Improving Power System Reliability Calculation Efficiency With EPSO Variants

Vladimiro Miranda, *Fellow, IEEE*, Leonel de Magalhães Carvalho, Mauro Augusto da Rosa, Armando M. Leite da Silva, *Fellow, IEEE*, and Chanan Singh, *Fellow, IEEE*

***Abstract*—This paper presents an application of evolutionary particle swarm optimization (EPSO)-based methods to evaluate power system reliability. Population-based (PB) methods appear as competitors to the traditional Monte Carlo simulation (MCS), because they are computationally efficient in estimating a variety of reliability indices. The work reported in this paper demonstrates that EPSO variants can focus the search in the region of the state space where contributions to the formation of a reliability index may be found, instead of conducting a blind sampling of the space. The results obtained with EPSO are compared to MCS and with other PB methods.**

***Index Terms*—Evolutionary algorithms, Monte Carlo sampling, particle swarm, population-based methods, reliability analysis.**

I. Introduction

MONTE Carlo simulation (MCS) remains the standard method to calculate estimates of reliability indices in power systems. This statistically-based method has gained importance over analytical models since the growth in computing power in the beginning of the 1990s, coupled with the adoption of efficient acceleration techniques. The two basic advantages of MCS are: 1) allowing simulation of realistic characteristics of systems, even those not necessarily reducible to formal mathematical models, and 2) allowing the calculation of distributions and not only of mean values (in its simplest form, allowing the estimation of variance).

Nonchronological models became successful. However, the growth in computer power opened the way to perform chronological simulations, and this demanded increased computing power. At the same time, even nonchronological models became more complex because of the availability of computing power at desktop level.

Recently, an alternative to MCS started to emerge: *population-based (PB)* methods. While MCS is a statistically-based method, relying on the theorems of sampling to provide an estimate of a result plus some interval of confidence, PB methods are basically enumeration algorithms. If all states contributing to a certain index could be identified and their probabilities known, the index would be accurately calculated. PB methods try, therefore, to discover the majority of states, if not the totality, so that a good approximation of the index is calculated.

The methods are called *population based* because they rely on metaheuristics that have a population of solutions (individuals, particles) as their core. In this class, one counts evolutionary algorithms (EAs)—evolutionary programming or genetic algorithms (GAs)—and particle swarm optimization algorithms (PSOs). They were all developed to be optimization tools, but the problem now is the discovery of a set of states that have maximum contribution to the index to be calculated. Thus, some mechanism to generate diversity must be devised; otherwise, all solutions would tend to converge to a maximizing state, and space exploration would be hampered.

This paper presents new results confirming the efficiency of a population-based method—evolutionary particle swarm optimization (EPSO)—over Monte Carlo to calculate reliability indices in a powersSystem. The results obtained are compared with the results from other researchers and conclusions drawn from the experiments designed.

II. Population-Based Methods

PB methods are enumeration methods, which count different states in the state space [1]. PB methods are not statistical, and therefore, they do not allow the direct calculation of an interval of confidence for the result. Their stopping criterion is usually based on the stability of the index being calculated: after a number of iterations without meaningful progress, the process is considered to have reached the neighborhood of the real value and is stopped. If the search process is effective, this will typically happen long before any acceptable confidence interval may be calculated by an MC simulation (counting in terms of iterations or visited states). Of course, this is a pragmatic approach taking advantage of the fact that, usually, power systems are very reliable and the subset of meaningfully contributing states to a reliability index is much smaller than the entire state space.

In PB methods, the estimate $\hat{F}$ of an index F is given by

$$\hat{F} = \sum_{i \in D} p_i F_i \tag{1}$$

where $D \subseteq U$ is the set of sampled failure states (a subset of all possible states U), p_i is the probability of failure state i, and F_i is the value of the variable being assessed in state i.

It is usual in PB methods to accept that some truncation of the space of all failure states D_f is ensured $(D \subset D_f \subset U)$. This is usually done for a state i whose probability is very small (unless the value of F_i becomes unusually large). Moreover, the truncation of the state space was an accepted fact in the past, when an-

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alytical models prevailed. Besides, a Monte Carlo process does not guarantee an exact value, anyway.

