**RELIABILITY ASSESSMENT OF ELECTRIC**

**POWER SYSTEMS USING GENETIC ALGORITHMS**

A Dissertation

by

NADER AMIN AZIZ SAMAAN

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

DOCTOR OF PHILOSOPHY

August 2004

Major Subject: Electrical Engineering

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Approved as to style and content by:

________________________________
Chanan Singh
(Chair of Committee)

________________________________
Karen L. Butler-Purry
(Member)

________________________________
Ohannes Eknoyan
(Member)

________________________________
Reza Langari
(Member)

________________________________
Chanan Singh
(Head of Department)

August 2004

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# ABSTRACT

Reliability Assessment of Electric Power Systems
Using Genetic Algorithms. (August 2004)

Nader Amin Aziz Samaan, B.S., University of Alexandria, Egypt;
M.S., University of Alexandria, Egypt.
Chair of Advisory Committee: Dr. Chanan Singh

The first part of this dissertation presents an innovative method for the assessment of generation system reliability. In this method, genetic algorithm (GA) is used as a search tool to truncate the probability state space and to track the most probable failure states. GA stores system states, in which there is generation deficiency to supply system maximum load, in a state array. The given load pattern is then convoluted with the state array to obtain adequacy indices.

In the second part of the dissertation, a GA based method for state sampling of composite generation-transmission power systems is introduced. Binary encoded GA is used as a state sampling tool for the composite power system network states. A linearized optimization load flow model is used for evaluation of sampled states. The developed approach has been extended to evaluate adequacy indices of composite power systems while considering chronological load at buses. Hourly load is represented by cluster load vectors using the k-means clustering technique. Two different approaches have been developed which are GA parallel sampling and GA sampling for maximum cluster load vector with series state revaluation.

The developed GA based method is used for the assessment of annual frequency and duration indices of composite system. The conditional probability based method is used to calculate the contribution of sampled failure states to system failure frequency using different component transition rates. The developed GA based method is also used for evaluating reliability worth indices of composite power systems. The developed GA

approach has been generalized to recognize multi-state components such as generation units with derated states. It also considers common mode failure for transmission lines.

Finally, a new method for composite system state evaluation using real numbers encoded GA is developed. The objective of GA is to minimize load curtailment for each sampled state. Minimization is based on the dc load flow model. System constraints are represented by fuzzy membership functions. The GA fitness function is a combination of these membership values. The proposed method has the advantage of allowing sophisticated load curtailment strategies, which lead to more realistic load point indices.

# DEDICATION

To my late father, my mother and my wife Marguerite.

## ACKNOWLEDGEMENTS

It is a very difficult task to dedicate one or two pages to mention and thank all those wonderful people who helped me during my journey that stretched over four years of exciting work at Texas A&M University.

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Last, but not the least, I would like to dedicate this dissertation to the spirit of my deceased father who always inspired me to continue in the research field following his footsteps. His words are always in my mind.

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# CHAPTER I

# INTRODUCTION

The primary objective of an electric utility is to provide electricity to satisfy its customer needs and expectations. This is expected to be achieved at a reasonable level of reliability and as economically as possible. Recent trends of power industry towards deregulation coupled with the diversity in customer requirements have generated a competitive market for power delivery. Power companies will need to perform in the most cost effective manner in order to maximize return to their investors while maintaining an acceptable reliability and quality of supply to consumers. Within this competitive environment, fast and accurate power system reliability assessment techniques can play an important role in shaping the criterion for judging the robustness of delivered services.

Reliability of power supply has always been an important issue in the electric utility systems. Availability of high quality uninterrupted electric power is essential to the industrial and economic growth of a nation. It is evident from the major power outage events during the last year that reliability of electric power networks cannot be taken for granted in the new free market structure.

The largest power outage in the history of North America occurred on August 14th, 2003 and had catastrophic social and economical effects. This blackout effected more than 50 million people in the north east of USA and Canada. People were trapped in subways and elevators, there were no traffic lights or transportation to return home, communication system was paralyzed and people had to spend night in the dark. Power restoration took between 10 hours up to several days for some customers. Power restoration after such a widespread blackout was a complicated process and many customers were subject to rolling load shedding for up to one week. Just few weeks after

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This dissertation follows the style and format of *IEEE Transactions on Power Systems*.

this event, major blackouts happened in the United Kingdom, Sweden and Italy.

With the current restructuring in power systems, these blackouts raise warning flags indicating that something may be going wrong. Perhaps one of the reasons is that most utilities are not basing their decisions on well designed probabilistic reliability studies. Probabilistic reliability studies can determine weak points in the power network and consequently find solutions to improve reliability at load points.

More realistic and sophisticated but easy to apply techniques for probabilistic power system reliability studies are needed. These new tools should be able to overcome the drawbacks of conventional tools used for power system reliability assessment. These new tools should also be able to adapt to the current changes in the power market.

## I. Research Objectives and Dissertation Organization

Even though considerable amount of research work has been done in the area of power system reliability, there is still a need for more suitable methods for representing the system more realistically and yet be computationally tractable. Although some analytical methods are available, most of the research in composite system reliability uses state sampling using Monte Carlo simulation. Evaluation of sampled states is still very computation intensive but has not received much attention because of complexity of this problem.

Genetic algorithms (GAs) have shown a rapid growth of applications in power systems. An area which has not yet been investigated for their application is power system reliability. Application of GAs to power systems is found in areas such as economic dispatch, power system planning, reactive power allocation and the load flow problem. In all these applications, GA is used primarily as an optimization tool.

The objective of this dissertation is to develop several novel and efficient GA based techniques for power system reliability assessment. These techniques use GA as a smart state sampling tool. These techniques have the advantage of being intelligent, requiring less computational effort, flexible to consider different factors such as chronological load curves and multi-state components. These techniques are applied to calculate adequacy, frequency and duration, and reliability cost/worth indices. This dissertation also presents an innovative approach for state evaluation. This approach uses GA guided by Fuzzy Logic constraints to implement sophisticated practical load curtailment techniques.

The organization of this dissertation is as follows:

Chapter II includes a brief review of power system reliability studies, classical and recent methods developed for generation and composite power system reliability assessment. It also gives a general idea of genetic algorithms.

Chapter III introduces a new method to calculate generation system adequacy indices. The proposed method is based on a simple genetic algorithm which searches the state space to scan the most probable failure states and stores them in a state array. GA search process is guided through its fitness function. Hourly load values are then discretely convoluted with the state array to obtain various adequacy indices of generating system. The use of the state array to get information about contribution of system states and different generating units combinations to system failure is demonstrated. This can be helpful in some decision making.

Chapter IV develops an innovative method for composite power system reliability. The proposed method uses GA as an intelligent search tool to search for failure states that result in load curtailment. The performance of GA depends on the suitable choice of the chromosome evaluation function. States sampled by GA are saved with all their related data in the state array. After finishing the search process, states saved in the state array are used to calculate the annualized adequacy indices for the whole system and for load buses. A linear programming model is used to evaluate each state taking into consideration importance of loads. It is shown that the proposed method is superior over other conventional methods due to the intelligence it uses in its search process. Moreover, it has the merits of reporting the most probable failure scenarios and most severe ones. Case studies on the RBTS test system are given.

In chapter V the preceding method has been extended to evaluate adequacy indices of composite power systems while considering chronological load at buses. Hourly load is represented by cluster load vectors using the k-means clustering technique. The GA is used as a state sampling tool for the composite power system network. Binary encoded GA is used to represent system states. Two different approaches have been developed. In the first approach GA samples failure states for each load level separately. Thus, adequacy indices are calculated for each load level and then combined to obtain the annual adequacy indices. In the second approach, GA samples failure states only with load buses assigned the maximum cluster load vector. Failure states are then reevaluated with lower cluster load vectors until a success state is obtained or all cluster load levels have been evaluated. In both approaches, GA is able to trace failure states in a more intelligent manner than conventional methods. A linearized optimization load flow model is used for the evaluation of sampled states. Case studies on the RBTS test system considering correlated chronological load curves of load buses are presented. Results obtained from the two different approaches are compared and analyzed.

Chapter VI uses the developed GA based technique to calculate annual frequency and duration indices of the composite system. The system hourly load for the year is represented as a multi-state component using k-means clustering technique. Transition rates between the load states are calculated. The conditional probability based method is used to calculate the frequency of sampled failure states using different component transition rates. The GA samples network failure states with the system load assigned its maximum state value. Failure states are then reevaluated with lower load states until a success state is obtained or all load states have been evaluated.

Chapter VII develops a GA based method for evaluating reliability worth indices of composite power systems. An optimization model based on linearized load flow is used for the evaluation of sampled states. Two different objectives are used in state evaluation. The first objective is to minimize load curtailment considering load category and load bus relative importance. The second objective is to minimize load interruption cost. Instead of using the raw interruption cost associated with failure state mean duration time, random sampling is used to calculate mean interruption cost associated with each failure state.

Chapter VIII introduces an improved GA based approach for the assessment of composite power system reliability. This enhanced approach recognizes multi-state components such as generation units with derated states. It also considers common mode failure for transmission lines. Binary encoded GA is used as a state sampling tool for the composite power system network states. Each two-state component is represented by one gene. Meanwhile, every multi-state component is represented by two or more genes, e.g., two genes are able to represent up to four-state component. Both annual and annualized adequacy indices are calculated. Case studies on a sample test system considering chronological load curves, derated states and common mode failures are presented. Results are analyzed to determine the effect of considering multi-state components.

Chapter IX presents a new method for composite system state evaluation using GA. The objective of GA is to minimize load curtailment for each sampled state. Minimization is based on the dc load flow model. System constraints are represented by fuzzy membership functions. Membership value indicates the degree of satisfaction of each constraint for an individual in a GA population. The GA fitness function is a combination of these membership values. The proposed method has the advantage of allowing sophisticated load curtailment strategies which lead to more realistic load point indices.

Finally, chapter X gives the summary of this dissertation and reviews of the significance of this research. It also suggests future research topics.

Appendix A gives data of the RBTS test system.

# CHAPTER II

# REVIEW

## I. Reliability Assessment of Electric Power Systems

### *A. Introduction*

Reliability is a measure of the ability of a system to perform its designated functions under the conditions within which it was designed to operate. Given this concept, power system reliability is a measure of the ability to deliver electricity to all points of utilization at acceptable standards and in the amount desired.

Power systems reliability assessment, both deterministic and probabilistic, is divided into two basic aspects: system adequacy and system security [1]. System adequacy examines the availability of sufficient facilities within the system to satisfy the consumer load demand without violating system operational constraints. These include the facilities necessary to generate sufficient energy and the associated transmission and distribution facilities required to transport the energy to consumer load points. Adequacy is therefore associated with static conditions which do not include system disturbances. System security presents the ability of the system to respond to sudden shocks or disturbances arising within the system such as the loss of major generation and/or transmission facilities and short circuit faults. Under such condition, security studies show system ability to survive without cascading failures or loss of stability.

Power system reliability evaluation is important for studying the current system to identify weak points in the system, determining what enforcement is needed to meet future demand and planning for new reliable power system, i.e., network expansion. Reliability studies is vital to avoid economic and social losses resulting from power outages.

Adequacy analysis of power systems essentially consists of identification and evaluation of failure states, states in which the power system can not satisfy customer demand and load shedding action is needed to maintain the system integrity. Since the number of possible states can run into millions, straightforward enumeration and evaluation is not feasible even for moderate sized networks. Monte Carlo simulation is currently the most common method used in states sampling, yet it suffers from three major drawbacks. The first one is the excessive simulation time. The second one is the lack of information about outage scenarios that can happen and the contribution of different system components to these outages. The third one is the difficulty to sample failure states when system reliability is very high which is the case in most practical systems.

Adequacy assessment methods in power systems are mainly applied to three different hierarchical levels [1]. At Hierarchical level I (HLI), the total system generation is examined to determine its adequacy to meet the total system load requirements. This is usually termed "generating capacity reliability evaluation". The transmission system and its ability to transfer the generated energy to the consumer load points are ignored in HLI. The only concern is estimating the necessary generation capacity to satisfy the demand and to have sufficient capacity to perform corrective and preventive maintenance on the generating facilities.

In HLII studies, the adequacy analysis is usually termed composite system or bulk transmission system evaluation. HLII studies can be used to assess the adequacy of an existing or proposed system including the impact of various reinforcement alternatives at both the generation and transmission levels. In HLII, two sets of indices can be evaluated; the first set includes individual load point indices and the second set includes overall system indices. These indices are complementary, not alternatives. The system indices give an assessment of the overall adequacy and the load-point indices indicate the reliability of individual buses and provide input values to the next hierarchical level.

The HLIII studies include all the three functional zones of the power system, starting at generation points and terminating at the individual consumer load points. To decrease complexity of these studies, the distribution functional zone is usually analyzed as a separate entity using the HLII load-point indices as the input. The objective of the HLIII study is to obtain suitable adequacy indices at the actual consumer load points.

Power system reliability has been an active research area for more than three decades. A comprehensive recent list of publications can be seen from bibliographies on power system reliability evaluation [2], [3]. A survey of the state-of-art models and analysis methods used in power system reliability assessment is given in [4].

### *B. Reliability Evaluation of Generation Systems*

Generation system reliability evaluation is the most mature area in power system reliability studies. Many methods have been developed to calculate the adequacy of power system generation (HLI). These methods can be divided into two main categories, analytical methods and simulation methods using Monte Carlo technique. The analytical methods are further divided into two main categories, the discrete distribution methods and continuous distribution methods. The most efficient method is the unit addition algorithm presented in [5]. Different Monte Carlo strategies are given in detail in [6].

### *C. Reliability Evaluation of Composite Generation-Transmission Systems*

Adequacy assessment of composite generation-transmission systems is a more complex task. It is divided into two main parts, state sampling and state evaluation. Each sampled state consists of the states of generating units and transmission lines, some of them are in the up state and others are in the down state. The purpose of state evaluation is to judge if the sampled state represents a failure or success state. After state sampling stops, data from evaluated states is used to calculate adequacy indices of the composite power system. A wide range of techniques has been proposed for composite system reliability evaluation. These techniques can be generally categorized as either analytical or simulation.

Analytical techniques represent the system by analytical models and evaluate the indices from these models using mathematical solutions. The most widely used analytical method is the contingency enumeration approach [7].

Monte Carlo simulation methods estimate the indices by simulating the actual process and random behavior of the system. Monte Carlo simulation methods are divided into random sampling methods and sequential methods. In both techniques, Monte Carlo simulation is used for state sampling. Sampled states are evaluated through linearized flow equations to calculate the amount of load curtailment if needed [8], [9]. Monte Carlo techniques can take a considerable computation time for convergence. Convergence can be accelerated by using techniques such as variance reduction to reduce the number of the analyzed system states [10].

A Monte Carlo simulation approach to generation-transmission reliability evaluation assuming the loads are defined by fuzzy numbers was developed in [11]. In this approach, data uncertainties were modeled more adequately, system component outages were represented by probabilistic models and load uncertainties were modeled by fuzzy numbers. For each sampled state, one can obtain the power not supplied membership function by running a fuzzy optimal power flow.

Hybrid methods that take the advantages of both analytical methods and Monte Carlo simulation has been developed in [12]. This technique was based on pruning the state space of composite systems. This is achieved by performing Monte Carlo simulation selectivity on those regions of the state space where loss of load states are more likely to occur. These regions are isolated by performing state decomposition to remove coherent acceptable subspaces. It has been shown that this method results in a significant reduction in the number of sampled states, thereby reducing the computational effort required to compute the system and bus indices.

A novel approach for power system reliability evaluation combining Monte Carlo simulation and learning vector quantization (LVQ) of Neural Networks has been introduced in [13] . This new method greatly reduces the computing burden of the loss of load probability calculation compared to Monte Carlo simulation only.

A probabilistic method, designated as system well-being analysis has been used for evaluating the effect of peak load, load factor, load curtailment philosophy and percentage load curtailed on composite system reliability [14]. This approach incorporates the conventional risk index as well as the accepted deterministic criteria identified as being in the healthy and marginal states. It calculates the well-being indices in generation and transmission systems.

## II. Genetic Algorithms

### *A. Genetic Algorithm Construction*

Genetic algorithm is one of the most powerful and broadly applicable stochastic search and optimization technique based on concepts from evolution theory. It is a technique that simulates the nature where a new generation is coming from old generation with more fit properties. A genetic algorithm is a simulation of evolution where the rule of survival of the fittest is applied to a population of individuals. Genetic algorithm has been applied to a wide range of difficult optimization problems that are relevant to engineering and operation research [15], [16], [17].

The GA has many advantages over other conventional optimization methods. Some of these are:

1.GA works with a coding of solution set rather than solutions themselves.

2. It searches a population of solutions rather than a single solution.

3. It uses payoff information through fitness function, there is no need to get the derivatives or other auxiliary knowledge for the function that is need to be optimized.

4. It uses probabilistic transition rules, not deterministic rules.

Suppose we have a function in a set of variables. We want to find the values of these variables to maximize or minimize this function. When using GA to solve this problem, a random initial population is first created. This population consists of a set of individuals called chromosomes. Each chromosome consists of a certain number of genes. Each chromosome represents a potential solution and it consists of a decoded set of variables that represents the original variables. Each original variable can be represented by a group of genes or a single gene. A fitness function is used to evaluate the goodness of each chromosome. The fitness function is usually the objective function that we want to maximize or minimize.

The basic construction of a genetic algorithm is as follows:

1. Create an initial population, usually a randomly generated string of individuals.

2. Evaluate all the individuals by applying some function or formula usually called a fitness function.

3. Select a new population from the old population based on the fitness of the individuals as given by the evaluation function.

4. Apply some genetic operators such as mutation and crossover to the members of the new population to create new solutions.

5. Evaluate these newly created individuals.

6. Repeat steps 3-5 applied on one generation until the termination criterion has been satisfied. A commonly used criterion is to stop after a fixed number of generations.

### *B. Chromosome Representation*

A chromosome is made of sequence of genes from a certain alphabet. An alphabet may consists of binary digits, floating point numbers, integers, symbols, i.e., A, B, C,…. or matrices. Each GA population consists of pop_size chromosomes.

### *C. Genetic Algorithm Operators*

Genetic algorithm operators are applied to the old population to obtain a new population with better solutions. There are many types of GA operators, the most essential ones are crossover, mutation and selection.

#### *1. Crossover operator*

Crossover operates on two chromosomes at a time and generates offspring by combing features of both chromosomes . There are many types of crossover operators. Some of them can be applied to any type of decoded GA such as one point crossover and two point crossover. Others can be applied only to specific types of GA such as arithmetical crossover operator which can be applied only to real number encoded GA. Some crossover operators can result in unfeasible solutions, others always result in feasible solutions.

A crossover probability $P_c$ is chosen at first. For each pair of chromosomes a random number is drawn, if this number is less than or equals $P_{c,}$ this pair of chromosomes is subjected to crossover.

*a) One point crossover operator*

This is the most commonly used crossover operator. Suppose two chromosomes X and Y are subjected to cross over. Each chromosome length is k. Generate a random number “pos” in the range [1..k-1]. The genes of the new chromosomes will be:

$$x_i^{\backslash} = x_i \ \text{ if } \ i < pos \ \text{ and } \ x_i^{\backslash} = y_i \ \text{ otherwise} \tag{2.1}$$

$$y_i^{\backslash} = y_i \ \text{ if } \ i < pos \ \text{ and } \ y_i^{\backslash} = x_i \ \text{ otherwise} \tag{2.2}$$

where $x_i$ represents gene number i in the X chromosome and $y_i$ represents gene number i in the Y chromosome.

*b) Two point crossover operator*

Generate two random numbers “pos1” and “pos2” in the range [1..k-1]. Supposing pos1<pos2, the genes of the new chromosomes will be:

$$x_i^{\backslash} = x_i \ \text{ if } \ pos1 < i < pos1 \ \text{ and } \ x_i^{\backslash} = y_i \ \text{ otherwise} \tag{2.3}$$

$$y_i^{\backslash} = y_i \ \text{ if } \ pos1 < i < pos2 \ \text{ and } \ y_i^{\backslash} = xi \ \text{ otherwise} \tag{2.4}$$

*c) Arithmetical crossover operator*

Arithmetical genetic operators are used to produce children by applying them to parents. The offspring ($Y_1$ , $Y_2$) for two parent chromosomes ($X_1$ , $X_2$) eligible for crossover are:

$$Y_1=\lambda_1.X_1 + \lambda_2.X_2 \tag{2.5}$$

$$Y_2=\lambda_1.X_2 + \lambda_2.X_1 \tag{2.6}$$

If $\lambda_1 + \lambda_2 = 1$ and $\lambda_1 > 0$, $\lambda_2 > 0$, it will be called convex crossover. Each time crossover will be applied, a random number between 0 and 1 will be picked as a value for $\lambda_1$.

*d) Direction-based crossover:*

A single offspring $X^\backslash$ is generated from two parents $X_1$ and $X_2$. Each gene $x_k'$ of the offspring is produced form the parents corresponding genes according to the following rule:

$$x_k' = r.(x_{1k} - x_{2k}) + x_{2k} \tag{2.7}$$

where $0 < r \leq 1$.

*2. Mutation operator*

The mutation operator produces spontaneous random changes in various chromosomes. A mutation probability $P_m$ is set at first. For each gene in the current chromosomes a random number r will be drawn from [0..1]. If $r \leq pm$, this gene will be subjected to mutation.

*a) Uniform mutation*

For each bit in each chromosome in the new population, generate a number r from [0..1]. If $r < p_m$ flip that bit from 1 to zero or zero to one in case of binary representation. In the case of real number representation, choose a random number for the selected gene between the gene corresponding variable lower and upper bounds.

*b) Non uniform mutation*

For each gene in each chromosome in the population pick a random number between 0 and 1. If this number is less than or equal to mutation probability then this gene is eligible for mutation. For a given chromosome X, if one of its genes $x_k$ is selected for mutation, the resulting offspring is:

$X^\backslash = [x_1, x_2, \ldots\ldots\ldots\ldots\ldots, x_k', \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots x_n]$,

where $x_k'$ is randomly selected from two possible choices:

$$x_k' = x_k + \Delta(t, x_k^U - x_k) \text{ or} \tag{2.8}$$

$$x_k' = x_k - \Delta(t, x_k - x_k^L) \tag{2.9}$$

where $x_K^U$ and $x_K^L$ are the upper and lower bounds for $x_k$.

The function $\Delta(t,n)$ returns a value in the range [0 , n ] such that the value of $\Delta(t,n)$

approaches to 0 as t increases.

$$\Delta(t,n) = n.r.\left(1-\frac{t}{T}\right)^{b} \tag{2.10}$$

where t is the current generation number,

T is the maximum generation number,

r is a random number from [0..1],

b is a parameter determining the degree of non uniformity.

*3. Selection operator*

The selection operator directs the GA search toward a promising region in the search space. In this process, new chromosomes are selected to construct the population of the new generation from the sampling space. There are two types of the sampling space. Regular sampling space which contains all offspring but just part of parents. Enlarged sampling space which contains all parents and offspring. There are many strategies for the selection process, two of them are explained in next sections.

*a) Top selection*

Assume that population size equals to pop_size and the number of offspring produced after applying crossover and mutation operators equals to child_size. If the optimization problem is a maximization problem, top selection means that the new generation will consist of the highest fitness value chromosomes among the chromosomes of old population and offspring, i.e., new generation consists from the best pop_size chromosomes chosen from the previous pop_size parents and child_size children.

*b) Roulette wheel selection*

The fitness value is calculated for each chromosome in the current population. Consequently, the total fitness of the whole population is calculated. The probability of a selection for each chromosome is calculated as the ratio of chromosome fitness value and the total fitness value. The cumulative probability $q_i$ is calculated for each chromosome i. The selection process is based on spinning the roulette wheel pop_size times. Each time a single chromosome is selected for the new population. This is achieved by generating a random number r from the range [0..1]. If $r < q_1$ then select the first chromosome, otherwise select the ith chromosome such that $q_{i-1} < r \leq q_i$. Through this selection schema, some chromosomes will be selected more than once. The best chromosomes get more copies, the average stay even, and the worst die off.

# CHAPTER III

# ADEQUACY ASSESSMENT OF POWER SYSTEM GENERATION USING A MODIFIED SIMPLE GENETIC ALGORITHM

## I. Introduction

Many methods have been developed to calculate the adequacy of power system generation. These methods can be divided into two main categories: analytical methods and simulation methods using Monte Carlo technique. The analytical methods are further divided into two main categories: the discrete distribution methods and continuous distribution methods. Genetic algorithms have shown a rapid growth of applications in power systems. An area which has not yet been investigated for their application is power system reliability. Application of genetic algorithms (GA) to power systems is found in areas such as economic dispatch, power system planning, reactive power allocation and the load flow problem. A list of papers of GA application to power systems can be found in [18]. In all these applications GA is used primarily as an optimization tool.

An innovative technique to calculate the full set of indices of power system generation adequacy is presented in this chapter [19],[20],[21]. These indices are loss-of-load expectation (LOLE), expected energy not supplied (EENS), loss-of-load frequency (LOLF) and loss of load duration (LOLD). The developed technique uses the GA as a search tool to find the most probable system failure states. These states are stored in an array during the search operation, and then this array is convoluted discretely with hourly load values to find all the indices. The developed technique is based on the simple genetic algorithm (SGA) [15] with some modification to be suitable for adequacy assessment. The new algorithm is called a modified simple genetic algorithm (MSGA).

The developed method has been tested both on the standard IEEE RTS-79 system consisting of 32 generation units and IEEE RTS-96 system consisting of 96 generation units. The results obtained have been compared with other methods such as Monte Carlo simulation for accuracy and efficiency.

An interesting feature of this method is that the state array can be used to find the contribution of system states and individual unit combinations to the probability of system failure. This information can be helpful in determining the sensitivity of system reliability to individual units and can be used for making system improvements.

## II. Basis of the Proposed Method

The primary use of the GA is to find the optimal value of a certain function under some constraints. A GA is a simulation of evolution where the rule of survival of the fittest is applied to a population of individuals. In the basic GA [16], an initial population is randomly created. Population individuals, called chromosomes, are then evaluated by applying some function or formula. A new population is selected from the old one based on the fitness value of the individuals. Some genetic operators are then applied to some of the newly selected population to create the final new generation. The most commonly used genetic operators are crossover and mutation. The process is repeated from one generation to another until reaching a stopping criterion.

In the proposed method, GA is used as a sampling tool to construct the generating system state array. Demand is modeled as hourly loads. A discrete convolution is performed between power-generating states and load values to determine different generation system adequacy indices. Every generation unit is assumed to have two states, up and down. It has its own forced outage rate (FOR), failure rate $\lambda$ and repair rate $\mu$. The probability of any unit down is equal to its FOR. The total number of states for all possible combinations of "*m*" generating units in the system is

$$K = 2^m \tag{3.1}$$

The MSGA is used to truncate this state space into a small fraction of $K$. Population of the MSGA consists of "pop_size" individuals, each called a chromosome. Binary numbers are used to represent each chromosome. Each binary number represents a single unit in the generating system. Length of any chromosomes “*L*” equals the total number of system generators. System generators are divided into groups. Each group consists of “$L_i$” units which are identical, i.e., have the same generation capacity, λ and μ. Each chromosome is divided into “*n*” parts, each part consisting of adjacent binary numbers representing identical units in the same group. In this manner any chromosome is represented as shown in Fig. 1.

| Part # 1 | Part # 2 | ……… | Part # n |
|---|---|---|---|
| $g_{11}$ $g_{12}$ $g_{13}$ $g_{14}$ | $g_{21}g_{22}g_{23}$ $g_{24}$ $g_{25}$ $g_{26}$ | ………. | $g_{n1}$ $g_{n2}$ $g_{n3}$ |
| 1 0 1 1 | 1 1 1 0 1 0 | ………... | 0 1 0 |

Fig. 1. Chromosome representation for generation system.

