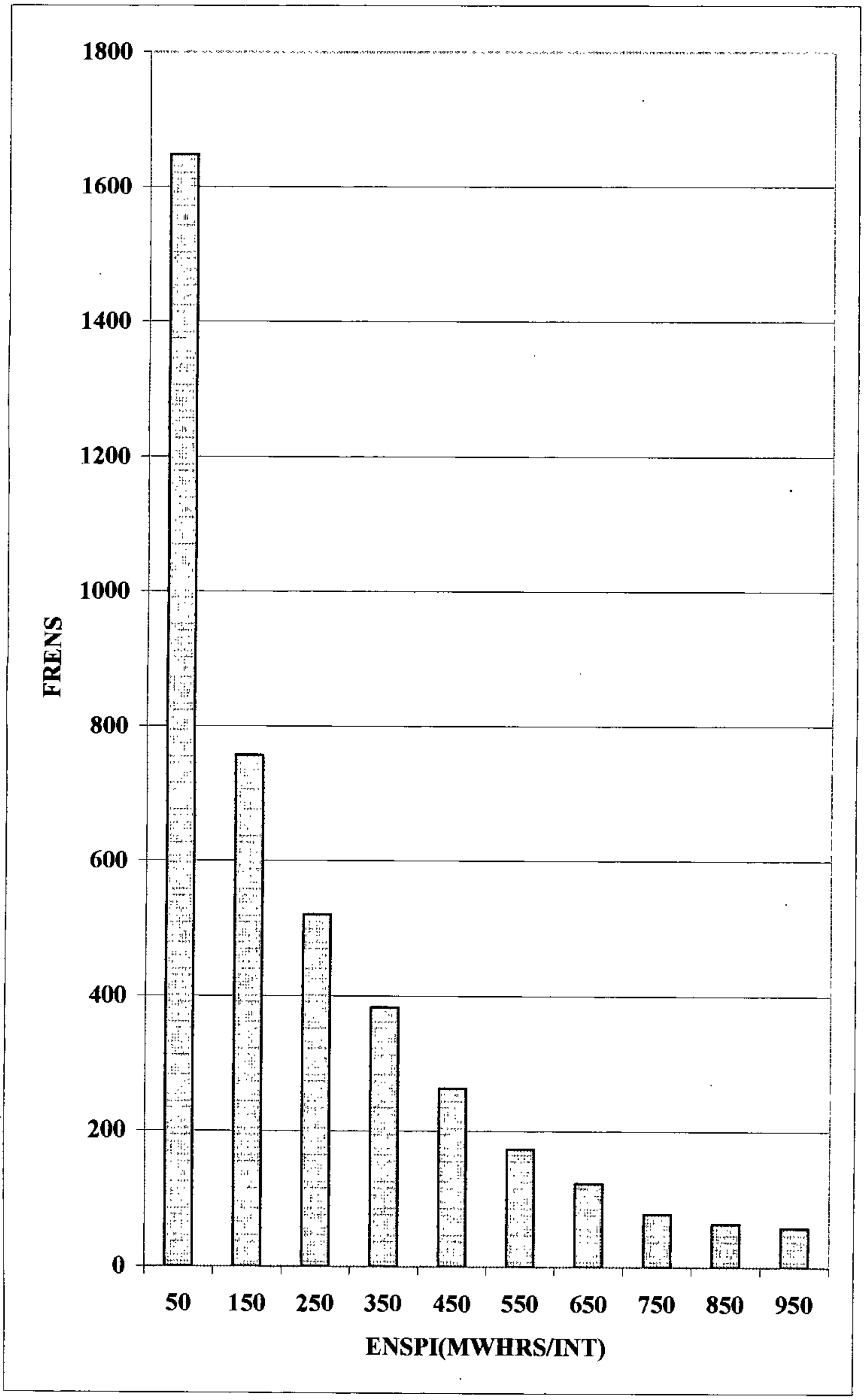


Figure 5.6 : Histogram of ENSPI for Case-I

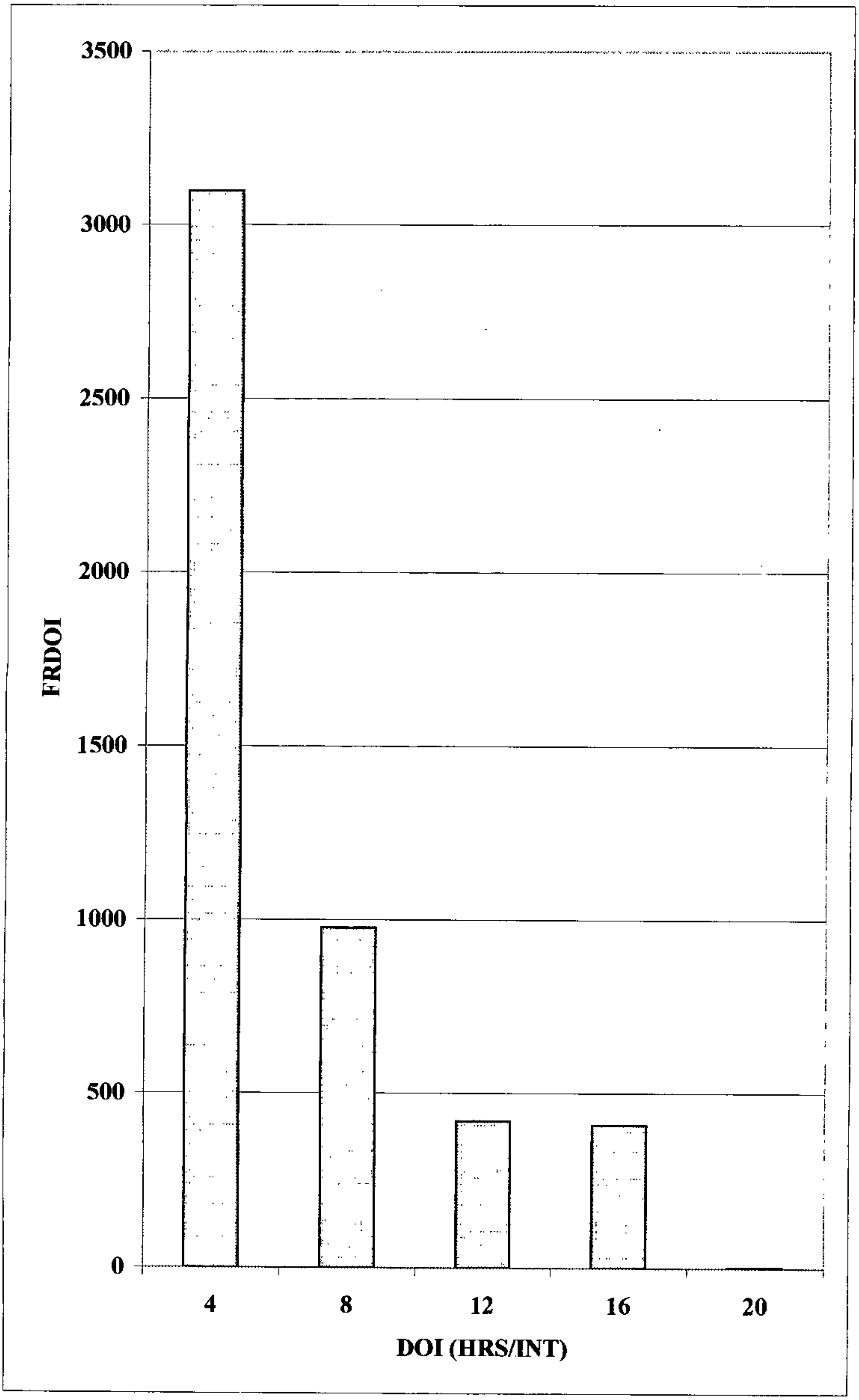


Figure 5.7 : Histogram of DOI for Case-I

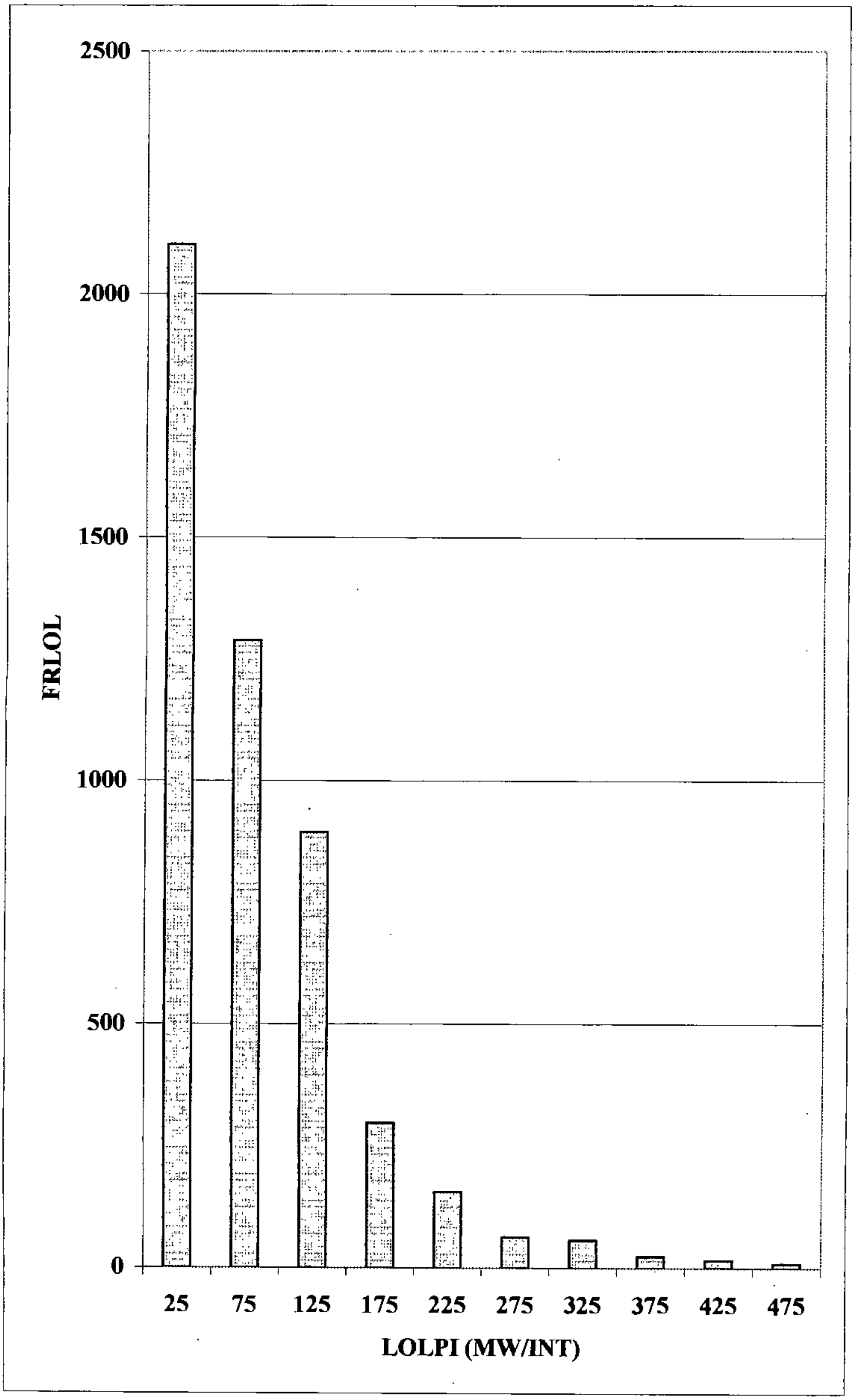


Figure 5.8 : Histogram of LOLPI for Case-I

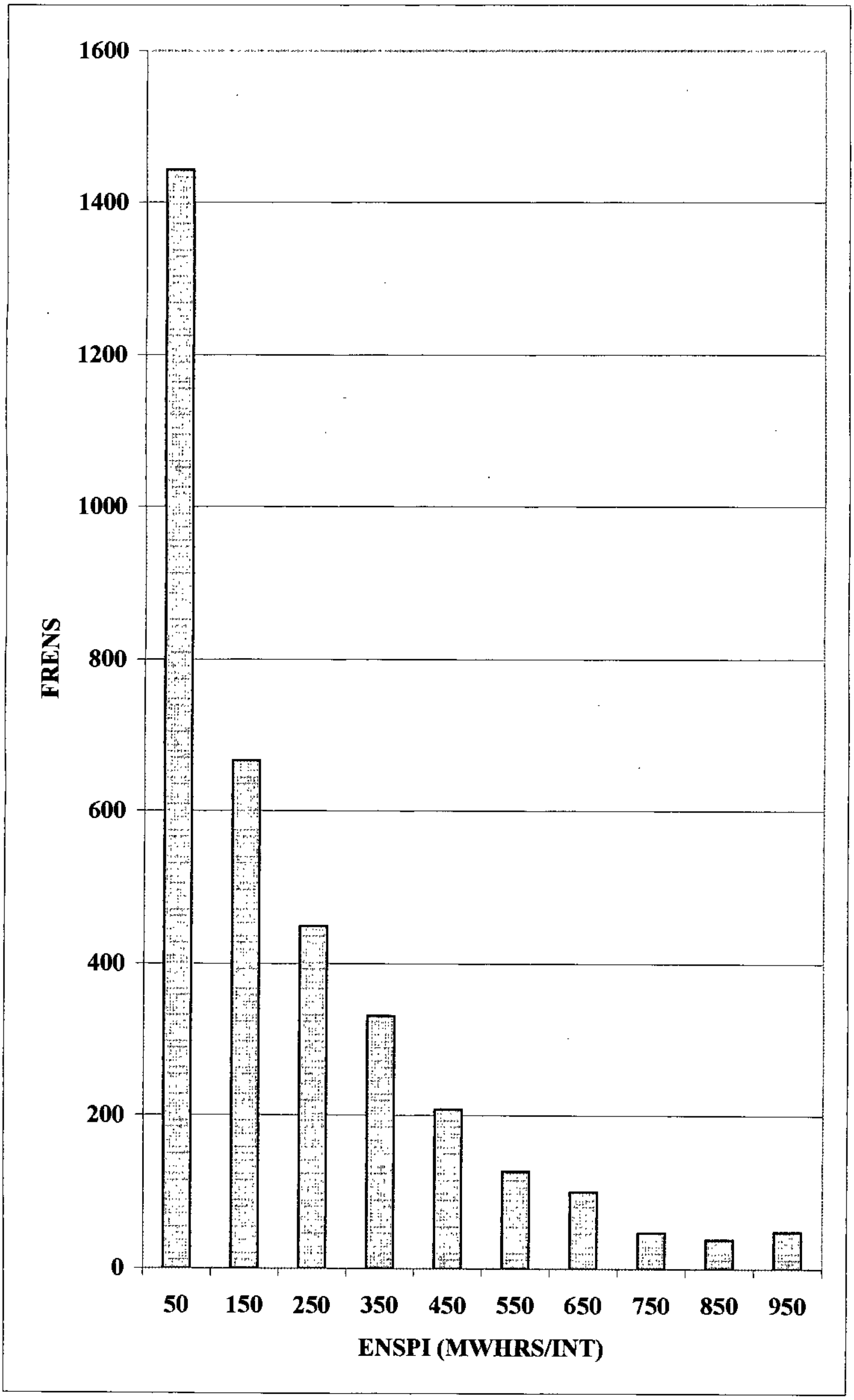


Figure 5.9 : Histogram of ENSPI for Case-II

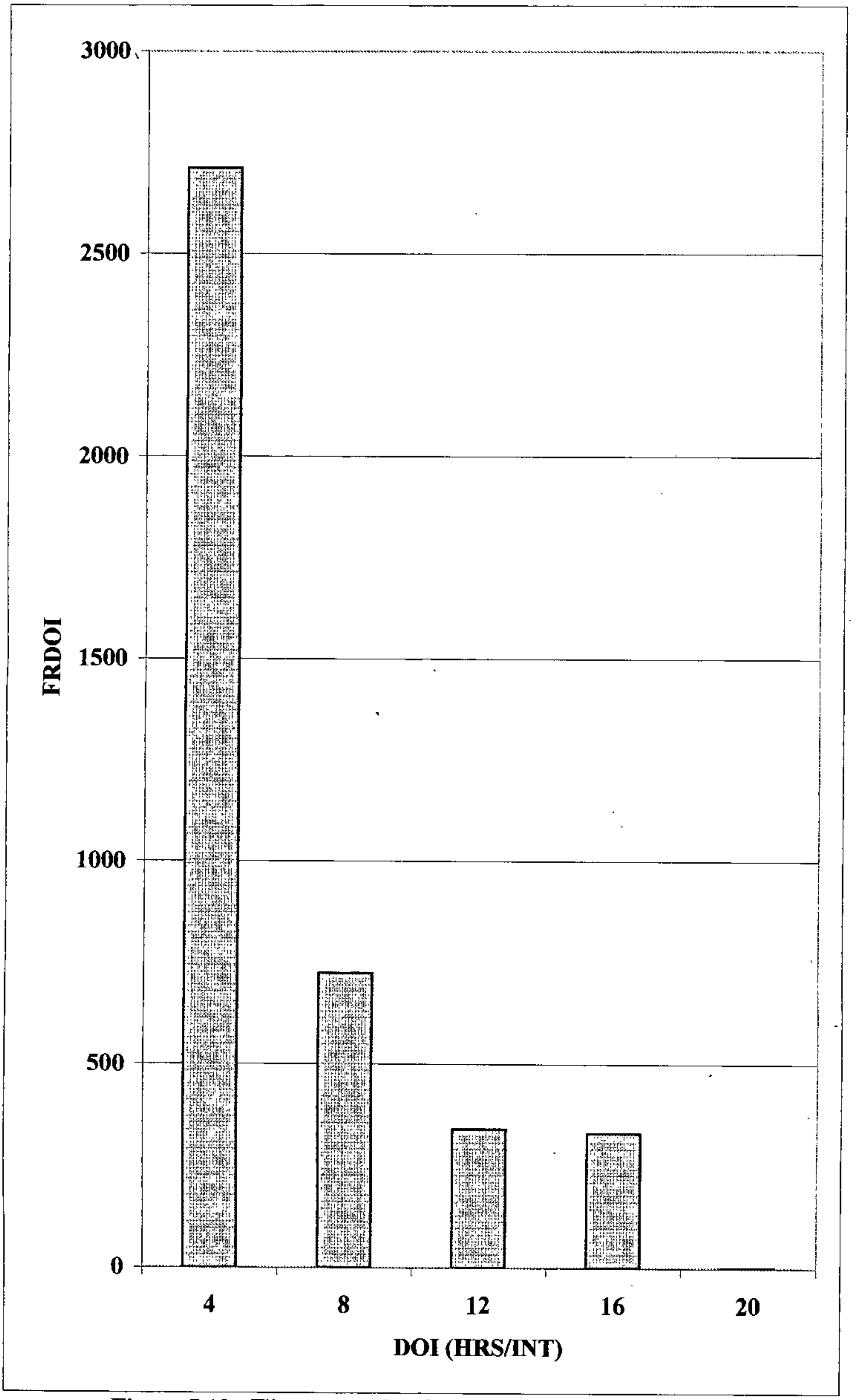


Figure 5.10 : Histogram of DOI for Case-II

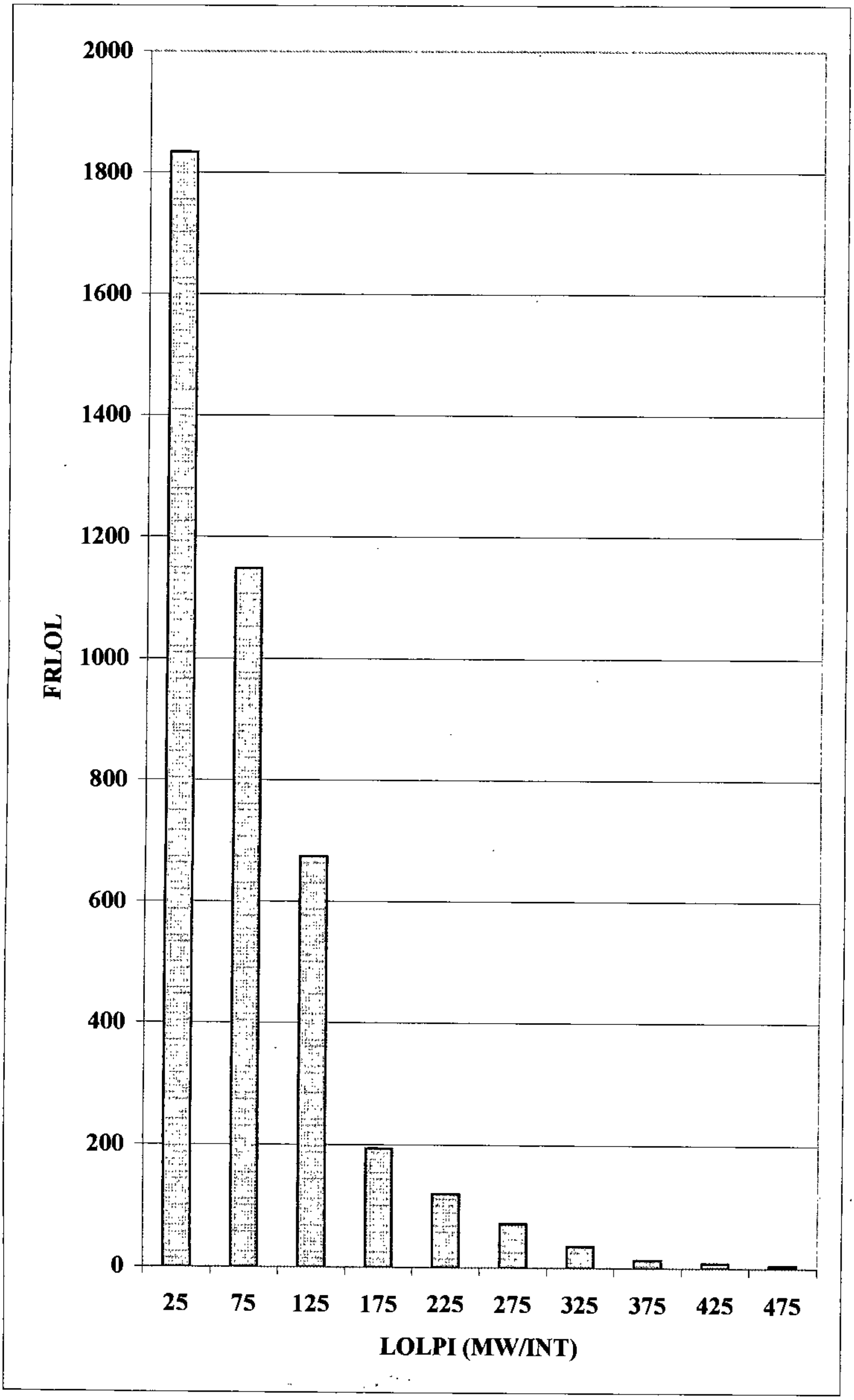


Figure 5.11 : Histogram of LOLPI for Case-II

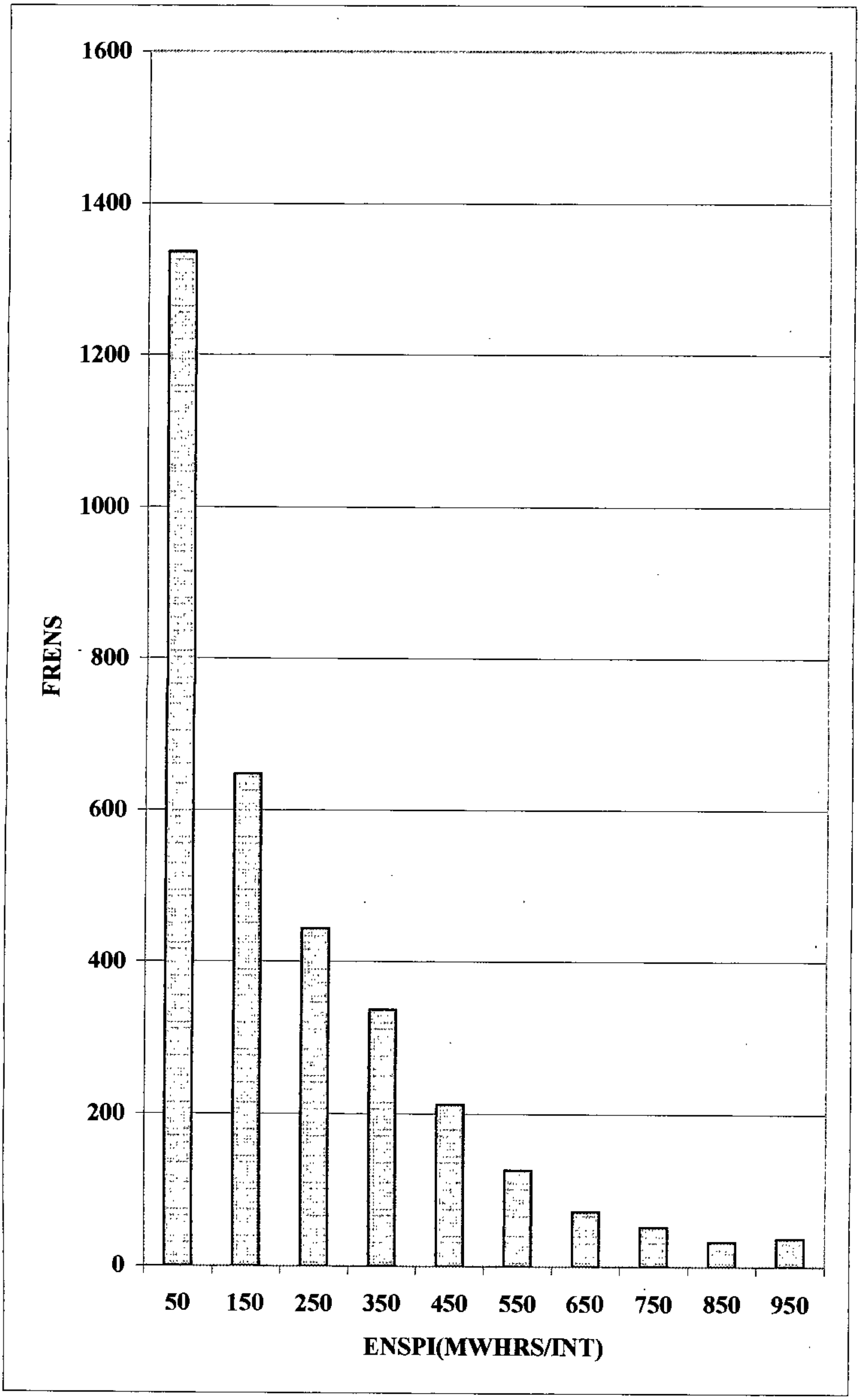


