Artificial Immune System Based Reliability Appraisal Methodology of Power Generation Systems with Wind Power Penetration

Lingfeng Wang, *Student Member, IEEE* and Chanan Singh, *Fellow, IEEE*

Department of Electrical and Computer Engineering
Texas A&M University
College Station, TX 77843-3128
Emails: l.f.wang@ieee.org, singh@ece.tamu.edu

***Abstract*— Reliability appraisal of power-generating system is an effective measure to ensure proper system operations in the face of various uncertainties such as equipment failures and variations of generation and load. The integration of time-dependent sources such as wind turbine generators (WTGs) makes the reliability evaluation process more challenging. Due to the large number of system states involved in a power-generating system, it is normally not feasible to enumerate all possible failure states to calculate the reliability indices. Thus, some metaheuristics-based search algorithms, through their inherent convergence mechanisms, appear promising to find out the most meaningful system states within reasonable time. In this paper, an artificial immune system (AIS) based optimization procedure called CLONALG is adopted to assess the power-generating system adequacy including wind power integration. The most probable failure states are searched out by CLONALG and they contribute most significantly to the adequacy indices including loss of load expectation (LOLE), loss of load frequency (LOLF), and expected energy not supplied (EENS). A modified IEEE Reliability Test System (IEEE-RTS) is used to verify the applicability and validity of the proposed approach.**

I. Introduction

Probabilistic methods are now being used more widely in power system operations and planning due to a variety of uncertainties involved. For instance, adequacy assessment is an important component to ensure the proper operations of power system. Different adequacy indices are defined to evaluate the existence of sufficient facilities within the system to satisfy load demand as well as system operational constraints. Power generation system adequacy relates to the facilities necessary to generate sufficient energy in the presence of different uncertainties. More recently, wind power has attracted much attention as it does not consume depleting fossil fuels and it is also environmentally friendly. However, due to the intermittency of wind power availability, the reliability issue should be addressed when integrating the wind power into the traditional power grid. The fluctuation of wind power during different time periods should be considered since it may compromise the power system reliability.

The work reported in this paper was partially supported by The National Science Foundation (Grant No. ECS0406794: Exploring the Future of Distributed Generation and Micro-Grid Networks).

In today's power-generating systems, the number of generating units has become large. Inevitably, adequacy assessment of power systems becomes more challenging due to their larger scale and increasing complexity. Thus, in adequacy assessment, exhaustive enumeration is usually impractical due to an innumerable number of system states. To solve the problem, in this study artificial immune system (AIS) is used to find out a set of probable failure states, which contribute most significantly to the entire system adequacy indices. AIS is based on the guided stochastic search inspired by biological immune systems (BIS) [2]. In this study, based on its optimization mechanism, AIS is used to scan and find out a set of most probable failure states which contribute considerably to system reliability indices. Like genetic algorithm (GA) [5], AIS is also a population-based stochastic search algorithm. Instead of attempting to find a single optimal or near-optimal solution, AIS here is used as a search tool to find a set of eligible solutions due to this feature. Based on the system states derived by AIS, adequacy indices including loss of load expectation (LOLE), loss of load frequency (LOLF), and expected energy not supplied (EENS) are subsequently calculated. An IEEE Reliability Test System (IEEE-RTS) is modified by incorporating multiple wind turbine generators (WTGs) in order to demonstrate the applicability and effectiveness of the proposed evaluation procedure.

The remainder of the paper is organized as follows. Section II presents some calculation fundamentals of adequacy evaluation for hybrid power-generating systems. In Section III, the proposed AIS-based evaluation procedure is discussed in detail. Simulation results and analysis are fleshed out in Section IV. Finally, the paper wraps up with some conclusions and future work suggestions.

II. Reliability Evaluation of Hybrid Generating Systems

The reliability analysis of hybrid generating systems including time-dependent sources has been investigated by several researchers in an analytical fashion [4], [10], [11]. These proposed reliability evaluation techniques are usually intended to calculate reliability indices including EENS, LOLE, and LOLF, which are three fundamental indices for adequacy assessment of generating systems.