It can be seen that each chromosome represents a system state. Each state “*i*” has its own probability “$PG_i$”, contribution to system failure frequency “$FG_i$,” generation capacity “$Cap_i$” and total number of equivalent permutations “$copy_i$.” At the beginning, “pop_size” chromosomes are initialized by choosing random binary numbers for their bits. Each chromosome is evaluated. The value of evaluation function for any chromosome equals state probability if state capacity is less than the maximum load or equals a very small number otherwise. The data of each evaluated chromosome is stored in state array. Each element in the array consists of five fields. The first one is itself an array containing number of columns equal to the number of chromosome parts. Each column contains the number of generators in the up state in the corresponding part. The remaining fields are the state probability, contribution to system failure frequency, generation capacity and total number of permutations. The element of state array representing the chromosome shown in Fig. 1 is shown in Fig. 2.

| Number of ones | | | | $P_i$ | $FG_i$ | $Cap_i$ MW | $Copy_i$ |
|---|---|---|---|---|---|---|---|
| 3 | 4 | ……….. | 1 | | | | ${}^4C_3 . {}^6C_4 \ldots\ldots {}^3C_1$ |

Fig. 2. State array construction.

After evaluation of all population chromosomes, total fitness of the population is calculated. A new population is generated through applying selection, crossover and mutation operations on the old population. Through selection process, states with higher probabilities appear again in the next generation. Crossover and mutation operations produce new states. Before adding any new state to state array, a test is made to see if an equivalent permutation for this state was added previously. The test is done by comparing the number of ones in each part of this state with those of all previously saved states in state array. If the test is failed, i.e., there was no permutation of this state saved before, the new state data are added to state array. New generations are produced until reaching a stopping criterion. The main role of GA is to truncate state space by tracing states that contribute most to failure at maximum load.

## III. MSGA Algorithm Structure

### *A. Construction of Generation System State Array*

The construction of the power generation system state array is summarized in the following steps:

1. Each chromosome is divided into "*n*" parts. Each part consists of adjacent binary numbers representing generating units of the same capacity and reliability

parameters.

2. The length of part number $i$ is $L_i$, i.e.,

$$m = \sum_{i=1}^{n} L_i \tag{3.2}$$

3. In this way, each chromosome represents a system state.

4. Input parameters are pop_size, crossover probability "$P_c$," mutation probability "$P_m$," system yearly peak load "max_load" and reliability parameters (FOR, λ, μ) of generation units. A threshold probability "*tp*" is set.

5. Construct the state array to save scanned states.

6. Initial population is generated randomly. For each bit (representing a generation unit) in the chromosome, a random binary number (zero or 1) is chosen, i.e., $m$ random binary numbers for each chromosome. This process is repeated for all population chromosomes.

7. For a state with a probability less than *tp*, its fitness is taken as its state probability multiplied by a small number, e.g., 1e-5. This state is ignored and is not added to state array. The algorithm proceeds to step 11.

8. Calculate state-generating capacity $\text{Cap}_i$

$$Cap_i = \sum_{j=1}^{m} b_j . g_j \tag{3.3}$$

where $b_j$ is the value of the binary number representing generating unit $j$, and $g_j$ is its generating capacity. If $\text{Cap}_i \geq$ max_load, then this state represents a success state. Hence, its fitness "$\text{Fit}_i$" equals a very small number, e.g. 1e-100. Proceed to step 11. If $\text{Cap}_i <$ max_load then continue to step 9.

9. This chromosome represents a failure state. Calculate the number of "ones" in each part of the chromosome. Compare these numbers with the first field in state array. If a state is found to have the same value of the "ones," this means that this state has been scanned previously. Leave the remaining of this step and go to step 10. Otherwise this chromosome represents a new state. The fitness of any chromosome "$i$" representing a new state is evaluated as follows:

a. Calculate chromosome probability

$$\mathrm{P_i} = \prod_{j=1}^{m} gp_j \tag{3.4}$$

where $gp_j$ is generating unit state probability which can take one of the following values: $gp_j = 1\text{-FOR}_j$ if $b_j = 1$ or $gp_j = \text{FOR}_j$ if $b_j = 0$

b. Calculate the number of all possible permutations of the evaluated state that equals the multiplication of all permutations of each part in the chromosome.

$$\text{copy}_i = \binom{L_1}{O_1} x \binom{L_2}{O_2} x .....x \binom{L_j}{O_j} .....x \binom{L_n}{O_n} \tag{3.5}$$

where $O_j$ is the number of "ones" in part j of length $L_j$.

c. The fitness of the chromosome can be calculated as

$$Fit_i = copy_i \,.\, P_i \tag{3.6}$$

d. The state contribution to system failure frequency is calculated using the conditional probability method described in [22] and [23].

$$\mathrm{FG_i} = \mathrm{P_i} \;.\; \left( \sum_{j=1}^{m} (1-b_j).\mu_j - \sum_{j=1}^{m} b_j.\lambda_j \right) \tag{3.7}$$

e. Save all chromosome data in state array fields, and increase state array counter by one.

f. Update the probability of loss of load for max load.

$$lolp(max\ load)_{new} = lolp(max\ load)_{old} + Fit_i \tag{3.8}$$

g. Skip step 10 and jump to step 11.

10. In this case, the chromosome represents a state, one of whose permutations was stored previously. The fitness of this chromosome is calculated according to (3.6), using state data previously stored in state array. This fitness value is multiplied by a small number, e.g., 1e-5, to decrease its opportunity to appear in new generations.

11. Steps 7 to 10 are repeated for all chromosomes comprising this population. When the last chromosome in the current population is reached, go to the next section to produce a new generation.

*B. Evolution of a New Generation*

Evolution of a new generation from the old one in SGA is described in detail in [15] and [16]. The summary of the process is that old population passes through three operations. The first one is the selection from parents; the second one is applying the crossover operator; and the third one is applying the mutation operator. Selection procedures are as follows:

1. Calculate the total fitness of the population

$$F = \sum_{i=1}^{pop\_size} Fit_i \tag{3.9}$$

2. Calculate the probability of a selection for each chromosome $i$.

$$ps_i = \frac{Fit_i}{F} \tag{3.10}$$

3. Calculate the cumulative probability $q_i$ for each chromosome "$i$" by adding its selection probability to those of all previous "$i$-1" chromosomes in the current population.

$$q_i = \sum_{j=1}^{i} ps_j \tag{3.11}$$

4. The selection process is based on spinning the roulette wheel pop_siz times. A single chromosome is selected for the new population each time.

5. Generate a random number $r$ from the range [0..1]. If $r < q_1$ then select first chromosome otherwise select the $i^{th}$ one such that $q_{i-1} < r \leq q_i$.

6. In this manner, some chromosomes are selected more than once. The best chromosomes get more copies; the average stay even; and the worst die off.

The second operation is to apply the crossover operator. For each pair of chromosomes in the new population, generate a random number $r$ from [0..1]. If $r < P_c$ select given chromosome pair for crossover. At the end, $j$ pairs of chromosomes are eligible to apply crossover to them. Assume the pair X and Y is subjected to crossover. Generate a random number "pos" in the range [1..m-1]; the two new chromosome genes are:

$x_i^{\backslash} = x_i$ if $i < pos$ and $y_i$ otherwise (for $i = 1$ to m)

$y_i^{\backslash} = y_i$ if $i < pos$ and $x_i$ otherwise (for $i = 1$ to $m$)

An illustration for the crossover operation is shown in Fig. 3.

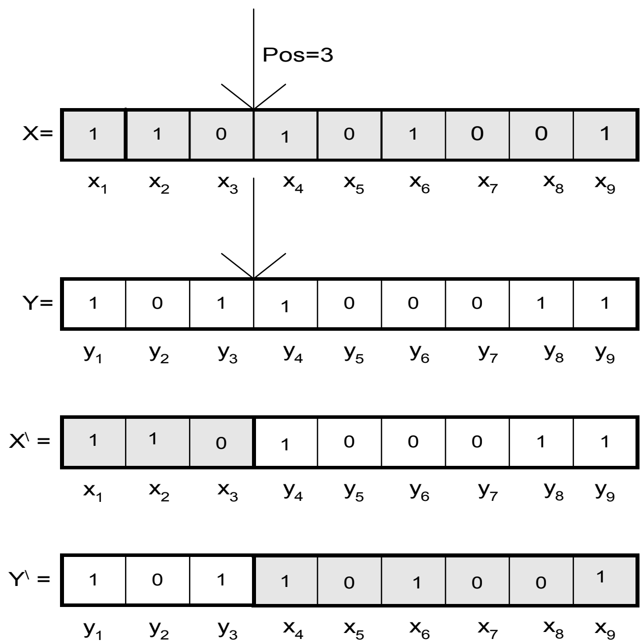


Fig. 3. Crossover of X and Y chromosomes.

The third operation is to apply the mutation operator. For each bit in each chromosome in the new population, generate a random number $r$ from [0..1]. If $r < P_m$ convert that bit from one to zero or zero to one.

Now a new population is generated, and the process is repeated until a stopping criterion is reached. The main idea of the proposed method is that at each GA generation, more states are scanned, especially those with higher failure probabilities, i.e., have higher fitness values. Each of them is saved in the state array. If dealing with an ordinary optimization problem, the purpose is to obtain the maximum value of the fitness function and the decoded decimal value for its chromosome. But here, GA is used to scan or, in other words, to sample system states which have higher fitness values. Illustration of GA search process is shown in Fig. 4.

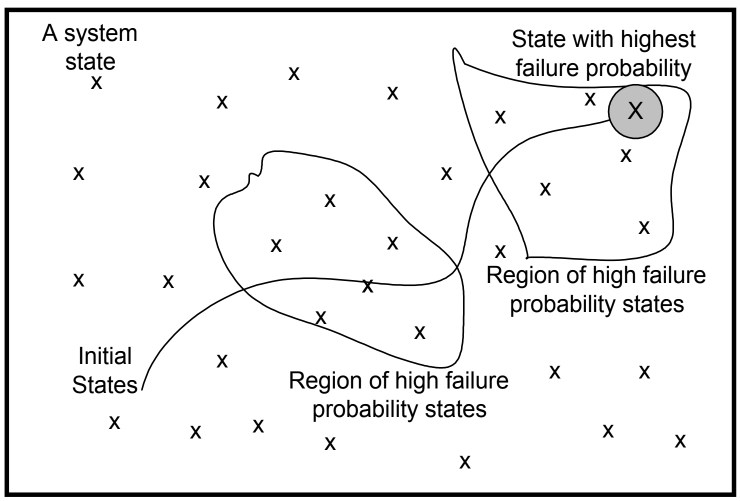


Fig. 4. The GA searching the state space.

## *C. Choosing a Stopping Criterion*

Any of the following three criteria can be used to stop the algorithm:

The first stopping criterion is to stop the algorithm after reaching a certain number of GA generations. If a small number of generations is used, this leads to inaccurate results, as not enough states would have been scanned.

The second one is to stop after the scanning of a certain number of system failure states by adding all the numbers of the permutations in the state array. Taking into consideration that only states resulting in failure at maximum load are stored, this stopping criterion gives accurate results taking into consideration system size and the difference between the installed generation capacity and system maximum load.

The third stopping criterion is to stop when the increase in the probability of failure of supplying maximum load is below a certain value within certain number of generations, i.e., max.{lolp(max_load)$_{new}$ – lolp(max_load)$_{old}$ for certain consequent number of generations} < certain value.

*D. Calculating Reliability Indices*

After the MSGA is stopped, using any of the previously mentioned stopping criteria, it is time to calculate adequacy indices of the power-generating system. These indices are LOLE, EENS, LOLF and LOLD. These indices are calculated by discrete convolution of hourly load values during a full year with the state array developed previously. Consider the load value at hour "i" is $LH_i$ . Loss-of-load probability (LOLP) for this load value is calculated as follows:

$$\text{LOLP}(\text{LH}_i) = \sum_{j=1}^{ae} S_j . P_j . copy_j \tag{3.12}$$

where "*ae*" is the total number of state array elements, and $S_j$ is the state status. It equals one if it is a failure state, i.e., $\text{Cap}_j < \text{LH}_i$ , or equals zero if it is a success state i.e. $\text{Cap}_j \geq \text{LH}_i$.

After calculating LOLP for all load values, LOLE in hours per year is calculated

$$\text{LOLE} = \sum_{j=1}^{8760} \text{LOLP}(\text{LH}_j) \tag{3.13}$$

Power not supplied (PNS) in megawatts is calculated for each hourly load value $\text{LH}_i$, and consequently, expected energy not supplied in megawatts hour is calculated

$$\mathrm{PNS}(\mathrm{LH}_i) = \sum_{j=1}^{ae} S_j.P_j.\mathrm{copy}_j.(\mathrm{LH}_i - \mathrm{CAP}_j) \tag{3.14}$$

$$\mathrm{EENS} = \sum_{j=1}^{8760} \mathrm{PNS}\,(\mathrm{LH}_j) \tag{3.15}$$

LOLF consists of two components: frequency of generating capacity "FG" and frequency due to load changes "FL." Each component is calculated separately as follows:

$$\mathrm{LOLF}(\mathrm{LH}_i) = \sum_{j=1}^{ae} S_j.FG_j.\mathrm{copy}_j \tag{3.16}$$

$$FG = \sum_{j=1}^{8760} \mathrm{LOLF}(\mathrm{LH}_j) \tag{3.17}$$

$$\mathrm{FL} = \sum_{j=2}^{8760} V_j.[\mathrm{LOLP}(\mathrm{LH}_j) - \mathrm{LOLP}(\mathrm{LH}_{j-1})] \tag{3.18}$$

where $V_j$ equals zero if the value between bracts is -ve and equals "1" otherwise.

Now LOLF in occurrences per year is calculated

$$\mathrm{LOLF} = \mathrm{FG} + \mathrm{FL} \tag{3.19}$$

The last indices is the LOLD in hours is calculated:

$$\mathrm{LOLD} = \frac{\mathrm{LOLE}}{\mathrm{LOLF}} \tag{3.20}$$

Other data that can be collected from state array is the generation outage capacity table. The advantage of this proposed method over other methods is that the obtained outage capacity table is close to the exact capacity outage table without any round off. This table is constructed from the state array by arranging the states in ascending order according to their capacities. At first, subtract the smallest state capacity from the total installed generating capacity. Save the corresponding outage capacity and state probability as the first element of capacity outage table. Go to the next element of the state array if the next state has the same capacity like the previous one; then, add its probability to the previous element in the capacity outage table; otherwise subtract its capacity from the total installed capacity, and save this new outage capacity as a new element in the table. Its corresponding probability is the summation of this state probability and the probability of the previous elements in the capacity outage table. These procedures are repeated until the last element of the state array. In this way, the outage capacity table is obtained with the smallest outage representing approximately the difference between total installed generation and maximum load. If the complete capacity outage table is required then run the MSGA, taking the maximum load of value higher than the installed capacity so that all the scanned states will be failure states and will be saved in the state array.

Another advantage of the proposed method is that from the analysis of the state array the following information can be obtained.

1. The scenario of the states that is likely to lead to system failure. This can be done by taking a certain number of failure states with higher probabilities and multiplying each state probability by the probability of the load to be higher than this state capacity. Ordering the obtained values, the results give a picture of the most probable scenarios of failures expected to occur. This scenario is described by the status of generating units in this state given from the first field of the state array.

2. Another piece of information that can be derived is the contribution of different generating unit combinations to system failure. This is helpful for improving reliability of these units or trying to add more units in the system.

## IV. Case Studies

The proposed method has been tested on the IEEE RTS-79 [24] and the larger RTS-96 system [25]. The choice of population size, crossover probability, mutation probability and threshold probability affects the accuracy of results. This is discussed in section V.

### *A. Case I: IEEE RTS-79*

The RTS-79 consists of 32 generating units with the smallest unit capacity of

12MW and the largest unit capacity of 400MW. The total installed capacity is 3405MW. The input parameters of the MSGA are taken as follows: pop_size = 40, $P_c$ = 0.6, $P_m$ = 0.06, max_load = 2850 MW and tp =1e-15. Results obtained in comparison with those obtained by the traditional unit addition algorithm [5] are given in Table I. The number of yearly hours used is 8736 and not 8760 as indicated in previous equations since the load data are given for only 364 days in the IEEE-RTS. The MSGA stops after producing 750 GA generations. The total number of elements saved in the state array is 10428 states. The total number of their permutations is $1.91983*10^7$.

Table I. MSGA Results for RTS-79

| Adequacy Indices | Results of [5] | MSGA results | Percentage error |
|---|---|---|---|
| LOLE (hrs/year) | 9.355 | 9.324 | 0.3% |
| EENS (MWH) | 1168 | 1163 | 0.43% |
| LOLF (occ./year) | 2.0197 | 2.0037 | 0.09% |

The MSGA has two advantages over the Monte Carlo simulation method. The first is that, like analytical methods, the state array construction is independent of system load curve. Therefore, if adequacy indices are required to be calculated for different load curves for the same system configuration, only the maximum of the set of each load curve maximum value is needed. The MSGA uses this value for scanning system state space, and the state array is constructed. State array is then convoluted with any load curve, provided that its maximum load is less than the one used in construction of the state array. In the case of Monte Carlo simulation, if results are required for different load curves, simulation must be done separately for each of them.

Table II(a)-(c), gives a comparison of the results obtained for different load curves using Monte Carlo method [6], unit addition algorithm [5], and the MSGA method. The state array is constructed with maximum load value of 3050 MW and then convoluted with the four different load curves. It can be seen that MSGA gives results more accurate than those of Monte Carlo in comparison to the unit addition algorithm, although they are all close.

The second advantage of MSGA over Monte Carlo methods is that in case of highly reliable systems where the FOR is very small, Monte Carlo simulation takes excessive simulation time for reaching a well-converged solution. In contrast MSGA, takes the same computational effort for more reliable systems, as the generation of new failure states depends on the relative comparison of the state fitness value. It is also possible to magnify the fitness value by multiplying it by a big number so that the relative difference between states increases.

The computational effort for the proposed method is compared with Monte Carlo simulation and the unit addition algorithm in Table III. The Monte Carlo simulation is stopped when the coefficient of variation reaches 5%. As can be seen from Table III, the MSGA is faster than the Monte Carlo simulation. The computational effort compared with the unit addition algorithm depends upon accuracy desired. The MSGA method, however, can provide additional information (as discussed later), and like Monte Carlo simulation is more flexible for dealing with complex system configurations like the composite systems. The MSGA is, in fact, like Monte Carlo simulation with the search process more directed by using a fitness function.

The Capacity outage table can also be obtained from the state array as described in the previous section. Table IV shows a comparison between part of the obtained table and the capacity outage table given in [24]. The results in [24] are in increment of 20 MW.

Table II. (a) LOLE Hours per Year Comparison. (b) EENS Megawatts per Year Comparison. (c) LOLF Occurrences per Year Comparison

| Max. Load MW | 2750 | 2850 | 2950 | 3050 |
|---|---|---|---|---|
| Monte Carlo [6] | 4.8516 | 9.3716 | 17.3696 | 30.7172 |
| MSGA | 4.8283 | 9.3435 | 17.461 | 31.0178 |
| Unit add. Alg. | 4.8454 | 9.355 | 17.499 | 31.0312 |

(a)

| Max. Load MW | 2750 | 2850 | 2950 | 3050 |
|---|---|---|---|---|
| Monte Carlo [6] | 586.49 | 1197.44 | 2335.73 | 4385.69 |
| MSGA | 558.58 | 1165.89 | 2310.1 | 4383.72 |
| Unit add. Alg. | 561.8 | 1168 | 2311.5 | 4379.9 |

(b)

| Max. Load MW | 2750 | 2850 | 2950 | 3050 |
|---|---|---|---|---|
| Monte Carlo [6] | 1.0348 | 1.9192 | 3.4228 | 5.8652 |
| MSGA | 1.0764 | 2.0090 | 3.6242 | 6.1908 |
| Unit add. Alg. | 1.0843 | 2.0197 | 3.6346 | 6.1919 |

(c)

Table III. Computational Time Comparison Between MSGA , Unit Addition Algorithm and Sequential Monte Carlo Simulation

| Method | Monte Carlo | Unit addition algorithm | MSGA | | | | |
|---|---|---|---|---|---|---|---|
| | | | Number of generations | | | | |
| | | | 100 | 250 | 500 | 750 | 1000 |
| LOLE hr/yr | 9.541 | 9.355 | 7.343 | 8.165 | 8.744 | 9.324 | 9.354 |
| Comp. time sec | 372 | 50 | 8 | 21 | 59 | 177 | 245 |
| error % | 1.9% | 0% | 21% | 12.7% | 6.5% | 0.3% | 0.01% |

Table IV. Part of the Capacity Outage Table

| X out MW | Exact [24] | MSGA | X out MW | Exact [24] | MSGA |
|---|---|---|---|---|---|
| 1000 | 0.004341 | 0.00431 | 989 | ---- | 0.00519 |
| 999 | ---- | 0.00433 | 988 | ---- | 0.00520 |
| 998 | ---- | 0.00433 | 987 | ---- | 0.00530 |
| 997 | ---- | 0.00508 | 986 | ---- | 0.00530 |
| 996 | ---- | 0.00510 | 985 | ---- | 0.00530 |
| 995 | ---- | 0.00516 | 984 | ---- | 0.00530 |
| 994 | ---- | 0.00516 | 983 | ---- | 0.00531 |
| 993 | ---- | 0.00517 | 982 | ---- | 0.00532 |
| 992 | ----- | 0.00517 | 981 | ----- | 0.00540 |
| 991 | ----- | 0.00518 | 980 | 0.005433 | 0.00540 |
| 990 | ----- | 0.00519 | 979 | ----- | 0.00544 |

Even though the unit addition algorithm may be computationally more efficient than MSGA depending on the accuracy desired, the MSGA has the ability of providing additional useful information. It is possible to know the most probable failure scenarios and their contribution to system adequacy indices. From the state array, the chromosome shown in Fig. 5 has the highest failure probability. If states are sorted according to their total failure probabilities, the first five elements of the resulting array are shown in Table V.

| 20MW | 76MW | 100MW | 197MW | 12MW | 400MW | 50MW | 115MW | 350MW |
|---|---|---|---|---|---|---|---|---|
| 1111 | 1111 | 111 | 110 | 11111 | 10 | 111111 | 1111 | 1 |

Fig. 5. Highest chromosome failure probability of RTS-79.

Table V. The Highest Failure Probability Generating States

| No. of ones | | | | | | | | | Prob. $P_i$ | $copy_i$ | Cap MW | Total Prob. $P_i.copy_i$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 4 | 3 | 2 | 5 | 1 | 6 | 4 | 1 | 0.0017 | 6 | 2808 | 0.0102 |
| 4 | 4 | 3 | 3 | 5 | 1 | 6 | 4 | 0 | 0.0028 | 2 | 2655 | 0.0056 |
| 3 | 4 | 3 | 3 | 5 | 1 | 6 | 3 | 1 | 0.00015 | 32 | 2830 | 0.0047 |
| 3 | 4 | 3 | 2 | 5 | 1 | 6 | 4 | 1 | 0.00019 | 24 | 2788 | 0.0045 |
| 4 | 4 | 3 | 3 | 5 | 0 | 6 | 4 | 1 | 0.0044 | 1 | 2605 | 0.0044 |

To see how this information can be utilized, consider first the state which has maximum total probability $P_1 = 0.0102$. The probability of the load to exceed this value equals the number of hours load exceeds this value divided by 8736. P( LH > 2808 ) = 3/8736 = 0.00034341. The probability of this state to cause system failure is $P_1$* P( LH > 2808 ) = 4.121e-6. So the contribution of this state to system failure is 4.121e-6 / (9.39/8736) = 0.3834%, i.e., this scenario (failure of one 197MW unit & one 76MW unit} contributes by this percent to system LOLP. Calculating the same value for the remaining four states the contribution of each of them is 0.227%, 0.1018%, 0.2407% and 3.1395% respectively.

Additional information that can be derived is the generating unit combinations that contribute to system failure at a certain load level. For example, different unit combinations contributing to failure at maximum load (2850MW) can be obtained. The probability of failure to supply maximum load is 0.0835. If the contribution of the different combinations of the two 400 MW units is needed, from the state array the following results can be obtained:

States including success of the two 400 MW generators contribute 25.6% of failure probability at maximum load. States including the failure of only one 400 MW unit contribute 74.4% and those including two 400 MW failure have negligible contribution. The contribution of different combinations of 20,76,100 and 197 MW units are given in Table VI. Consider the entry corresponding to 1 unit failed under the unit capacity of 20 MW, it means that the contribution to failure probability by states in which there is one failed 20 MW unit is 34.3%.

Another result that can be obtained is the generating unit combinations contributing to system lole. for example failure of one of the 197MW units appears 3.5313 hours from the total time of LOLE ,i.e., its percentage contribution is 38%. this value is obtained by discrete convolution of state array and hourly load values adding only states causing load loss with only one 197mw unit failed. Table VII shows contribution of different generating units combinations in LOLE.

Previous analysis shows how state array generated by MSGA can be used to gain more information about system states and different units contribution, and this is one of the features of the proposed method.

*B. Case II: IEEE RTS-96*

The MSGA was also tested on IEEE RTS-96 [25] which consists of three interconnected areas each of them identical to RTS-79. The total number of generating units is 96. The total installed capacity is 10215 MW. It is assumed that each single area has a maximum load of 3000 MW, i.e., the system maximum load is 9000 MW. This gives a system percentage reserve of 13.5%. The input parameters of the MSGA are taken as follows: pop_size= 200 , $P_c$=0.6, $P_m$=0.02 and tp=1e-20. The algorithm stops after 2000 GA generations. Results obtained by MSGA in comparison with those obtained by unit addition algorithm are given in Table VIII.

Table VI. Contribution of Different Generating Units Combinations to Failure Probability at Maximum Load

| No. of Failed units | Units Capacity in MW | | | | |
|---|---|---|---|---|---|
| | 20 | 76 | 100 | 197 | 12 |
| 0 | 60.4% | 89.62% | 84.15% | 54.35% | 89.83% |
| 1 | 34.3% | 10.28% | 14.88% | 43.05% | 10.54% |
| 2 | 5.28% | 0.454% | 0.9671% | 2.598% | 0.3976% |
| 3 | 0.0341% | 0.0021% | 0.0027% | 0.029% | 0.0047% |
| 4 | 0.0016% | ≅ 0% | -------- | --------- | ≅ 0% |
| 5 | -------- | --------- | ---------- | --------- | ≅ 0% |

Table VII. Contribution of Different Generating Units Combinations to LOLE

| No. of Failed units | Units Capacity in MW | | | | |
|---|---|---|---|---|---|
| | 20 | 76 | 100 | 197 | 12 |
| 0 | 61.7% | 87.81% | 78.61% | 54.80% | 90.23% |
| 1 | 32.05% | 12.14 | 20.01 | 38.32 | 9.9% |
| 2 | 5.76% | 0.574% | 1.36% | 6.87% | 0.385% |
| 3 | 0.300% | 0.0066% | 0.008% | 0.27% | 0.0046% |
| 4 | 0.0013% | ≅ 0% | -------- | --------- | ≅ 0% |
| 5 | -------- | --------- | --------- | --------- | ≅ 0% |

Table VIII. MSGA Results for RTS-96 after Evolving 2000 GA Generations

| Adequacy Indices | Unit addition algorithm | MSGA | Percentage error |
|---|---|---|---|
| LOLE (hrs/year) | 1.1402 | 1.1139 | 2.3% |
| EENS (MWh) | 229 | 220.5 | 3.7% |
| LOLF (occ./year) | 0.3977 | 0.3867 | 2.8% |

# V. Analysis of the Method

## *A. Effect of GA Parameters*

In all the applications of GA, a suitable choice of (pop_size, $P_c$, $P_m$) is important to obtain accurate results. Many sample runs on RTS-79 were done to study the effect of different parameter values. MSGA was analyzed by fixing all parameters and changing only one of them to study its effect. Analysis of results shows that MSGA is not strongly dependent on pop_size or $P_c$ but is affected by $P_m$. Low values of $P_m$ give high error, due to reaching premature failure state probabilities and sticking with them and decreasing the probability of generating new states. At the same time, higher values of $P_m$ increase errors, as this converts the search process into a random search.