The proposal of PB methods as a competitor to MC may be traced back to 2001 [2], [3], when a modified GA was used to perform basic reliability indices evaluation of generating systems. In [4], one finds a wrapping up of the technique. In all these publications, the authors adopted

$$\mathrm{Max_i} \in \mathrm{D_f} p = p_i \tag{2}$$

as the fitness function to drive the GA, i.e., the algorithm conducts a search for states maximizing the probability of occurrence p_i given that system failure is detected. This means that the GA tends to discover failure states with high probability and to reject or move away from success states.

The method uses binary chromosomes and takes advantage of possible permutations among equal components of the system, such as generators of equal power and forced outage rate (states of equal probability) to speed up enumeration.

In [5], the technique is extended to composite generation-transmission systems. Furthermore, the authors now proposed a second objective function to evaluate chromosomes according to the severity of the load curtailment consequences, through the calculation of the expected contribution $EPNS_i$ of state i to system power not supplied:

$$EPNS_i = p_i L_i \tag{3}$$

where L_i is the load curtailment associated with state i. The second criterion becomes

$$\mathrm{Max}_i \in D_f EPNS = EPNS_i. \tag{4}$$

The paper, however, falls short of suggesting a push of the GA iterations towards the Pareto-optimal border of a two-criterion problem, represented by (2) and by (4).

In [6], the same authors propose two new models aimed at calculating reliability worth in composite generation-transmission systems, where the GA is no longer driven by state probabilities but by load curtailment value and interruption cost. In [7], a particle swarm method was applied to a bi-objective formulation with two points of attraction ($\mathrm{Max}L$ and $\mathrm{Max}p$). In [8]–[10], a continuation of the techniques inspired in [4] was proposed, using binary chromosomes combining with genetic algorithms, particle swarm optimization, artificial immune systems, and ant colony optimization. The same approach proved in other areas [11].

In contrast to MCS, PB methods require the identification of the probability p_i of each visited state i. This is easily performed with the analysis of the composition of the state and the probabilities of failure of each component. Assuming independence among system components, the probability p_i of a failure state i is calculated by multiplying the probabilities of failure of each failed component and the probabilities of surviving of the non-failed components.

The consequence F_i of a failure in state i must be evaluated exactly in the same way one assesses such value in an MC process. For instance, if one is evaluating the *EPNS* in a composite generation-transmission system, an optimal power flow (OPF) may be necessary to determine the minimum value of load interruption. Even if dc models are used, it may be a time-consuming task if performed over and over again for all sampled states. This is why reducing the number of analyzed states becomes so rewarding in terms of computing effort.

This attempt to reduce the number of cases for which a full calculation is necessary has taken several directions. One of them has been the adoption of intelligent pattern recognition methods, such as neural networks, to discriminate between failure and success states so that only the former are examined [12]–[14]. Another is the one discussed in this paper.

The possible drawback of PB methods is the lack of mechanisms preventing the revisiting of states: repeated visits to the same state may well happen if the method does not perform satisfactorily. This leads to the concepts of PB method *efficiency* and *efficacy*. Efficacy measures how good the approximation of a PB model to the real value is, while efficiency measures the ratio of different states visited against the total number of states visited. If the efficiency is low, the algorithm will be causing many repeated visits to the same states prior to discovering new states not previously counted.

Also, because states must be enumerated, some sort of memory must be organized to keep track of visited states and recognize new ones. Searching through such memory will become a increasingly time-consuming task towards the end of the process, when many states have already been visited. However, it is at the end that this search becomes more relevant because the rate of visit repetition grows when the majority of significant states have already been visited.

But, differently from MC, in PB methods, one may take advantage of the fact that many components exhibit the same characteristics (for instance, one may have many equal generators with the same forced outage rate). This allows the calculation of the permutations or combinations of these elements that produce the same effect and add the global effect of this set to the index under calculation, discarding the need to visit all states. If carefully programmed, this may result in considerable savings in computing effort.

