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Adequacy Evaluation of Composite Power Systems Using an Evolutionary Swarm Algorithm

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ABSTRACT The generation and transmission capacities of many power systems in the world are significantly increasing due to the escalating global electricity demand. Therefore, the adequacy evaluation of power systems has become a computationally challenging and time-consuming task. Recently, population-based intelligent search methods such as Genetic Algorithms (GAs) and Binary Particle Swarm Optimization (BPSO) have been successfully employed for evaluating the adequacy of power generation systems. In this work, the authors propose a novel Evolutionary Swarm Algorithm (ESA) for the adequacy evaluation of composite generation and transmission systems. The random search guiding mechanism of the ESA is based on the underlying philosophies of GAs and BPSO. The main objective of the ESA is to find out the most probable system failure states that significantly affect the adequacy of composite systems. The identified system failure states can be directly used to estimate the system adequacy indices. The proposed ESA-based framework is used to evaluate the adequacy of the IEEE Reliability Test System (RTS). The estimated annualized and annual adequacy indices such as Probability of Load Curtailments (PLC), Expected Duration of Load Curtailments (EDLC), Expected Energy Not Supplied (EENS) and Expected Frequency of Load Curtailments (EFLC) are compared with those obtained using Sequential Monte Carlo Simulation (SMCS), GA and BPSO. The results show that the accuracy, computational efficiency, convergence characteristics, and precision of the ESA outperform those of GA and BPSO. Moreover, compared to SMCS, the ESA can estimate the adequacy indices in a more time-efficient manner.

INDEX TERMS Composite system adequacy, evolutionary algorithms, genetic algorithms, particle swarm optimization, population-based methods, reliability assessment.

I. INTRODUCTION

The global electricity demand is expected to grow by 2.4% per year up to 2040 [1]. Therefore, power systems must gradually grow in both size and supply capability to satisfy the continuously increasing consumer demand. Hence, the adequacy assessment of future power systems will become a more complicated and time-consuming task due to the increased number of system components such as generators, transformers, and transmission lines.

Analytical and simulation based probabilistic methods are widely used in power system adequacy evaluation in order to model the stochastic nature of power system components and estimate more realistic adequacy indices. The outage probability of each power system component can be used to determine the status of the component i.e. unit up or unit down. Then, the system state space can be generated by convolving the status of each of the power system components. The system states associated with zero load curtailment are success states, whereas the states with load curtailment are considered as failure states. The derived system state space can be analyzed to quantify the system adequacy using different adequacy indices such as Probability of Load Curtailments (PLC), Expected Duration of Load Curtailments (EDLC), Expected Energy Not Supplied (EENS) and Expected Frequency of Load Curtailments (EFLC).

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However, the state space of a composite generation and transmission system is significantly large due to the combined number of generation and transmission components. For e.g., if a power system has x number of components, then the size of the state space will be 2^x. Therefore, the larger the power system the higher the complexity of the system adequacy evaluation. On the other hand, composite system states are evaluated by the Optimal Power Flow (OPF) analysis and, this optimization problem requires a significant amount of computational time especially when there is a large number of system states. Moreover, in power generation and transmission system planning, the system adequacy indices are estimated for numerous case studies. Hence, conventional analytical and simulation-based power system adequacy evaluation methods may not cope with modern power system planning as the cumulative time for such studies may be discouraging their application. Thus, more effective and efficient methods are needed to assess the system adequacy more accurately and conveniently.

Monte Carlo Simulation (MCS) is widely used for evaluating the adequacy of power systems due to the increased computational performance and storage of modern computers [2]. In Sequential Monte Carlo Simulation (SMCS), the system states are simulated and analyzed chronologically [2]–[7]. On the other hand, in Non-Sequential Monte Carlo Simulation (NSMCS), the system states are randomly sampled from the system state space [2], [8]–[11]. Despite their popularity, MCS methods require a significant amount of computational time especially when the system is large and highly reliable [3]. The OPF analysis is the main time-consuming task of composite system adequacy evaluation. Several methods are proposed in the literature to reduce the application of OPF analysis in the adequacy evaluation of composite systems [6]–[17], [20]–[24].

The convergence time of MCS methods can be reduced by incorporating variance reduction techniques such as importance sampling [6], [8], [9], [11] and Latin Hypercube sampling [7], [10]. Variance reduction methods increase the precision of the estimates of the reliability indices while reducing the number of states that need to be evaluated until the convergence is reached.

In [12] and [13], MCS is conducted on parallel and distributed processing environments instead of a single processor based environment. However, the total computational cost remains the same because the number of total system states evaluated is not changed.

Artificial Intelligence (AI) based learning and optimization techniques are recently employed for adequacy evaluation of power systems. The Machine Learning (ML) classification methods such as K Nearest Neighbor (KNN) [14], Artificial Neural Network (ANN) [15], Support Vector Machine (SVM) [16], Fisher Linear Discriminant (FLD) [17], Kohonen self-organizing map, K-means, K-medoids [18] and transfer learning [19] can be used to classify the system states either as success or failure. The available or unavailable bus generation, generation reserve capacity and unavailable transmission capacity are used as the input variables to the classification models. These methods can be incorporated into the MCS and only the states that are classified as system failures are evaluated instead of applying the OPF analysis on all the sampled states. This significantly reduces the computational cost of MCS [14]–[17]. However, the training of the aforementioned ML models is a time-consuming task. Therefore, with the training stage, actual reliability evaluation times should be larger than the values stated in [14]–[17].