The load demand is represented as a chronological sequence of N_T discrete load values P_{d_t} for successive time steps $t = 1, 2, \ldots, N_T$. Each time step has equal duration $\Delta T = \frac{T}{N_T}$ where T is the entire period of observation. The general expressions for calculating the three indices are as follows:

$$EENS = \Delta T \sum_{t=1}^{N_T} U_t \tag{II.1}$$

where U_t is the unserved load during the time step t and it can be calculated by

$$U_t = \sum_{X_t > X_{cco_t}} (X_t - X_{cco_t}) P(X_t) \tag{II.2}$$

where X_t is the total capacity outage at time instant t, $P(X_t)$ is the probability that a system capacity outage occurs exactly equal to X_t, X_{cco_t} is the critical capacity outage at time instant t:

$$X_{cco_t} = P_{g_t} + P_{w_t} - P_{d_t} \tag{II.3}$$

In the above definition, the term $P_{g_t} + P_{w_t}$ indicates the effective total system capacity (that is, the summation of conventional sources of power P_g and wind power P_w) at time instant t provided that all the units are available, P_{d_t} is the load demand in period t. When $X_t > X_{cco_t}$, capacity deficiency occurs.

$$LOLE = \frac{\Delta T}{T} \sum_{t=1}^{N_T} LOLP_t \tag{II.4}$$

where $LOLP_t$ is the loss of load probability during hour t;

$$LOLF = \frac{\Delta T}{T} \sum_{t=1}^{N_T} (F_t^d + F_t^c + F_t^u) \tag{II.5}$$

where F_t^d is the frequency component caused by the load variation and fluctuation in the intermittent sources; and F_t^c and F_t^u are components of frequency due to interstate transitions in conventional and unconventional sources of power.

III. Optimization Version of AIS: CLONALG

The biological immune system (BIS) is a complex adaptive pattern-recognition system which defends the mammalian body from foreign pathogens such as viruses and bacteria. From the computational viewpoint, it is a parallel and distributed adaptive system and it uses learning, memory, and associative retrieval mechanisms to handle challenging problems including pattern classification. Artificial immune system (AIS) is inspired from its natural counterpart BIS, and some computational models are built based on corresponding biological mechanisms [2]. Besides the machine learning and pattern recognition tasks, AIS can also be used for accomplishing complex optimization tasks. An optimization procedure called CLONALG is proposed to handle the optimization problems based on the clonal selection principle [3]. It is based on the idea that only the cells that recognize the antigens are selected to proliferate and the selected cells proceed with an affinity maturation process which increases their affinity to the selective antigens. Its major features include: 1) Selection and cloning of the most stimulated antibodies (Ab's); 2) Elimination of nonstimulated Ab's; 3) affinity maturation; 4) reselection of the clones proportionally to their antigenic affinity; 5) creation and maintenance of population diversity.

In AIS, an Ab repertoire ($\mathbf{Ab}$) is exposed to an antigenic (Ag) stimulus (in our context $\mathbf{Ab}$ stands for the set of potential solutions and Ag refers to an objective function to be optimized) and those higher affinity Ab's will be chosen to create a population of clones. During proliferation, a few Ab's will experience somatic mutation proportional to their antigenic affinities. Low-affinity Ab's are placed through simulating the process of receptor editing. The CLONALG carries out its search through somatic mutation and receptor editing, which is intended to balance the exploitation of the best solutions with the exploration of entire search space. It reproduces those individuals with higher affinity, performing blind variation and keeping improved maturated progenies. CLONALG conducts a kind of greedy search, where single members are optimized locally and newcomers perform a wider search in the whole solution space.

Assume the population size of Ab's is N and the length of each Ab is L. The nomenclature used in the computational iteration is listed in the following:

- $\mathbf{Ab}_{\{N\}}$: Available Ab repertoire ($\mathbf{Ab}_{\{N\}} \in S^{N \times L}$).
- $\mathbf{Ab}_{\{n\}}$: Ab's from $\mathbf{Ab}$ with the highest affinities to Ag ($\mathbf{Ab}_{\{n\}} \in S^{n \times L}$, $n \leq N$).
- $\mathbf{Ab}_{\{d\}}$: Set of d new Ab's that will replace d lowest affinity Ab's from $\mathbf{Ab}_{\{N\}}$ ($\mathbf{Ab}_{\{d\}} \in S^{d \times L}$, $d \leq N$).
- $\mathbf{f}$: Vector containing the affinity of all Ab's with respect to the antigen ($\mathbf{f} \in \Re^N$).
- $\mathbf{C}$: Population of N_c clones generated from $\mathbf{Ab}_{\{n\}}$ ($\mathbf{C} \in S^{N_c \times L}$). After the maturation (i.e., hypermutation) process, the population $\mathbf{C}$ is termed as $\mathbf{C}^*$.

