Genetic Algorithm Based Adequacy Evaluation of Hybrid Power Generation System Including Wind Turbine Generators

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Abstract—The adequacy of power generation should be properly evaluated to facilitate the reliable operations of power systems under uncertainties. More recently, wind power has attracted significant attention primarily because it does not consume fossil fuels and is environmentally benign. However, the output from wind turbine generator (WTG) cannot be precisely predicted due to the intermittent nature of wind resources. In this paper, a genetic algorithm (GA) based search procedure is adopted to accomplish the adequacy assessment for power generating system including wind turbine generators. The most probable failure states are sought out, which contribute significantly to the adequacy indices including loss of load expectation (LOLE), load 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 effectiveness 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 primarily since it does not consume depleting fossil fuels and 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.

In power-generating systems nowadays, 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 incurred. To solve the problem, in this study genetic algorithm (GA) is used to find out a set of probable failure states, which contribute most significantly to the entire system adequacy indices. Genetic algorithm is based on the guided stochastic search inspired by natural evolution, and it has turned out to be quite useful in truncating the solution space and thus reducing resultant computational effort. Unlike most GA applications for achieving optimal or near-optimal solutions, in this study, GA is used to find out a set of most probable failure states which contributes considerably to system reliability indices. GA here is used as a pattern classifier instead of a pure optimizer due to its nature of population-based search. Based on the system states derived by GA, the adequacy indices including loss of load expectation (LOLE), load 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 fundamentals of adequacy evaluation for hybrid power-generating systems. In Section III, the proposed GA-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 [2], [9], [10]. These proposed reliability evaluation techniques are usually intended to calculate the 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 $P_{dt}$ 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:

\[
EENS = \Delta T \sum_{t=1}^{N_T} U_t \quad \text{(II.1)}
\]
where $U_t$ is the unserved load during the time step $t$ and it can be calculated by

$$U_t = \sum_{X_t > X_{cco}} (X_t - X_{cco})P(X_t) \quad \text{(II.2)}$$

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 $X_t$, $X_{cco}$, is the critical capacity outage at time instant $t$:

$$X_{cco} = P_{g_t} + P_{w_t} - P_{d_t} \quad \text{(II.3)}$$

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 $X_t > X_{cco}$, capacity deficiency occurs.

$$LOLE = \Delta T \sum_{t=1}^{N_T} LOLP_t \quad \text{(II.4)}$$

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

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

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. GA-BASED ADEQUACY EVALUATION

Conventional derivative-based optimization methods are effective in resolving “smooth,” i.e., continuous and differentiable problems, since they deploy derivatives to determine the direction of descent. However, derivative-based methods are often ineffective in dealing with problems lacking of smoothness, for instance, the problems with discontinuous, nondifferentiable, or stochastic objective functions. Genetic Algorithm (GA) is a population-based stochastic search procedure inspired by natural evolution [3]. GA has turned out to be an effective alternative for this kind of “nonsmooth” problems. Another reason for adopting GA in this study is due to the large scale of solution space. The inherent directed search mechanism of GA helps to achieve outstanding convergence performance by truncating the solution space and avoiding inferior solutions.

In GA, each chromosome is deemed a potential solution. Here binary coding scheme is used to represent each chromosome, where each bit 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 chromosome 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 chromosome 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).

![Chromosome representation](image1)

The adopted scheme is extended from a two-stage method proposed in [6] 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 GA, and then the 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 chromosomes randomly. The states of both conventional generators and WTGs are initialized by binary numbers.
- **Step 2**: Evaluate each chromosome $i$ 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 genetic 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:

$$\text{Cap}_{i,\text{max}} = \sum_{j=1}^{m_g} c_j g_j + \sum_{j=1}^{m_w} u_j w_r \quad \text{(III.6)}$$

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 $\text{Cap}_{i,\text{max}}$ is larger than the maximum load demand $L_{max}$, the fitness of its corresponding chromosome 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:

\[ P_i = \prod_{j=1}^{m} p_j \]  

(III.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 \( i \):

\[ Copy_i = \left( \frac{G_1}{O_1} \right) \ldots \left( \frac{G_l}{O_l} \right) \ldots \left( \frac{G_n}{O_n} \right) \]  

(III.8)

where \( O_j \) is the number of “ones” in group \( j \) of length \( G_j \).

- The fitness of this state is

\[ Fit_i = Copy_i \times P_i \]  

(III.9)

It is the objective function to be maximized by the GA-based optimizer.

- Frequency of this state can be calculated as follows [5], [7]:

\[ F_i = P_i \times (\sum_{j=1}^{m} (1 - b_j)\mu_j - \sum_{j=1}^{m} b_j\lambda_j) \]  

(III.10)

where \( b_j \) indicates the generator state; \( \mu_j \) and \( \lambda_j \) 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 chromosomes until all of them are evaluated. Before each evaluation, the configuration of chromosome 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 fitness will be assigned a very small number in order to make it die off very soon in the following genetic operations.