Population-based Intelligent Search (PIS) methods such as Genetic Algorithms (GAs), Ant Colony Optimization (ACO), Artificial Immune Systems (AISs), and Binary Particle Swarm Optimization (BPSO) are AI-based optimization methods which are inspired by biological or social systems. These PIS methods can be used to find out either a set of probable failure states or success states from the system state space. In [20]–[24], the ability of the population-based guided random search is used to identify the most probable system success or failure states (e.g., *the states with a state probability* $> 1e^{-10}$) instead of attempting to find a single optimal solution. In [20], GAs, ACO, AISs, and BPSO are used for pruning the system state space. Firstly, the PIS methods are used to search for most probable system success states. Then, the MCS is applied on the pruned system state space until the simulation converges. After that, the previously found system success states are reintroduced in the adequacy indices calculation. In [21], a differential evolution algorithm is used to prune the system state space. Then, the pseudo-sequential Monte Carlo simulation is used to obtain the system reliability indices. In [22], a combination of MCS, state-space classification and BPSO is used to estimate the adequacy of composite systems. However, in the aforementioned hybrid PIS-MCS methods, the MCS phase tends to reduce the overall sampling efficiency of the algorithm [21]. On the other hand, in [23] and [24], PIS methods such as GAs, BPSO, ACO, and AISs are used to find out the most probable system failure states. The adequacy indices can be directly derived from the recorded system failure states. Even though these methods are well established, significant changes to the searching mechanism may improve the overall computational efficiency of these methods. Moreover, PIS methods do not need to be trained as ML methods [23], [24]. However, there are several limitations native to the application of two widely used PIS methods (i.e. GAs and BPSO) in power system adequacy evaluation which leads to a low sampling efficiency. The failure system states are not randomly distributed in the state space i.e., most of the system failure states may have common component failures (e.g.: in most of the system failure states, the largest generator of the system may be at the downstate). When a new population is being generated, the offspring generation should have these fit qualities of the parents. In GAs, the crossover operator does not maintain this genealogical link between parent and offspring generations. On the other hand, the ability to search in new areas of the system state space is limited in BPSO due to the velocity limitations of the particles.

This study extends the work presented in [23] and [24] in which PIS methods are directly used for *generation system* adequacy evaluation without incorporating the MCS. In this work, the applicability of PIS without MCS is investigated for evaluating the adequacy of *composite power systems* where transmission and generation are considered together. A novel PIS guiding mechanism called Evolutionary Swarm Algorithm (ESA) is proposed for this application by combining the useful features of GAs and BPSO while eliminating their limitations. The proposed PIS guiding mechanism consists of two population guiding operators namely selection and dynamic mutation. The selection operator is inherited from the GAs and the dynamic mutation operator is derived by using the features of swarm intelligence. The dynamic mutation operator helps to deliberately search failure states in the system state space using the most probable failure states that are already found. Instead of randomly searching system failure states, the ESA attempts to search the most probable system failure states that significantly affect the system adequacy indices. This is done by eliminating the least probable system states as in GAs ("survival of the fittest") and following the most probable failure states as in BPSO ("following the leader"). The adequacy studies are conducted on IEEE Reliability Test System (RTS) [25] using the proposed ESA. The ESA based composite system adequacy evaluation framework is validated using the reference values obtained from the literature [5]. Then, the computational efficiency, sampling efficiency and precision of the proposed ESA are compared with those of GAs and BPSO. Moreover, the correlation between computational time and different sampling mechanisms (MCS and PIS) is conceptually and numerically compared.

The rest of the paper is organized as follows. Section II describes the application of PIS methods such as GAs and BPSO for the adequacy evaluation of power systems. An improved PIS algorithm called Evolutionary Swarm Algorithm is proposed in section III. SMCS, a GA, BPSO, and the proposed ESA are used in section IV to evaluate the adequacy of composite systems. In section V, the proposed ESA is validated and, the computational efficiency, sampling efficiency and precision of the proposed ESA are compared with those of GA and BPSO. Conclusions are given in section VI.

II. POWER SYSTEM ADEQUACY EVALUATION USING POPULATION-BASED INTELLIGENT SEARCH METHODS

In power system adequacy evaluation, three basic steps are needed to estimate the adequacy indices. Firstly, system states are sampled from the system state space. Then, each sampled state is evaluated to find out whether it is a success state or a failure state. Finally, the adequacy indices are derived from the sampled system states.

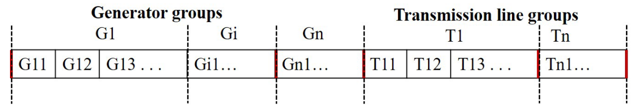

FIGURE 1. The representation of a system state.