It has been found that 85% accuracy can be obtained in a small number of GA generations. To increase this accuracy, more than double the number of GA generations is needed. This is due to the efficiency of the genetic algorithm in optimization, as the maximum state probability can be reached in a relatively small number of generations. New stored states then result mainly from mutation process. This has been overcome by penalizing the fitness function value of states that has been stored in the state array previously, and they reappear in new generations. This forces GA to search for new states.

The computational effort for this method depends on software used, i.e., algorithmic implementation and hardware configuration for the system used. It also depends on the stopping criteria used, i.e., number of states required to be scanned or number of generations. The time burden in this method is the search process for each chromosome to check if the state it represents or one of its permutations has been scanned previously or not. This problem can be overcome using parallel operation as described later.

*B. Selecting MSGA Parameters*

This section suggests a way for choosing GA parameters for a certain system. It begins by choosing any set of parameters. It is recommended for $P_m$ to be in the range of 0.005 to 0.08. $P_m$ should decrease as the system gets larger. $P_c$ can be in the range form 0.1 to 0.9. Pop_size should be higher than the total number of generating units. Set the maximum load to a value slightly higher than the total installed capacity. This means all scanned states are failure states and probability of failure of such a load is 1. Run MSGA and note LOLP value. If it is increasing rapidly towards 0.9 this means these parameters are suitable. Otherwise change one of the parameters and repeat the process. The threshold probability should decrease as the system size increases. Parameter tuning is needed to be done just once for each system depending on its size.

*C. Parallel Operation of MSGA*

For large systems, the number of states needed to be saved in the state array makes the search process in the state array a burden on the computational effort. This problem can be solved by using parallel or distributed computation methods. MSGA can be preformed on different machines at the same time saving only a small portion of the state space on each machine. Each portion is not overlapping with other portions. Hence, each MSGA searches only its state array, which has smaller number of stored elements. The non-overlapping parts can be based on states portability or load outage level. In the first case, MSGA runs on the first machine storing states having probabilities in the range from 1 to higher than 1e-10 for example, on the second machine probabilities ranging from 1e-10 to 1e-15 are scanned and so on. Then all saved states are combined together in one state array and then convoluted with load curve to obtain adequacy indices. It is also possible to make the parallel operation based on load level e.g. states causing failure at load level 10% to 50% of maximum load are scanned on one machine, states contributing to failure at load higher than 50% and less than or equal to 60% of system maximum load are scanned on another machine and so one. On each machine a modified fitness function is used to search for the highest probable states in its range. An illustration of this idea is shown in Fig. 6.

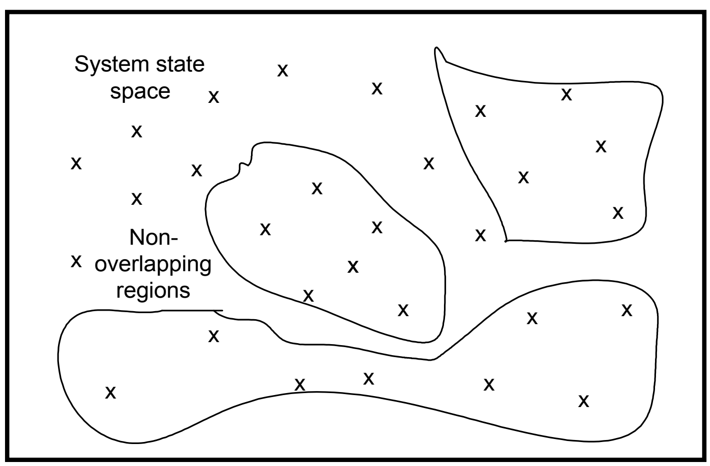


Fig. 6. Dividing the state space through GA parallel sampling.

*D. Summary of Advantages*

Advantages of the proposed method as compared with the traditional methods have been indicated in the text and are summarized below:

1. Because of the inherent property of GA algorithms to search for optimal solutions, the proposed method can yield information on the most probable failure scenarios and their contribution to the system adequacy indices. Such information can be helpful in the sensitivity analysis and provide additional information to system operators and planners for reliability improvement and this is illustrated in Section IV using case studies.

2. The method can also give generating unit combinations contributing to system failure at a given load level. This is also illustrated in Section IV using case studies.

3. Additionally, the directed-search property of GA can be used in another fashion. Suppose the effect of a certain group of generators on system adequacy is required to be evaluated. This can be studied through GA fitness function by giving credits to states including the failure of units under consideration and disregarding other states from addition to state array. In this manner GA finds the most probable states satisfying the required search criterion.

4. The parallel or distributed computation can be achieved simply using partitioning based on the probabilities or load levels.

5. Compared with the Monte Carlo simulation, the computation time is not significantly effected depending on the reliability of the system. In Monte Carlo, the computation time increases with the increase in the reliability of the system.

## VI. Conclusions

This chapter has presented a new method to calculate generation system adequacy indices. The proposed method is based on a simple genetic algorithm that searches the state space to scan most probable failure states and stores them in a state array. The GA search process is guided through its fitness function. Hourly load values are then discretely convoluted with state array to obtain various adequacy indices of generating system. Advantages and disadvantages of the proposed method in comparison with other conventional methods were shown. The developed method has been tested on IEEE RTS-79 and RTS-96. It has been demonstrated how the state array can be used to get information about contribution of system states and different generating units combinations to system failure, which is helpful for decision making.

# CHAPTER IV

# A NEW METHOD FOR COMPOSITE SYSTEM ANNUALIZED RELIABILITY INDICES BASED ON GENETIC ALGORITHMS

## I. Introduction

Reliability analysis of large power networks when generation and transmission are considered together is a complex and computationally difficult problem. There are two basic approaches for evaluating adequacy indices of composite power systems. The first approach is based on analytical evaluation. The second is based on Monte Carlo simulation techniques of either random sampling or sequential sampling. Monte Carlo simulation based methods show promise because of their ability to represent complex system configurations. The main difficulty in analytical techniques is the burden to trace the numerous system states. The analytical methods try to overcome this by pruning the huge state space. This can be achieved by state ranking or limiting state evaluation to a certain level of component outages.

In chapter III, GA was used as a powerful search tool to truncate the huge state space and trace most probable failure states to find generation system adequacy. Their success in generation system state sampling was a motivation to modify this technique to be used for the assessment of composite system adequacy indices.

This chapter presents an innovative state sampling method based on GA to truncate the huge state space by tracing failure states, i.e., states which result in load curtailment. States with failure probability higher than a threshold minimum value will be scanned and saved in a state array. The key to the success of the proposed method is the appropriate choice of a GA fitness function, a scaling method for fitness function and GA operators. Each scanned state will be evaluated through a linearized optimization load flow model to determine if a load curtailment is necessary. Load value at each bus will be treated as fixed and equal to its maximum yearly value so that annualized adequacy system indices can be assessed. The proposed method is validated through its application to RBTS test system [26]. Results are compared with those of different Monte Carlo techniques. The proposed method is superior to the conventional Monte Carlo method because of its ability for intelligent search through its fitness function. In addition, it reports the most common failure scenarios and severity of different scanned states [27].

## II. Genetic Algorithms Approach

A genetic algorithm is a simulation of evolution where the rule of survival of the fittest is applied to a population of individuals. In the basic genetic algorithm [15]-[17] an initial population is randomly created from a certain number of individuals called as chromosomes. All of the individuals are evaluated using a certain fitness function. A new population is selected from the old population based on the fitness of the individuals. Some genetic operators, e.g., mutation and crossover are applied to members of the population to create new individuals. Newly selected and created individuals are again evaluated to produce a new generation and so on until the termination criterion has been satisfied.

The proposed method can be divided into two main parts. First GA searches intelligently for failure states through its fitness function using the linear programming module to determine if a load curtailment is needed for each sampled state. Sampled state data are then saved in state array. After the search process stops, the second step begins by using all of the saved states data to calculate the annualized indices for the whole system and at each load bus. Each power generation unit and transmission line is assumed to have two states, up and down. The probability of any generation unit to be down is equal to its forced outage rate "FOR". The failure probability of any transmission line "$i$" is "$PT_i$," which is calculated from its failure rate "$\lambda_i$" and repair rate "$\mu_i$" as follows:

$$PT_i = \frac{\lambda_i}{\lambda_i + \mu_i} \tag{4.1}$$

The total number of states "$N_{states}$" for all possible combinations of generating units and transmission lines installed is:

$$N_{states} = 2^{ng + nt} \tag{4.2}$$

where "ng" is the total number of generation units and "nt" is the total number of transmission lines in the system. GA is used to search for failure states and save such states in the state array. This is achieved by making each chromosome represent a system state. Each chromosome consists of binary number genes. Each gene represents a system component. The first "ng" genes in the chromosome represent generation units while the remaining "nt" genes represent transmission lines. If any gene takes a zero value this means that the component it represents is in the down state and if it takes a one value that means its component is in the up state. To illustrate the chromosome construction, consider the small RBTS test system [26] shown in Fig. 7. It consists of 2 generator (PV) buses, 4 load (PQ) buses, 9 transmission lines and 11 generating units. Consider the state that all system components are up, the chromosome representing this state is shown in Fig. 8.

Each chromosome is evaluated through an evaluation function. The suitable choice for the evaluation function can add the required intelligence to GA state sampling. Many evaluation functions can be used. The simplest one returns zero, if it is a success state and the state probability if it is a failure state. The evaluation function then calls a linear programming optimization load flow model that returns the amount of load curtailment to satisfy power system constraints. If there is no load curtailment, the chromosome represents a success state otherwise, it represents a failure state. The fitness value for each chromosome will be the resultant value after linearized scaling of the evaluation function value. Scaling of the evaluation function enhances the performance of GA since it results in more diversity in the chromosomes of the new generations. After calculating the fitness value of all chromosomes in the current population, GA operators are applied to evolve a new generation. These operators are selection schema, cross over and

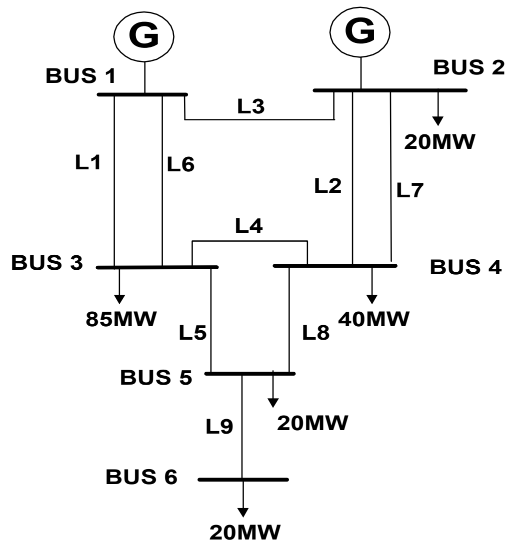


Fig. 7. Single line diagram of the RBTS test system.

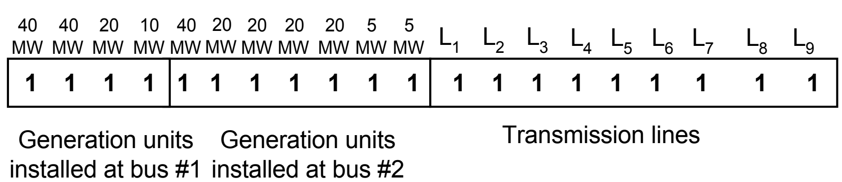


Fig. 8. Chromosome representation for composite system.

mutation. There are many types of such operators and the ones used are explained later. For each chromosome produced with a state probability higher than a threshold value, the binary number it represents will be converted to its equivalent decimal number. A search for this number in the state array is performed and if such a number is found it means this state has been previously sampled and is not added again. There is also no need to call the linear programming module for this state as the load curtailment value for this state has been calculated and saved previously in state array. If the decimal number representing a state is not found in the state array, the linear programming module is then called to determine the load curtailment amount for the whole system and for each load bus, if necessary. All calculated data are saved in the state array. New generations are produced until reaching a stopping criterion. The main role of GA is to truncate state space searching for states that contribute most to system failure. The next phase is to calculate the full set of annualized adequacy indices for the whole system and for each load bus. This is achieved via the use of data stored in the state array.

## III. Algorithmic Structure

### *A. Construction of System State Array*

GA searches for failure states and saves sampled states with all their related data in the state array. This process can be summarized in the following steps:

1.Each chromosome represents a system state. The first "ng" binary genes represent generation units in the system. The last "nt" binary genes represent transmission lines.

2.Intial population is generated randomly. For each bit in the chromosome, a random binary number (0 or 1) is chosen, i.e., "ng+nt" random binary numbers for each chromosome. This process is repeated for all population chromosomes.

3.The state probability "SP*j*" for each chromosome "*j*" is calculated.

$$SP_j = \prod_{i=1}^{ng} G_i . \prod_{i=1}^{nt} T_i \tag{4.3}$$

where $G_i$=1-$FOR_i$ if its gene =1 (up state) or $G_i$ =$FOR_i$ if its gene =0 (down state), and $T_i$=1-$PT_i$ if its gene = 1 or $T_i$ = $PT_i$ if its gene = 0.

4.A threshold probability value is set depending on the required accuracy. If the state probability calculated in step 3 is less than the threshold value this state is ignored and linear programming module is not called.

5.If the state probability is higher than the threshold value the binary number representing this state is converted into the equivalent decimal number. A search is carried out in the state array to find if this decimal number has been saved previously. If the equivalent decimal number is found, this means that this state has been scanned and evaluated previously. Hence, its evaluation function value is retrieved and the algorithm proceeds to step 9 otherwise, it goes to next step.

6.The linear programming optimization module for calculating load curtailment is called to evaluate the new state. The amount of load curtailment ,if necessary to satisfy system constraints, for the whole system and for each load bus is obtained and saved in the state array. The state equivalent decimal number is also saved in the state array to prevent any state from being added to the state array more than once.

7.State contribution to system failure frequency is calculated using the conditional probability approach [22], [23] and the resultant value is also saved in the state array.

$$FS_j = SP_j . \sum_{i=1}^{ng+nt}[(1-b_i).\mu_i - b_i.\lambda_i] \tag{4.4}$$

where $FS_j$ is state "$j$" contribution to system failure frequency, and $b_i$ is the binary value of gene number "$i$" representing a generator unit or transmission line.

8.Expected Power not supplied "EPNS" for the new state is calculated and the result is saved in the state array.

$$\text{EPNS}_j = LC_j \,.\, SP_j \tag{4.5}$$

where $LC_j$ is the amount of load curtailment for the whole system calculated in step 6.

9.The chromosome is evaluated. Many evaluation functions can be used. Two of them are explained here. The first considers the state failure probability.

$$eval_j = \begin{cases} SP_j & \text{if new or old chromosome j represents a failure state.} \\ SP_j.\alpha & \text{if new or old chromosome j represents a success state.} \\ SP_j & \text{if chromosome probability is less than the fixed threshold value.} \end{cases} \quad (4.6)$$

where "new chromosome" means it has not been previously saved in the state array, "old chromosome" means it has been found in the state array and $\alpha$ is a very small number, e.g., $10^{-30}$ to decrease the probability of success states to appear in next generations.

The second evaluation function considers the severity of the failure state which is presented by EPNS.

$$eval_j = \begin{cases} EPNS_j + \beta & \text{if new or old chromosome j represents a failure state} \\ \beta & \text{for all other chromosomes} \end{cases} \quad (4.7)$$

where $\beta$ is a very small number, e.g., $10^{-20}$ to prevent obtaining a zero value for the evaluation function.

The first evaluation function guides GA to search for states with higher failure probabilities. The second evaluation function guides GA to search for more severe states that have high value of failure probability multiplied by the associated load curtailment.

10.The fitness of any chromosome "j" is calculated by linearly scaling its evaluation function value.

$$\text{fitness}_j = A \, . \, eval_j + C \quad (4.8)$$

where A and C are fixed constant numbers. Scaling has the advantage of maintaining a reasonable difference between fitness values of different chromosomes. It also enhances the effectiveness of the search by preventing an earlier super-chromosome from dominating other chromosomes which decreases the probability of obtaining new more powerful chromosomes [17].

11.Repeat previous steps to calculate fitness value for all chromosomes in current population.

12.Apply GA operators to evolve a new population. These operators are selection, crossover and mutation. The suitable choice for the appropriate types of operators enhances the search performance of GA.

13.The evolution process is continued from one generation to another until a prespecified stopping criterion is reached.

14.Data saved in the state array are then used to calculate the full set of adequacy indices for the whole system and at each load bus.

Some of the previous steps are explained in more detail in the next subsections.

*B. Evolution of a New Generation*

In the evolution of a new population from the old one in the simple GA, old population passes through three operations.

The first one, is the selection from parents. There are many types of selection operators like roulette wheel selection, ranked selection and tournament selection. The three types have been tested and tournament selection has been chosen as it improves the search process more than the other types. Tournament selection can be explained briefly as follows [17]:

A set of chromosomes is randomly chosen. The chromosome that has the best fitness value, the highest in the proposed algorithm, is chosen for reproduction. Binary tournament is used in which the chosen set consists of two chromosomes. The probability of choosing any chromosome in the selected set is proportional to its fitness value relative to the whole population fitness value. Consider population size of GA is equal to pop_size chromosomes. Binary tournament selection is repeated pop_size times, i.e., until obtaining a new population.

The second step is to apply the crossover operator on the selected chromosomes. Single point cross over is used with cross over probability of $P_c$. For each pair of chromosomes in the new population generate a random number r from [0,1]. If $r < P_c$ select given chromosome pair for crossover. At the end j pairs of chromosomes are eligible to apply crossover to them . Assume the pair X and Y is subjected to crossover. Generate a random number “pos” in the range [1,ng+nt-1], the new two chromosomes genes are:

$$x_i` = x_i \quad \text{if } i < pos \quad \text{and } y_i \quad \text{otherwise} \quad (\text{for } i=1 \text{ to } ng+nt)$$

$$y_i` = y_i \text{ if } i < pos \text{ and } x_i \text{ otherwise (for } i=1 \text{ to } ng+nt)$$

The third step is to apply the mutation operator. Uniform mutation with probability of $P_m$ is used. For each gene in each chromosome in the newly created population after applying the previous two operators, generate a random number r from [0,1]. If $r < P_m$ convert that gene from one to zero or zero to one. Now a new population has been generated and the process is repeated until a stopping criterion is reached.

### *C. Stopping Criterion*

Any of the following three criteria can be used to stop the algorithm:

i. The first stopping criterion is to stop the algorithm after reaching a certain number of generations. If a small number of generations has been used this will lead to inaccurate results as not enough states would have been sampled.

ii. The second one is to stop when the number of new states that has been added to state array is less than a specified value within certain number of GA generations.

iii. The third stopping criterion is by updating the value of system Loss of Load Probability "LOLP" for each new failure state added to the state array. The algorithm will stop when the change of LOLP is below a specified value within certain number of GA generations.

### *D. State Evaluation Model*

State evaluation is a very important stage in composite power system reliability assessment. Through this stage the current system state is evaluated as a failure or success state. If it is a failure state the amount of load curtailment for the whole system and the share of each load bus in this amount is determined. These values are needed to calculate this state contribution in adequacy indices for the whole system and for load buses. Each state is evaluated using a linear programming optimization model based on dc load flow equations [8], [9]. For the current state to be evaluated, the elements of the power system susceptance matrix B are modified according to transmission line outages. The amount of available real power generation at each PV bus is also updated according to the status of generation units installed at such a bus. The objective of this optimization problem is to minimize the total load curtailment for the whole system which is equivalent to maximizing the load value at each load bus. This objective is subject to the following constraints:

i. Real power balance at each system bus.

ii. Real power flow limits on each transmission line.

iii. Maximum amount of load curtailed at each load bus.

iv. Maximum and minimum available real power at each PV bus.

For the same optimal solution it is possible to have many scenarios of load curtailment at each bus. A load curtailment philosophy should be used, otherwise adequacy indices of load buses may be meaningless. In this work, importance of load is taken into consideration as a load curtailment philosophy as given in [9]. Each load is divided into three parts, i.e., three variables in the objective function. Weights are given for each part in the objective according to the relative importance for each bus in comparison with the remaining buses. Weights are also adjusted so that the first part of each load is the least important and the third part is the most important. In this manner load is curtailed from the first part at each load in the order of their importance, then from second and third parts sequentially, if it is possible without violating any constraint. The linear programming maximization problem is formulated as follows:

$$\max \sum_{i=1}^{nl} \sum_{p=1}^{3} W_{ip}.X_{ip} \tag{4.9}$$

Subject to:

$$PG_i - \sum_{p=1}^{3} X_{ip} = \sum_{j=2}^{n} B_{ij}.\theta_j \qquad \forall \ i=1,2,\ldots\ldots\ldots,n \tag{4.10}$$

$$-B_{ij}.(\theta_i - \theta_j) \le PT_k \qquad \forall \ k=1,2,\ldots\ldots\ldots,nt \tag{4.11}$$

$$-B_{ij}.(\theta_j - \theta_i) \le PT_k \qquad \forall \ k=1,2,\ldots\ldots\ldots,nt \tag{4.12}$$

$$0 \le X_{ip} \le C_{ip}.PD_i \qquad \forall \ p=1,2,3 \quad \forall \ i=1,2,\ldots\ldots\ldots,nl \tag{4.13}$$

$$PG_{i\,\min} \le PG_i \le PG_{i\,\max} \qquad \forall \;\; i=1,2,\ldots\ldots,nv \tag{4.14}$$

where:

n is the total number of system buses,

nt is the total number of the system transmission lines,

nl is the total number of buses that have installed load,

nv is the total number of buses that have installed generation,

$B_{ij}$ is the element at the $i^{th}$ row and $j^{th}$ column in the system susceptance matrix,

$\theta_i$ is the voltage angle at bus $i$ (bus 1 is assumed the reference bus with $\theta_1 = 0$),

$PD_i$ is the yearly maximum load demand at bus $i$,

$X_{ip}$ is the value of part p of load installed at bus $i$,

$W_{ip}$ is the relative weight of part p of load installed at bus $i$, these weights are chosen so that $W_{1i} \le W_{2i} \le W_{3i}$,

$C_{ip}$ is the percentage of part p of load installed at bus $i$ to total load demand at the same bus,

$PG_i$ is the real power generation at bus $i$,

$PG_{i\,\max}$ is the maximum available generation at bus $i$, and

$PG_{i\,\min}$ is the minimum available generation at bus $i$.

The variables vector that is calculated by the linear programming solver is $\{X_{ip}, PG_j, \theta_k\}$ $\forall p=1,2,3$, $\forall i=1,2,\ldots nl$, $\forall j=1,2,\ldots..nv$ and $\forall k=2,3,\ldots.,n$

The optimization problem is solved using the dual simplex method. The total amount of system load curtailment "$LC_s$" is:

$$LC_s = \sum_{i=1}^{nl} PD_i - \sum_{i=1}^{nl}\sum_{p=1}^{3} X_{ip} \tag{4.15}$$

The load curtailment at load bus $i$ "$LC_i$" is

$$LC_i = PD_i - \sum_{p=1}^{3} X_{ip} \tag{4.16}$$

*E. Assessment of Composite System Adequacy Indices*

Annualized adequacy indices for the whole system and for each load bus are calculated using the data saved in the state array. These indices are, Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), Expected Power Not Supplied (EPNS), Expected Energy Not Supplied (EENS), Loss of Load Frequency (LOLF) and Loss of Load Duration (LOLD). These indices are calculated considering only saved failure states and ignoring success ones. Let the total number of saved failure states to be "nf", then the adequacy indices for the whole system are calculated as follows:

$$\text{LOLP} = \sum_{j=1}^{nf} SP_j \tag{4.17}$$

$$\text{LOLF} = \sum_{j=1}^{nf} FS_j \tag{4.18}$$

$$\text{EPNS} = \sum_{j=1}^{nf} EPNS_j \tag{4.19}$$

$$\text{LOLE} = \text{LOLP} \;.\; 8760 \tag{4.20}$$

$$\text{LOLD} = \frac{\text{LOLE}}{\text{LOLF}} \tag{4.21}$$

$$\text{EENS} = \text{EPNS} \;.\; 8760 \tag{4.22}$$

The same set of indices can be calculated for each load bus considering only failure states resulting in load curtailment at this bus and ignoring all other states.

## IV. Case Study

The proposed algorithm has been implemented through C++ programming language. A C++ library of GA objects called GAlib developed by [28] has been integrated into the implementation. The proposed method has been tested on the RBTS [26] test system. Total number of hours in one year is considered to be 8736 instead of 8760 as only these numbers of hours are given in the RBTS load curve. The input parameters of the GA are taken as follows: pop_size = 40, $P_c$ = 0.7, and $P_m$=0.05. The stopping criterion used is 1000 GA generations. Linear scaling, tournament selection, one point crossover, uniform mutation, and the first evaluation function given in (4.6) are used. Calculated system annualized indices with threshold probability value of 1e-8 compared with results reported in [29] using different Monte Carlo methods techniques are given in Table IX.

Table IX. Annualized Adequacy Indices Comparison between GA Sampling and Different Monte Carlo Sampling Techniques

| Adequacy Indices | GA sampling | Sequential sampling [29] | State Transition Sampling [29] | State Sampling [29] |
|---|---|---|---|---|
| LOLP | 0.009753 | 0.00989 | 0.00985 | 0.01014 |
| EENS (MWh/Yr) | 1047.78 | 1081.01 | 1091.46 | 1082.63 |
| LOLF (occ./Yr) | 4.15097 | 4.13 | 4.14 | 5.21 |
| LOLE (hr/Yr) | 85.198 | 86.399 | 86.0496 | 88.58 |
| PNS (MW/Yr) | 0.119938 | 0.12374 | 0.12494 | 0.12393 |
| LOLD (hr) | 20.5249 | 20.9198 | 20.7849 | 17.0019 |

It can be shown from the comparison of results that the proposed method gives similar results to those obtained using different Monte Carlo techniques. The best match is with sequential Monte Carlo Method. The slight differences between the results are due to the fact that all these methods are approximation methods. The accuracy of Monte Carlo methods depends on how low the variance has been reached. The accuracy of the proposed method will depend on the fixed threshold failure probability value and the total number of sampled and saved failure states. The total number of states that GA has sampled and has saved in the state array is 2198 states from which 1449 states result in load curtailment, i.e., 66% of saved states are failure states.  It can be seen that GA truncated the huge states space of the 20 components in the system which is larger than 1 million states into a very small fraction of it.

The failure state with the highest probability is represented by the chromosome shown in Fig. 9, in which only line 9 is down and all other components are up. This failure state probability is equal to 0.000906. If the severity of a certain contingency is considered by EPNS, the second evaluation function given in (4.7) can be used to construct state array and find the most severe state. The most severe state is represented by the chromosome given in Fig. 10, in which two generation units of 40MW capacity installed at bus number one are in the down state and the reaming components are in the up state. The total load curtailment for this state is 25 MW. The state failure probability is 0.00075914. Hence, the EPNS for this state is 25*0.00075914 = 0.0189785.