- Step 3: Increase the generation 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 genetic operators including selection, crossover, and mutation 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:

\[ Cap_{i,t} = \sum_{j=1}^{m_g} c_j g_j + \sum_{j=1}^{m_w} u_j w_j \]  

(III.11)

where \( w_j \) is the actual output of WTG \( j \) at hour \( t \). It can be calculated by \( w_j = \alpha_t \times w_{jr} \), where \( \alpha_t \) 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 the subsequent calculations.

\[ LOLP_t = \sum_{j=1}^{sn} S_j \times P_j \times Copy_j \]  

(III.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 per year can be calculated as follows:

\[ LOLE = \sum_{t=1}^{8760} LOLP_t \]  

(III.13)

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

\[ EENS = \sum_{t=1}^{8760} PNS_t \]  

(III.14)

where \( PNS_t \) is the power not supplied for hour \( t \):

\[ PNS_t = \sum_{j=1}^{sn} S_j \times F_j \times Copy_j \times (L_t - Cap_{j,t}) \]  

(III.15)

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

\[ FG = \sum_{t=1}^{8760} LOLF_t \]  

(III.16)

where \( LOLF_t \) is the loss of load frequency at hour \( t \):

\[ LOLF_t = \sum_{j=1}^{sn} S_j \times F_j \times Copy_j \]  

(III.17)

\[ FL = \sum_{t=2}^{8760} V_t \times [LOLP_t - LOLP_{t-1}] \]  

(III.18)

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

The LOLF in occurrences per year is calculated as

\[ LOLF = FG + FL \]  

(III.19)
Furthermore, based on the state array achieved, the contribution of each system state to the total system adequacy is 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.

IV. SIMULATIONS AND EVALUATION

The GA parameters used in the simulations are listed in Table I. There are totally 300 chromosomes in the mating pool.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>GA PARAMETERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>300</td>
</tr>
<tr>
<td>Fitness scaling</td>
<td>Rank</td>
</tr>
<tr>
<td>Elite count</td>
<td>2</td>
</tr>
<tr>
<td>Selection function</td>
<td>Stochastic uniform</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>0.05</td>
</tr>
<tr>
<td>Crossover rate</td>
<td>0.6</td>
</tr>
<tr>
<td>Max. No. of generations</td>
<td>100</td>
</tr>
</tbody>
</table>

There are three stopping criteria that may be used in GA for the target problem. That is, the maximum number of generations, the maximum number of system failure states scanned, and the threshold indicating the failure probability of supplying the maximum load within a certain number of generations. Here the stopping criterion used is the maximum iteration number, which is set as 100. This stopping criterion may lead to inaccurate results due to insufficient failure states sampled. After some tuning, we found 100 is a suitable number of generations to achieve reasonably accurate results in relation to other methods.

A WTGs-augmented IEEE Reliability Test System (IEEE RTS-79) is used in simulations [4]. The original RTS has 24 buses (10 generation buses and 17 load buses), 38 lines and 32 conventional 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. 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 [2]. 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.

For peak load of 2850 MW with wind power penetration, the system adequacy indices obtained using the exact method [2], MCS, and GA are listed from Table II to Table IV. The units of LOLE, EENS, and LOLF are h/week, MWh, and occ./week, respectively. The time is in seconds. Here GA is used to derive the meaningful system states. The population size is set 300. We can see that the performance of MCS is somehow the worst among all methods in all scenarios of our problem in terms of solution quality and computational cost. For comparison with another analytical approximation method, a clustering method is used to calculate the EENS [2]. It uses fixed margin increment of 10 MW and clustering with the nearest centroid sorting algorithm. The number of clusters is set as 80. The EENS’s derived are 207.6943 MWh, 159.1898 MWh, and 98.8874 MWh for integrated wind power capacities of 100 MW, 200 MW, and 400 MW, respectively. We can see that the results obtained from GA slightly outperform the clustering method in terms of EENS accuracy in such settings. Furthermore, as the system complexity increases (in this context it means more WTGs are integrated), the computational efficiency advantage of the population-based stochastic search becomes more evident in relation to the exact method. We can also see that as the power system becomes more reliable, the effectiveness and efficiency of MCS method are decreased in terms of both solution quality and computational expense. That is, with more WTGs incorporated, the solutions become more inaccurate and higher computational costs are caused in relation to GA.

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>RELIABILITY INDICES FOR UNCONVENTIONAL CAPACITY 100 MW.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>LOLE</td>
</tr>
<tr>
<td>GA</td>
<td>1.487820</td>
</tr>
<tr>
<td>MCS</td>
<td>1.493532</td>
</tr>
<tr>
<td>Exact method</td>
<td>1.487951</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>RELIABILITY INDICES FOR UNCONVENTIONAL CAPACITY 200 MW.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>LOLE</td>
</tr>
<tr>
<td>GA</td>
<td>1.185560</td>
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<tr>
<td>MCS</td>
<td>1.174901</td>
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<td>Exact method</td>
<td>1.185692</td>
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<table>
<thead>
<tr>
<th>TABLE IV</th>
<th>RELIABILITY INDICES FOR UNCONVENTIONAL CAPACITY 400 MW.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>LOLE</td>
</tr>
<tr>
<td>GA</td>
<td>0.789740</td>
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<tr>
<td>MCS</td>
<td>0.771991</td>
</tr>
<tr>
<td>Exact method</td>
<td>0.789840</td>
</tr>
</tbody>
</table>

V. CONCLUDING REMARKS

Due to the large number of system states in modern power-generating systems, it is difficult to adopt exhaustive enumeration method to accomplish reliability assessment. Thus, partial enumeration of representative and meaningful system states is quite desirable since it can reduce the computational cost with reasonable approximation. In this study, genetic algorithm is used as a search tool to find out a set of system states which contributes significantly to the overall system reliability indices. Three commonly used adequacy indices for power generation are calculated according to the most probable failure-states singled out by the GA optimizer. Some simulations based on an IEEE RTS are carried out to show the advantage of this GA-based evaluation procedure due to its
capability of truncating the solution space. In the future work, a larger reliability test system can be used to further verify the applicability and validity of the proposed method. More comparative studies with other analytical and computational methods are also desired. The optimal penetration level of wind power can be investigated to achieve the balance between benefits and risk. Furthermore, the method can be applied to other scenarios such as composite or multi-area power systems including time-dependent sources of power. Also other combinatorial optimizers and pattern classifiers may be explored for possible more effective and efficient solutions.

REFERENCES