Figure 5.12 : Histogram of ENSPI for Case-III

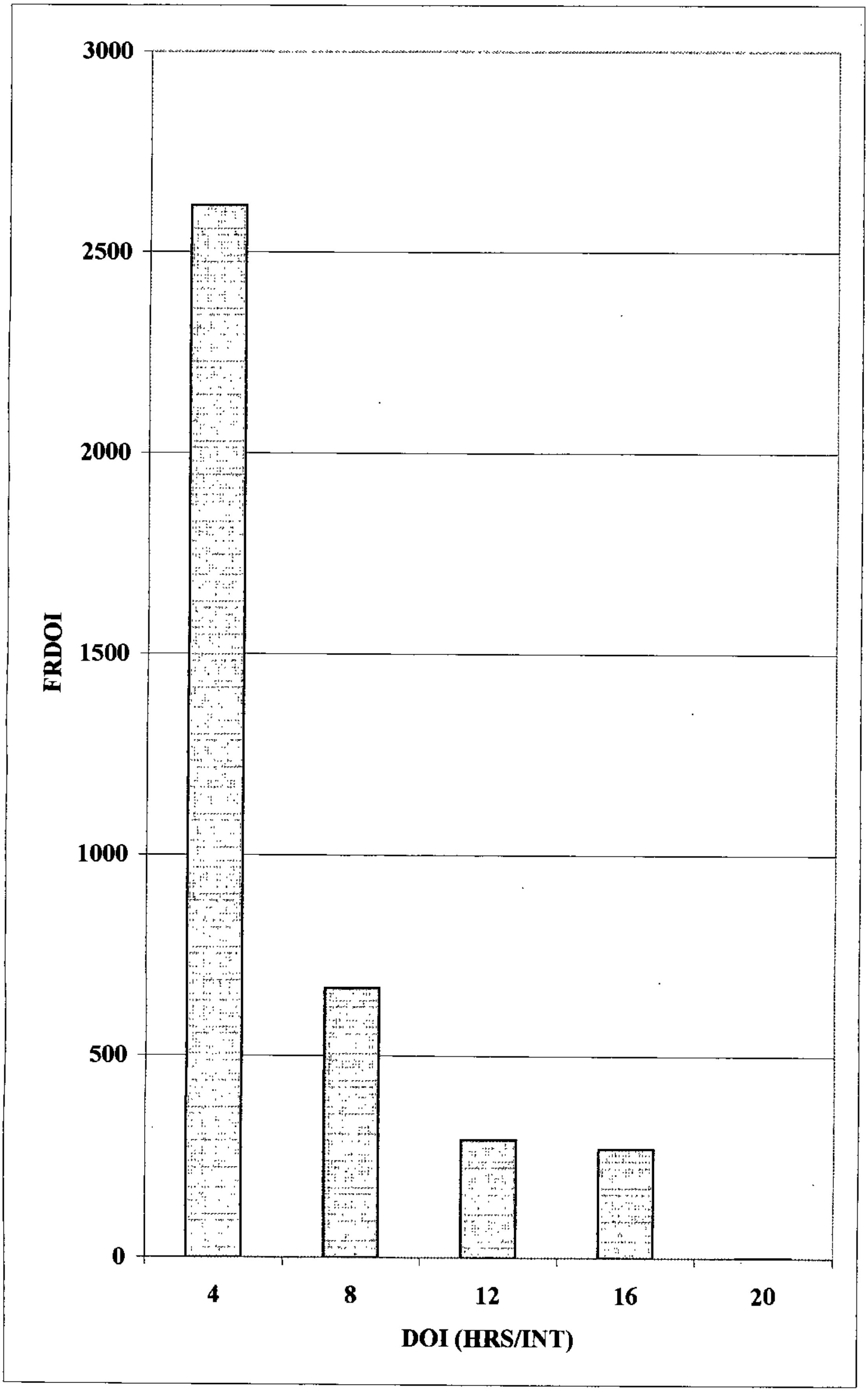


Figure 5.13 : Histogram of DOI for Case-III

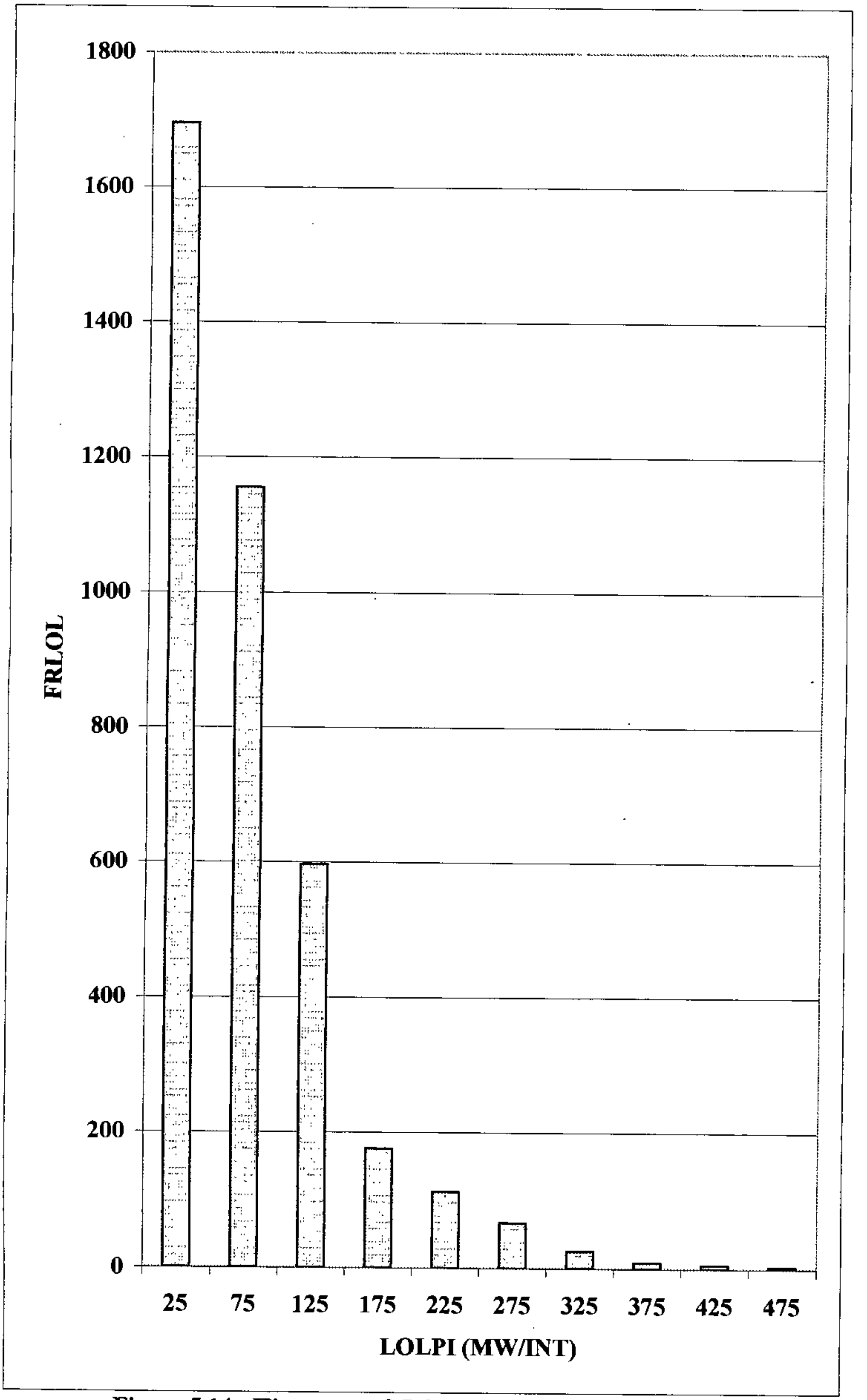


Figure 5.14 : Histogram of LOLPI for Case-III

Chapter-six

Observations and Conclusions

6.1 Observation and discussions

Simulation techniques estimate the reliability indices by simulating or sampling the actual behavior of the system. The values of output results of simulation study depend on a number of factors including the seed or starting value of the sequence of random numbers, the pseudo-random number generator, the