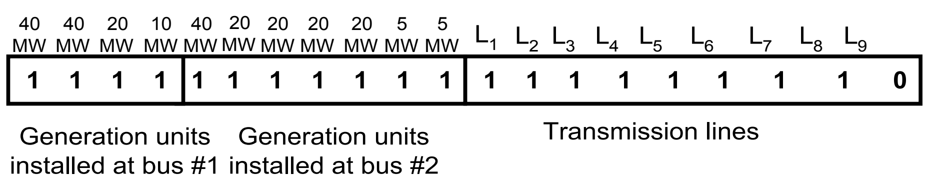


Fig. 9. Chromosome with the highest failure probability.

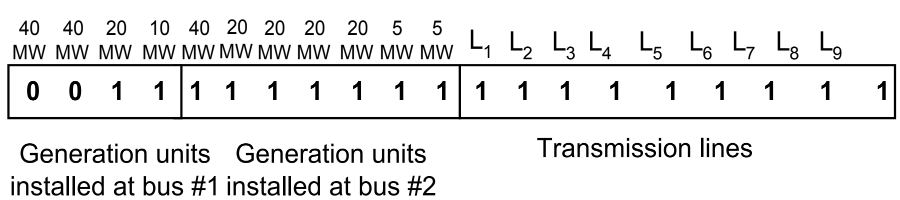


Fig. 10. Chromosome represents the highest severe state.

Annualized bus indices obtained using the load curtailment philosophy explained previously are given in Table X. These indices have been obtained by dividing each load into three parts. The first and second parts range between 0 and 20% of the maximum load at the corresponding bus. Meanwhile, third part ranges from 0 to 60% of the same value. Hence curtailed load, if necessary, should be first obtained from the first part of all loads then the second part and finally the third part. Weighting factors are used to represent importance of each part. Load at bus 2 is considered to be the most important and load at bus 6 is considered to be the least important. In this manner the weighting factor for the first part of load at bus 2 is 5 and weighting factor for the first part of load at bus 6 is 1. The biggest weighting factor is 15 which is associated with the third part of load at bus 2.

It is possible to obtain totally different bus indices if bus importance order has been changed, e.g., bus 6 is the most important and bus 2 is the least important. Results in such a case are given in Table XI. Buses indices can also be varied if the maximum limit of each load part has changed, e.g., if the ranges are 0.1, 0.4 and 0.5 instead of 0.2, 0.2 and 0.6.

## V. Conclusions

This chapter presented an innovative method for composite power system reliability evaluation. The proposed method uses GA as an intelligent search tool to search for failure states that result in load curtailment. The performance of GA depends on the suitable choice of the chromosome evaluation function. States sampled by GA were saved with all their related data in a state array. After finishing the search process, states saved in the state array were used to calculate the annualized adequacy indices for the whole system and for load buses. A linear programming model was used to evaluate each state taking into consideration loads importance. The proposed method was tested on a small practical system. Results obtained were compared with those of different Monte Carlo based techniques. Comparison showed that the proposed method gave acceptable results. It was shown that the proposed method is superior over other conventional methods due to the intelligence it uses in its search process. Moreover, it has the merits of reporting the most probable failure scenarios and most severe ones.

Table X. Annualized Adequacy Indices for Load Buses, Loads Importance from the Most Important to the Least One Are 2,3,4,5,6

| Adequacy Indices | LOLP | EENS (MWh/Yr) | LOLF (occ./year) | LOLD (hr) |
|---|---|---|---|---|
| Bus#2 | 0.000229 | 7.373 | 0.1204 | 16.616 |
| Bus#3 | 0.002382 | 202.133 | 0.9845 | 21.137 |
| Bus #4 | 0.002624 | 177.847 | 1.1145 | 20.568 |
| Bus#5 | 0.008614 | 153.547 | 3.1537 | 23.861 |
| Bus#6 | 0.009753 | 506.707 | 4.1509 | 20.526 |

Table XI. Annualized Adequacy Indices for Load Buses, Loads Importance from the Most Important to the Least One Are 6,5,4,3,2

| Adequacy Indices | LOLP | EENS (MWh/Yr) | LOLF (occ./year) | LOLD (hr) |
|---|---|---|---|---|
| Bus#2 | 0.008605 | 306.324 | 3.1372 | 23.963 |
| Bus#3 | 0.008614 | 437.757 | 3.1549 | 23.854 |
| Bus #4 | 0.002283 | 90.989 | 0.8626 | 23.1245 |
| Bus#5 | 0.000275 | 8.776 | 0.1505 | 15.999 |
| Bus#6 | 0.001371 | 206.580 | 1.1208 | 10.684 |

# CHAPTER V

# USING GENETIC ALGORITHMS FOR COMPOSITE SYSTEM RELIABILITY INDICES CONSIDERING CHRONOLOGICAL LOAD CURVES

## I. Introduction

There are two main types of composite system adequacy indices. The first set of indices are called annualized adequacy indices in which the system maximum load only is considered, i.e., load value at each load bus is fixed at its maximum yearly value. The second set of indices are called annual adequacy indices in which the yearly chronological load curve at each bus is considered. Each set of indices has its own importance. Annualized indices are used to compare the reliability of two different systems while annual indices is used for detecting system weak load points and as a planing criterion.

Both random sampling and sequential Monte Carlo simulation can be used for the assessment of composite system annual adequacy indices. Chronological load is aggregated into a certain number of steps or represented by a certain number of clusters when using Monte Carlo random sampling technique. On the other hand sequential Monte Carlo simulation is able to represent different chronological load curves of load buses on hourly basis, and hence it is the most suitable method for the assessment of annual adequacy indices. However, this technique suffers from the extensive computational effort it needs.

In chapter IV, GA has been used as a sampling tool to calculate composite system annualized adequacy indices. In this approach GA truncates the huge state space by tracing states which result in load curtailment. Sampled states with probability higher than a threshold minimum value are evaluated through a linearized optimization load flow model to determine if a load curtailment is necessary.  Evaluated state data are then saved in a state array which is used later for calculating adequacy indices.

This chapter presents a new technique in which the preceding approach has been extended to consider the chronological load curve at each load bus. There are many methods in the literature for representing the chronological load curve. The clustering method using k-means technique is the most developed one and is used on the proposed methods. Two different approaches based on GA are presented to calculate annual adequacy indices [30]. In the first approach, GA samples failure states for each cluster load vector separately and consequently adequacy indices for this load level are calculated. Composite system annual indices are then obtained by adding adequacy indices for each load level weighted by the probability of occurrence of its cluster load vector. In the second approach, GA samples only failure states with load buses assigned the values of maximum cluster load vector. Failure states are then reevaluated with lower cluster load vectors until a success state is obtained or all load levels have been evaluated.

Chronological loads at different load buses usually have a certain degree of correlation. Degree of correlation depends on the type of installed loads, i.e., residential, commercial, or industrial loads. It also depends on the regional time difference between load buses due to their geographical location. The two developed approaches have been applied to the RBTS test system [26]. A comparison between results of the two different approaches is given. Both fully and partially correlated chronological load curves have been considered.

## II. State Sampling Using GA for a Single Load Level

The GA approach presented in chapter IV is summarized in this section. It is divided into two main parts. First GA searches intelligently for failure states using its fitness function. The fitness function uses a linear programming module to evaluate if a sampled state represents a failure or a success state. The objective of the linear programming module is to minimize load curtailment without violating system constraints. Load at each load bus is considered fixed and equals to its yearly maximum value. A sampled state represents a failure state when load is curtailed to prevent transmission line overloading and/or there is a deficiency in the available generation to supply demand. Sampled state data are then saved in a state array. After the search stops, the second step begins by using all of the saved states to calculate the annualized indices for the whole system and at each load bus. These procedures are explained in more detail in the remaining part of this section.

Each power generating unit and transmission line is assumed to have two states, up and down. The total number of network states "$N_{states}$" for all possible combinations of generating units and transmission lines installed is:

$$N_{states} = 2^{ng + nt} \tag{5.1}$$

where "ng" is the total number of generating units and "nt" is the total number of transmission lines in the system. GA is used to search for failure states and to save such states in the state array. Each GA chromosome represents a system state. Each chromosome consists of binary number genes. Each gene represents a system component. The first "ng" genes in the chromosome represent generating units while the remaining "nt" genes represent transmission lines. If any gene takes a zero value this means that the component it represents is in the down state and if it takes a one value that means its component is in the up state.

Each chromosome is evaluated through the fitness function. Fitness function calls the state evaluation module only if the state probability is higher than a threshold value and it represents a new state. New state means that it has not previously been included in the state array. For each chromosome produced with a state probability higher than a threshold value the binary number it represents is converted to its equivalent decimal number. A search for this number in the state array is performed and if such a number is found it means this chromosome represents an old state otherwise it represents a new state. State evaluation module determines if the chromosome represents a failure or success state and the amount of load curtailment in case of failure state. Evaluated state date, its decimal equivalent number and the results of its evaluation are added to the state array. In case of chromosomes representing old states their evaluation data is retrieved from the state array and there is no need to reevaluate them. The suitable choice for the fitness function can add the required intelligence to GA state sampling. One possible choice of the fitness function is given in (5.2).

$$fit_j = \begin{cases} SP_j & \text{if new chromosome j represents a failure state} \\ SP_j.\beta & \text{if old chrmsome j represents a failure state} \\ SP_j.\alpha & \text{if new or old chromosome j represents a success state} \\ SP_j & \text{if chromosome probability is less than the fixed threshold value} \end{cases} \tag{5.2}$$

where $SP_j$ is the state probability, β is a small number in the range of 0.1 to 0.0001and α is a very small number, i.e., 1e-20. In this manner the fitness value of old failure chromosome is reduced to enable GA to search for more failure states and prevent that failure state with higher probability to dominate other failure states. Fitness function is scaled to enhance the performance of GA search process.

After calculating the fitness value of all chromosomes in the current population, GA operators are applied to evolve a new generation. These operators are selection schema, cross over and mutation. New GA generations are produced until reaching a stopping criterion. A flowchart for GA sampling procedures is shown in Fig. 11. The main role of GA is to truncate the state space by tracing states that contribute most to system failure. After the search process stops, data saved in the state array is used to calculate the full set of annualized adequacy indices for the whole system and for each load bus.

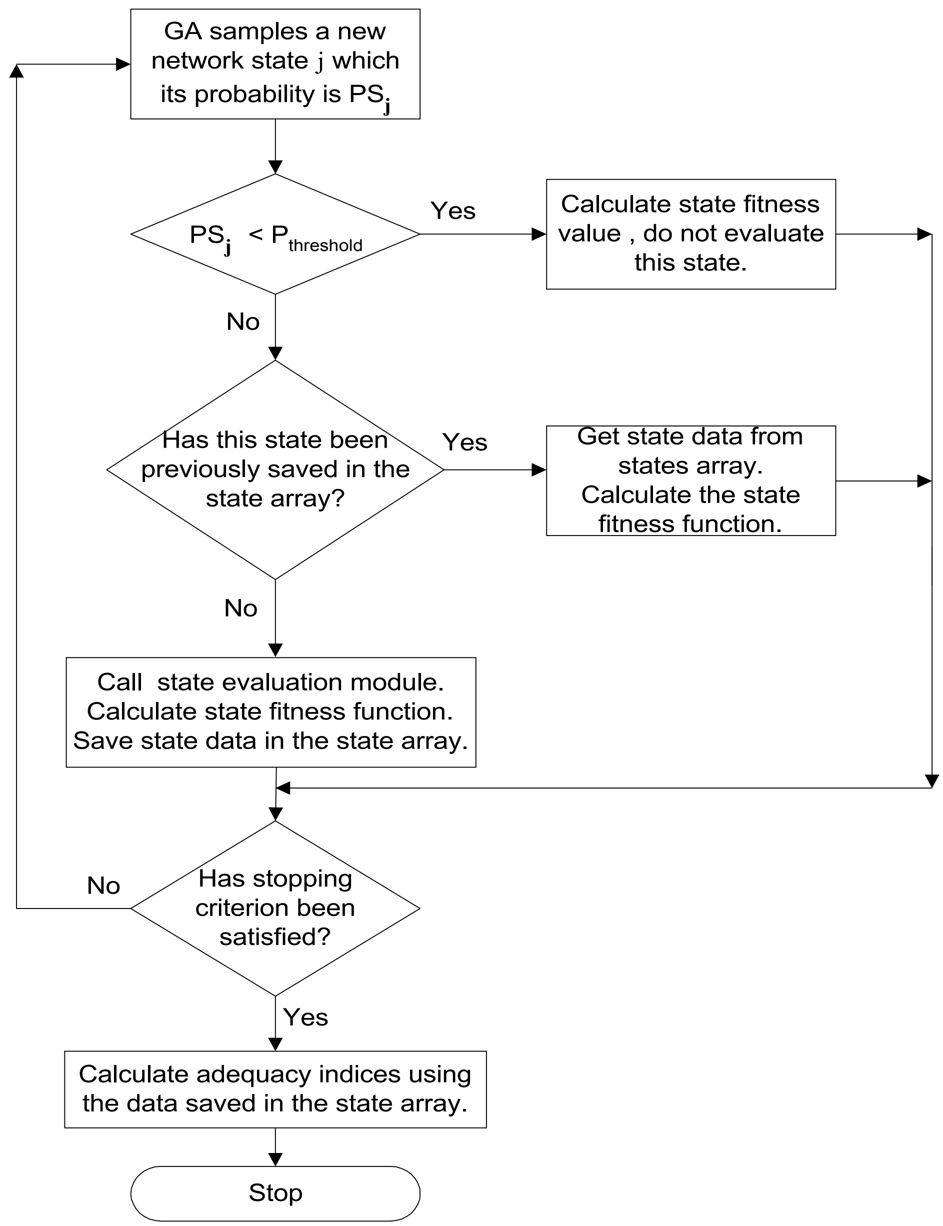


Fig. 11. GA state sampling procedures for single load level.

## III. Modeling of Chronological Load Curve

System annual load is usually represented by system load at each hour in one year. Many techniques have been used to represent system load in composite system reliability. The most common one is to approximate load curve into certain number of steps of load levels. Each load step has its probability of occurrence. A more efficient model is based on clustering techniques [31]. This model has shown good results when used for both generation system reliability [32] and multi-area reliability [33]. In this chapter, clustering has been used to represent the system load curve. Load at each bus has certain degree of correlation with load at other buses. When in a group of load buses, each bus always has an hourly load with the same percentage of group maximum load at this hour, these loads are called fully correlated. Usually in real life there is certain level of correlation between each group of fully correlated load buses. Consider that load buses are divided into *n* groups, each group containing a set of fully correlated buses. The vector of loads at certain hour *i* is:

$$\underline{L}^i = (L_1^i, L_2^i, L_3^i, \ldots\ldots, L_r^i, \ldots\ldots\ldots, L_n^i) \tag{5.3}$$

where $L_r^i$ is the maximum load of group r at hour i and n is the number of load groups. The 8760 load vectors are represented by m cluster vectors. Each cluster vector *j* is represented as:

$$\underline{C}^j = (C_1^j, C_2^j, C_3^j, \ldots\ldots\ldots\ldots, C_r^j, \ldots\ldots\ldots\ldots, C_n^j) \tag{5.4}$$

where $C_r^j$ is the cluster mean load value of group *r* in cluster *j*. Steps for applying the k-means clustering technique to obtain *m* clusters with their associated probability are as follows:

1. Choose initial values of cluster means. The following initial values are suggested to be used. Initial cluster mean for group *r* at first cluster vector as $C_r^1 = 0.98 L_r^{\max}$. For the second cluster vector $C_r^2 = 0.96 L_r^{\max}$. This process is repeated for all cluster vectors so that the last cluster vector m has cluster means

$$C_r^m = (1 - 0.02m).L_r^{\max} \quad \forall \text{ r} = 1,2,\ldots\ldots,\text{n} \tag{5.5}$$

where $L_r^{\max}$ is the annual maximum load of group r. The 0.02 step is allowing maximum number of 50 clusters.

2. For each hour $i$ calculate the Euclidean distance $DIST_{i-j}$ between its load vector and cluster $j$ load mean values vector

$$DIST_{i-j} = \sqrt{\sum_{r=1}^{n}(C_r^j - L_r^i)^2} \tag{5.6}$$

Repeat this process with all other cluster vectors. Load vector at hour $i$ belongs to the cluster with the least Euclidean distance form it.

3. In this manner load vector at each hour belongs to a certain cluster after repeating step 2 for each of them.

4. For each cluster vector $j$ calculate the new mean for each group r.

$$C_r^j new = \frac{\sum_{i=1}^{8760} b * L_r^i}{T_j} \tag{5.7}$$

where
$$b = \begin{cases} 1 & \text{if } \underline{L}^i \in \underline{C}^j \\ 0 & \text{otherwise} \end{cases}, \tag{5.8}$$

and $T_j$ is the total number of load vectors belonging to cluster $j$.

5. For each cluster vector calculate the Euclidean distance between old and new means.

$$change_j = \sqrt{\sum_{r=1}^{n}(C_r^j new - C_r^j)^2} \tag{5.9}$$

6. Repeat steps from 2 to 5 until "change$_j$" is less than a prespecified limit for all clusters.

7. Calculate the probability of occurrence of each cluster vector.

$$P(\underline{C}^j) = \frac{T_j}{8760} \tag{5.10}$$

## IV. GA Sampling with m Cluster Load Vectors

When considering the annual load curve, the total number of system states increases dramatically. Considering that the annual load curve is represented by *m* cluster load vectors the total number of system states is:

$$N_{states} = m.2^{ng + nt} \tag{5.11}$$

Two different approaches have been developed to deal with the multiple load vector levels. GA parallel sampling and GA sampling for maximum cluster load vector with series state reevaluation. These two techniques are explained in the next sections.

### *A. GA Parallel Sampling*

In this approach GA samples system failure states with load at each bus fixed and equal to one of the cluster load vectors. Adequacy indices are then calculated for this fixed load level. This process is repeated for all cluster load vectors. The system annual adequacy indices are calculated as follows:

$$LOLP = \sum_{i=1}^{m} LOLP_i . P(\underline{C}^i) \tag{5.12}$$

$$EENS = \sum_{i=1}^{m} EENS_i . P(\underline{C}^i) \tag{5.13}$$

where $LOLP_i$ and $EENS_i$ are loss of load probability and expected energy not supplied calculated with cluster load vector *i*. This approach has the advantage of giving more accurate results but has the disadvantage of the high computational effort required as the search process is repeated *m* times. Parallel computation can be used with this approach. Failure states for each load level are sampled separately on different machines and in the final step different load level indices are added together to obtain the annual adequacy indices. An illustration for this method is shown in Fig. 12.

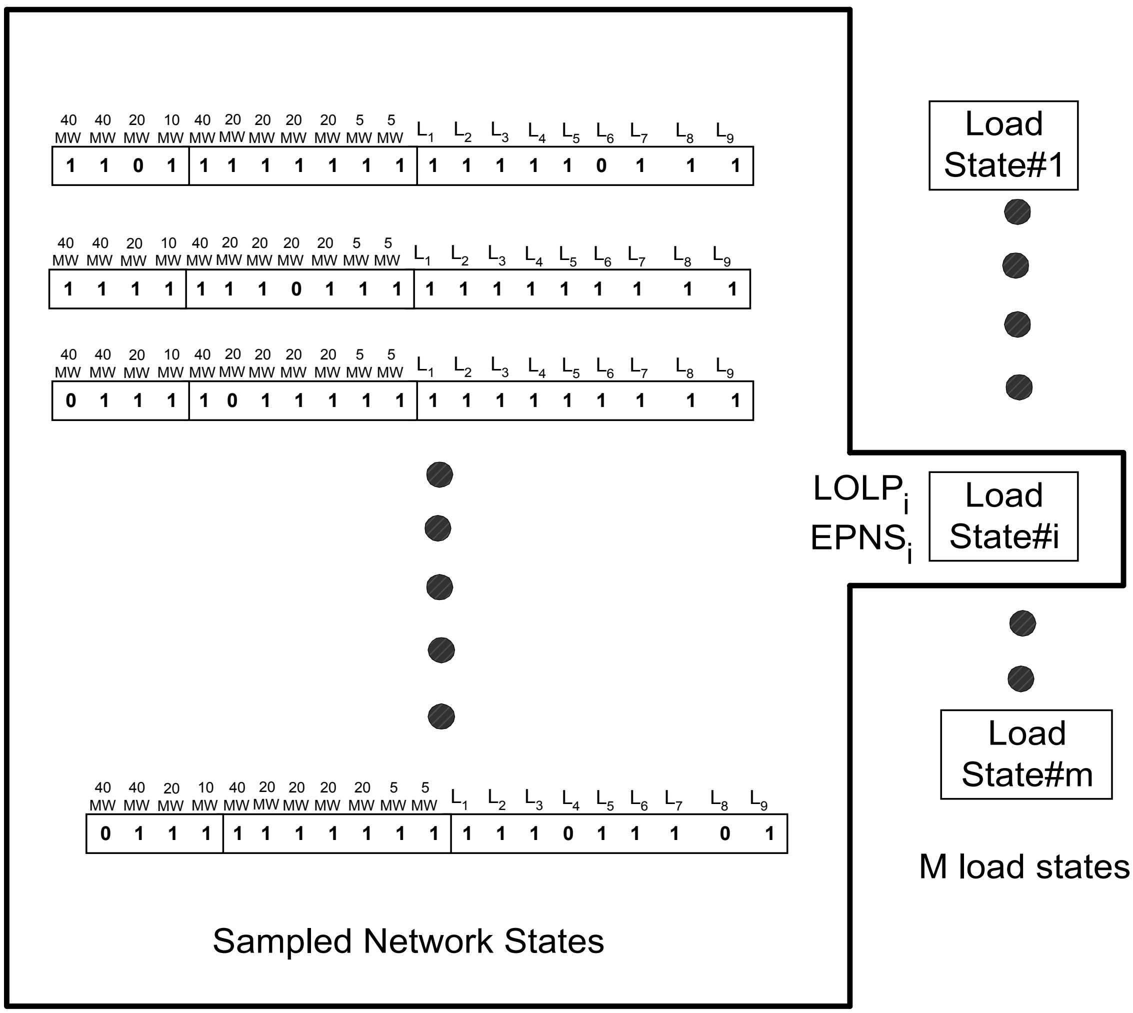


Fig. 12. GA parallel sampling for each load state.

*B. GA Sampling for Maximum Cluster Load Vector with Series State Revaluation*

In this approach GA searches for states which result in system failure while load buses are assigned the maximum cluster load vector. These failure states are then reevaluated while assigning load buses the values of other cluster load vectors in a descending order from the highest to the lowest cluster load vector. This series state revaluation process stops when there is no load curtailment at a certain cluster load vector, or it has been reevaluated with all cluster load vectors. Adequacy indices are updated with each state evaluation process. An illustration for this method is shown in Fig. 13.

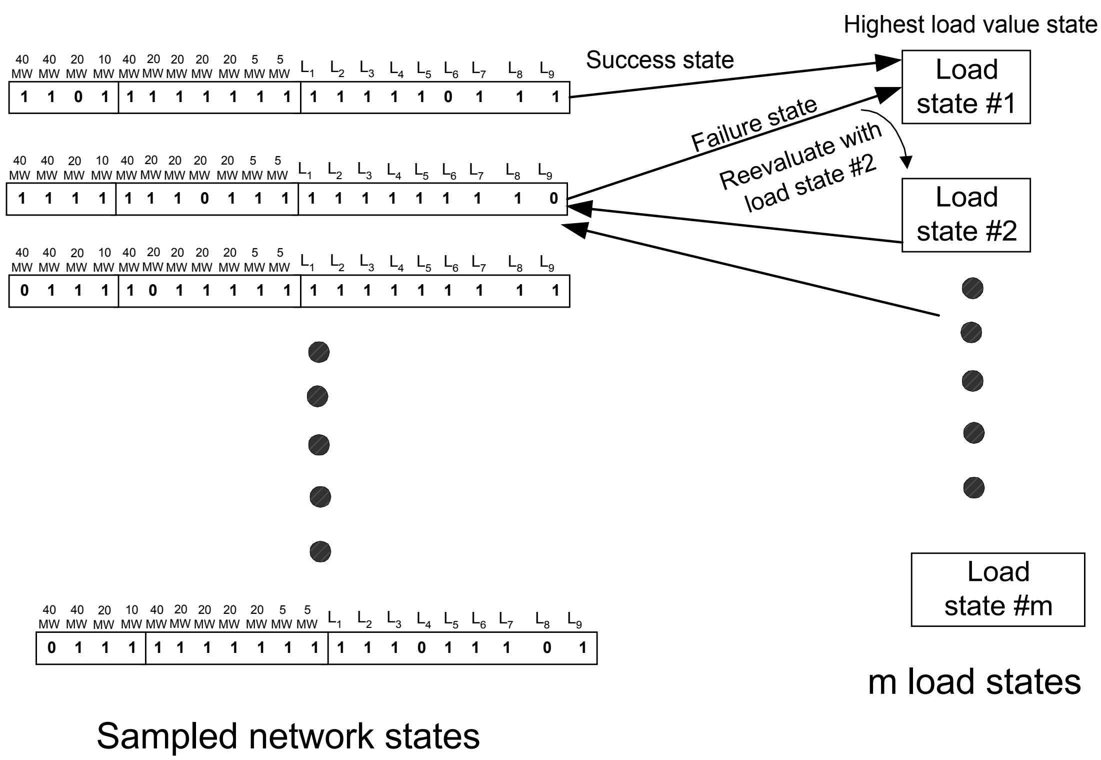


Fig. 13. GA sampling for maximum cluster load vector with series state reevaluation.

The main steps for this approach are:

1. Order cluster load vectors in a descending order according to the value of their total load. Consider cluster 1 has the highest rank and cluster m has the lowest rank. It is assumed that:

$$C_r^j \le C_r^{j-1} \quad \forall\, \mathrm{r} = 1,2,.....,\mathrm{n}\,,\ \forall\, \mathrm{j} = 2,.......,\mathrm{m} \tag{5.14}$$

2. Assign bus loads the maximum cluster load vector $\underline{C}^1$.

3. GA samples a new network state k (states of generators and transmission lines), this state is evaluated using the assigned load values in step 2.

4. If the evaluated state represents a success state, i.e., there is no load curtailment, ignore all the remaining cluster load vectors as it is guaranteed there is no load curtailment with lower load values and jump to step 7. Otherwise, proceed to step 5.

5. If the evaluated state represents a failure state, i.e., there is load curtailment, update the annual adequacy indices.

$$LOLP_{new} = LOLP_{old} + SP_k.P(\underline{C}^1) \tag{5.15}$$

$$EPNS_{new} = EPNS_{old} + SP_k.P(\underline{C}^1).LC_k^1 \tag{5.16}$$

where $SP_k$ is the probability of network state k, $LC_k^1$ is the amount of load curtailment for the whole system with network state k and system loads assigned the values of cluster load vector 1, and *EPNS* is the expected power not supplied.

6. Assign bus loads the lower cluster load vector $\underline{C}^2$. Hence, a new system state has been created that is formed from network state k and the new cluster load vector. This new system state is evaluated. If it represents a success state the remaining cluster load vectors are ignored and hence jump to step 7. Otherwise, it is a failure state, adequacy indices are updated using (5.15) and (5.16) substituting cluster 1 date with cluster 2 data.

A new system state is formed from state k and the next cluster load vector 3. This process for network state k is repeated until encountering a system success state or network state k has been evaluated considering all the m cluster load levels.

7. If stopping criterion for GA sampling has been satisfied proceed to step 8. Otherwise, return to step 3 for GA to sample a new network state.