A. SYSTEM STATE SELECTION

The system success and failure states are scattered over the system state space. In PIS methods, the most probable system failure states are enumerated from the system state space as they significantly affect the system adequacy [23], [24].

A system state is a combination of the states of system individual components such as generators and transmission lines. In PIS, each system state is represented as an array in which the component status are assigned to the respective cells of the array. The configuration of the system state is illustrated in Fig. 1. Similar components are grouped, and each cell represents the availability of the corresponding generator or transmission line i.e. 0 or 1.

Various power system adequacy evaluation methods use different sampling mechanisms for system state selection. In this study, the main emphasis is given for the sampling mechanisms of widely used PIS methods i.e. GAs and BPSO. In the aforementioned methods, the most probable system failure states are found by iteratively applying evolutionary or swarm intelligence-based operations on a set of randomly selected system states.

1) GENETIC ALGORITHMS

In GAs, genetic operators such as selection, crossover, and mutation are applied to the exiting population i.e. a set of system states to generate a new population with a large number of system failure states [26]. Firstly, individuals i.e. system states with comparatively high fitness values are selected from the existing population to form a new population. Roulette Wheel Selection (RWS) is a widely used selection method in GAs. In RWS, the probability of selection of an individual is proportional to its fitness value. The higher the fitness the larger the probability of selection. Individuals with high fitness values may be selected more than once and worst will die off eventually. Secondly, the selected individuals are considered as parents and the crossover operation is applied to each pair of selected individuals. This is illustrated in Fig. 2. The crossover operation is applied according to the crossover probability which is defined according to the nature of the application. The crossover position is selected randomly. Finally, the child chromosomes are subjected to the mutation operator for introducing random changes in the chromosomes. The genes i.e. bits in each chromosome are changed according to the defined mutation probability. This avoids the GA being trapped in a local area of the system state space.

However, there exist several limitations that are native to the application of GAs in power system adequacy evaluation. The failure system states are not randomly distributed in

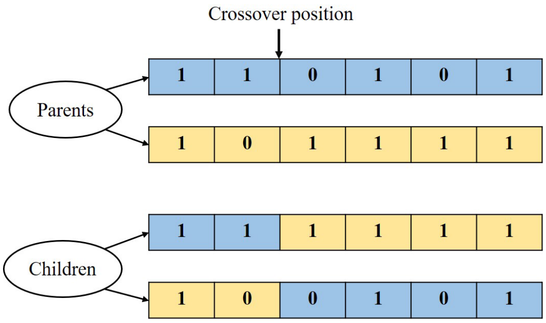

FIGURE 2. The crossover operation.

the state space i.e. most of the system failure states may have common component failures (For e.g. in most of the system failure states, the largest generator of the system will be at the downstate). When a new population is being generated, the offspring generation should have these fit qualities of the parents. In GAs, the crossover operator does not maintain these genealogical links between parent and offspring generations. Furthermore, the crossover operator does not provide a significant advantage over mutation because it is a form of mutation itself.

2) BINARY PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is a form of swarm intelligence in which the optimization problem is solved by a swarm of particles roaming in a multi-dimensional search space [27]. The swarm particles have two main features i.e. position and velocity. The particles record the best positions (p_best) that they have visited and then, the best position of the whole swarm is identified (g_best). The velocity provides an idea of the solution distance w.r.t the current particle position. For each particle, the velocity is calculated using p_best and g_best and then, the next particle positions are computed according to respective velocities. In BPSO, each swarm particle is represented by a binary number. Hence, the system state representation illustrated in Fig. 1 can also be employed in the BPSO for composite system adequacy evaluation. Thus, a swarm particle represents a system state. The system component states i.e. individual binary digits are changed according to their respective velocities to form the next population of swarm particles. The velocity of each individual component is calculated using (1) [28]. V_i^K is the velocity of i^{th} component at K^{th} generation. c_1 and c_2 are learning factors known as cognitive acceleration constant and social acceleration constant, respectively. $r_1^{(K+1)}$ and $r_2^{(K+1)}$ are uniformly distributed random numbers between 0 and 1 that are generated for the $(K+1)^{th}$ generation. $p\_best_i^K$ is the status of the i^{th} component (i^{th} bit) of the most probable system failure state that the swarm particle has encountered up to the K^{th} generation. $g\_best_i^K$ is the status of the i^{th} component (i^{th} bit) of the most probable system failure state that any of the swarm particles has encountered up to the K^{th} generation. x_i^K is the status of the i^{th} component (i^{th} bit) at K^{th} generation.

$$V_i^{(K+1)} = (V_i^K) + c_1 r_1^{(K+1)}(p\_best_i^K - x_i^K) + c_2 r_2^{(K+1)}(g\_best_i^K - x_i^K) \quad (1)$$

Similarly, the component velocities are calculated for the other particles present in the population. The velocity of an individual component provides an idea of the probability of the component availability. The Sigmoid limiting transformation function explained by (2) is used to transform the velocity of component i (V_i) to a probability of availability. Then, the new state of the component i (x_i^{K+1}) can be derived using (3) where r is a uniform random number between 0 and 1 [28]. Moreover, the velocities should be limited by an upper bound $Vmax$ and a lower bound $Vmin$ to avoid the ultimate probability of availability of a bit in a particle being zero or one.

$$S(V_i^{K+1}) = \frac{1}{1 - e^{-V_i^{K+1}}} \quad (2)$$

$$x_i^{K+1} = 1 \; if \; r < S(V_i^{K+1}), \quad 0 \; else \quad (3)$$

However, the ability to search in new areas of the system state space is limited in BPSO. Generally, the velocity of a bit i.e. component in a particle will be bounded by $[Vmin, Vmax]$ and then, probability of availability of the component $S(V_i)$ will become a fixed value.