The basic computational iteration of CLONALG is laid out as follows [3]:

- The objective function and its associated constraints are treated as the antigen Ag, and its feasible solutions are deemed as N antibodies $\mathbf{Ab}_{\{N\}}$.
- Determine the vector $\mathbf{f}$ that contains the affinity of Ag to all the N Ab's in $\mathbf{Ab}$.
- Select the n highest affinity Ab's from $\mathbf{Ab}$ to constitute a new set $\mathbf{Ab}_{\{n\}}$ of high affinity Ab's with respect to Ag.
- The n selected Ab's are cloned independently and proportionally to their antigenic affinities, generating a repertoire $\mathbf{C}$ of clones: the higher the antigenic affinity, the higher the number of clones generated for each of the n selected Ab's.
- The repertoire $\mathbf{C}$ is continued with an affinity maturation process inversely proportional to the antigenic affinity, generating a population $\mathbf{C}^*$ of matured clones: the higher the affinity, the smaller the mutation rate.
- Determine the affinity $\mathbf{f}^*$ of the matured clones $\mathbf{C}^*$ with respect to antigen Ag.
- From this set of matured clone $\mathbf{C}^*$, reselect n Ab's to compose the set ($\mathbf{Ab}$).
- Replace the d lowest affinity Ab's from $\mathbf{Ab}_{\{N\}}$ with

respect to Ag by new individuals in $\mathbf{Ab}_{\{d\}}$.

In running the algorithm, the stopping criterion is a predefined maximum number of iterations.

IV. AIS-based Adequacy Evaluation

In CLONALG, each antibody comprised of a set of attributes is deemed a potential solution. Here binary coding scheme is used to represent each antibody, where each bit (attribute) takes one or zero to indicate the generator state. "One" and "zero" represent the working and failed status of each generator, respectively. Since there may be several groups of identical generators used in terms of generator types (conventional or wind turbine generators), generator capacities, and reliability parameters, all of these generators are grouped accordingly to reduce computational cost. Assume the generators are divided into n groups, where each group is composed of states of single or multiple generators, which are represented by binary numbers. In this way, multiple binary bits are used in the antibody to indicate various generation combinations. The target problem is concerned with combinatorial optimization, and its objective is to find out the failure state array which can be used to calculate different adequacy indices. The configuration of each antibody can be illustrated as in Figure 1. All the generators involved are divided into n groups and each bit indicates the corresponding generator condition (i.e., working or failure status).

G_1	G_2	....	G_{n-1}	G_n
C_1........C_{G1}	C_{G1+1}........C_{G2}	....	........C_{mg}	U_1........U_{mw}

Fig. 1. Antibody representation.

The adopted scheme is extended from a two-stage method proposed in [8] by incorporating the intermittent wind power. There are two major stages in the procedure: First the failure-state array with respect to the maximum load demand is derived using CLONALG, and then reliability indices are calculated by convoluting the effective total capacity with the hourly load based on the state array achieved previously. The computational flow of the proposed evaluation procedure is laid out in the following:

- Step 1: Generate a population of antibodies randomly. The states of both conventional generators and WTGs are initialized by binary numbers.
- Step 2: Evaluate each antibody i based on the defined objective function ($LOLP$ with respect to the maximum load demand L_{max}). If its value is less than the specified LOLP threshold (a small LOLP value below which the corresponding states are filtered out), it is assigned a very small fitness value in order to reduce its chance in participating subsequent immunological operations. Based on the attained state array, the overall system LOLP against the maximum load demand is calculated. The objective value of state i is calculated as follows:
  - Calculate the effective generating capacity of state i including WTGs:
$$Cap_{i,max} = \sum_{j=1}^{m_g} c_j g_j + \sum_{j=1}^{m_w} u_j w_r \qquad \text{(IV.6)}$$
    where m_g is the number of conventional generators; c_j indicates the state of conventional generator j; g_j is the capacity of generator j; m_w is the number of WTGs; u_j indicates the state of WTG j; w_r is the rated power capacity of WTG. Here if the capacity $Cap_{i,max}$ is larger than the maximum load demand L_{max}, the fitness of its corresponding antibody is assigned a very small value so as to reduce its chance to contribute to the next generation, since it represents a success state. The rated WTG capacity is used here in order to ensure that all possible failure states are included for further evaluations.
  - The failure probability of state i can be calculated as follows:
$$P_i = \prod_{j=1}^{m} p_j \qquad \text{(IV.7)}$$
    where $m = m_g + m_w$ is the total number of conventional and unconventional generators, p_j can take one of the following two values: for the conventional units, if $c_j = 1$, then $p_j = 1 - FOR_j$; and if $c_j = 0$, then $p_j = FOR_j$. In a similar manner, for WTGs, if $u_j = 1$, then $p_j = 1 - FOR_j$; and if $u_j = 0$, then $p_j = FOR_j$. FOR_j represents the forced outage rate (FOR) of generator j. The probability of each generator down equals to its FOR. Also note that only full outages are considered in this investigation.
  - Calculate the number of all possible permutations (i.e., duplicates) of the evaluated state i:
$$Copy_i = \binom{G_1}{O_1} \cdots \binom{G_j}{O_j} \cdots \binom{G_n}{O_n} \qquad \text{(IV.8)}$$
    where O_j is the number of "ones" in group j of length G_j.
  - The fitness of this state is
$$Fit_i = Copy_i * P_i \qquad \text{(IV.9)}$$
    It is the objective function to be maximized by the AIS-based optimizer CLONALG. The fitness is indicated by the affinity values for Ab's (potential solutions) and Ag (objective function).
  - Frequency of this state can be calculated as follows [7], [9]:
$$F_i = P_i * (\sum_{j=1}^{m} (1 - b_j)\mu_j - \sum_{j=1}^{m} b_j \lambda_j) \qquad \text{(IV.10)}$$
    where b_i indicates the generator state; μ_j and λ_j are repair rate and failure rate of generator j, respectively.
  - Save information on eligible states including P_i, F_i, and $Copy_i$, which will be used in subsequent calculations.

– Repeat the above procedure for the remaining antibodies until all of them are evaluated. Before each evaluation, the configuration of antibody under consideration will be checked to ensure it is not the duplicate of any previously evaluated ones. If it is a previously evaluated state, its affinity will be assigned a very small number in order to make it die off very soon in the following optimization operations.

- Step 3: Increase the iteration number by one;
- Step 4: Check if any stopping criterion is met. If yes, halt the algorithm and output the state array derived. If no, go to next step.
- Step 5: Different immunological operators including clone and hypermutation are applied for producing the next generation, and then repeat the procedure from Step 2 to Step 4 until any stopping criterion is satisfied.
- Step 6: Calculate the adequacy indices based on the achieved state array. Due to the time-dependent nature of wind power, the total effective generating capacity of state i at hour t should be calculated as follows:

$$Cap_{i,t} = \sum_{j=1}^{m_g} c_j g_j + \sum_{j=1}^{m_w} u_j w_j \quad \text{(IV.11)}$$

where w_j is the actual output of WTG j at hour t. It can be calculated by $w_j = \alpha_t * w_r$, where α_t is the ratio of WTG output at hour t with respect to the rated WTG power capacity, and this derating factor is used to calculate the effective WTG output during hour t. If $Cap_{i,t}$ is larger than or equal to the load demand L_t at hour t, it is in fact a success state and will not be accounted for in calculating reliability indices; Or else, it will be included in subsequent calculations.

$$LOLP_t = \sum_{j=1}^{sn} S_j * P_j * Copy_j \quad \text{(IV.12)}$$

where sn is the number of failure states attained previously. S_j is a flag indicating if the loss of load occurs at hour t for state j: it is zero when $Cap_{i,t} \geq L_t$; otherwise it is set as one. The value of sn may be smaller than the total number of states obtained at the first stage, since some of the states may become success ones at different time periods due to the variations of both loads and derating factors. LOLE in hours during the observation horizon T can be calculated as follows:

$$LOLE = \sum_{t=1}^{N_T} LOLP_t \quad \text{(IV.13)}$$

The expected energy not supplied (EENS) in megawatts hour can be calculated as follows:

$$EENS = \sum_{t=1}^{N_T} PNS_t \quad \text{(IV.14)}$$

where PNS_t is the power not supplied for hour t:

$$PNS_t = \sum_{j=1}^{sn} S_j * P_j * Copy_j * (L_t - Cap_{j,t}). \quad \text{(IV.15)}$$

LOLF includes two components: frequency of generating capacity "FG" and frequency due to load change "FL".

$$FG = \sum_{t=1}^{N_T} LOLF_t \quad \text{(IV.16)}$$

where $LOLF_t$ is the loss of load frequency at hour t:

$$LOLF_t = \sum_{j=1}^{sn} S_j * F_j * Copy_j; \quad \text{(IV.17)}$$

$$FL = \sum_{t=2}^{N_T} V_t * [LOLP_t - LOLP_{t-1}] \quad \text{(IV.18)}$$

where V_t is zero if the value between brackets is negative, and otherwise it equals to one.