8. Composite system annual adequacy indices are calculated:

$$LOLP = LOLP_{new} \tag{5.17}$$

$$EENS = EPNS_{new}.8760 \tag{5.18}$$

V. State Evaluation Model

State evaluation depends on the power flow model used for this purpose. Linearized state evaluation model is based on dc load flow equations. In each sampled state one or more generators and/or transmission lines are in the down state. For the current state to be evaluated, elements of the power system susceptance matrix B are modified according to transmission line outages. The amount of available real power generation at each PV bus is also updated according to the status of generating units installed at such a bus. Load values equal the corresponding cluster load vector. State evaluation is represented as an optimization problem with the objective of minimizing the total load curtailment for the whole system, which is equivalent to maximizing the load value at each load bus. The linearized optimization model is formulated as follows (the subscript that refers to the number of the current network state is omitted from all equations):

$$\max \sum_{i=1}^{nl} X_i^z \tag{5.19}$$

Subject to:

$$PG_i - X_i^z = \sum_{j=2}^{n} B_{ij}.\theta_j \qquad \forall \ \text{i=1,2,……...n} \tag{5.20}$$

$$y_k.(\theta_i - \theta_j) \le PT_k \qquad \forall \ \text{k=1,2,……..nt} \tag{5.21}$$

$$y_k.(\theta_j - \theta_i) \le PT_k \qquad \forall \ \text{k=1,2,……..nt} \tag{5.22}$$

$$0 \le X_i^k \le PD_i^k \qquad \forall \ \text{i=1,2,……...nl} \tag{5.23}$$

$$PG_{i\,\min} \leq PG_i \leq PG_{i\,\max} \qquad \forall \text{ i=1,2,……...nv} \tag{5.24}$$

where:

n is the total number of system buses,

nt is the total number of the transmission lines,

nl is the total number of load buses,

nv is the total number of buses that has installed generation,

$B_{ij}$ is the element at the i[th] row and j[th] column in the system susceptance matrix,

$\theta_i$ is the voltage angle at bus i (bus 1 is assumed the reference bus with $\theta_1 = 0$ ),

$PD_i^z$ is the load demand at bus i corresponding to cluster *z* load vector,

$X_i^z$ is the amount of load that could be supplied at bus *i* while demand at load buses assigned cluster *z* load vector,

$PT_k$, $y_k$ are the maximum flow capacity and susceptance of transmission line k connecting between bus i and bus j,

$PG_i$ is the real power generation at bus i,

$PG_{i\,max}$ is the maximum available generation at bus i and

$PG_{i\,min}$ is the minimum available generation at bus i.

This model can be solved using linear programming methods like the dual simplex or interior point method. The variables vector to be calculated by the linear programming solver is { $X_i^z$ , $PG_j$, $\theta_r$}

$\forall$ i=1,2….,nl , $\forall$ j=1,2,…..nv and $\forall$ r= 2,3,……n

The total amount of system load curtailment "$LC_s$" is:

$$LC^z = \sum_{i=1}^{nl} PD_i^z - \sum_{i=1}^{nl} X_i^z \tag{5.25}$$

The load curtailment at load bus i "$LC_i$" is

$$LC_i = PD_i^z - X_i^z \tag{5.26}$$

# VI. Case Studies

The proposed algorithm has been implemented through C++ programming language. A C++ library of GA objects called GAlib developed by [28] has been integrated into the implementation. The proposed method has been tested on the RBTS test system [26]. Studies have been made considering partially and fully correlated load buses.

## *A. Fully Correlated Load Buses*

Yearly load curve data in per unit of RBTS system maximum load (185 MW) are given in [24]. The full correlation assumption means that all the system load buses construct one load group, i.e., percentage of any load value at any load bus to system maximum load is fixed throughout the year. Hence, each cluster load vector consists of one element corresponding to system maximum load. Results of clustering the chronological load curve into 8 and 15 points are given in Table XII. Comparison of results when using different number of clusters while using GA sampling for maximum cluster load vector with series state revaluation are given in Table XIII.

It can be shown from Table XIII that results obtained with 8 points are approximately equal those obtained using 30 points. Total number of evaluated system states using 8 points is about 31% of those for 30 points. These results indicate that clustering is an efficient way of representing the chronological load curve.

Comparison of results when using the two different GA sampling approaches, explained previously, is given in Table XIV. In the first approach, GA samples each of the 8 cluster load values separately. In the second approach, GA samples failure states for the maximum load value of 164.147 MW only with failure states reevaluated for other load points in descending order until encountering a success state or considering all load levels.

It can be seen from Table XIV that when GA is used for calculating adequacy indices for each load separately and then combined, the results are more accurate but the computational burden is increased. This method is equivalent to Monte Carlo simulation with random sampling in which states for each load level are sampled and evaluated separately. When parallel operation is available it is possible to calculate adequacy indices for each load level on a separate machine. When GA samples failure state for maximum load value and reevaluate failure states only with other load levels in descending order the total number of evaluated states is reduced significantly, about 27% of those obtained when evaluating each load level separately.

Table XII. Results of Clustering the System Chronological Load Curve Considering all Load Buses Belong to the Same Load Group

| No. of Clusters 8 points | | No. of Clusters 15 points | |
|---|---|---|---|
| Cluster mean value MW | Cluster probability | Cluster mean value MW | Cluster probability |
| 164.147 | 0.048191 | 174.294 | 0.007669 |
| 150.438 | 0.109661 | 164.213 | 0.025298 |
| 137.868 | 0.112523 | 156.763 | 0.041209 |
| 125.056 | 0.140682 | 150.531 | 0.053800 |
| 113.546 | 0.153159 | 144.263 | 0.059867 |
| 100.443 | 0.141369 | 137.356 | 0.061126 |
| 88.852 | 0.171932 | 129.915 | 0.074176 |
| 75.792 | 0.122482 | 122.864 | 0.086195 |
| | | 116.193 | 0.089286 |
| | | 109.506 | 0.077953 |
| | | 101.880 | 0.081273 |
| | | 94.599 | 0.100618 |
| | | 87.824 | 0.099359 |
| | | 79.961 | 0.089400 |
| | | 71.461 | 0.052770 |

Table XIII. Comparison OF Annual Adequacy Indices and
Other Factors with Different Number of Clusters

| No. of Clusters | 8 points | 15 points | 30 points |
|---|---|---|---|
| LOLP | 0.00127786 | 0.00125581 | 0.00125708 |
| EENS (MWH/Yr) | 132.0736 | 132.6160 | 132.6658 |
| no. of failure states | 2691 | 5670 | 13204 |
| no. of sampled network states by GA | 2206 | 2175 | 2195 |
| no. of evaluated system states | 4699 | 7648 | 15204 |

Table XIV. Annual Adequacy Indices Comparison Using Two Different GA Sampling
Approaches with Fully Correlated Load Buses

| Sampling approach | | GA samples each load level separately | GA samples maximum load only |
|---|---|---|---|
| LOLP | | 0.00127768 | 0.00127786 |
| EENS (MWH/Yr) | | 132.0568 | 132.0736 |
| no. of failure states | | 2680 | 2691 |
| no. of sampled network states by GA | | 17210 | 2206 |
| no. of evaluated states | | 17210 | 4699 |
| Bus 2 | LOLP | 0.00000416 | 0.00000416 |
| | EENS | 0.1216 | 0.1216 |
| Bus 3 | LOLP | 0.00001543 | 0.00001551 |
| | EENS | 1.3944 | 1.3984 |
| Bus 4 | LOLP | 0.00003732 | 0.00003741 |
| | EENS | 1.738606 | 1.7431 |
| Bus 5 | LOLP | 0.00013831 | 0.00013847 |
| | EENS | 1.8409 | 1.8448 |
| Bus 6 | LOLP | 0.00127768 | 0.00127786 |
| | EENS | 126.9613 | 126.9660 |

A comparison between annualized adequacy indices obtained in chapter IV (EENS≅1048 MWh/Yr) and annual adequacy indices (EENS≅132 MWh/Yr) shows that annual indices are much smaller than annualized indices. This is because annualized indices are calculated assuming system hourly load values equal to system yearly maximum load.

*B. Partially Correlated Load Buses*

System buses are assumed to be located in three different time zones. They are divided into three groups with load buses in each group are fully correlated. Bus 2 belongs to the first group, bus 3 belongs to the second group and buses 4,5,6 belong to the third group. It is assumed that the bus loads of the third group have the load curve given in [24] as per unit of the group maximum load of 80 MW. Bus loads of the first group have the same load curve as per unit of the group maximum load of 20MW but shifted earlier by one hour. Bus loads of the third group have the same load curve as per unit of the group maximum load of 85MW but shifted later by one hour. Load vector at each hour consists of three elements. Using k-means clustering technique the 8736 load vectors have been represented by 8 cluster load vectors given in Table XV. Calculated annual adequacy indices are given in Table XVI.

Comparison between the results in Table XIV and Table XVI shows that when bus load correlation is considered, annual adequacy indices are decreased. This is expected as each group peak load occurs at a different time and not simultaneously.

Table XV. Results of Clustering the System Chronological Load Curves Considering Load Buses Belong to Three Different Load Groups

| Cluster Load Vectors | | | Cluster probability |
|---|---|---|---|
| Group I | Group II | Group III | |
| 17.3652 | 74.8161 | 70.3534 | 0.0562042 |
| 15.9181 | 68.4577 | 64.3613 | 0.115614 |
| 14.4572 | 62.6707 | 58.9248 | 0.115614 |
| 13.1868 | 57.0087 | 53.5125 | 0.149954 |
| 12.2187 | 51.7321 | 48.6647 | 0.14549 |
| 10.9559 | 45.7813 | 43.2648 | 0.150298 |
| 9.77761 | 40.5867 | 38.2292 | 0.162775 |
| 8.42486 | 34.7781 | 32.8293 | 0.115614 |

Table XVI. Annual Adequacy Indices Comparison Using Two Different GA Sampling Approaches with Partially Correlated Load Buses

| GA sampling approach | | GA samples each load level separately | GA samples maximum load only |
|---|---|---|---|
| LOLP | | 0.001296928 | 0.001297081 |
| EENS (MWH/Yr) | | 130.9428 | 130.9637 |
| no. Of failure states | | 2661 | 2672 |
| no. Of sampled network states by GA | | 17161 | 2209 |
| no. Of evaluated states | | 17161 | 4684 |
| Bus 2 | LOLP | 0.00000449 | 0.00000450 |
| | EENS | 0.1046 | 0.1049 |
| Bus 3 | LOLP | 0.00001682 | 0.00001695 |
| | EENS | 1.3724 | 1.3799 |
| Bus 4 | LOLP | 0.00004039 | 0.00004052 |
| | EENS | 1.5402 | 1.5473 |
| Bus 5 | LOLP | 0.00004530 | 0.00004542 |
| | EENS | 1.3868 | 1.3897 |
| Bus 6 | LOLP | 0.00129693 | 0.00129708 |
| | EENS | 126.5388 | 126.5417 |

## VII. Conclusions

This chapter has presented two new approaches for the assessment of annual adequacy indices of composite power systems. The two methods are based on GA as a sampling tool to search for failure states. In the first approach, GA samples failure states for each load level separately. In the second approach, GA samples only failure states with load buses assigned the values of maximum cluster load vector. Failure states are then reevaluated with lower cluster load vectors until a success state is obtained or all load levels have been evaluated. Bus chronological load curves have been represented using k-means clustering technique. The two methods have been applied to the RBTS test system. Results for fully and partially correlated load buses have been reported. Results show that clustering technique gives a good approximation for the load curve. Results also show that the second approach gives reasonably accurate results with much less computational effort compared with the first approach. The first approach is recommended to be used when it can be implemented on more than one machine simultaneously.

# CHAPTER VI

# ASSESSMENT OF THE ANNUAL FREQUENCY AND DURATION INDICES IN COMPOSITE SYSTEM RELIABILITY USING GENETIC ALGORITHMS

## I. Introduction

Many vital industries can suffer serious losses as a result of a few minutes of power interruption. In the current competitive environment where power customers are free to choose their power supplier, it is expected that failure frequency will be an important factor in their decision to select such a supplier. This should be a motivation for the utilities in the restructured power environment to consider failure frequency in their planing for system expansion and to improve the failure frequency and duration of existing systems. Such calculations require the development of faster and reliable methods for state sampling and evaluation.

Sequential Monte Carlo simulation is perhaps the most suitable method to calculate frequency and duration indices because of its ability to represent chronological load of buses on an hourly basis. System behavior is simulated from one year to another and the number of system transitions from success states to failure states is calculated for each year. After enough simulation years, the average value of this number represents the expected value of system failure frequency. However, this technique suffers from the extensive computational effort it needs.

Meanwhile, the assessment of composite system frequency and duration indices is more complex than the assessment of other adequacy indices when using analytical methods or non-sequential Monte Carlo simulation for state sampling. This is due to the fact that calculation of failure frequency for a single sampled state is not straightforward like other adequacy indices. The state transition for each system component in the current sampled state needs to be considered to determine if this transition results in a success state, i.e., system state crosses the boundary between failure and success states.

Such an operation is computationally burdensome for large systems. To solve this problem a conditional probability based approach has been introduced in [23] and [34]. This approach is based on the forced frequency balance approach introduced in [22].

This chapter presents a new approach to calculate the annual frequency and duration indices [35]. In calculating the annual indices, the system yearly chronological load curve is considered rather than considering only system maximum load in case of annualized indices. The k-means clustering technique is used to represent the system yearly load curve as a multi-state component. Transition rates between different load states are calculated. The GA is used to sample failure states while the system load is assigned its maximum value. Failure states are then reevaluated with lower load states until a success state is obtained or all load states have been evaluated. The developed methodology has been applied to a sample test system. Results are compared with those obtained by non-sequential Monte Carlo simulation. The results are analyzed to validate the efficiency of the developed method.

## II. Modeling of the Chronological Load

Many techniques have been used to represent system load in composite system reliability evaluation. The most common one is to aggregate the chronological load curve into a certain number of steps. Each load step has its probability of occurrence. Another efficient technique is the use of k-means clustering technique [36]. This technique has shown efficiency when applied to both generation system reliability [32] and multi-area reliability [33]. In the proposed method, clustering has been used to represent the system load curve. It is assumed that loads installed at different load buses are fully correlated. This means that each bus always has an hourly load value with the same percentage of the system total load at this hour.

### *A. Clustering Technique*

The following procedure is used to represent the system yearly load curve by m clusters. The objective of clustering is to obtain the mean value $L(C^j)$ and its probability of occurrence $P(C^j)$ for each load cluster $C^j$.

1. The first step is to choose initial values of cluster means. Consider that the system load at hour i is $LH^i$ and the system yearly maximum load is $L^{max}$. The following initial values are suggested to be used. Initial cluster mean for first cluster is chosen as $L(C^1) = 0.98L^{\max}$. For the second cluster $L(C^2) = 0.96L^{\max}$. This process is repeated for all clusters so that the last cluster m has cluster mean :

$$L(C^m) = (1 - 0.02m).L^{\max} \tag{6.1}$$

The 0.02 step size allows maximum number of 50 clusters and can be decreased to obtain more clusters.

2. For each hour i calculate the distances $DIST_{ij}$ between the system load value at hour i and every cluster mean value:

$$DIST_{ij} = \left| L(C^j) - LH_i \right| \qquad \forall \text{j=1,2,……,m} \tag{6.2}$$

3. Load value at hour i belongs to the cluster with the least distance, i.e.,

$$LH_i \in C^k \text{ if } \min(DIST_{i1}, DIST_{i2}, \ldots\ldots\ldots, DIST_{im}) = DIST_{ik} \tag{6.3}$$

In this manner load value at each hour is assigned to a certain cluster after repeating step 3 for each of them.

4. Calculate the new mean load value for each cluster.

$$L_{new}(C^j) = \frac{\sum_{i=1}^{8760} b * LH_i}{T_j} \qquad \forall \text{j =1,2 ,……,m} \tag{6.4}$$

where $b = \begin{cases} 1 & \text{if } LH_i \in C^j \\ 0 & \text{otherwise} \end{cases}$

and $T_j$ is the total number of hourly load values belonging to cluster $C^j$.

5. For each cluster calculate the absolute difference between old and new means.

$$change_j = \left| L_{new}(C^j) - L_{old}(C^j) \right| \qquad \forall \text{j =1,2 ,……,m} \tag{6.5}$$

6. Repeat steps from 2 to 5 until "$\text{change}_j$" is less than a prespecified limit for all

clusters.

7. Calculate the probability of occurrence of each cluster mean load value.

$$P(C^j) = \frac{T_j}{8760} \tag{6.6}$$

8. Using such initial values as given in step 1 ensures that final clusters mean values are in descending order where cluster $C^1$ has the highest mean value and cluster $C^m$ has the lowest mean value, i.e.,

$$L(C^1) > L(C^2) > ............. > L(C^m) \tag{6.7}$$

*B. Calculating Transition Rates Between Load Clusters*

An important issue in calculating frequency and duration indices is to preserve the chronological transition of load levels from one hour to another. Load transition contribution to system failure frequency is usually higher than the combined contribution of generation and transmission systems. Using k-means clustering technique the chronological load curve is represented as a multi-state component. Each cluster represents a single state associated with its probability and capacity. It is necessary to calculate transition rates between different load states to be used later for calculation of failure frequency for each sampled failure state. The following procedure is used to calculate transition rates between load clusters:

1. Each cluster consists of hourly load values at different hours during one year. The cluster number, to which each hourly load value belongs, is saved.

2. Initialize transition frequencies between different clusters.

$$f_{xy} = 0 \quad \forall \text{ x=1,2,……,m ; } \forall \text{y=1,2,……….m ; x} \neq \text{y} \tag{6.8}$$

3. Transition frequencies between clusters are calculated by repeating the following process for each hourly load value:

$$f_{xy}^{new} = \begin{cases} f_{xy}^{old} + 1 & \text{if } LH_i \in C^x \text{ , } LH_{i+1} \in C^y, \;\; x \neq y \\ f_{xy}^{old} & \text{otherwise} \end{cases} \tag{6.9}$$

4. Transition rates between different clusters are calculated:

$$\lambda_{xy} = \begin{cases} \dfrac{f_{xy}}{P(C^x)} & \forall \mathrm{x} = 1,2,......., \mathrm{m}\,; \forall \mathrm{y} = 1,2,....., \mathrm{m}\,; \mathrm{x} \neq \mathrm{y} \\ 0 & \mathrm{x} = \mathrm{y} \end{cases} \tag{6.10}$$

where $\lambda_{xy}$ is the transition rate of system load from state x to state y.

III. Calculating Failure State Contribution to System Failure Frequency

Each sampled state represents a system contingency where one or more generation units and/or transmission lines are in the down state. Load level can also be sampled when using non-sequential Monte Carlo simulation. A sampled stated "i" is identified as a failure state if a load curtailment "$LC_i$" is needed for reasons of generation deficiency to meet load demand or/and transmission line overloading. Consider the load is in state r in the current sampled state i, the state probability "$SP_i$" is:

$$SP_i = P(C^r).\prod_{j\in gs}(1 - FOR_j).\prod_{j\in gf} FOR_j.\prod_{j\in ts}(1 - PT_j).\prod_{j\in tf} PT_j \tag{6.11}$$

where gs is the set of generation units in the up state, gf is the set of generation units in the down state, ts is the set of transmission lines in the up state, tf is the set of transmission lines in the down state, $FOR_j$ is the forced outage rate of generator unit j and $PT_j$ is the failure probability of transmission line j.

Power not supplied for the current state weighted by its probability is:

$$PNS_i = SP_i.LC_i \tag{6.12}$$

The contribution of a failure state to system failure frequency consists of three components. The first component "FG" is due to transitions of generation units, the second component "FT" is due to transition of transmission lines and the third component "FL" is due to load level transition from its current state to another load state. The failure state contribution to system failure frequency "$LOLF_i$" is calculated:

$$LOLF_i = FG_i + FT_i + FL_i \tag{6.13}$$

Each frequency component is calculated using the conditional probability approach described in [23] and [34]. This approach is applicable under two assumptions:

The first assumption is that system is coherent which implies that:

i. System remains in its success state if a component makes transition from its current state to a higher state. In case of generation unit, higher state means a state with higher generation capacity. In case of transmission lines, higher state means the line is restored to service. In case of load state it means load level is decreased.

ii. System remains in its failure state if a component makes transition from its current state to a lower state. In case of a generation unit, lower state means a state with lower generation capacity. In case of transmission lines, lower state means the line goes out of service. In case of load state it means load level is increased.

The second assumption is that system components are frequency balanced, i.e., transition frequency between two states is the same in both directions. This assumption is satisfied in case of two state components. It is artificially enforced in case of multi-state components as is the case with load states.

Generating units are represented by two states, up state and down state. In the up state, generating unit is able to deliver power up to its rated capacity and deliver no power in the down state. Each transmission line is represented by two states, up state, i.e., in service and down state, i.e., out of service. The contributions of generating units and transmission lines transition to the sate failure frequency are :

$$FG_i = SP_i.(\sum_{k \in gf} \mu_k - \sum_{k \in gs} \lambda_k) \tag{6.14}$$

$$FT_i = SP_i.(\sum_{k \in tf} \mu_k - \sum_{k \in ts} \lambda_k) \tag{6.15}$$

where $\mu_k$ is the repair rate and $\lambda_k$ is the failure rate of component k.

System load is represented as a multi-state component. The first state has the highest load value and the m$^{th}$ state has the lowest. Consider load in the r$^{th}$ state within the current sampled failure state, the contribution of load transition to the sate frequency is:

$$FL_i = SP_i.[\sum_{j=r+1}^{m}\lambda_{rj} - \sum_{j=1}^{r-1}\lambda_{jr}.\frac{P(C^j)}{P(C^r)}] \tag{6.16}$$

In the second term of (6.16) fictitious transition rates from state r to higher load levels "$\lambda'_{rj}$" have been used instead of the actual transition rates $\lambda_{rj}$ to satisfy the frequency balance assumption.

$$\lambda'_{rj} = \lambda_{jr}.\frac{P(C^j)}{P(C^r)} \qquad \text{where j < r} \tag{6.17}$$

IV. Non-Sequential Monte Carlo Sampling

When using non-sequential Monte Carlo simulation for state sampling, a random number in the range [0,1] is picked for each system component. In case of two-state components, if this number is less than the component failure probability the component is considered to be in the down state otherwise, it is in the up state. In case of multi-state load model the range [0,1] is divided into m parts, load is in the r$^{th}$ state if the picked random number z falls in the r$^{th}$ part, i.e.,

$$L_i = L(C^r) \quad \text{where} \sum_{j=1}^{r-1}P(C^j) < z \le \sum_{j=1}^{r}P(C^j) \tag{6.18}$$

where $L_i$ is the system load value at state i.

Each sampled state is evaluated using the minimum load curtailment linear optimization module. Composite system adequacy indices are calculated after N samples as follows:

$$LOLP = \frac{N_f}{N} \tag{6.19}$$

where *LOLP* is the system loss of load probability and $N_f$ is the total number of failure state in the N samples.

$$LOLF = \frac{1}{N}.\sum_{j \in fs} \frac{(FG_j + FT_j + FL_j)}{PS_j} \tag{6.20}$$

where $LOLF$ is the system loss of load frequency and $fs$ is the set of sampled failure states.

$$EPNS = \frac{1}{N}.\sum_{j \in fs} LC_j \tag{6.21}$$

where $EPNS$ is the system expected power not supplied.

Expected energy not supplied is calculated from $EPNS$ :

$$EENS = 8760.EPNS \tag{6.22}$$

Loss of load duration in hours per year can be calculated once $LOLP$ and $LOLF$ are known.

$$LOLD = \frac{LOLP.8760}{LOLF} \tag{6.23}$$

Coefficient of variance for $EPNS$ is usually used as a convergence indicator to stop sampling. It is calculated as follows:

$$COV(EPNS) = \sqrt{\frac{\sum_{j=1}^{N} (LC_j - EPNS)^2}{N.(N-1)}}.\frac{1}{EPNS} \tag{6.24}$$

V. GA Sampling for Maximum Load State with Series State Reevaluation

In the proposed approach, GA searches for states which result in system failure while system load equals the maximum load state value as explained previously in chapter IV. These failure states are then reevaluated while assigning system load the values of other load states in a descending order. This series state evaluation process stops when there is no load curtailment in a certain load state or the current network sampled state i.e. states of generating units and transmission lines, has been reevaluated with all load states. Adequacy indices are updated with each state evaluation process. The main steps for this approach are:

1. Each chromosome in the current GA population represents a sampled network state, i.e., states of generators and transmission lines. Each chromosome with probability higher than the threshold value is checked wither it has been previously saved in the state array i.e. represents old network state, or not i.e. represents a new network state. Steps from 2 to 5 are repeated for each new network state k in the current population.

2. Evaluate the new system state "i" which is formed from the new network state and the system maximum load state $L(C^1)$.

3. If the evaluated state represents a success state i.e. there is no load curtailment, ignore all the remaining load states as it is guaranteed there is no load curtailment with lower load states and return to step 2 for considering the next new network state.

4. If the evaluated state represents a failure state i.e. there is load curtailment, update the system adequacy indices.

$$LOLP_{new} = LOLP_{old} + PS_i \tag{6.25}$$

$$EPNS_{new} = EPNS_{old} + PNS_i \tag{6.26}$$

$$LOLF_{new} = LOLF_{old} + FS_i \tag{6.27}$$

$PS_i$ , $PNS_i$ and $FS_i$ are calculated for state i using (6.11), (6.12) and (6.13) respectively.

5. Assign system load the lower load state $L(C^2)$. Now a new system state "i+1" has been created which is formed from network state k and the new load state. This new system state is evaluated. If it represents a success state the remaining load states are ignored and hence jump to step 2 for considering a new network state. Otherwise, it is a failure state, adequacy indices are updated using (6.25),(6.26) and (6.27). A new system state "i+2" is formed from network state k and the next lower load state $L(C^3)$. This process for network state k is repeated until encountering a system success state or network state k has been evaluated considering all the m load states.

6. If GA sampling stopping criterion has been satisfied proceed to step 7.

Otherwise produce a new population and return to step 1.

7. After GA stops the searching process, the final updated indices represent the composite system adequacy indices. *EENS* and *LOLD* can be calculated using (6.22) and (6.23).

VI. Case Studies

Both non-sequential Monte Carlo simulation and the proposed GA based method have been applied to the RBTS test system [26] to calculate its annual frequency and duration indices. Sampled states in both methods are evaluated using linearized minimum load curtailment model based on dc load flow equations, which is explained previously in chapters IV and V.

Yearly load curve data for the RBTS system in per unit of its maximum load (185 MW) is given in [24]. The full correlation assumption means that each load bus hourly load values have a fixed percentage of the system total load throughout the year. The chronological load curve is represented by eight clusters. Load value and probability of occurrence for each load state were give previously in Table XII. Transition rates between load states are given in Table XVII. The annual adequacy indices for RBTS system using both non-sequential Monte Carlo simulation method and the proposed GA based method are given in Table XVIII. In the GA method, states are evaluated with the highest load state and failure states are reevaluated for lower load states in descending order until encountering a success state or if all load states are considered. The percentage contributions of generation units, transmission lines and load state transitions to the system LOLF using both methods are also given in Table XVIII. A comparison of different types of sampled states by both methods is given in Table XIX.

Monte Carlo simulation is stopped after 50,000 samples as the coefficient of variance of *EPNS* reaches 13%. GA is stopped after producing 1000 generations. GA parameters are: population size = 40, crossover probability = 0.7, mutation probability = 0.05 and threshold network probability = 1e-8.

The relationship between number of samples, computational time and adequacy indices when using non-sequential Monte Carlo simulation is shown in Table XX. The relationship between GA generations, computational time and adequacy indices when using the proposed GA based method is shown in Table XXI.