B. SYSTEM STATE EVALUATION

In state evaluation, each selected system state is analyzed to identify the respective load curtailments associated with the state. DC OPF analysis can be used to evaluate the sampled system states. The main objective of the optimization is to minimize the cost of load curtailments. A general representation of DC OPF problem is explained by (4)-(8) [2].

$$Min\, f = \sum_{i=1}^{k} x_i\, C_i \quad (4)$$

$$\sum_{i=1}^{k} Pg_i + \sum_{i=1}^{k} C_i = \sum_{i=1}^{k} Pl_i \quad (5)$$

$$|[A].[P]| \le [T_{limit}] \quad (6)$$

$$0 \le Pg_x \le Pcap_x \quad (7)$$

$$0 \le C_i \le Pl_i \quad (8)$$

where x_i and C_i are the cost of load curtailment and the curtailed load at the i^{th} bus, respectively. k is the total number of buses in the transmission system. Pg_i and Pl_i are the power generation and load requirement at the i^{th} bus, respectively. A is the sensitivity matrix in which the transmission line power flows are expressed, P is the net bus injection vector, T_{limit} is the transmission line capacity vector. Pg_x is the power generation of x^{th} generator with a maximum capacity of $Pcap_x$. For a selected system state, if $\sum_{i=1}^{k} C_i > 0$ then, the state is classified as a failure state and stored for further analysis.

C. ESTIMATION OF SYSTEM ADEQUACY INDICES

Several adequacy indices that are employed to quantify the composite system adequacy are described by (9)-(12) [2].

1) PROBABILITY OF LOAD CURTAILMENTS (PLC)

$$PLC = \sum_{i=1}^{n} State\_p_i \tag{9}$$

where $State\_p_i$ is the probability of failure of the system failure state i and, n is the total number of system failure states.

2) EXPECTED DURATION OF LOAD CURTAILMENTS (EDLC) (HOURS PER YEAR)

$$EDLC = 8760 \times PLC \tag{10}$$

3) EXPECTED ENERGY NOT SUPPLIED (EENS) (MWh PER YEAR)

$$EENS = \sum_{i=1}^{n} LC_i \times State\_p_i \tag{11}$$

where LC_i is the load curtailment of the system failure state i.

4) EXPECTED FREQUENCY OF LOAD CURTAILMENTS (EFLC) (OCC. PER YEAR)

$$EFLC = \sum_{i=1}^{n} (F_i - f_i) \tag{12}$$

where F_i is the frequency of the departing system state i and, f_i is the portion of F_i which corresponds to the subsequent system failure states.

III. PROPOSED EVOLUTIONARY SWARM ALGORITHM

The proposed ESA inherits the useful features of GAs and BPSO while eliminating the limitations mentioned in Section II A. The ESA generates a new population using two main steps namely selection and dynamic mutation that are explained in subsections A and B respectively. The composite system adequacy evaluation procedure is explained in subsection C.

A. SELECTION OPERATOR

The selection operator is inherited by GAs. It is used to select the most probable system failure states from the present population to form a new population. The RWS that is explained in Section II A is used in this work.

B. DYNAMIC MUTATION OPERATOR

In the dynamic mutation mechanism, variable mutation probabilities are used to mutate each bit of the particles (i.e. the state of each component in the system states) in the population. Hence, for each particle, a mutation probability array should be maintained. This is somewhat similar to the velocity principle of BPSO. However, the Sigmoid transfer function is not required in the proposed mechanism because the mutation probability of system components is directly derived by the dynamic mutation operator. The dynamic mutation mechanism can be explained by (13).

$$P_i^{(K+1)} = Pm + r^{(K+1)} * |p\_best_i^K - x_i^K| \tag{13}$$

$P_i^{(K+1)}$ is the dynamic mutation probability of the i^{th} component at the $(K+1)^{th}$ generation. Pm is the permanent mutation constant. Pm is commonly a small constant e.g. 0.03 that is used to avoid premature convergence. Instead of always following the fittest particles, new search areas are explored due to the introduction of Pm. In composite system reliability evaluation, different Pm values may be used for generators and transmission lines according to their forced outage rates. The value of the Pm is determined using the trial-and-error method. The Pm value which provides the best result is used in the algorithm. $r^{(K+1)}$ is a uniform random number between zero and one which is used to exploit new solutions around the p_best states while avoiding particles from moving exactly towards them. Similarly, the component mutation probabilities are calculated for the other particles present in the population.