III. Evolutionary Particle Swarm Optimization

EPSO is a hybrid in concepts of EA and PSO, first proposed in [15] and with an improved version in [16] and [17]. It is an evolutionary algorithm with an adaptive recombination operator inspired in the "movement rule" of particle swarm optimization (PSO). This rule generates a new individual as a weighted combination of parents, which are: a given individual, its best ancestor, and the best ancestor of the present generation. This may be seen as a form of intermediary recombination. In this operator, a new individual is formed from a weighted mix of ancestors, and this weighted mix may vary in each space dimension. The mutation operator is only applied to the weights.

The recombination rule for EPSO is the following: given a particle X_i, a new particle X_i^{new} results from

$$X_i^{(k+1)} = X_i^{(k)} + V_i^{(k+1)} \tag{5}$$

$$V_i^{(k+1)} = w_{i1}^* V_i^{(k)} + w_{i2}^*(b_i - X_i) + w_{i3}^* P(b_g^* - X_i) \tag{6}$$

where the symbol "$*$" indicates that these parameters will undergo evolution under a mutation process, and

b_i best point found by the line of ancestors of individual i up to the current generation;

b_g best overall point found by the swarm of particle in its past life up to the current generation;

b_g^* $= b_g + w_{i4}^* N(0,1) \Rightarrow$ particle in the neighborhood of b_g;

$X_i^{(k)}$ location of particle i at generation k;

$V_i^{(k)}$ $= X_i^{(k)} - X_i^{(k-1)} \Rightarrow$ "velocity" of X_i in generation k;

w_{i1} weight of the *inertia* term (a new particle is created in the same direction as its previous couple of ancestors);

w_{i2} weight of the *memory* term (the new particle is attracted to the best position occupied by its ancestors);

w_{i3} weight of the *cooperation* or *information exchange* term (the new particle is attracted to the overall best-so-far found by the swarm);

w_{i4} weight affecting dispersion around the best-so-far;

P diagonal matrix with each element, in the main diagonal, being a binary variable equal to 1 with a given communication probability p, and 0 with probability $(1-p)$; in basic models, $p = 1$ but, in advanced models, p must be chosen from experiments, and values of $0.7 < p < 0.8$ have been shown to be optimal in many problems [16], although highly complex problems seem to require a very low nonzero value such as $p < 0.2$.

Weights w_{ik} are mutated at each iteration according to $w_{ik}^* = w_{ik}^*[\log N(0,1)]^\tau$, $k = 1, 3$, and $w_{i4}^* = w_{i4} + \sigma N(0,1)$, where $\log N(0,1)$ is a random variable, which follows a Lognormal distribution from a Gaussian with zero mean and unit variance, and τ and σ are externally fixed learning parameters that controls the amplitude of mutations.

IV. Search for Meaningful States

This paper reports a set of experiments made to investigate and compare the effect in PB methods (especially in EPSO) of some factors that may influence performance: 1) the type of objective function that induces the algorithm search, and 2) the search mechanism.

To benefit from an enumeration process, a *case* C will be defined as a set of states resulting from permutations of generators of equal rating (capacity) and forced outage rate (FOR) leading to the same probability of occurrence of their combined states and the same load curtailment value. To use this concept, one must divide the set of generators into G subsets, each with equal generators.

The probability of *case* C_k is given by $n_k \times p_k$, where p_k is the probability of any state belonging to C_k and n_k is the number of repetitions given by

$$n_k = \binom{N_{1k}}{M_{1k}} \times \binom{N_{2k}}{M_{2k}} \times K \times \binom{N_{Gk}}{M_{Gk}} \tag{7}$$

where, for each *case*, k, N_{jk} is the number of equal generators of type j, $j = 1, \ldots, G$, and M_{jk} is the number of generators of type j in the down state.