Table XVII. Transition Rates Per Year Between the Load Eight States

| From state no. | To state no. | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| 1 | 0 | 1536 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 629 | 0 | 1441 | 82 | 0 | 0 | 0 | 0 |
| 3 | 44 | 1271 | 0 | 1662 | 780 | 0 | 0 | 0 |
| 4 | 0 | 135 | 1251 | 0 | 2047 | 313 | 0 | 0 |
| 5 | 0 | 0 | 359 | 1684 | 0 | 0 | 1965 | 183 |
| 6 | 0 | 0 | 0 | 216 | 1507 | 0 | 2440 | 7 |
| 7 | 0 | 0 | 0 | 0 | 506 | 1605 | 0 | 1221 |
| 8 | 0 | 0 | 0 | 0 | 0 | 90 | 1633 | 0 |

Table XVIII. Comparison of Annual Adequacy Indices and Failure Frequency Components with the Two Assessment Methods

| Assessment method | Non-Sequential Monte Carlo | GA Sampling | Percentage difference |
|---|---|---|---|
| LOLP | 0.00130 | 0.00128248 | 1.3% |
| EENS (MWH/Y) | 133.98 | 132.09 | 1.4% |
| LOLF (occ./Y) | 1.3398 | 1.2538 | 6.4% |
| FG/LOLF | 2.8% | 4.6% | ----- |
| FT/LOLF | 76.5% | 79.8% | ----- |
| FL/LOLF | 20.7% | 15.6% | ----- |

Table XIX. Comparison of Sampled States with the Two Assessment Methods

| Assessment method | non-seq. Monte Carlo | GA sampling |
|---|---|---|
| no. of sampled failure states | 65 | 2747 |
| no. of sampled network states by GA | N/A | 2189 |
| no. of system sampled states by Monte Carlo | 50000 | N/A |
| no. of evaluated system states | 50000 | 4738 |

Table XX. Relationship Between Number of Samples, Computation Time and Adequacy Indices When Using Non-Sequential Monte Carlo Simulation

| No. of samples | Comp. time in sec[1] | EENS MWH/Y | LOLF occ/y | Coefficient of variance COV(EPNS) | No. of failure states |
|---|---|---|---|---|---|
| 10 000 | 334 | 206.05 | 2.1431 | 23.3% | 20 |
| 20 000 | 662 | 146.50 | 1.5040 | 19.2% | 30 |
| 30 000 | 990 | 155.74 | 1.6537 | 15.4% | 46 |
| 40 000 | 1318 | 136.12 | 1.3837 | 14.2% | 54 |
| 50 000 | 1646 | 133.98 | 1.3398 | 12.9% | 65 |

[1]On AMD K6-II 450 MHz processor based PC.

Table XXI. Relationship Between GA Generations, Computation Time and Adequacy Indices When Using the Proposed GA Based Method

| No. of GA generations | Comp. time in sec[2] | EENS MWH/Y | LOLF occ/y | No. of network sampled states | No. of evaluated system states | No. of system failure states |
|---|---|---|---|---|---|---|
| 50 | 25 | 13.40 | 0.1710 | 334 | 656 | 346 |
| 100 | 58 | 122.68 | 1.0995 | 678 | 1586 | 986 |
| 200 | 110 | 129.91 | 1.2245 | 1325 | 2984 | 1803 |
| 400 | 162 | 131.92 | 1.2506 | 1804 | 4077 | 2457 |
| 800 | 218 | 132.06 | 1.2535 | 2123 | 4645 | 2720 |
| 1000 | 240 | 132.09 | 1.2538 | 2189 | 4738 | 2747 |

[2]On AMD K6-II 450 MHz processor based PC.

The following observations can be made from Tables XVIII, XIX, XX and XXI:

1. Transitions of transmission system contribute about 80% to system failure frequency while load state transitions contribute 15.4%. Usually load state transitions have much more contribution to system failure frequency. The reason for these results for the RBTS system is that bus number 6 is connected by only one transmission line to the remaining network, hence, transition of this line from up state to down state results in system failure.

2. After about 20,000 samples, results obtained by Monte Carlo simulation fluctuate around the values obtained by GA.

3. GA was able to reach EENS value that is less than the final value by only 2% after 200 generations. This result is obtained after sampling 990 failure states. It took Monte Carlo simulation 40,000 samples to reach such accuracy.

4. Computational effort of the proposed GA based method is about 12% of that of non-sequential Monte Carlo simulation to reach same accuracy level.

5. As GA samples more failure states, EENS increases which means value obtained by GA is sure less than the actual value. However, when using Monte Carlo simulation the obtained EENS cannot be guaranteed to be lower or higher than the actual value.

6. In case of Monte Carlo simulation, even with coefficient of variance 15% after 30,000 samples the obtained EENS is higher than actual value by 17%.

## VII. Conclusions

This chapter has presented a new approach for the assessment of annual frequency and duration indices of the composite power system. Annual load curve is represented as a multi-state component and GA is used as a sampling tool to search for failed network states. GA samples failure states with system load assigned the value of maximum load state. Failure states are then reevaluated with lower load states until a success state is obtained or all load states have been evaluated. The proposed method has been tested on the RBTS test system. Results are compared with those obtained by non-sequential

Monte Carlo simulation. Comparison shows that the computational effort needed by the proposed method is much less than that of Monte Carlo simulation.

# CHAPTER VII

# GENETIC ALGORITHMS APPROACH FOR THE EVALUATION OF COMPOSITE GENERATION-TRANSMISSION SYSTEMS RELIABILITY WORTH

## I. Introduction

Reliability cost/worth studies are very important for system planning. Reliability worth indices can be used in the optimal planning of power systems. These can be used as part of the objective function or as a constraint. In the first case, the planning problem is represented as a multi-objective problem. These objectives are minimizing power interruption cost, the cost of adding new generating units and building new transmission lines. These can also be incorporated as a constraint so that expected power interruption cost is less than a pre-selected value. Reliability worth can be represented by two indices which are loss of load cost (LOLC) in $ per year and the interrupted energy assessment rate (IEAR) in $ per kWh. Cost of power interruption depends on many factors such as interruption duration and the categories of interrupted loads. The most popular way to express interruption cost is the use of customer damage function (CDF) for each load type. The CDF for each load category is a function of interruption duration and can be obtained by customer surveys and has been reported for some countries such as Canada, the United Kingdom and Nepal [37].

Reliability worth evaluation of composite systems is divided into two main stages. The first stage is to sample system states, each sampled state represents a system contingency. The second stage is to evaluate each sampled state to determine if it is a failure or success state. State sampling or selection is performed through Monte Carlo simulation methods or analytical methods. State evaluation is formed as an optimization problem with the objective of minimizing load curtailment.

Random sampling, sequential and pseudo-sequential Monte Carlo simulation have been used for the assessment of reliability worth [38] . A key issue in determining LOLC is calculation of the interruption time. This is because LOLC depends on the value of CDF which is a function of the state failure time. Using the mean interruption time can lead to a significant error in LOLC as it represents approximation of state duration. Sequential Monte Carlo simulation using system state transition can be a good way to represent the actual interruption duration. A comparison between different methods of calculating LOLC is given in [39].

In this chapter, the two GA sampling approaches developed in chapter V are used to calculate reliability worth indices [40]. The GA is used as a state sampling tool for the composite power system network. Binary encoded GA is used to represent network states. System yearly load curve is represented as a multi-state component. In the first approach, GA samples failure states for each load level separately. Thus reliability worth indices are calculated for each load level and then combined to obtain the annual reliability worth indices. In the second approach, GA samples failure states with load buses assigned the maximum load state. Failure states are then reevaluated with lower load level states until a success state is obtained or all load levels have been evaluated. In both approaches, GA is able to trace failure states in a more efficient manner than conventional methods. An optimization model based on linearized load flow is used for the evaluation of sampled states. Two different objectives are used in state evaluation. The first one is to minimize load curtailment considering load category and load bus relative importance. The second objective is to minimize load interruption cost. Instead of using the raw interruption cost associated with failure state mean duration time, random sampling is used to calculate mean interruption cost associated with each failure state. Case studies on the RBTS test system considering different state evaluation methods and cost calculation methods are described.

## II. Calculating Reliability Worth Indices

A sampled state consists of the states of generating units, transmission lines and system load. Generating units and transmission lines are represented as two-state components. System load is represented as a multi-state component. Using the k-means clustering technique [32], [33], the system yearly load curve is represented by m clusters. It is assumed that the first state has the highest load value and the m$^{th}$ state has the lowest load value.

A sampled stated "i" is identified as a failure state if a load curtailment $LC_i$ is needed for reasons of generation deficiency or/and transmission line overloading. The following indices are calculated for each sampled failure state "i":

i. The state probability "$SP_i$" is :

$$SP_i = P(C^r).\prod_{j \in gs}(1 - FOR_j).\prod_{j \in gf} FOR_j.\prod_{j \in ts}(1 - PT_j).\prod_{j \in tf} PT_j \tag{7.1}$$

where $P(C^r)$ is the probability of the system load state r, gs is the set of generating units in the up state, gf is the set of generating units in the down state, ts is the set of transmission lines in the up state, tf is the set of transmission lines in the down state, $FOR_j$ is the forced outage rate of generating unit j and $PT_j$ is the failure probability of transmission line j.

ii. Power not supplied for the current state weighted by its probability is:

$$PNS_i = SP_i.LC_i \tag{7.2}$$

iii. The frequency of state i, "$FS_i$" is :

$$FS_i = SP_i.(\sum_{k \in gf} \mu_k + \sum_{k \in gs} \lambda_k + \sum_{k \in tf} \mu_k + \sum_{k \in ts} \lambda_k) + FL_i \tag{7.3}$$

where $\mu_k$, $\lambda_k$ are the repair rate and failure rate of component k and $FL_i$ is the contribution by load transition from its current state to other load states.

$$FL_i = SP_i.\sum_{j=1}^{m} \lambda_{rj} \qquad j \neq r \tag{7.4}$$

where $\lambda_{rj}$ is the transition rate from load state r to state j.

iv. The state mean duration "$D_i$" is:

$$D_i = \frac{1}{\sum_{k \in gf} \mu_k + \sum_{k \in gs} \lambda_k + \sum_{k \in tf} \mu_k + \sum_{k \in ts} \lambda_k + \sum_{j=1}^{m} \lambda_{rj}} \tag{7.5}$$

v. It is assumed that system loads at different buses are categorized into seven types [6] which are agriculture, large users, residential, governmental and institutional, commercial, industrial and offices. The load curtailed can be presented as:

$$LC_i = \sum_{j=1}^{7} LT_i^j \tag{7.6}$$

where $LT_i^j$ is the total amount of curtailment of load category j in state i. The cost in $ due to load curtailment in state i is:

$$LOLC_i = FS_i . \sum_{j=1}^{7} LT_i^j .CDF^j(D_i) \tag{7.7}$$

where $CDF^j$ ($D_i$) is the value of the cost damage function in $ per kW of curtailed load of category j. It can been seen that $LOLC_i$ depends on the value of CDF which is a function of the interruption duration. In real life, interruption duration is a random event and is difficult to estimate. Hence, it is more appropriate to calculate a mean CDF value associated with each failure state rather than the use of raw CDF value associated with the mean interruption duration. Assuming that the interruption duration follows exponential distribution, the mean CDF value for a given failure state is:

$$\overline{CDF^j} = \frac{1}{N} . \sum_{k=1}^{N} CDF^j(-D_i . \ln Z_k) \tag{7.8}$$

where $Z_k$ is a random number between 0 and 1 and N is the number of times a random number is picked. Now, $LOLC_i$ can be calculated by using $\overline{CDF^j}$ instead of $CDF^j$ ($D_i$) in (7.7).

It should be noted that the use of either (7.7) or (7.8) considers each failure state separately. It is possible to encounter two failure states successively and in such a case interruption time would include not only the failure state under investigation but also the following state. Thus the value of the CDF will be different than considering each state separately. Detailed discussions about considering successive failure states are given in [38] and [39]. Considering each failure state separately represents an acceptable approximation for the following reasons:

1. The likelihood for a failure state to be followed by another failure state is small as a remedial action would be taken to restore the system to its success state.

2. The value of CDF for different load categories is almost constant as the interruption duration increases. Hence, it will not make much difference to consider each state separately.

After calculating the previous indices for each sampled failure state, reliability worth indices for composite system are calculated as follows:

The expected energy not supplied in MWh/Year is

$$EENS = 8760.\sum_{j \in fs} PNS_j \tag{7.9}$$

where fs is the set of sampled failure states. The system LOLC in \$/Year is :

$$LOLC = \sum_{j \in fs} LOLC_j \tag{7.10}$$

The system IEAR in \$/kWh is :

$$IEAR = \frac{LOLC}{1000.EENS} \tag{7.11}$$

The same indices can be calculated for each load bus by considering only the subset of failure states where the bus under consideration has encountered load curtailment.

## III. GA Sampling with M Load States

As described in chapter IV, the developed GA based method is divided into two main parts. First GA searches intelligently for failure states using its fitness function. The fitness function uses a linear programming module to determine if a sampled state represents a failure or a success state. Two different objectives can be used for the linear programming module. The first one is to minimize load curtailment. The second one is to minimize interruption cost. The objective in both cases must be achieved without violating system constraints. A sampled state represents a failure state when load is curtailed to prevent transmission line overloading and/or there is a deficiency in the available generation to supply demand. Data of each sampled state by GA is then saved in a state array. After the search stops, the second step begins by using all the saved states to calculate the adequacy indices for the whole system and at each load bus. The

Two different GA sampling methods when considering load curves were introduced in chapter V. Explanation of how these methods are used for reliability worth evaluation is given in the next two sections.

*A. GA Parallel Sampling*

In this approach GA searches for failure states considering each load state separately. Each GA chromosome represents a system state. Each chromosome consists of binary numbered genes. Each gene represents a system component. The first “ng” genes in the chromosome represent generation units while the remaining “nt” genes represent transmission lines. If any gene takes a zero value this means that the component it represents is in the down state and if it takes a “1” value that means the component is in the up state.

Each chromosome is evaluated through the fitness function. Fitness function calls the state evaluation module only if the state probability is higher than a threshold value and it represents a new state. New state means that it has not been previously included in the state array. For each chromosome produced with a state probability higher than a threshold value the binary number it represents is converted to its equivalent decimal number. A search for this number in the state array is performed and if such a number is found it means this chromosome represents an old state otherwise it represents a new state. State evaluation module determines if the chromosome represents a failure or success state and the amount of load curtailment in case of failure state. Evaluated state data, its decimal equivalent number and the results of its evaluation are added to the state array. In case of chromosomes representing old states their evaluation data is retrieved from the state array and there is no need to reevaluate them. The suitable choice for the fitness function can add the required intelligence to GA state sampling. One possible choice of the fitness function is given in (7.12).

$$fit_j = \begin{cases} SP_j & \text{if new chromosome j represents a failure state} \\ SP_j.\beta & \text{if old chrmsome j represents a failure state} \\ SP_j.\alpha & \text{if new or old chromosome j represents a success state} \\ SP_j & \text{if chromosome probability is less than the fixed threshold value} \end{cases} \quad (7.12)$$

where $SP_j$ is the state probability, $\beta$ is a small number in the range of 0.1 to 0.0001and $\alpha$ is a very small number i.e. 1e-20. In this manner the fitness value of old failure chromosome is reduced to enable GA to search for more failure states and prevent that failure state with higher probability to dominate other failure states. Fitness function is scaled to enhance the performance of GA search process.

After calculating the fitness value of all chromosomes in the current population, GA operators are applied to evolve a new generation. These operators are selection schema, cross over and mutation. New GA generations are produced until reaching a stopping criterion.

Reliability worth indices are calculated for the current load state. This process is repeated for all load states. Transition rates between current load state and other load states must be considered as descried in chapter VI when calculating state duration and state frequency. The system reliability worth indices are calculated as follows:

$$LOLC = \sum_{k=1}^{m} LOLC_k \quad (7.13)$$

$$EENS = \sum_{k=1}^{m} EENS_k \quad (7.14)$$

where $LOLC_k$ and $EENS_k$ are loss of load cost and expected energy not supplied calculated while the system load is assigned the value of load state k. This approach has the advantage of giving more accurate results but has the disadvantage of the high computational effort required as the search process is repeated m times. Parallel computation can be used with this approach. Failure states for each load level are sampled separately on different machines and in the final step different load level indices are added together to obtain reliability worth adequacy indices.

*B. GA Sampling for Maximum Load State with Series State Reevaluation*

In this proposed approach GA searches for states which result in system failure while system load equals the maximum load state value. These failure states are then reevaluated while assigning system load the values of other load states in a descending order. This series state evaluation process stops when there is no load curtailment in a certain load state or the current network sampled state i.e. states of generating units and transmission lines, have been reevaluated with all load states. Reliability worth indices are updated with each state evaluation process. The main steps for this approach are:

1. Each chromosome in the current GA population represents a sampled network state, i.e., states of generators and transmission lines. Each chromosome with probability higher than the threshold value is checked whether it has been previously saved in the state array. Steps from 2 to 5 are repeated for each new network state k in the current population.

2. Evaluate the new system state “i” which is formed from the new network state and the system maximum load state i.e. state number 1.

3. If the evaluated state represents a success state i.e. there is no load curtailment, ignore all the remaining load states as it is guaranteed there is no load curtailment with lower load states and return to step 2 for considering the next new network state.

4. If the evaluated state represents a failure state, i.e., there is load curtailment, update the system reliability worth indices.

$$LOLC_{new} = LOLC_{old} + LOLC_i \tag{7.15}$$

$$PNS_{new} = PNS_{old} + PNS_i \tag{7.16}$$

$LOLC_i$ and $PNS_i$ are calculated for state i using (7.7) and (7.2) respectively.

5. Assign system load the lower load state i.e. state number two. Now a new system state “i+1” has been created which is formed from network state k and the new load state. This new system state is evaluated. If it represents a success state the remaining load states are ignored and hence jump to step 2 for considering a new network state. Otherwise, it is a failure state, reliability worth indices are updated using

(7.15) and (7.16). A new system state "i+2" is formed from network state k and the next lower load state number 3. This process for network state k is repeated until encountering a system success state or if network state k has been evaluated considering all the m load states.

6.If GA stopping criterion has been satisfied proceed to step 7 otherwise produce a new population and return to step 1.

7.After GA stops the search process, the final updated indices represent the composite system reliability worth indices. *EENS* and *IERA* can be calculated using (7.9) and (7.11).

## IV. State Evaluation Model

The state evaluation model is based on dc load flow equations. In each sampled state, one or more generators and/or transmission lines are in the down state. For the current state to be evaluated, elements of the power system susceptance matrix B are modified according to transmission line outages. The amount of available real power generation at each PV bus is also updated according to the status of generation units installed at such a bus. System load is assigned the value of the current load state. Load value for each load bus has a fixed percentage of current system load. Different load categories at certain load bus have in turn a fixed percentage of their bus total load.

State evaluation is formulated as an optimization problem. Two different objectives are presented. The first objective is to minimize the total load curtailment for the whole system. This optimization problem has multiple optimal solutions. Hence, using different load curtailment polices results in the same system indices but different bus indices. System loads are divided into seven categorizes as mentioned before. Through weighting factors the following load curtailment policy can be implemented:

1. The relative importance of each load category in comparison with other load categories.

2. The relative importance for each load bus in comparison with the remaining load buses.

The following optimization model implements this load curtailment policy.

$$\min \sum_{i=1}^{nl} \sum_{c=1}^{7} W_{ic} . LT_{ic} \tag{7.17}$$

Subject to:

$$PG_i - PD_i^r + \sum_{c=1}^{7} LT_{ic} = \sum_{j=2}^{n} B_{ij} . \theta_j \qquad \forall \text{ i=1,2,……...n} \tag{7.18}$$

$$y_k . (\theta_i - \theta_j) \le PT_k \qquad \forall \text{ k=1,2,……..nt} \tag{7.19}$$

$$y_k . (\theta_j - \theta_i) \le PT_k \qquad \forall \text{ k=1,2,……..nt} \tag{7.20}$$

$$0 \le LT_{ic} \le PD_{ic}^r \qquad \forall \text{ i=1,2,……...nl, c=1,2,……..,7} \tag{7.21}$$

$$PG_{i\min} \le PG_i \le PG_{i\max} \qquad \forall \text{ i=1,2,……...nv} \tag{7.22}$$

where:

n is the total number of system buses,

nt is the total number of the transmission lines,

nl is the total number of load buses,

nv is the total number of buses that has installed generation,

$B_{ij}$ is the ij$^{th}$ element in the system susceptance matrix,

$\theta_i$ is the voltage angle at bus i (bus 1 is assumed the reference bus with $\theta_1 = 0$ ),

$PD_{ic}^r$ is the load demand of category "c" at bus "i" corresponding to load state number "r",

$LT_{ic}$ is the amount of load from category "c" to be curtailed at bus i,

$W_{ic}$ is the weighting factor of load from category c installed at bus i, its values ranges from 1 to 7nl, i.e., the least important load category installed at the least important bus will have a value of 1 and the most important category installed at the most important bus has the value of nl*7,

$PT_k$ ,$y_k$ are the maximum flow capacity and susceptance of transmission line k connecting bus i and bus j,

$PG_i$ is the real power generation at bus i, $PG_{i\ max}$ is the maximum available generation at bus i and $PG_{i\ min}$ is the minimum available generation at bus i.

This model can be solved using linear programming methods like the dual simplex or interior point method. The variable vector to be calculated by the linear programming solver is $\{LT_{ic}$ , $PG_j$ , $\theta_r\}$ $\forall$i=1,2….,nl , $\forall$c=1,2….,7, $\forall$ j=1,2,…..nv and $\forall$ r= 2,3,……n.

The total amount of system load curtailment "$LC_i$" is:

$$LC_i = \sum_{i=1}^{nl} \sum_{c=1}^{7} LT_{ic} \tag{7.23}$$

The load curtailment at load bus i "$LB_i$" is:

$$LB_i = \sum_{c=1}^{7} LT_{ic} \tag{7.24}$$

Another objective that can be used in the optimization model is to minimize the system interruption cost for the sampled state [41]. This objective is difficult to be used in practice as the interruption cost is a function of failure state duration that is usually difficult to predict. A more realistic approach is to use the mean unit interruption cost associated with each load category that can be calculated by (7.8). This objective can be represented as:

$$\min \sum_{i=1}^{nl} \sum_{c=1}^{7} \overline{CDF_c}.LT_{ic} \tag{7.25}$$

V. Case Studies

The proposed algorithm has been implemented through C++ programming language. A C++ library of GA objects called GAlib developed by [28] has been integrated into the implementation. The proposed method has been tested on the RBTS test system [26] shown in Fig. 7. Different load categories as a percentage of bus total load are given in Table XXII [6]. The customer damage function (CDF) for each load type is given in Table XXIII. Points given in Table XXIII are connected by straight lines when using logarithmic scale on both axes. It is assumed that for interruption duration higher than 480 minutes CDF for each load category has the same slope as between 240 and 480 minutes. These CDFs were obtained through different customer surveys which were carried out by the power systems research group at university of Saskatchewan university in 1987. All interruption costs are given in Canadian dollars.

Table XXII. Different Load Categorizes as a Percentage of Total Bus Load

| Load type | Bus 2 | Bus 3 | Bus 4 | Bus 5 | Bus 6 |
|---|---|---|---|---|---|
| Agriculture | 0.0 | 0.0 | 0.0 | 0.0 | 37.0 |
| Large User | 0.0 | 65.29 | 0.0 | 0.0 | 0.0 |
| Residential | 50.95 | 23.16 | 37.12 | 50.05 | 40.8 |
| Governmental | 22.20 | 0.0 | 0.0 | 33.30 | 0.0 |
| Industrial | 12.95 | 4.58 | 42.08 | 0.0 | 12.95 |
| Commercial | 13.90 | 4.35 | 20.80 | 9.25 | 9.25 |
| Office | 0.0 | 2.62 | 0.0 | 7.40 | 0.0 |

Table XXIII. Customer Damage Functions for Different Load Categorizes

| Load Type | Interruption Cost ($/kW) | | | | |
|---|---|---|---|---|---|
| | 1 min | 20 min | 60 min | 240 min | 480 min |
| Agriculture | 0.060 | 0.343 | 0.649 | 2.064 | 4.120 |
| Large User | 1.005 | 1.508 | 2.225 | 3.968 | 8.240 |
| Residential | 0.001 | 0.093 | 0.482 | 4.914 | 15.690 |
| Governmental | 0.044 | 0.369 | 1.492 | 6.558 | 26.040 |
| Industrial | 1.625 | 3.868 | 9.085 | 25.163 | 55.808 |
| Commercial | 0.381 | 2.969 | 8.552 | 31.317 | 83.008 |
| Office | 4.778 | 9.878 | 21.065 | 68.830 | 119.160 |

Yearly load curve data in per unit of RBTS system maximum load (185 MW) is given in [24]. System loads are assumed fully correlated. The k-means clustering technique is used to represent yearly load curve by 15 points given in Table XII.

### *A. Using Minimum Load Curtailment for State Evaluation*

In this case study sampled states are evaluated by the minimum load curtailment module. Weighting factors are adjusted to implement the following load curtailment policy:

1. Importance of different load categories from the least important to the most important are residential, agriculture, commercial, industrial, offices, governmental and large users.

2. Importance of load buses from the least to the most important are 2, 3,4,5 and 6. This means that the weighting factor associated with the residential load at bus 2 "$W_{21}$" has a value of 1. The weighting factor associated with large user load at bus 6 (in our case its lower and upper limit is zero) "$W_{67}$" is 35 (7 load categorizes multiplied by 5 load buses).

Reliability worth indices are calculated twice. First, they are calculated using the raw unit interruption cost associated with the mean duration of interruption of the sampled failure state. Then, they are calculated using the mean interruption cost obtained from the mean value of 1000 raw interruption cost values each obtained by random samples using the mean duration of the state.

Reliability worth indices are also calculated using the two different GA sampling approaches explained previously. In the first approach GA samples each of the 15 load states separately. In the second approach GA samples failure states for the maximum load state only with failure states reevaluated for other load points in descending order until encountering a success state or considering all load levels. Reliability worth indices for the whole system and for load buses using different strategies are given in Table XXIV.

Table XXIV. Reliability Worth Indices Using Minimum Load Curtailment State Evaluation Module

| Sampling method / Reliability worth indices & other factors | | GA samples maximum load state with series state reevaluation | | GA parallel sampling |
|---|---|---|---|---|
| | | Using raw interruption costs | Using mean interruption costs | Using mean interruption costs |
| EENS (MWh/Yr) | | 132.639 | 132.639 | 132.635 |
| LOLC ($/Yr) | | 326,095 | 338,037 | 309,648 |
| IEAR ($/kWh) | | 2.4585 | 2.5485 | 2.3345 |
| no. of sampled network states by GA | | 2169 | 2177 | 32,032 |
| no. of evaluated states | | 7650 | 7656 | 32,032 |
| no. of failure states | | 5675 | 5672 | 5698 |
| Bus 2 | LOLC | 5,337 | 7,972 | 8,673 |
| | IEAR | 0.8625 | 1.2883 | 1.4036 |
| Bus 3 | LOLC | 2,610 | 3,898 | 4,268 |
| | IEAR | 0.8357 | 1.2481 | 1.3688 |
| Bus 4 | LOLC | 313 | 468 | 497 |
| | IEAR | 0.8092 | 1.2094 | 1.2855 |
| Bus 5 | LOLC | 486 | 547 | 520 |
| | IEAR | 2.8620 | 3.1745 | 3.0163 |
| Bus 6 | LOLC | 317,347 | 325,151 | 295,689 |
| | IEAR | 3.1721 | 3.2502 | 2.9555 |

It can be seen in Table XXIV that LOLC value is higher when using the mean interruption cost value. Another observation is that when GA samples failure state for maximum load value and reevaluates failure states only with other load levels in descending order the total number of evaluated states is reduced significantly, about 24% of those obtained when evaluating each load level separately.