The LOLF in occurrences during the observation horizon T is calculated as

$$LOLF = FG + FL. \quad \text{(IV.19)}$$

Furthermore, based on the state array achieved, the contribution of each system state to the total system adequacy becomes clear. And capacity outage table can be also built from it. Another advantage of this approach is that as long as the actual peak load is not larger than the one used for deriving the state array, the state array achieved can always be used for calculating the actual adequacy indices for various scenarios with different peak loads.

V. Simulations and Evaluation

An IEEE Reliability Test System (IEEE RTS-79) is used in simulations [6]. It has 24 buses (10 generation buses and 17 load buses), 38 lines and 32 generating units. The system annual peak load is 2850 MW. The total installed generating capacity is 3405 MW. In this study, one unconventional subsystem comprising of multiple identical WTGs is added to the RTS [4]. Each WTG has an installed capacity of 1 MW, a mean up time of 190 hours and a mean down time of 10 hours. The hourly derating factors for WTG output can be found in [4]. Reliability indices are calculated for a time span of one week and the load cycle for week 51 with peak load 2850 MW, low load 1368 MW and weekly energy demand 359.3 GWh. Different wind power penetration levels are examined by incorporating three installed wind power capacities of 100 MW, 200 MW, and 400 MW.

There are totally 300 antibodies in the search space. In determining the mutation rate, clones are first sorted by their affinity values in the descendent order. The mutation operator is applied using a small value initially and then it is increased until a prespecified destination value is reached. The initial mutation rate is $1/L$, where L is the length of the binary string. The destination value is set as 0.32. Other CLONALG parameters used in simulations are listed in Table I.

For different levels of wind power penetration, system adequacy indices obtained using the exact and proposed methods are listed from Table II to Table IV. The computation time shown is in unit of seconds. We can find that the solutions derived by AIS are comparable to the exact ones with a shorter

TABLE I

CLONALG PARAMETERS

Population size	300
Mutation type	Uniform
Hypermutation rate	0.05
Percentage d	0.20
Max. No. of generations	100

time. As the penetration level increases, the computation efficiency of the proposed method becomes a more evident advantage in relation to the analytical method. For comparison with other approximation method, a clustering method is used to calculate the EENS [4]. It uses fixed margin incremental 10 MW and clustering with the nearest centroid sorting algorithm. The number of clusters is set as 80. The EENSs derived are 207.7 MWh, 159.2 MWh, and 98.9 MWh for integrated wind power capacities of 100 MW, 200 MW, and 400 MW, respectively. The results of the proposed method and clustering method are comparable, with the proposed method having slightly higher accuracy.

TABLE II

RELIABILITY INDICES FOR UNCONVENTIONAL CAPACITY 100 MW.

Method	LOLE	EENS	LOLF	Time
CLONALG	1.487879	207.740	0.310563	6.8
Exact method [4]	1.487951	207.902	0.310602	8.4

TABLE III

RELIABILITY INDICES FOR UNCONVENTIONAL CAPACITY 200 MW.

Method	LOLE	EENS	LOLF	Time
CLONALG	1.185601	159.223	0.258264	12.4
Exact method [4]	1.185692	159.402	0.258305	16.5

TABLE IV

RELIABILITY INDICES FOR UNCONVENTIONAL CAPACITY 400 MW.

Method	LOLE	EENS	LOLF	Time
CLONALG	0.789768	98.912	0.193229	22.7
Exact method [4]	0.789840	99.085	0.193275	29.9

The growth of adequacy indices with the increase of generation number for the wind power penetration level of 400 MW is shown in Table V. Since more system states are evolved as the optimization process proceeds, the solutions will become more accurate with more iterations. Thus, there should be a tradeoff between computational cost and solution accuracy. Here the stopping criterion used is the maximum iteration number, which is set to 100. It turns out to be a reasonable number since comparable results are obtained by this generation.

In summary, the proposed method primarily has the following advantages.

- The contribution of each system state to the overall adequacy indices can be calculated and identified. This feature is important when a sensitivity study is desired to determine system states which have the most significant impact on the entire system reliability.

TABLE V

GROWTH OF RELIABILITY INDICES WITH THE INCREASING GENERATIONS.