number of samples and above all the system upon which the simulation study has been done. As the sequential simulation algorithm is well established without the multi-state failures, the new approach is included in the sequential Monte Carlo simulation procedures and then used to evaluate the reliability of IEEE-RTS system at hierarchical level I (HLI). After some initial runs it was decided to simulate the IEEE-RTS for 3000 years. At the end of each year the yearly values of reliability indices are stored. At the end of the simulation the expected values are calculated.

Tables 5.1 and 5.2 show the annual reliability indices and interruption indices respectively for all four cases. Table 5.1 shows that annual indices decrease with the inclusion of more and more multi-state outages. As more multi-state outages are included, some capacity is still available from these multi-state generators when they are not in fully up state. As a whole more generation is available from the generating system. Therefore, system adequacy indices should decrease with more multi-state representation as clearly indicated by Table 5.1. The results shown in Table 5.2 represents that interruption indices also decrease with the inclusion of more and more multi-state outages.

It is well known that LOEE and LOLE indices for a generation system (HLI) can also be calculated accurately by using analytical technique. In these studies segmentation method [58] is utilized for calculating these indices in analytical domain. Table 5.3 is provided for comparing the results with those obtained using the new algorithm developed in this thesis for accommodating multi-state generators in sequential Monte Carlo simulation procedures.

The results shown in Tables 5.1 and 5.3 demonstrate very positively that the developed new algorithm for considering multi-state generators in sequential simulation gives results that compare extremely well with those obtained from the analytical technique; the latter can be considered as a good basis for realistic comparison at HLI. However, although the analytical method could produce the expected or average values more quickly than the simulation approach, the latter method also provides values for standard deviation, confidence limits and the actual probability distributions associated with the reliability indices.