### *B. Using Minimum Interruption Cost for State Evaluation*

In the second case sampled states are evaluated by the minimum cost state evaluation module. System Reliability worth indices for the whole system and for load buses using this load curtailment policy are given in Table XXV. It can be seen that the difference in the system LOLC using the two different load curtailment methods is about 1%. Meanwhile, LOLC indices at different buses are totally different. It can also be observed that LOLC at bus 6 dominates LOLC at other load buses. This is due to the poor connectivity of bus 6 to the remaining network.

Table XXV. Reliability Worth Indices Using Minimum Interruption Cost State Evaluation Module

| Type of Interruption costs | | Using raw interruption costs | Using mean interruption costs |
|---|---|---|---|
| EENS (MWh/Yr) | | 132.6165 | 132.6169 |
| LOLC ($/Yr) | | 324,473 | 333,911 |
| IEAR ($/kWh) | | 2.4467 | 2.5179 |
| Bus 2 | LOLC | 6 | 1 |
| | IEAR | 0.8162 | 0.9762 |
| Bus 3 | LOLC | 3,412 | 5,263 |
| | IEAR | 0.8232 | 1.1775 |
| Bus 4 | LOLC | 402 | 171 |
| | IEAR | 0.7563 | 0.8807 |
| Bus 5 | LOLC | 509 | 488 |
| | IEAR | 2.5391 | 3.7142 |
| Bus 6 | LOLC | 320,144 | 327,988 |
| | IEAR | 3.0489 | 3.1209 |

## VI. Conclusions

This chapter has presented a GA based approach for composite system reliability worth evaluation. Genetic algorithm (GA) is used as a state sampling tool for the composite power system network. Two different sampling methods are presented. In the first method, GA samples failure states for each load level separately. The second method samples failure states while system load is assigned the highest load state and then reevaluates the same network state with other load states. Two different load curtailment polices have been presented. Different load categories are considered in the state evaluation model. Instead of using the raw interruption cost associated with failure state mean duration, random sampling is used to calculate mean interruption cost associated with each failure state.

# CHAPTER VIII

# GENETIC ALGORITHMS APPROACH FOR THE ASSESSMENT OF COMPOSITE POWER SYSTEM RELIABILITY CONSIDERING MULTI-STATE COMPONENTS

## I. Introduction

In chapter IV, GA has been introduced as a sampling tool to calculate composite system annualized adequacy indices. In chapter V, two different GA based approaches have been introduced for the assessment of composite power system annual adequacy indices.

This chapter shows how the GA approach can be used with multi-state components such as generating units with derated states [42]. It also considers common mode failure for transmission lines. Binary encoded GA is used as a state sampling tool for the composite power system network states. Populations of GA generations are constructed from chromosomes, each chromosome representing a network state, i.e., the states of generation units and transmission lines. Each chromosome consists of several genes. A two-state component is represented by one gene. Meanwhile, every multi-state component is represented by two or more genes, e.g., two genes are able to represent up to four-state component. When calculating annual indices, hourly load is represented by m load states using the k-means clustering technique. The GA searches for failure states while load buses are assigned the maximum load state. Failure states are then reevaluated with lower load states until a success state is obtained or all load states have been evaluated. The superiority of the proposed approach over other conventional methods comes from the ability of GA to trace failure states in an intelligent, controlled and prespecified manner through the selection of a suitable fitness function. A linearized optimization load flow model is used for the evaluation of sampled states. Case studies on a sample test system considering chronological load curves, derated states and common mode failures are presented. Results are analyzed to determine the effect of considering multi-state components.

## II. State Representation Using GA

In the GA sampling approach each chromosome represents a system state. Each chromosome consists of binary number genes. Each gene represents a system component. The first “ng” genes in the chromosome represent generating units while the remaining “nt” genes represent transmission lines. If any gene takes a zero value this means that the component it represents is in the down state and if it takes a one value that means its component is in the up state. To illustrate the chromosome construction, consider the small RBTS test system [26] shown in Fig. 7. It consists of 4 generating units installed at bus 1, 7 generating units installed at bus 2 and 9 transmission lines. Consider the state when one 40MW generating unit installed at bus 1 is down, transmission line number 5 is down and all other system components are up; the chromosome representing this state is shown in Fig. 14.

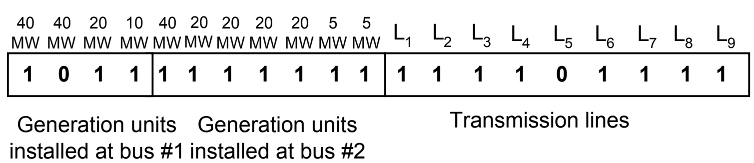


Fig. 14. Chromosome representation assuming each component has only two states.

Each power generation unit and transmission line is assumed to have two states, up and down. The probability of any generation unit to be down is equal to its forced outage rate "FOR". The failure probability of any transmission line "i", "$PT_i$" is calculated from its failure rate "$\lambda_i$" and repair rate "$\mu_i$" as follows:

$$PT_i = \frac{\lambda_i}{\lambda_i + \mu_i} \tag{8.1}$$

The total number of states "Nstates" for all possible combinations of generating units and transmission lines installed is:

$$N_{states} = 2^{ng + nt} \tag{8.2}$$

where "ng" is the total number of generation units and "nt" is the total number of transmission lines in the system.

*A. Representation of Generating Unit Derated States*

It is common for generating units to operate in other states between "up" and "down", these states are called derated states. In this case, generating unit models are more detailed than the two state model. Generating units are often modeled as three-state components. These states are "up" with full capacity, "down" with zero capacity and "derated" with a certain percentage of the full capacity. Each state has its probability of occurrence. The state transition diagram for a three-state model is shown in Fig. 15. The two state model is a special case of this model where there is no derated state 2.

The GA sampling method can be modified to consider multi-state components such as generating units with derated states and transmission line states when considering weather effect. Instead of using one gene to represent one component, n genes can be used to represent up to $2^n$-state component, e.g., a three-state generating unit is represented by two genes as shown in Fig. 16.

Assuming that each of the two 40MW thermal units installed at bus 1 in the RBTS system is modeled as three-state component. Each of these two units is presented by two genes. Consider the state when one of these units is in the down state and the other is in derated state and all other system components are up; the chromosome representing this state is shown in Fig. 17.

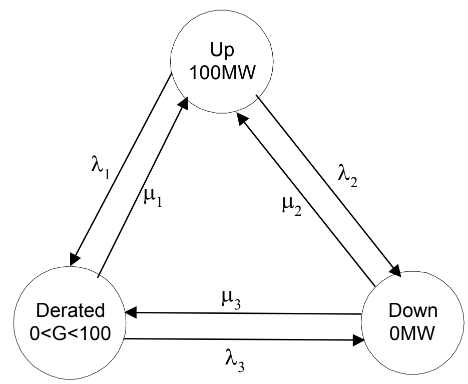


Fig. 15.  Three-state model of a 100MW generating unit.

| Unit State | Gene 1 | Gene 2 | Capacity | Probability |
|---|---|---|---|---|
| Up State | 1 | 1 | 100MW | $P_{up}$ |
| Derated State | 0 | 1 | 0<G<100 | $P_{derated}$ |
| Down State | 0 | 0 | 0MW | $P_{down}$ |
| Unused State | 1 | 0 | ---- | 0 |

Fig. 16. GA representation of three-state unit.

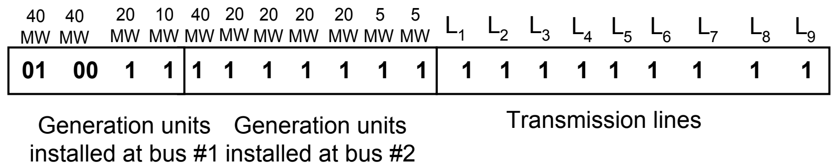


Fig. 17. Chromosome representation considering multi-state component.

*B. Consideration of Common Mode Failure in Transmission Lines*

The common mode failure is an event when multiple outages occur because of one common external cause. A typical example of common mode failure is the lightning stroke into a tower causing a back-flashover to two or more circuits supported by this tower. Other reasons such as the failure of a transmission tower supporting two circuits. A simple common mode failure model for two components is shown in Fig. 18.

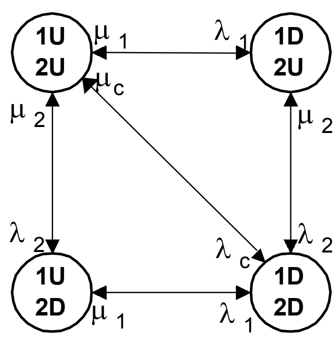


Fig. 18. State transition diagram for two transmission lines subjected to common mode failure.

When two transmission lines are subjected to common mode failure, they must be treated as two dependent components. Using frequency balance equations [43] for each state, and assuming $\lambda_1=\lambda_2=\lambda$, $\mu_1=\mu_2=\mu$; the probability of each state is calculated as:

$$P(1U,2U) = (\frac{\mu_c\lambda + 2\mu^2 + \mu_c\mu}{3\mu\lambda_c + 2\mu^2 + 4\mu\lambda + \lambda\lambda_c + 3\mu_c\lambda + \mu\mu_c + 2\lambda^2}) \quad (8.3)$$

$$P(1D,2D) = (\frac{\mu\lambda_c + \lambda\lambda_c + 2\lambda^2}{3\mu\lambda_c + 2\mu^2 + 4\mu\lambda + \lambda\lambda_c + 3\mu_c\lambda + \mu\mu_c + 2\lambda^2}) \quad (8.4)$$

$$P(1D,2U) = P(1U,2D) = (\frac{\mu\lambda_c + 2\mu\lambda + \mu_c\lambda}{3\mu\lambda_c + 2\mu^2 + 4\mu\lambda + \lambda\lambda_c + 3\mu_c\lambda + \mu\mu_c + 2\lambda^2}) \quad (8.5)$$

In the GA sampling approch, each transmition line in a group of lines that is subjected to common mode failures is still represented by one gene. The only difference will be the using of comined state probaility instead of using the indpendent state probability for each transmitiom line.

## III. Case Studies

The proposed algorithm has been implemented through C++ programming language. A C++ library of GA objects called GAlib developed by [28] has been integrated into the implementation. The proposed method has been tested on the RBTS test system Studies have been made considering generation unit derated states and transmission lines common outage failure.

### A. Generating Unit Derated States

The two 40 MW thermal units installed at bus 1 are assumed to have derated states. Four different models given in [6] are considered. These models are shown in Fig. 19. In model (a) each 40 MW is represented by four states with two derated states of 20 MW and 32 MW. In Models (b) and (c) each 40 MW is represented by three-state model. In model (d) each 40 MW unit is represent by two-state model. Data for all other components are given in appendix A.

Annualized adequacy indices are calculated by considering the system load fixed and equal to 185 MW. A comparison between annualized indices obtained using random sampling and GA based method is given in Table XXVI . Annual adequacy indices are calculated by considering the system chronological load curve. Yearly load curve data in per unit of RBTS system maximum load (185 MW) are given in [24]. Using k-means clustering techniques, the yearly load curve is represented by 8 states which are given in Table XII. A comparison of annual indices when using random sampling Monte Carlo simulation and the GA based method is given in Table XXVII.

Table XXVI. Comparison of Annualized Adequacy Indices Considering Different Derated State Models

| | | Model (a) | Model (b) | Model (c) | Model (d) |
|---|---|---|---|---|---|
| LOLP | GA | 0.008169 | 0.0068417 | 0.007692 | 0.009759 |
| | Monte Carlo | 0.007849 | 0.0067099 | 0.007509 | 0.009540 |
| | diff. % | 3.92% | 1.93% | 2.38% | 2.24% |
| EENS | GA | 815.08 | 651.75 | 698.84 | 1052.23 |
| | Monte Carlo | 776.66 | 638.02 | 678.65 | 1001.55 |
| | diff. % | 4.71% | 2.11% | 1.60% | 4.8% |

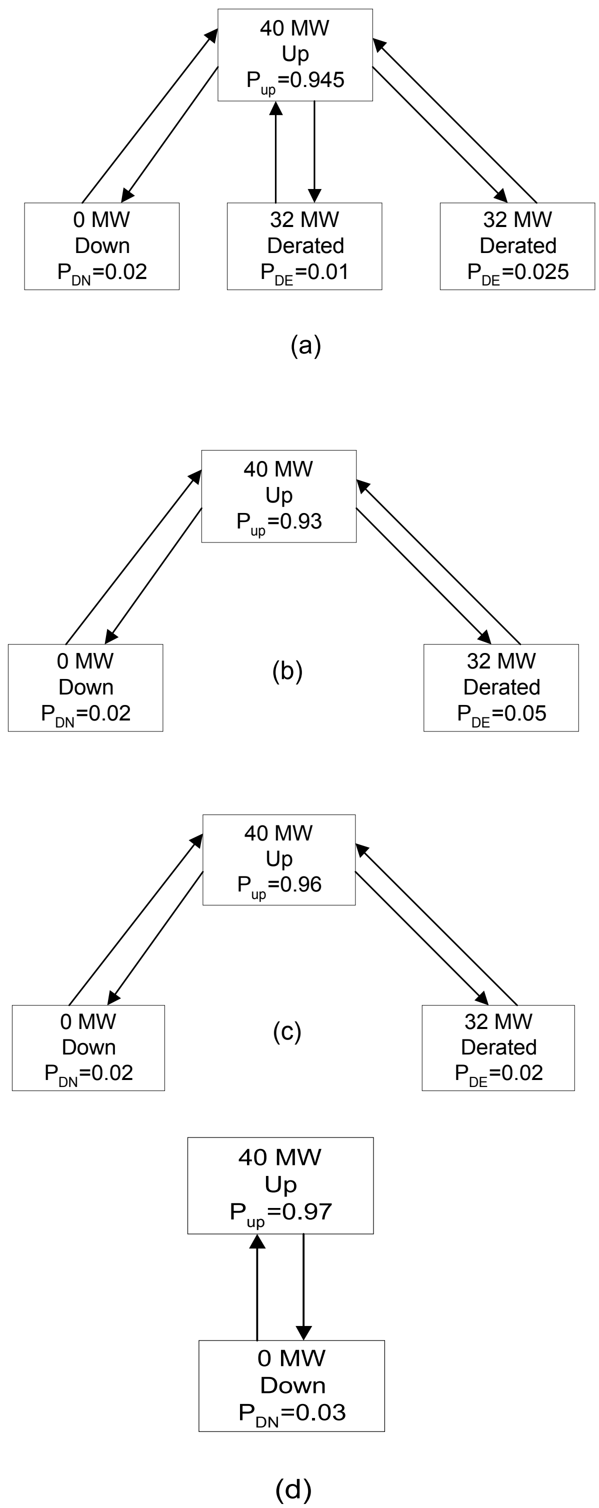


Fig. 19. 40 MW Generating unit derated state models.

Table XXVII. Comparison of Annual Adequacy Indices Considering Different Derated State Models

| | | Model (a) | Model (b) | Model (c) | Model (d) |
|---|---|---|---|---|---|
| LOLP | GA | 0.001226 | 0.001191 | 0.001224 | 0.001284 |
| | Monte Carlo | 0.001160 | 0.001160 | 0.001169 | 0.001210 |
| | diff. % | 5.38% | 2.60% | 4.49% | 5.76% |
| EENS MWh/Yr | GA | 128.20 | 124.725 | 127.893 | 132.31 |
| | Monte Carlo | 122.08 | 122.088 | 122.450 | 124.60 |
| | diff. % | 4.77% | 2.11% | 4.26% | 5.83% |

It can be seen from Table XXVI and Table XXVII that consideration of derated states has larger effect on annualized indices than on annual indices.

Indices obtained by the GA based method are higher than those obtained by Monte Carlo simulation. If GA samples more failures states the value of LOLP and EENS will be higher, thus the proposed GA based method provides more accurate results than Monte Carlo simulation. When calculating annual indices the computational effort of the GA based method was about 10% of random sampling Monte Carlo simulation.

### *B. Common Mode Outage*

Two pairs of transmission lines, lines 1&6 and lines 2&7, are assumed to be installed on a common tower for their entire length. The common mode failure data for these line as given in [26], is shown in Table XXVIII. Each pair of transmission lines is represented by a four-state model as shown in Fig. 18. The probability of each state is calculated using (8.3), (8.4) and (8.5). These values are given in Table XXIX. Annualized and annual adequacy indices have been calculated using the proposed GA based method, and results are given in Table XXX. It can be seen from these results that consideration of common mode failure slightly increases the values for LOLP and EENS of the RBTS system.

Table XXVIII. Common Mode Outage Data for Transmission Lines on Common Tower

| | First Line Pair | | Second Line Pair | |
|---|---|---|---|---|
| Line no. | 1 | 6 | 2 | 7 |
| Common length km | 75 | 75 | 250 | 250 |
| Outage rate per year $\lambda c$ | 0.150 | | 0.500 | |
| Outage duration (hours) rc | 16.0 | | 16.0 | |

Table XXIX. State Probability for Transmission Lines on Common Tower

| | First Line Pair | Second Line Pair |
|---|---|---|
| Probability of the two lines being up | 0.996391844 | 0.988066635 |
| Probability of the two lines being down | 0.001770425 | 0.005846548 |
| Probability of first line down and the second is up | 6.73059e-5 | 2.40269e-4 |
| Probability of first line up and the second is down | 6.73059e-5 | 2.40269e-4 |

Table XXX. Adequacy Indices with and without Considering Common Mode Outage

| Indices | Annualized Indices | | Annual Indices | |
|---|---|---|---|---|
| | Base Case | WITH COMMON MODE OUTAGE | Base Case | WITH COMMON MODE OUTAGE |
| LOLP | 0.009753 | 0.009854 | 0.00128248 | 0.0012902321 |
| EENS | 1047.78 | 1071.251 | 132.090 | 132.965 |

## IV. Conclusions

A new genetic algorithm (GA) based approach for the assessment of composite system adequacy indices while considering multi-state components has been presented. The proposed method has the merits of intelligent search through GA fitness function. The computational effort is less than other traditional methods because each sampled state is evaluated only once. The proposed method has been applied to the RBTS test system. Results have been compared with those obtained using random sampling. It has been shown that results obtained by the proposed method are more accurate than those of Monte Carlo Simulation. Results show that consideration of derated states has more effect on annualized indices than annual indices. Consideration of derated states results in lower values for LOLP and EENS. Meanwhile, consideration of common mode failure gives slightly higher indices.

# CHAPTER IX

# STATE EVALUATION IN COMPOSITE POWER SYSTEM RELIABILITY USING GENETIC ALGORITHMS GUIDED BY FUZZY CONSTRAINTS

## I. Introduction

Composite system reliability evaluation is divided into two main parts, state sampling and state evaluation. Most of the research on this subject has focused on developing new techniques for state sampling. There is a need for suitable state evaluation methods for representing the system more realistically and yet be computationally tractable.

The GA has the advantage of the generality of its objective function [44]. Any objective function can be used as long as it reflects the goodness of a certain feasible solution in comparison with others. In case of conventional mathematical programming methods, each method is suited for certain kind of problems depending on linearity, differentiability and continuity. GA shows more success in unconstrained optimization problems. In case of constrained optimization problems, representation of the constraints is still an active research area. The most commonly used method is the integration of penalty functions into the objective function to represent constraint violation. An example of constrained problem in power systems is the solution of the ac load flow problem proposed in [45]. Penalty functions were used to represent the mismatch in real and reactive power. A new method presented in [46] uses the fuzzy logic to describe system constraints to calibrate gas turbine blade cooling model using GA. Fuzzy rules are used to judge the goodness of the solution and as a way to represent engineering judgment on the solution quality.

In previous chapters GA was used as an intelligent sampling tool for the composite power system states. This chapter presents a novel method based on GA for composite system state evaluation [47]. The GA is used as an optimization tool for evaluating system states to find a viable solution for a sampled state that satisfies system constraints. Evaluation model is based on the linearized dc load flow equations. Real number encoded GA is used to represent different system variables. Fuzzy membership functions are used to represent system constraints. GA fitness function is constructed from the values of different fuzzy membership functions. Different load curtailment philosophies can be implemented through the construction of fitness functions . The fuzzy membership functions guide the GA to find a viable solution faster and in a more intelligent manner than the use of traditional penalty functions. Fuzzy membership parameter values can be adaptive according to available generation and load levels. The proposed method is applied to a simple test system to show the results of using different load curtailment policies on load point indices. Advantages of the proposed method over other traditional methods are also discussed.

## II. State Sampling and Evaluation Model

The first stage in composite power system reliability is to sample system states. Each sampled state represents a system contingency, i.e., one or more of generator units and/or transmission lines are in the down state. Monte Carlo simulation is one of the commonly used methods for system state sampling. The GA sampling technique represented in chapter IV can also be used.

State evaluation depends on the power flow model used for this purpose. Linearized state evaluation model is based on dc load flow equations. In each sampled state one or more generators and/or transmission lines are in the down state. For the current state to be evaluated, elements of the power system susceptance matrix B are modified according to transmission line outages. The amount of available real power generation at each PV bus is also updated according to the status of generation units installed at such a bus. State evaluation is represented as an optimization problem with the objective of minimizing the total load curtailment for the whole system, which is equivalent to maximizing the load value at each load bus. The linearized optimization model is formulated as follows:

$$\max \sum_{i=1}^{nl} L_i \tag{9.1}$$

Subject to :

$$PG_i - L_i = \sum_{j=2}^{n} B_{ij}.\theta_j \qquad \forall\ i=1,2,\ldots\ldots..n \tag{9.2}$$

$$y_k.(\theta_i - \theta_j) \le PT_k \qquad \forall\ k=1,2,\ldots\ldots..nt \tag{9.3}$$

$$y_k.(\theta_j - \theta_i) \le PT_k \qquad \forall\ k=1,2,\ldots\ldots..nt \tag{9.4}$$

$$0 \le L_i \le PD_i \qquad \forall\ i=1,2,\ldots\ldots..nl \tag{9.5}$$

$$PG_{i\min} \le PG_i \le PG_{i\max} \qquad \forall\ i=1,2,\ldots\ldots..nv \tag{9.6}$$

where:

n is the total number of system buses,

nt is the total number of the transmission lines,

nl is the total number of load buses ,

nv is the total number of buses that has installed generation,

$B_{ij}$ is the element at the $i^{th}$ row and $j^{th}$ column in the system susceptance matrix,

$\theta_i$ is the voltage angle at bus i (bus 1 is assumed the reference bus with $\theta_1 = 0$ ),

$PD_i$ is the yearly maximum load demand at bus i,

$L_i$ is the amount of load that could be supplied at bus i,

$PT_k$ ,$y_k$ are the maximum flow capacity and susceptance of transmission line k connecting between bus i and bus j,

$PG_i$ is the real power generation at bus i,

$PG_{i\ max}$ is the maximum available generation at bus i and

$PG_{i\ min}$ is the minimum available generation at bus i.

This model can be solved using linear programming methods like the dual simplex method or interior point method. The variables vector to be calculated by the linear programming solver is { $L_i$ , $PG_j$ , $\theta_k$}

$\forall$ i=1,2….,nl , $\forall$ j=1,2,…..nv and $\forall$ $\theta_k$ = 2,3,……n

The total amount of system load curtailment “$LC_s$” is:

$$LC_s = \sum_{i=1}^{nl} PD_i - \sum_{i=1}^{nl} L_i \tag{9.7}$$

The load curtailment at load bus i "$LC_i$" is

$$LC_i = PD_i - L_i \tag{9.8}$$

It is well known that this optimization problem has multiple solutions. A load curtailment philosophy should be applied and integrated in the objective function to obtain a unique optimal solution.

## III. Proposed Technique for State Evaluation

### *A. Motivation*

Implementing sophisticated load curtailment philosophies is difficult using traditional linear programming methods. The proposed algorithm uses GA Guided by Fuzzy Constraints and is abbreviated as "GAGFC". The proposed algorithm is very flexible for incorporating practical load shedding philosophies and results in more realistic bus indices.

### *B. Chromosome Representation*

Real number encoded GA is used to find an optimal solution that satisfies system constraints with minimum load curtailment. Each chromosome in each population represents a candidate solution for the linearized state evaluation model. Each chromosome consists of "nv+nl-1" real number genes. Each one of the first "nv-1" genes represents real power generation value at a certain PV bus. Generation at the selected slack bus is not included. Each one of the next "nl" genes represents load value at a certain load bus. The chromosome representation is shown in Fig. 20.

| Generation Bus Real Power (MW) | | | | Bus Load Values (MW) | | | |
|---|---|---|---|---|---|---|---|
| $PG_2$ | $PG_3$ | ...$PG_k$.... | $PG_{nv}$ | $L_1$ | $L_2$ | ......$L_r$........ | $L_{nl}$ |

Fig. 20. Chromosome representation for state evaluation.

*C. Constraint Representation Using Fuzzy Membership Functions*

Instead of using hard constraints, soft fuzzy constraints are used to guide GA to find a viable solution. Load values, slack bus real power to enforce system power-load balance and transmission line capacity, each is represented by a fuzzy membership function. The resultant value of each fuzzy membership function refers to the degree of satisfaction of its corresponding constraint. Membership functions can have adaptive parameters that can be changed according to the ratio of current available generation to system maximum load. The following simple membership functions are used:

1.For each load value $L_i$ selected by GA, its membership value $\mu_{Li}$ is calculated from the triangular membership function, triang($0.6PD_i$, $PD_i$, $1.01PD_i$), shown in Fig. 21.

2.The amount of slack bus generation $PG_1$ is calculated using the generation load balance constraint:

$$PG_1 = \sum_{i=2}^{nv} PG_i - \sum_{j=1}^{nl} L_j \tag{9.9}$$

Knowing the available generation at the slack bus for the current state to be evaluated, a fuzzy membership function is used to represent the degree of satisfaction of the chromosome calculated slack bus generation in comparison with the actual power available at the slack bus. A simple membership function representing slack bus real power satisfaction is given in Fig. 22.

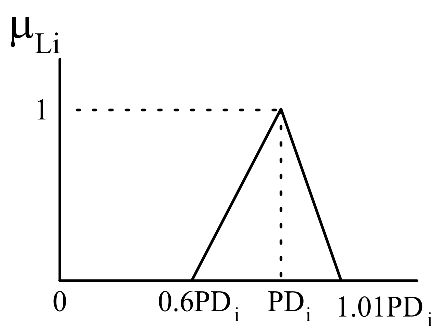


Fig. 21. Membership function of load $L_i$.

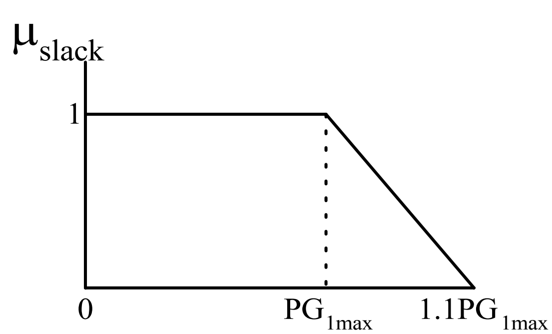


Fig. 22. Membership function of slack bus.

3. Line flow constraints are softened by allowing the power flow in any line to be overloaded by a small percentage of its rated capacity. Power flow in line k has a membership value $\mu_{flow,k}$ which is calculated using the trapezoidal membership function trapiz($-1.05PT_k$, $-PT_k$, $PT_k$, $1.05PT_k$), shown in Fig. 23.

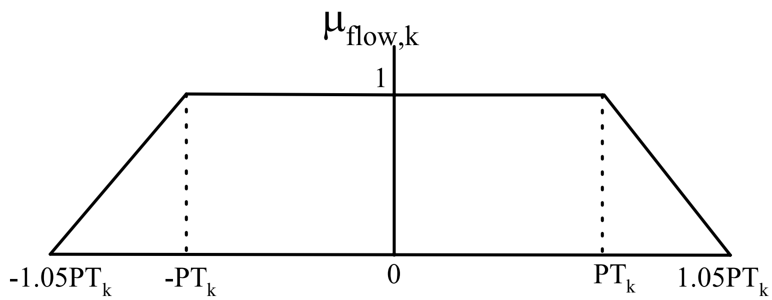


Fig. 23. Membership function of line k power flow.