Both $p\_best_i^K$ and x_i^K are two arrays and the each bit of these arrays can take either 1 or 0. The i^{th} bit of $p\_best_i^K$ is the status of the i^{th} component of the most probable system failure state that the swarm particle has encountered up to the K^{th} generation. The i^{th} bit of x_i^K is the status of the i^{th} component at the K^{th} generation. The term $|p\_best_i^K - x_i^K|$ provides an idea of how close x_i^K to the best solution identified so far. If $|p\_best_i^K - x_i^K| = 0$, the mutation probability will be only Pm e. g. 0.03. This means that x_i^K should not be changed during the mutation. If $|p\_best_i^K - x_i^K| = 1$, then, x_i^K should be changed to get close to the best possible value $p\_best_i^K$.

According to the mutation probability, the state of each component of the particle population is updated using (14) where r is a uniform random number between zero and one. r is used to stochastically determine the mutation of each component of the particle population. The symbol ¬ is used to denote the negation operation (''NOT'') in symbolic logic, which is also called ''logical not.''

$$x_i^{(K+1)} = \neg x_i^K \ if\ r < P_i^{(K+1)}, \quad x_i^K\ else \tag{14}$$

C. COMPOSITE SYSTEM ADEQUACY EVALUATION PROCEDURE

The generation system adequacy evaluation procedure proposed in [23] is extended in this work to evaluate the adequacy of composite systems as follows. The adequacy evaluation procedure is illustrated in Fig. 3.

Step 1: Generate a population of particles i.e. system states randomly where the states of generators and transmission lines are initialized using binary digits.

Step 2: Calculate the probability of each system state using (15) and select the most probable system states e.g., *state probability* $> 1e^{-10}$.

$$P_i = \prod_{j=1}^{m} P\_comp_j \tag{15}$$

where m is the total number of individual components and P_comp_j is the state probability of j^{th} component. The fitness of the unqualified system states e.g., *state probability* $\leq 1e^{-10}$ is assigned to a small value e.g., $P_i \times 1e^{-5}$.

Step 3: Select a most probable system state and evaluate it using DC OPF w.r.t the maximum load demand. Derive the load curtailment LC_i.

Step 4: If $LC_i = 0$ (success state) a very small fitness value is assigned to the state and repeat from step 3. If $LC_i > 0$ (failure state) go to the next step.

Step 5: Calculate the number of all possible permutations of the evaluated system failure state as follows.

$$Perm_i = \binom{G_1}{n_1} \times \ldots \times \binom{G_i}{n_i} \times \ldots \times \binom{G_n}{n_n} \tag{16}$$

where G_i is the length of group i and n_i is the number of available components in group i.

Step 6: The fitness of the state is calculated by (17).

$$Fit_i = Perm_i \times P_i \tag{17}$$

Step 7: Frequency of the state can be calculated by (18).

$$F_i = P_i \times (\sum_{j=1}^{m}(1 - b_j) \times \mu_j - \sum_{j=1}^{m} b_j \times \lambda_j) \tag{18}$$

where b_j indicates the component status i.e. 0 or 1. μ_j and λ_j are the expected repair rate and the expected failure rate of component j, respectively.

Step 8: Save the derived information e.g., *system state*, P_i, $Perm_i$, F_i and LC_i of the failure state in an array.

Step 9: Repeat steps 3-8 until the remaining system states i.e. individuals are evaluated. Before each evaluation, the selected system state is checked to ensure that it is not previously evaluated. If it is a previously evaluated state, the fitness of the state is assigned to a very small value. Therefore, it will not appear in the following generations.

Step 10: Increase the iteration number by one. Check whether any stopping criterion is satisfied. If yes go to step 13 else go to the next step.

Step 11: PIS guidance mechanism is applied to the current population for generating the next population.

Step 12: Repeat steps 2-11.

Step 13: Calculate the annualized composite system adequacy indices described by (9), (10), (11) and (12) using the derived system state array where $State\_p_i = Perm_i \times P_i$. The EFLC explained in (12) is calculated as follows.

$$EFLC = \sum_{i=1}^{n} Fi \times Perm_i \tag{19}$$

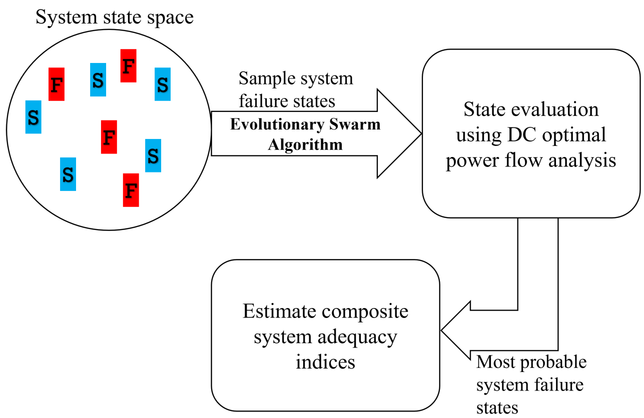

FIGURE 3. Proposed composite system adequacy evaluation framework.