Tables 5.4 and 5.5 represent the standard deviations of annual and interruption indices for all cases. Table 5.4 shows that standard deviation of annual indices also decrease with the inclusion of more and more multi state outages. Also the standard deviation of interruption indices shown in Table 5.5 generally follow the same pattern.

Table 5.6 and 5.7 represent the confidence interval for annual and interruption indices for all cases. These show the indices having their minimum and maximum ranges more clearly. These confidence intervals are built for a probability value of 99%. Table 5.8 shows the expected energy generations of individual generating unit for all four cases.

The frequency histograms shown in Figures 5.3-5.14 indicate the variations of the interruptions based reliability indices. Figures 5.3, 5.6, 5.9 and 5.12 represent the frequency histograms of ENSPI for base case, case-I, case-II and case-III respectively. Frequency histograms of DOI for four cases are shown in Figures 5.4, 5.7, 5.10 and 5.13. On the other hand frequency histograms of LOLPI for all four cases are shown in Figures 5.5, 5.8, 5.11 and 5.14.

From all these histograms the initial impression is that they all exhibit very similar pattern, i.e. interruptions having higher energy curtailment or higher duration or higher load curtailment occur less frequently. The other observations made from the frequency histograms are the extreme skewness of the distributions. For example in the case-III the average value of ENSPI, i.e. EENSPI, is around 504.36 MWhr/int as shown in Table 5.2 whereas the distribution of frequency histogram of ENSPI shown in Figure 5.12 show that the actual value of ENSPI can exceed 900 MWhr/int on a few occasions. As these tails give rise to most of the risk, these histograms indicate the potential importance of system evaluations using sequential simulation. These observations and detail are not possible to detect from average values only, i.e. not possible using analytical techniques or non-sequential simulation techniques. Ignoring these extreme values can create over confidence and false illusion of optimism in the potential future behaviour of a system and a destruction of confidence if one of these extreme conditions occurs. A price has to be paid in order to accomplish these additional information in the form of larger computing times for the sequential simulations. However it is worth paying in order to obtain a more comprehensive picture of system inadequacies.

6.2 Conclusion

In this research work inadequacies associated with multi-state failures are accommodated in the sequential Monte Carlo simulation procedures. From the observations and discussions given in this thesis, the following conclusions are made:

a) A new technique has been developed in this thesis to incorporate multi-state generating unit failures in generating system reliability evaluation procedures using sequential Monte Carlo simulation.

b) The models presented in this thesis extended the wider applicability of the sequential simulation for appreciating more accurate picture of generation system inadequacies.

c) The results obtained in these studies compare favourably with those obtained using an analytic technique.

d) Inclusions of multi-state generating unit outages changes the generation reliability indices significantly. However, the actual impact of multi-state outages depend on the system as a whole.

6.3 Recommendations for future work

The multi-state generating units in sequential simulation domain are developed in this thesis. The sequential simulation algorithm is well established without these multi-state failures, the new approach is included in the sequential Monte Carlo simulation procedures and then used to evaluate the reliability of IEEE-RTS system at hierarchical level I (HLI). Although the IEEE-RTS is used for numerical evaluation, the hydro units of this system are energy abundant units and treated similar to thermal units. In sequential simulation approach highlights the system operation is history dependent. On the other hand non-sequential approach does not care for that. Therefore the developed new approach for multi-state failures of generating units in non-sequential domain can be taken into account for further research work. The state residence time of the component are exponential distributions. This also may be considered for non-exponential distributions for further work. Besides this, maintenance schedule for generating unit may be also considered for future work.

APPENDIX-A

IEEE-RTS Generation data.

Unit No.	Rated capacity(MW)	MTTF (HR)	MTTR (HR)	COST $/ MWH
1	400.00	1100.00	150.00	0.30000
2	400.00	1100.00	150.00	0.30000
3	350.00	1150.00	100.00	0.70000
4	197.00	950.00	50.00	0.70000
5	197.00	950.00	50.00	0.70000
6	197.00	950.00	50.00	0.70000
7	155.00	960.00	40.00	0.80000
8	155.00	960.00	40.00	0.80000
9	155.00	960.00	40.00	0.80000
10	155.00	960.00	40.00	0.80000
11	100.00	1200.00	50.00	0.80000
12	100.00	1200.00	50.00	0.80000
13	100.00	1200.00	50.00	0.80000
14	76.00	1960.00	40.00	0.90000
15	76.00	1960.00	40.00	0.90000
16	76.00	1960.00	40.00	0.90000
17	76.00	1960.00	40.00	0.90000
18	12.00	2940.00	60.00	0.90000
19	12.00	2940.00	60.00	0.90000
20	12.00	2940.00	60.00	0.90000
21	12.00	2940.00	60.00	0.90000
22	12.00	2940.00	60.00	0.90000
23	20.00	450.00	50.00	5.00000
24	20.00	450.00	50.00	5.00000
25	20.00	450.00	50.00	5.00000
26	20.00	450.00	50.00	5.00000
27	50.00	1980.00	20.00	0.00000
28	50.00	1980.00	20.00	0.00000
29	50.00	1980.00	20.00	0.00000
30	50.00	1980.00	20.00	0.00000
31	50.00	1980.00	20.00	0.00000
32	50.00	1980.00	20.00	0.00000

APPENDIX-B

Hourly peak load data (in percent of daily peak load) IEEE-RTS system.