4.The fourth membership function represents the degree of solution optimality. In case of linearized model, transmission line losses are ignored. Therefore, for a sampled state a feasible solution with load curtailment equals to the amount of generation deficiency is for sure an optimal solution. This optimal solution can be reached only if there is no overloaded line. The value of $\mu_{optimal}$ is calculated from the trapezoidal membership function shown in Fig. 24.

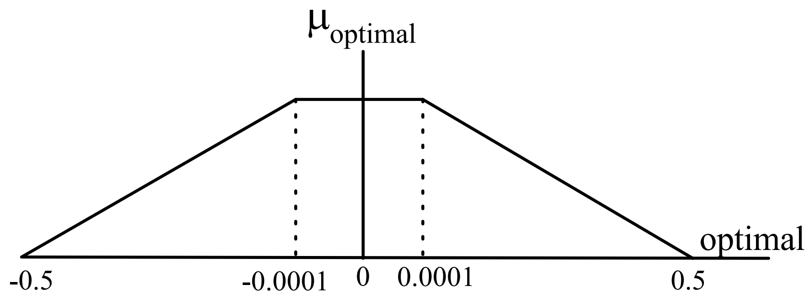


Fig. 24. Membership function of solution optimality.

The variable "optimal" is calculated for each chromosome as follows:

$$optimal = \frac{PG_{av} - \sum_{i=1}^{nl} L_i}{PG_{av}} \tag{9.10}$$

$$PG_{av} = \begin{cases} \sum_{i=1}^{ng} PG_i & if \ \ \sum_{i=1}^{ng} PG_i^{av} < L_{\max} \\ L_{\max} & if \ \ \sum_{i=1}^{ng} PG_i^{av} \geq L_{\max} \end{cases} \tag{9.11}$$

where $L_i$ is the chromosome gene value representing load at bus i, $PG_i$ is the chromosome gene value representing real power at bus i, $PG_i^{av}$ is the total available generation (real power) at bus i in the current state to be evaluated (not the gene values) and $L_{max}$ is the system annual maximum load.

*D. Construction of GA Fitness Function*

It is easier to construct the fitness function in case of unconstraint optimization problems. In case of constrained optimization problems, more sophisticated fitness function is needed. Dealing with constraints in GA can be done according to their types as follows :

i. Lower and upper limits for optimization variables can be enforced through the choice of the appropriate type of GA operators. These operators always produce new chromosomes in which all variables are within their upper and lower limits.

ii. Dealing with other constraints can be implemented using different techniques. The most commonly used one is the integration of penalty functions in the fitness function. In case of minimization problems, penalty values increase as the constraint violation increases.

The objective of GA in the proposed method is to find a solution with all membership functions equal or are very close to unity value, which represents a success state without load curtailment. Load curtailment becomes a necessity if the amount of generation is less than the load or to eliminate transmission line overloading. In this case, GA searches for a solution with the least amount of load curtailment. The objective of optimization is to maximize load value at each load bus. The fuzzy soft constraints guide the GA to reach an optimal feasible solution faster and more intelligently than the use of traditional penalty functions. Attention should be given to the feasibility of solution while constructing the fitness function. Chromosomes representing unfeasible solutions where one or more of the constraints are violated should have less fitness value than other feasible solutions. The proposed method provides the flexibility of implementing sophisticated load curtailment techniques through GA fitness function. The following fitness functions represent some possibilities of load curtailments techniques. It is assumed that load curtailment is a necessity for the sampled state to be evaluated.

*1. Maximum allowable load curtailment at each load bus*

The objective of this load curtailment philosophy is to find an optimal solution with load curtailment not to exceed certain value at each load bus. Membership function for a load bus equals zero if curtailed load is higher than the maximum allowable load curtailment at this bus. The fitness function to achieve such a load curtailment philosophy is constructed as follows:

$$fit = \begin{cases} 1 + \mu_{optimal} \cdot \sum_{i=1}^{nl} \mu_{L_i} \cdot \prod_{\mathrm{j=1}}^{\mathrm{nl}} \mu_{L_j} & if \quad \mu_{slack} \cdot \prod_{k=1}^{nt} \mu_{flow_K} = 1 \\ \mu_{slack} \cdot \prod_{k=1}^{nt} \mu_{flow_K} & if \quad \mu_{slack} \cdot \prod_{k=1}^{nt} \mu_{flow_K} < 1 \end{cases} \tag{9.12}$$

GA stops after producing a specified number of generations or finding an optimal solution with $\mu_{optimal} = 1$ and $\prod_{j=1}^{nl} \mu_{L_j} > 0$.

If the optimal solution found by GA has fitness value equal to one this means one or more of load membership functions equal zero. In this case, load membership functions are modified to allow more curtailed load and GA searches for a new solution.

The fitness function given in (9.12) will guide GA to find a feasible solution at first, i.e., $\mu_{slack} \cdot \prod_{k=1}^{nt} \mu_{flow_K} = 1$, which means generation-load balance is satisfied and there is no transmission line overloading. All unfeasible solutions will have a fitness value less than one. As the degree of constraint violation increases, the solution fitness value decreases. Feasible solutions will have a fitness value higher than one. This value will increase as the solution is more optimal, i.e., load curtailment is getting smaller.

*2. Allowing transmission line overloading*

In this case, GA tries to find a feasible solution with no load curtailment. If this is not possible, GA tries to find an optimal solution with the line overloading within the allowed range. The fitness function used to achieve this policy is constructed as follows:

$$fit = \begin{cases} 1 + \mu_{optimal} \cdot \sum_{i=1}^{nt} \mu_{flow_i} \cdot \prod_{\mathrm{j}=1}^{\mathrm{nl}} \mu_{L_j} & if \quad \mu_{slack} = 1 \\ \mu_{slack} & if \quad \mu_{slack} < 1 \end{cases} \tag{9.13}$$

### *3. Equal percent load loss for all buses*

The objective of this load curtailment philosophy is to find a feasible solution with the ratio of load curtailed to total installed load for all load buses as nearly equal as possible. The fitness function needed to achieve this philosophy is constructed as follows:

i. All loads are given triangular membership functions with the same slope.

ii. Calculate the average membership value for all loads.

$$\mu_{av} = \frac{\sum_{i=1}^{nl} \mu_{L_i}}{nl} \tag{9.14}$$

iii. Calculate the deviation of each load membership value from the calculated average.

$$dev_i = | \mu_{L_i} - \mu_{av} | \tag{9.15}$$

iv. Calculate a modified membership value $\beta_{Li}$.

$$\beta_{L_i} = (1 - dev_i).\mu_{L_i} \tag{9.16}$$

v. The fitness function is like (9.12) but $\beta_{Li}$ is used rather than $\mu_{Li}$.

It is possible to modify this policy by dividing system load buses into groups. Load loss is shared equally with buses in the same group with load curtailed first from groups with less importance.

## *E. Producing New GA Generations*

Each generation of GA represents a pop_size candidate solutions for the state evaluation problem. After calculating the fitness value for all individuals in the current solution, a new generation is evolved. Evolution of a new generation is done through the application of three GA operators. These operators are selection schema, crossover and mutation. Probability of crossover $P_c$ and probability of mutation $P_m$ are set at the beginning of the GA. There are many versions of each operator. In the proposed algorithm, best results are obtained using two-point crossover, non-uniform mutation and top selection operators [17]. The use of non-uniform mutation improves the GA performance more than any other type of mutation operators. Moreover, these two types of crossover and mutation operators have the advantage of keeping variables of newly produced chromosomes within their lower and upper limits. Crossover and mutation are applied separately to old population producing new chromosomes. Selection operation is then applied.

*1. Two points crossover operator*

For each adjacent pair of chromosomes in the old population, generate a random number r from [0,1]. If $r < P_c$ , select the given chromosome pair for crossover. At the end j pairs of chromosomes are eligible to apply crossover to them. Assume the pair X and Y is subjected to crossover. Generate two different random number "pos1" and "pos2" in the range [1,nv+nl-1]. Assuming pos1<pos2, the two new chromosome genes are:

$$x_i^{\backslash} = y_i \text{ if } pos1 \le i \le pos2 \text{ and } x_i^{\backslash} = x_i \text{ otherwise.} \tag{9.17}$$

$$y_i^{\backslash} = x_i \text{ if } pos1 \le i \le pos2 \text{ and } y_i^{\backslash} = y_i \text{ otherwise.} \tag{9.18}$$

*2. Non uniform mutation*

For each gene in each chromosome in the old population, pick a random number between 0 and 1. If this number is less than or equal to mutation probability then this gene is eligible for mutation. For a given parent X, if the element $x_k$ of it is selected for mutation, the resulting offspring X` is:

X` = [$x_1$, $x_2$, …………………… $x_k'$ …………………$x_n$], where $x_k'$ is randomly selected from two possible choices:

$$x_k' = x_k + \Delta(t, x_k^u - x_k) \text{ or} \tag{9.19}$$

$$x'_k = x_k - \Delta(t, x_k - x_L^k) \tag{9.20}$$

where $x_K^U$ and $x_K^L$ are the upper and lower bounds for $X_k$.

The function Δ(t,n) returns a value in the range [0 , n ] such that the value of Δ(t,n) approaches to 0 as t increases.

$$\Delta(t,n) = n.r.\left(1 - \frac{t}{T}\right)^b \tag{9.21}$$

where t is the current generation number, T is the maximum generations number, r is a random number in the range [0,1] and b is a parameter determining the degree of non uniformity. A typical value of b is 2 or 3.

### *3. Top selection*

Before applying selection operator, old and new chromosomes fitness values are calculated. Assuming that population size equals 'pop_size' and the number of offspring produced after applying the previously mentioned crossover and mutation operators is 'child_size'. Assuming the optimization problem is a maximization problem, top selection means that the new generation consists of the highest fitness value chromosomes. Hence new generation consists from the best pop_size chromosomes chosen from the previous pop_size parents and child_size children.

## IV. The Proposed Algorithm

The steps for implementation are summarized as follows:

1.Choose the type of selection, crossover and mutation for GA. Choose the values of population size, crossover probability, mutation probability and maximum number of generations for the algorithm to stop.

2.Construct the system susceptance matrix B with all transmission lines in the up state.

3. Choose the appropriate fuzzy membership functions for loads, slack bus real

power, line flows and optimality.

4. Construct GA fitness function according to the load curtailment philosophy selected.

5. The GAGFC module is called to evaluate the current sampled state.

6. Modify the B matrix according to which lines are in the down state for the current state to be evaluated. Calculate the inverse of the resultant matrix.

7. For each chromosome in the initial population, a random real number is chosen for each chromosome gene. For genes representing power generation choose a random value for $PG_i \in [PG_{i\min}, PG_{i\max}]$, where $PG_{i\max}$ is equal to the sum of power of all generators in the up state installed at bus i. For each gene representing load value, choose a random value for $L_i \in [L_{i\max}, L_{i\min}]$.

8. Each chromosome represents a solution for state evaluation. Each chromosome in the current population is evaluated as described in next steps.

9. Find the voltage angles using (9.22) for all buses except the slack bus whose angle $\theta_1$ equals zero and is taken as a reference for other angles.

$$\theta = B^{-1}.(PG - L) \tag{9.22}$$

The inverse of the B matrix is calculated once for the sampled state, i.e., there is no need to calculate it for each chromosome.

10. Calculate the real power flows in each transmission line.

11.Calculate membership values for each load, slack bus power, flow in each transmission line and optimality.

12. Calculate the fitness value for the current chromosome using the assigned fitness function.

13. Repeat steps 9 to 12 for all chromosomes in the current population

14. Stop the algorithm if the stopping criterion has been met, otherwise, proceed to evolve a new generation. Repeat steps 9 to 13 for the new population.

15. Return a success flag if there is no load curtailment, otherwise, return a failure flag with the amount of load curtailed at each load bus.

## V. Assessment of Composite System Adequacy Indices

Annualized adequacy indices for the whole system and for each load bus are calculated using the data saved in the state array, as explained in chapter IV, after evaluating each sampled state using GAGFC. Let the total number of saved failure states be "nf", then the adequacy indices for the whole system are calculated as follows:

$$\text{LOLP (Loss of Load Probability)} = \sum_{j=1}^{nf} PS_j \tag{9.23}$$

$$\text{LOLF (Loss of Load Frequency)} = \sum_{j=1}^{nf} FS_j \tag{9.24}$$

$$\text{EPNS(Expected Power Not Supplied)} = \sum_{j=1}^{nf} EPNS_j \tag{9.25}$$

$$\text{EENS(Expected Energy Not Supplied)} = \text{EPNS} \,.\, 8760 \tag{9.26}$$

where $PS_j$ , $FS_j$ and $EPNS_j$ are failure probability , state contribution to system failure frequency and expected power not supplied for state j.

The same set of indices can be calculated for each load bus considering only failure states resulting in load curtailment at this bus and ignoring all other states.

## VI. Case Study

The proposed algorithm has been implemented through C++ programming language. The proposed method has been tested on the RBTS test system. States with probability less than 1e-6 are ignored. Total number of saved states in the state array is 500. The input parameters of the GAGFC are taken as follows: pop_size= 50, $P_c$=0.7, and $P_m$=0.3. The stopping criterion used is total number of GA generations equal to 300. Three case studies are given depending on the load curtailment philosophy.

Annualized bus indices obtained using the fitness function given in (9.12) are given in Table XXXI. For transmission line overloading of 10% allowed through the use of fitness function (9.13), the obtained indices are shown in Table XXXI.

Table XXXI. Annualized Adequacy Indices Comparison between Dual Simplex Method and GAGFC

| Adequacy Indices | Dual Simplex Method | GAGFC no overload | GAGFC with 10 % overload |
|---|---|---|---|
| LOLP | 0.0096104 | 0.0096104 | 0.0093561 |
| EENS (MWH/Yr) | 1019.75 | 1019.29 | 1005.09 |
| LOLF (occ./Yr) | 3.9824 | 3.9824 | 3.7099 |
| no. of identified failure states | 224 | 224 | 209 |

These results are obtained assuming that GAGFC stops if it finds an optimal solution, i.e., line flow and slack bus constraints are satisfied and load curtailment equals the amount of available generation deficiency to supply system maximum load. This means an optimal solution is reached and there is no need for GA to continue. When this strategy is used there will be no control over the load curtailment methodology used on each bus. It should be used when only system indices are needed.

The next case study is the application of equal percentage load shedding policy explained previously. Different load point and system indices are given in Table XXXII.

Table XXXII. Annualized Adequacy Indices Using Equal Percentage Load Shedding Policy

| Adequacy Indices | LOLP | EENS (MWH/YR) | Percentage of curtailed to maximum annual required energy | LOLF |
|---|---|---|---|---|
| Bus#2 | 0.0084814 | 90.71 | 0.052% | 2.9989161 |
| Bus#3 | 0.0084930 | 422.22 | 0.057% | 3.0139949 |
| Bus #4 | 0.0084930 | 183.51 | 0.052% | 3.0139949 |
| Bus#5 | 0.0084912 | 86.79 | 0.050% | 3.0145671 |
| Bus#6 | 0.0096104 | 283.51 | 0.162% | 3.9824173 |
| System | 0.0096104 | 1066.74 | 0.066% | 3.9824173 |

It can be seen from Table XXXII that all load points with the exception of number 6 have approximately the same expected annual curtailed energy expressed as percent of annual maximum required energy. This means GAGFC was able to find a solution with equal load loss sharing policy. Load point 6 has the same LOLP as of the system. This means in all sampled failure states there was load curtailment associated with bus 6. Its LOLP is higher than other buses because it suffers from total isolation from the system in some sampled failure states. GAGFC was able to find optimal solution with load curtailment proportional to the installed load at each load bus except the case when bus 6 is subject to isolation from the system, i.e., its load is totally lost.

## VII. Advantages and Disadvantages

The main disadvantage of the proposed method in comparison with conventional linear programming solver is the computational effort. For the case study, the computational effort for GAGFC was approximately double that of dual simplex method. Advantages can be summarized as follows:

1.This method has the ability of implementing more sophisticated load curtailment philosophies. Many other load curtailment polices can be implemented through GA fitness function.

2.Conventional methods divide the solution space into two crisp areas, which are feasible and unfeasible. GAGFC through its use of the fuzzy constraints divides the solution space into three areas: feasible, semi-feasible and unfeasible. This representation for system constraints is more practical in system representation.

3.Consider the case of allowing a small percentage of transmission line over loading. GAGFC searches for optimal solution with no overloading or with least amount for overloading because the fitness function values decrease with the increase in over loading as the overload membership function decreases. In case of conventional methods allowing a percentage of overload means that any optimal solution within this region is a feasible solution, hence solutions with over load can have the same objective function value as solution with no overloading.

4. The proposed techniques can be extended with some modification to evaluate sampled states based on ac load flow equations instead of the linearized model.

## VIII. Conclusions

This chapter has presented a novel method for state evaluation in composite power systems reliability assessment. The proposed method uses GA to evaluate sampled states. System constraints and load values are represented by fuzzy membership functions. The GA fitness function is constructed as a combination from the fuzzy membership values. Different types of GA fitness function can be used to implement different load curtailment policies.  GA through its fitness function guided by the fuzzy membership functions is able to find solution satisfying required load curtailment policy. Results have shown the success of the proposed method to find reliability indices and the effect of different load curtailment polices on system indices. Advantages of the proposed method over other traditional methods have also been described.

# CHAPTER X

# SUMMARY AND SUGGESTIONS FOR FUTURE WORK

## I. Summary

Reliability studies play an important role in ensuring the quality of power delivery to customers. Developing more efficient and intelligent power system reliability assessment techniques plays a key role in improving reliability studies. This dissertation has presented innovative methods based on genetic algorithms (GAs) for reliability assessment of power systems. The GA has been introduced as a state sampling tool for the first time in power system reliability assessment literature.

The first part of this dissertation has presented an innovative method for the assessment of generation system reliability. The proposed method is based on a modified version of the simple genetic algorithm (MSGA). In this method, GA is used not for its traditional objective of optimization but as a search tool to truncate the probability state space and to track the most probable failure states. GA stores system states, in which there is generation deficiency to supply system maximum load, in a state array. The given load pattern is then convoluted with the state array to obtain adequacy indices. State array is also used to obtain useful information about the contribution of different states and generation unit combinations to the probability of system failure.

In the second part of the dissertation, a GA based method for state sampling of composite generation-transmission power systems is introduced. Binary encoded GA is used as a state sampling tool for the composite power system network states. Populations of GA generations are constructed from chromosomes, each chromosome representing a network state, i.e., the states of generation units and transmission lines. A linearized optimization load flow model is used for evaluation of sampled states. The model takes into consideration importance of load in calculating load curtailment at different buses in order to obtain a unique solution for each state.

The preceding method has been extended to evaluate adequacy indices of composite power systems while considering chronological load at buses. Hourly load is represented by cluster load vectors using the k-means clustering technique. Two different approaches have been developed. In the first approach, GA samples failure states for each load level separately. Thus adequacy indices are calculated for each load level and then combined to obtain the annual adequacy indices. In the second approach, GA samples failure states only with load buses assigned the maximum cluster load vector. Failure states are then reevaluated with lower cluster load vectors until a success state is obtained or all cluster load levels have been evaluated.

The developed GA based method is used for the assessment of annual frequency and duration indices of composite systems. Transition rates between the load states are calculated. The conditional probability based method is used to calculate the frequency of sampled failure states using different component transition rates.

The developed GA based method is also used for evaluating reliability worth indices of composite power systems. An optimization model based on linearized load flow is used for the evaluation of sampled states. Two different objectives are used in state evaluation. The first objective is to minimize load curtailment considering load category and load bus relative importance. The second objective is to minimize load interruption cost. Instead of using the raw interruption cost associated with failure state mean duration time, random sampling is used to calculate mean interruption cost associated with each failure state.

The developed GA approach is generalized to recognize multi-state components such as generation units with derated states. It also considers common mode failure for transmission lines. Each two-state component is represented by one gene. Meanwhile, every multi-state component is represented by two or more genes, e.g., two genes are able to represent up to four-state component.

Case studies on the IEEE-RBTS test system were presented. It has been shown that the developed methods have several advantages over other conventional methods such as Monte Carlo simulation. These advantages can be summed up as follows:

1. The superiority of the developed methods over other conventional methods comes from the ability of GA to trace failure states in an intelligent, controlled and prespecified manner through the selection of a suitable fitness function.

2. Through its fitness function, GA can be guided to acquire certain part of the state space. This can be done by giving more credit to the states belonging to the part of the state space that is of interest.

3. State evaluation is the most time consuming part in composite system reliability assessment. The same sampled states are evaluated more than once when Monte Carlo simulation is used. This is not the case with the developed methods where sampled states are evaluated once.

4. The computational effort of the developed algorithms is only 10% to 20% of the computational effort when using Monte Carlo simulation to calculate annual adequacy indices for composite power systems.

5. In case of very reliable systems, Monte Carlo simulation needs much more time to converge, which is not the case with GA as it depends on fitness value comparison.

6. Parallel operation of GA sampling can be easily applied providing computational time reduction.

7. The obtained state array, after the GA states sampling stops, can be analyzed to acquire valuable information about the sensitivity of system failure to different components in the power system under study.

The last part of the dissertation has presented a new method for composite system state evaluation using real number encoded GA. The objective of GA is to minimize load curtailment for each sampled state. Minimization is based on the dc load flow model. System constraints are represented by fuzzy membership functions. Membership value indicates the degree of satisfaction of each constraint for an individual in a GA population. The GA fitness function is a combination of these membership values. The proposed method has the advantage of allowing sophisticated load curtailment strategies, which lead to more realistic load point indices. Application to a simple test system using different load curtailment philosophies has been introduced.

## II. Suggestions for Future Work

1. The developed algorithms for composite power system reliability assessment can be enhanced for more efficient applications to large power systems. Some of these enhancements can be:

   i. Representing generation units at each PV bus by using the capacity outage table instead of representing each generation unit separately. This will result in representing a system state by less number of genes. This could significantly decreases the computational effort.

   ii. The use of parallel computations with GA sampling. This can be achieved by dividing the state space into several non-overlapping partitions construction the state array for each part separately.

   iii. When the chromosome length is larger than 50 genes, it will not be practical to use only one decimal number equivalent to the state binary number. A better approach is dividing the chromosome into two or more parts and an equivalent decimal number is calculated for each part. In this case, each state is identified by more than one decimal number.

2. The use of ac load flow equations instead of using dc load flow equations in the state evaluation module. This requires much more computational effort but will result in more realistic reliability indices for certain applications. Voltage level and reactive power will be considered when judging if a sampled state represents a failure or a success state.

3. Developing new methods that consider the effect of deregulation on power systems reliability. This could be achieved as follows:

   i. Developing more sophisticated models for power system components. These models should take into consideration operation constraints under the deregulation environment.

   ii. Developing state evaluation models that take into consideration power transaction contracts between different entities in the restructured power market.

4. Enhancing the GA sampling process. This can be done through:
   i. The use of different kinds of fitness functions for the GA sampling. A better fitness function will enhance the search process. It is also possible to use fitness functions that give a snap shot of the state space, e.g., the effect of certain group of transmission lines on composite system reliability.
   ii. There are many other GA operators that can be used other than the one used in this dissertation. It is possible that some of them could accomplish better search.
   iii. The use of adaptive values for the probability of mutation and the probability of crossover

6. Other potential extensions for the GAGFC methodology are:
   i. Implementing other load curtailment techniques using the GAGFC. It can also be modified to represent the state evaluation as a multi-objective optimization problem. One possible policy is to minimize both load curtailment and the interruption cost in the same time.
   ii. Applying the GAGFS to solve ac equations based state evaluation models.

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# APPENDIX A

## THE RBTS TEST SYSTEM DATA

The RBTS system has been developed by the power system research group at the University of Saskatchewan [26]. The basic RBTS system data necessary for adequacy evaluation of the composite generation and transmission system is given in this appendix.

The single line diagram of the RBTS test system is shown in Fig. 7. The system has 2 generator (PV) buses, 4 load (PQ) buses, 9 transmission lines and 11 generating units. The minimum and the maximum ratings of the generating units are 5MW and 40MW respectively. The voltage level of the transmission system is 230 kV and the voltage limits for the system buses are assumed to be 1.05 p.u. and 0.97 p.u. The system peak load is 185 MW and the total installed generating capacity is 240 MW.

The annual peak load for the system is 185 MW. The load at each bus will be considered fixed at its maximum value. The peak load at each bus is as given in Table XXXIII. It has been assumed that the power factor at each bus is unity.

The generating units rating and reliability data for the RBTS are given in Table XXXIV.

The transmission network consists of 6 buses and 9 transmission lines. The transmission voltage level is 230 kV. Table XXXV gives the basic transmission lines reliability data. The permanent outage rate of a given transmission line is obtained using a value of 0.02 outages per year per kilometer. The current rating is assumed on 100 MVA and 230 kV base.

Table XXXIII. RBTS System Load Data

| Bus number | Maximum load (MW) | User type |
|---|---|---|
| 1 | 0 | ----- |
| 2 | 20 | Small users |
| 3 | 85 | Large users &small users |
| 4 | 40 | Small users |
| 5 | 20 | Small users |
| 6 | 20 | Small users |

Table XXXIV. RBTS Generating System Data

| Unit size (MW) | Type | No. of units | Installed at bus no. | Forced Outage Rate |
|---|---|---|---|---|
| 5 | Hydro | 2 | 2 | 0.01 |
| 10 | Thermal | 1 | 1 | 0.02 |
| 20 | Hydro | 4 | 2 | 0.015 |
| 20 | Thermal | 1 | 1 | 0.025 |
| 40 | Hydro | 1 | 1 | 0.02 |
| 40 | Thermal | 2 | 2 | 0.03 |

Table XXXV. Transmission Lines Lengths and Outage Data

| Line no. | Buses | | Length (km) | Permanent outage rate λ(per year) | Outage duration (hours) | Current rating (p.u.) |
|---|---|---|---|---|---|---|
| | From | To | | | | |
| 1 | 1 | 3 | 75 | 1.5 | 10 | 0.85 |
| 2 | 2 | 4 | 250 | 5 | 10 | 0.71 |
| 3 | 1 | 2 | 200 | 4 | 10 | 0.71 |
| 4 | 3 | 4 | 50 | 1 | 10 | 0.71 |
| 5 | 3 | 5 | 50 | 1 | 10 | 0.71 |
| 6 | 1 | 3 | 75 | 1.5 | 10 | 0.85 |
| 7 | 2 | 4 | 250 | 5 | 10 | 0.71 |
| 8 | 4 | 5 | 50 | 1 | 10 | 0.71 |
| 9 | 5 | 6 | 50 | 1 | 10 | 0.71 |

# VITA

Nader Amin Aziz Samaan received the B.S. and M.S. degrees in electrical engineering from the University of Alexandria, Alexandria, Egypt, in 1996 and 1999, respectively. Since January 2000, he has been with Texas A&M University, working towards his Doctor of Philosophy degree in electrical engineering. During his Ph.D. program, he worked as Graduate Research Assistant and Graduate Teaching Assistant. His research interests include power system reliability, probabilistic methods in power systems, distributed generation, micorgrid power networks, and artificial intelligence and intelligent optimization techniques application to power systems.

Nader Amin Aziz Samaan received a Texas A&M Electric Power and Power Electronics Institute Fellowship in 2000 and 2003. He has been a fellow of the Texas A&M Graduate Teaching Academy since April 2003. He is also a student member of IEEE and a member of the Phi Kappa Phi honor society.

His e-mail address is: nasamaan@ieee.org

His permanent address is:

23 Kordahy St., Apt. 4
Roushdy
Alexandria
Egypt