Step 14: Calculate the annual adequacy indices as follows.

- The chronological load curve is transformed to a q number of load levels, for e.g. 15 load levels. Then sort the load levels in descending order in which the first state has the highest load value and the q^{th} state has the lowest.
- Calculate the load step probabilities and load transition rates per year (λ) between the load states.
- For each system failure state, DC OPF analysis is applied for different load levels. If $LC_{ix} = 0$ for a certain load cluster x, the state evaluation process is stopped, and it is restarted on the next system failure state.
- While evaluating all the system failure states for different load levels, calculate the composite system adequacy indices using (9), (10), (11) and (12) where $State\_p_{ix} = Perm_i \times P_i \times Lp_x$. $State\_p_{ix}$ is the state probability of the i^{th} state for the x^{th} load step. Lp_x is the probability of the x^{th} load step. The EFLC is calculated as follows [29].

$$\begin{aligned} EFLC =& \sum_{i=1}^{n}\sum_{x=1}^{q} Lp_x \times F_i \times Perm_i \\ &+ \sum_{i=1}^{n}\sum_{x=1}^{q}(\sum_{j=r+1}^{q} \lambda_{rj} - \sum_{j=1}^{r-1} \lambda_{jr} \\ &\times \frac{Lp_j}{Lp_x}) \times P_i \times Perm_i \times Lp_x \end{aligned} \tag{20}$$

TABLE 1. Annualized adequacy indices, number of failure states, and adequacy evaluation time of SMCS and PIS methods for IEEE RTS.

	SMCS	GA	BPSO	ESA
PLC	0.0849	0.0841	0.0813	**0.0844**
EDLC (hours/year)	743.57	736.5	711.95	**739.59**
EENS (MWh/year)	129145.9	127301.7	122269.7	**128138.2**
EFLC (occ. /year)	19.19	19.11	17.47	**19.33**
Failure states	-	10962	7722	**12068**
Time (s)	25817.6	267.11	243.08	**277.70**

There are several criteria to determine the stopping rule of metaheuristic algorithms [30]. In this work, the number of population iterations is set to a maximum number and, reaching this maximum number of iterations is used as the stopping rule. The appropriate number of iterations is determined using the trial and error method considering the required accuracy and the computational cost.

IV. APPLICATION STUDIES

In this section, SMCS, GA, BPSO, and the proposed ESA are used to estimate the annualized and annual adequacy indices of the IEEE RTS system. The results of a GA and BPSO are used for elaborating the accuracy, precision, and sampling efficiency of the proposed ESA.

The SMCS is used to compare the computational efficiency of PIS and Monte Carlo sampling methods. In SMCS, the number of simulation years is fixed to 500 years while maintaining coefficient of variation of PLC less than $1e^{-2}$. MATLAB is used to implement the PIS and SMCS methods in a single-core processing environment. The DC OPF analysis is conducted by a linear optimization function called "linprog." A system with the Intel Core i7-8750H processor and 8 GB RAM is utilized in this work.

A. COMPOSITE SYSTEM ADEQUACY EVALUATION OF IEEE RTS

IEEE RTS consists of 32 generators,38 transmission lines, and 24 buses. The peak load of the system is 2850 MW and the total generation capacity is 3405 MW. The total number of iterations and population size of GA, BPSO, and ESA are assigned as 1500 and 100 respectively. Annualized RTS adequacy indices, the number of failure states evaluated, and the adequacy evaluation time of SMCS, and PIS methods are tabulated in Table 1. Annual composite system adequacy indices and the respective evaluation time are shown in Table 2.

V. DISCUSSION

This section describes the results obtained in section IV. The proposed ESA is validated in subsection A. Subsection B compares several characteristics and improvements of the proposed ESA w.r.t SMCS, GA, and BPSO.

TABLE 2. Annual adequacy indices and adequacy evaluation time of SMCS and PIS methods for IEEE RTS.

	SMCS	GA	BPSO	ESA
PLC	0.001437	0.001416	0.001258	**0.001426**
EDLC (hours/year)	12.59	12.41	11.02	**12.49**
EENS (MWh/year)	1490.0	1285.4	1136.1	**1308.7**
EFLC (occ. /year)	2.3	2.13	1.88	**2.21**
Time (s)	26414.2	510.6	448.1	**566.7**

TABLE 3. Comparison of annualized adequacy indices obtained using the ESA and the reference SMCS [5].

	PLC	EDLC	EENS	EFLC
SMCS [5]	0.0858	751.17	131395.6	19.62
Percentage (%) difference of ESA results	**1.63**	**1.54**	**2.48**	**1.48**

A. VALIDATION OF THE PROPOSED ESA

The proposed ESA can be validated using the results of SMCS presented in [5]. Table 3 shows the comparison of annualized adequacy indices obtained from the ESA and the reference SMCS [5]. It can be seen that the adequacy indices obtained by the ESA are very close to the reference values presented in [5]. Given that SMCS is a probabilistic simulation method, a certain degree of estimation difference can be accepted.