Hour	Winter weeks 1-8 & 44-52		Summer weeks 18-30		Spring/ fall weeks 9-17 & 31-43	
	wkdy	wknd	wkdy	wknd	wkdy	wknd
12-1 am	0.67	0.78	0.64	0.74	0.63	0.75
1-2	0.63	0.72	0.60	0.70	0.62	0.73
2-3	0.60	0.68	0.58	0.66	0.60	0.69
3-4	0.59	0.66	0.56	0.65	0.58	0.66
4-5	0.59	0.64	0.56	.0.64	0.59	0.65
5-6	0.60	0.65	0.58	0.62	0.65	0.65
6-7	0.74	0.66	0.64	0.62	0.72	0.68
7-8	0.86	0.70	0.76	0.66	0.85	0.74
8-9	0.95	0.80	0.87	0.81	0.95	0.83
9-10	0.96	0.88	0.95	0.86	0.99	0.89
10-11	0.96	0.90	0.99	0.91	1.00	0.92
11-Noon	0.95	0.91	1.00	0.93	0.99	0.94
Noon-1Pm	0.95	0.90	0.99	0.93	0.93	0.91
1-2	0.95	0.88	1.00	0.92	0.92	0.90
2-3	0.93	0.87	1.00	0.91	0.90	0.90
3-4	0.94	0.87	0.97	0.91	0.88	0.86
4-5	0.99	0.91	0.96	0.92	0.90	0.85
5-6	1.00	1.00	0.96	0.94	0.92	0.88
6-7	1.00	0.99	0.93	0.95	0.96	0.92
7-8	0.96	0.97	0.92	0.95	0.98	1.00
8-9	0.91	0.94	0.92	1.00	0.96	0.97
9-10	0.83	0.92	0.93	0.93	0.90	0.95
10-11	0.73	0.87	0.87	0.88	0.80	0.90
11-12	0.63	0.81	0.72	0.80	0.70	0.85

wkdy = Week day wknd = Weekend

APPENDIX-C

Daily peak load data.

W	1	2	3	4	5	6	7
1	2284.70	2456.70	2407.60	2358.40	2309.30	1891.70	1842.50
2	2385.50	2565.00	2513.70	2462.40	2411.10	1975.10	1923.80
3	2327.10	2502.30	2452.30	2402.20	2352.20	1926.80	1876.70
4	2210.50	2376.90	2329.40	2281.80	2234.30	1830.20	1782.70
5	2332.40	2508.00	2457.80	2407.70	2357.50	1931.20	1881.00
6	2229.10	2396.80	2348.90	2300.90	2253.10	1845.60	1797.60
7	2205.20	2371.20	2323.80	2276.50	2228.90	1825.80	1778.40
8	2136.30	2297.10	2251.20	2205.20	2159.30	1768.80	1722.80
9	1961.40	2109.00	2066.80	2024.60	1982.50	1623.90	1581.80
10	1953.40	2100.50	2058.40	2016.40	1974.40	1617.40	1575.30
11	1895.10	2037.80	1997.00	1956.20	1915.50	1569.10	1528.30
12	1926.90	2071.90	2030.50	1989.10	1947.60	1595.40	1553.90
13	1865.90	2006.40	1966.30	1926.10	1886.00	1544.90	1504.80
14	1987.90	2137.50	2094.80	2052.00	2009.30	1945.90	1603.10
15	1911.00	2054.90	2013.80	1972.70	1931.60	1582.20	1541.10
16	2120.40	2280.00	2234.40	2188.80	2143.20	1755.60	1710.00
17	1998.50	2148.90	2105.90	2062.90	2019.90	1654.70	1611.70
18	2218.50	2385.50	2337.70	2290.00	2242.30	1836.80	1789.10
19	2305.90	2479.50	2429.90	2380.30	2330.70	1909.20	1859.60
20	2332.40	2508.00	2457.80	2407.70	2357.50	1931.20	1881.00
21	2268.80	2439.60	2390.80	2342.00	2293.20	1878.50	1827.70
22	2149.60	2311.40	2265.10	2218.90	2172.70	1779.70	1733.50
23	2385.50	2565.00	2513.70	2462.40	2411.10	1975.10	1923.40
24	2351.00	2527.90	2477.40	2426.80	2376.30	1946.50	1895.70
25	2374.90	2553.60	2502.50	2451.50	2400.40	1966.30	1915.20
26	2282.10	2453.90	2404.80	2355.70	2306.60	1889.50	1840.40

W	1	2	3	4	5	6	7
27	2001.10	2151.80	2108.70	2065.70	2022.70	1656.90	1613.40
28	2162.80	2325.60	2279.10	2232.60	2186.10	1790.70	1744.20
29	2123.10	2282.90	2237.20	2191.50	2145.90	1757.80	1712.10
30	2332.40	2508.00	2457.80	2407.70	2357.50	1931.20	1881.00
31	1913.70	2057.70	2016.60	1975.40	1934.20	1584.40	1543.30
32	2056.80	2211.60	2015.70	2123.10	2078.90	1702.90	1658.70
33	2120.40	2280.00	2234.40	2188.80	2143.20	1755.60	1710.00
34	1932.20	2077.70	2036.10	1994.50	1953.00	1599.80	1558.20
35	1924.30	2069.10	2027.70	1986.30	1944.90	1593.20	1551.80
36	1868.60	2009.30	1969.10	1928.90	1888.70	1547.10	1506.90
37	2067.40	2223.00	2178.50	2134.10	2089.60	1711.70	1667.30
38	1842.10	1980.80	1941.10	1901.50	1861.90	1525.20	1485.60
39	1918.90	2063.40	2022.10	1980.90	1939.60	1588.80	1547.60
40	1918.90	2063.40	2022.10	1980.90	1939.60	1588.80	1547.60
41	1969.30	2117.60	2075.20	2032.90	1990.50	1630.50	1588.20
42	1971.90	2120.40	2078.00	2035.60	1993.20	1632.70	1590.30
43	2120.40	2280.00	2234.40	2188.80	2143.20	1755.60	1710.00
44	2335.10	2510.90	2460.60	2410.40	2360.20	1933.40	1883.10
45	2345.70	2522.30	2471.00	2421.40	2370.00	1942.00	1891.70
46	2409.30	2590.60	2538.80	2487.00	2435.20	1994.00	1943.00
47	2491.50	2679.00	2625.40	2571.80	2518.30	2062.80	2009.20
48	2358.90	2536.50	2485.80	2435.10	2384.30	1953.10	1902.40
49	2496.80	2684.70	2631.00	2577.30	2523.60	2067.20	2013.50
50	2571.00	2764.50	2709.20	2653.90	2598.60	2128.70	2073.40
51	2650.50	2850.00	2793.00	2736.00	2679.00	2194.50	2137.50
52	2523.30	2713.20	2658.90	2604.70	2550.40	2089.20	2034.90

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