Generations	LOLE	EENS	LOLF
25	0.238932	29.980	0.040023
50	0.476673	60.006	0.099963
75	0.688923	81.334	0.148930
100	0.789768	98.912	0.193229

- The state array derived by the evaluation procedure may be reused for different load levels. As long as the actual peak load is smaller than the peak load used to derive the state array, the state array can be used to calculate reliability indices for different load demands. Moreover, the second-stage evaluation procedure can be generically used to calculate reliability indices for any set of failure states provided.
- The computation time is not considerably affected by the system reliability characteristics. In Monte Carlo simulations [1], longer time is needed to achieve simulation convergence with higher system reliability.
- The parallel or distributed computation can be accomplished simply using partitioning based on the probabilities or load demands [8].
- The computation time is reduced in evaluating scenarios where a large number of power sources with relatively small capacities are involved. For methods which need the construction of capacity outage table, it takes more time to build the outage table by incorporating the state of each WTG, which, however, has no significant impact on the entire system reliability if only one unit outage is considered each time. The optimization mechanism of AIS makes system states related to these small capacity additions die off or reproduce very fast and thus considerably reduces the computation expense required.
- The method can be generally used in adequacy evaluation for power-generating systems with and without time-dependent sources. Furthermore, it has no inherent limitations in dealing with larger-size systems due to its outstanding convergence performance. This is in actuality one salient merit of this population-based stochastic search approach. On the contrary, most analytical methods become much less efficient or even unable to resolve the problem as the system complexity and size increase.

VI. CONCLUDING REMARKS

Reliability appraisal of power-generating systems including wind power penetration is a challenging task to accomplish due to innumerable system states involved. In this paper, an artificial immune system based optimization procedure called CLONALG is used to find out a set of meaningful system failure states, which can then be used to calculate the three fundamental reliability indices. The method is shown to be able to achieve comparable results in relation to the exact method and appears to be more efficient than the clustering method. Some comparative work with respect to other population-based search methods is needed to fully investigate its advantages and limitations. Besides its optimization function, artificial immune system is also highly suitable for accomplishing complex pattern recognition tasks. It has shown superior performance in many pattern recognition applications over other pattern recognizers such as neural networks. In our future work, we intend to use AIS as a pattern classification tool to recognize eligible system states which can be used for reliability appraisal.

REFERENCES

[1] Billinton, R. and Li, W. (1994). *Reliability Assessment of Electric Power Systems Using Monte Carlo Methods*, New York: Plenum Press.

[2] de Castro, L. N. and Timmis, J. (2002). *Artificial Immune Systems: A New Computational Intelligence Approach*, London: Springer.

[3] de Castro, L. N. and Von Zuben, F. J. (2002). Learning and optimization using the clonal selection principle, *IEEE Transactions on Evolutionary Computation*, Vol. 6, No. 3, June, pp. 239–251.

[4] Fockens, S., van Wijk, A. J. M., Turkenburg, W. C., and Singh, C. (1992). Reliability analysis of generating systems including intermittent sources, *International Journal of Electric Power & Energy Systems*, Vol. 14, No. 1, pp. 2–8.

[5] Goldberg, D. E. (1989). *Genetic Algorithm in Search, Optimization, and Machine Learning*, Reading, MA: Addison-Wesley.

[6] IEEE Committee Report (1979). IEEE reliability test system, *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-98, No. 6, pp. 2047–2054.

[7] Melo, A. C. G., Pereira, M. V. F., and Leite da Silva, A. M. (1993). A conditional probability approach to the calculation of frequency and duration in composite reliability evaluation, *IEEE Transactions on Power Systems*, Vol. 8, No. 8, pp. 1118–1125.

[8] Samaan, N. and Singh, C. (2002). Adequacy assessment of power system generation using a modified simple genetic algorithm, *IEEE Transactions on Power Systems*, Vol. 17, No. 4, pp. 974–981.

[9] Singh, C. (1981). Rules for calculating the time-specific frequency of system failure, *IEEE Transactions on Reliability*, Vol. R-30, pp. 364–366.

[10] Singh, C. and Kim, Y. (1988). An efficient technique for reliability analysis of power systems including time dependent sources, *IEEE Transactions on Power Systems*, Vol. 3, No. 3, pp. 1090–1094.

[11] Singh, C. and Lago-Gonzalez, A. (1985). Reliability modeling of generation systems including unconventional energy sources, *IEEE Transactions on Power Apparatus & Systems*, Vol. PAS-104, No. 5, pp. 1049–1056.