B. COMPUTATIONAL EFFICIENCY, SAMPLING EFFICIENCY, AND PRECISION OF THE PROPOSED ESA

1) THE COMPUTATIONAL EFFICIENCY OF THE ESA

In SMCS, accurate estimations for system adequacy indices can be obtained by employing a tight coefficient of variation for the adequacy estimators as the stopping rule. However, the higher the accuracy of estimators the larger the computational time. Tables 1 and 2 show the computational time associated with each PIS method and SMCS. When comparing the computational times, PIS methods are more computationally efficient than the SMCS. When compared with the SMCS, ESA can estimate the system adequacy indices in a significantly short time period. The main reason is the difference between the sampling mechanism of PIS methods and SMCS. In SMCS, the system states are sampled stochastically and both success and failure states are used to estimate the system adequacy indices. Hence, the OPF analysis is conducted on both success and failure system states. This significantly increases the computational time. Moreover, when the system is more reliable, the probability of sampling failure states will be less, and the simulation convergence criterion may not be satisfied even for a large number of samples. On the other hand, PIS methods only focus on most probable system failure states that significantly affect the system adequacy indices. Hence, the OPF analysis will be conducted on a limited number of states and this can drastically reduce the computational time.

TABLE 4. Computational time, number of iterations, number of failure states of ESA, GA, and BPSO for difference tolerance levels of annualized EDLC.

Algorithm	Observations	Different Tolerance Levels of Annualized EDLC [5].		
		1.5% 739.9 (h/yr)	2% 736.15 (h/yr)	2.5% 732.39 (h/yr)
ESA	Time (s)	**250.15**	**157.46**	**89.88**
	No. of Iterations	**1574**	**783**	**525**
	No. of Failure states	**12070**	**8915**	**7080**
GA	Time (s)	363.81	203.34	123.92
	No. of Iterations	2657	1497	905
	No. of Failure states	14163	11134	8539
BPSO	Time (s)	2563.23	1260.74	762.72
	No. of Iterations	**15000	8137	5520
	No. of Failure states	16745	14335	12380

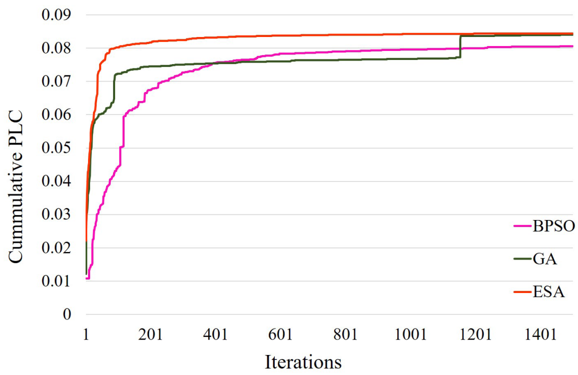

FIGURE 4. The evolution of PLC in terms of computational iterations.

The computational time of PIS methods depends mainly on two factors: the number of new most probable system states (for e.g. *state probability* $> 1e^{-10}$) identified and the complexity of the PIS guide operation. However, in applications of composite system adequacy evaluation, the computational time of the PIS methods significantly varies with the number of most probable system states evaluated. These most probable system states include both success and failure states. In PIS methods, the exploration of the system success states throughout the generation iterations are minimized as they are not needed in the calculation of system adequacy indices. Hence, the computational time of PIS methods significantly varies with the number of failure states evaluated. This can be observed in the Tables 1 and 2. Hence, the performance of the PIS methods cannot be compared by using the respective computational times observed for a given number of iterations (e.g. 1500). In fact the convergence characteristics of the PIS methods showcase the respective computational efficiencies.

The computational efficiency of the proposed ESA can be compared with that of GA and BPSO as follows. The computational times, the number of states and the number of iterations that are required for reaching different tolerance levels of EDLC (or PLC) can be obtained for ESA, GA and BPSO as shown in Table 4. The maximum number of iterations is limited to 15000. As can be seen in Table 4, the BPSO method significantly struggles to get into the defined tolerance levels of EDLC. Especially, the tolerance level of 1.5% cannot be reached even after 15000 iterations. The computational times of the ESA are the lowest for each EDLC tolerance level. The ESA computational time is reduced by 31.24% and 90.24% when compared with GA and BPSO for the EDLC tolerance level of 1.5%. Similarly, for the EDLC tolerance levels of 2% and 2.5%, the average computational time reduction of ESA is 25.02% and 87.86% w.r.t. GA and BPSO.

When comparing the results shown in Table 4, several interesting facts can be observed. In all the cases, ESA reaches the defined tolerance levels with the lowest number of system failure states, the lowest number of iterations and the lowest computational time. Although GA and BPSO have accumulated more system failure states, they were unable to reach EDLC tolerance levels faster than ESA. Hence, having the highest number of system failure states does not guarantee the accuracy of the derived adequacy indices. The sampled set of failure states should include the most probable failure states of the system. If the probabilities of sampled states are low, the estimations become inaccurate. The results show that ESA can sample the most probable system failure states within a fewer number of iterations than GA and BPSO.

The evolution of PLC in terms of computational iterations is illustrated in Fig. 4 for each PIS algorithm. When considering the first few iterations, both ESA and GA show the same rise-up characteristics. BPSO could not reach the rise-up performance of both ESA and GA. However, it can be seen that ESA converges significantly faster than GA and BPSO. The GA requires a significant number of iterations to reach convergence. This may have happened due to the elimination of important genealogical links between parent states and child states by the crossover operator. This limitation is addressed in the ESA and therefore, it rapidly reaches the convergence. The convergence rate is lowest, and time is highest in BPSO.

The PIS ability of BPSO is significantly reduced in the adequacy evaluation of IEEE RTS. This happens mainly due to the lack of mutation operator as in GAs. This causes the convergence of particle velocities to the maximum permitted values i.e. [$Vmin$, $Vmax$]. This will limit the BPSO's ability to search for new search spaces. The swarm intelligence philosophy i.e. "following the leader" cannot be applied for large state spaces because there may be a significant number of leaders (most probable system failure states) that needs to be followed.

In ESA, the selection of the best fitted individuals from the old generation has a significant impact on the final result. It was observed that PLC converges to 0.0835 instead of 0.0844 without the selection operator. Hence, the use of the selection operator is a must to obtain the maximum advantage of the dynamic mutation operator.

2) THE SAMPLING EFFICIENCY OF THE ESA

The sampling efficiency of PIS methods can be compared by observing the number of sampled failure states from a system state space with defined dimensions (e.g. population size and number of iterations). When considering the adequacy evaluation of IEEE RTS, GA, BPSO and ESA found 10962, 7722, and 12068 failure states respectively, from the search space of 100×1500 i.e. 150000.

PLC is a good measure for quantifying the ability of PIS in a more meaningful manner. In PIS-based adequacy evaluation methods, the larger the PLC the higher the accuracy of the PIS method. As can be seen in Tables 1 and 2, ESA found the largest number of system failure states and provides the largest PLC value. Thus, the proposed PIS mechanism outperforms GA and BPSO in terms of sampling efficiency.

In [23], the sampling efficiency (λ) of the PIS methods is measured using (21). The ratio explained by (21) varies according to the algorithm efficiency and the density of system failure states in the state space. In the adequacy evaluation of IEEE RTS, the sampling efficiencies of GA, BPSO, and ESA are found to be 7.3%, 5.1%, and 8% respectively. Therefore, the sampling efficiency of the proposed ESA is higher than that of GA and BPSO.

$$\lambda = \frac{Number\ of\ meaningful\ states\ sampled}{Number\ of\ total\ samples} \tag{21}$$

3) THE PRECISION OF THE ESA

When comparing the adequacy indices obtained by the PIS methods, the larger the adequacy indices such as PLC, EDLC, EENS and EFLC the higher the accuracy of the estimations. This means that the most probable system failure states are sampled during the PIS process. Tables 1 and 2 show that the proposed ESA has provided the most accurate system adequacy indices. However, the adequacy indices should be consistent throughout several executions of the algorithm. Therefore, to identify the consistency and precision of the PIS methods, the standard deviation of the annualized EDLC estimator of the IEEE RTS is calculated for the results of 50 executions. The standard deviation of EDLC obtained by GA, BPSO, and ESA, are found to be 1.15, 6.38, and 0.22 respectively. The standard deviation of EDLC is the lowest in the ESA. Hence, the precision of the proposed algorithm is significantly greater than that of the GA and BPSO.

VI. CONCLUSION

This paper proposes a new population-based random search guide mechanism called ESA for the adequacy evaluation of composite power systems. Then, the results of the proposed ESA are compared with those of GA, BPSO, and SMCS to investigate the application of PIS methods on the adequacy evaluation of composite power systems. The proposed algorithm provides more consistent and accurate estimations for adequacy indices in significantly lesser time than SMCS. Moreover, the computational and sampling efficiency of the proposed ESA is higher than that of GA and BPSO.

In this particular application, Population based Intelligent Search (PIS) methods such as GA, BPSO and ESA are used to scan and find out a set of most probable failure states which contribute significantly to system reliability indices, rather than attempting to find a single optimal or near-optimal solution. Therefore, convergence of these algorithms may not guarantee the accuracy of the solution. In this work, the accuracy of the solution provided by the proposed algorithm is checked by comparing that with the solution of well-established SMCS, instead of checking the convergence of the proposed ESA.

However, PIS methods cannot provide exact adequacy indices because the enumeration of every system failure state is computationally intractable. Hence, the adequacy indices obtained by the PIS methods are always somewhat less than the exact values. On the other hand, in SMCS, the estimated indices are somewhat larger or smaller than the exact values. Thus, a small error margin is acceptable in the adequacy estimation of composite systems. Therefore, the proposed ESA is able to provide acceptable estimations for composite system adequacy indices.

In the future, the authors intend to apply the proposed ESA for evaluating the adequacy of power distribution systems. AC optimal power flow analysis can be used to accurately estimate the distribution system adequacy indices especially when there is a large proportion of rooftop solar. Furthermore, emerging deep learning techniques can be used to identify the system failure states without using the time-consuming AC optimal power flow analysis [31], [32].

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