A *case* C_k is therefore described by a vector $[M_{1k}, \ldots, M_{Gk}]$. The estimation of the EPNS will be done with p_k being the

$$EPNS = \sum_k n_k p_k L_k \tag{8}$$

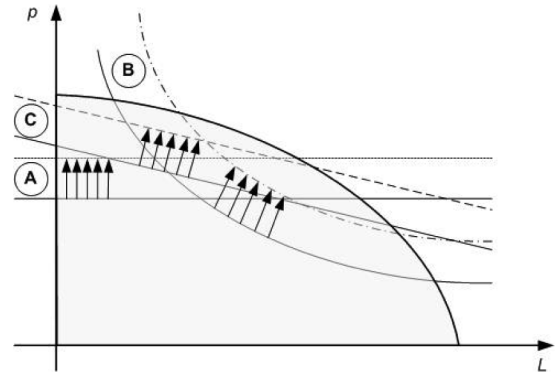

Fig. 1. Illustration of the effect of different objective functions in the way they push the search in the attribute space of p and L. (A) Maximizing p. (B) Maximizing $p \times L$. (C) Maximizing a weighted sum of p and L.

probability of any of the states in *case* k.

A. Coding

Some researchers tackled the problem of individual or particle coding as a search for system states represented by vectors of binary numbers. Then, some decimal equivalent of this vector is computed to keep track of visited states [2]. Other researchers code chromosomes for the generating capacity available in each generating bus as well as the capacity of each individual transmission line [7].

In this work, a particle or individual represents a *case* and not a system state. As mentioned before, it is defined as a vector of integers where each element is the number of equal components of a given type in the down state. This vector results from rounding the real values in a particle since each dimension is allowed to range in an interval of real numbers from 0 to the maximum number of equal components in the up state. This representation significantly reduces the dimension of a particle, especially in the case of power systems with a large number of components described by the same Markov model and the same indices. Simple rounding is acceptable because the aim is not to optimize but rather to cover a set.

B. Type of Objective Function

The aim is to conduct a biased search in the state space, identifying states that have L_i positive. Examining (8), one concludes that the states that the most relevant contributions to form the index EPNS will come from larger values of L, n, and p. If one disregards n, the search will take place in the space of states. If one considers the product $n \times p$, the search will take place in the space of cases. Either way, the search can be represented in a two-attribute space, having load curtailment L in one axis and probability (p or $n \times p$) in the other axis.

Fig. 1 illustrates the preferential push associated with each of the three types of objective functions studied:

- Type A—Objective functions based on maximizing the probability of states or cases: (A1) Max "p" and (A2) Max "$n \times p$";
- Type B—Objective functions based on maximizing expected power not supplied *EPNS* of a state or of a case: (B1) Max "$p \times L$" and (B2) Max "$n \times p \times L$";
- Type C—Objective functions pushing to the Pareto board of a two-objective problem: (C1) Max "$\alpha_1 n \times p + \alpha_2 L$" and (C2) Max "$\alpha_1 n \times p + \alpha_2 n \times p \times L$".

C. Spreading Technique

An innovation brought by this work is the replacement of an optimization procedure by a swarm spreading procedure. In fact, the previous works all used the "population effect" to identify states, having the population attracted by or towards the optimum state (as defined by the objective function). However, the interest of the process is not to discover the optimum state but rather, actually, to visit as much significant states as possible. So, instead of attracting the population to a point in space, this work explores several techniques to provoke the spreading of the population or swarm, so that more states are visited and fewer repetitions caused. This hopefully increases efficiency and leads to more efficacy in the process.

Three methods of spreading the search were tested. They result from handling (6):

- Type X—forgetting the global best b_g and resetting the memory term b_i;
- Type Y—adding an extra velocity term when particles overlap or are very close to one another;
- Type Z—adding a term related with the best neighbor of each particle.
- Beside these three spreading strategies, one must count a forth one, which is applied to objective functions of type C:
- Type W—causing an oscillation on the objective function by a periodical variation of the weights α.

The application of these techniques is done under a set of rules described below in algorithm form:

TYPE X:

Do in all iterations

If a pre-specified number of generations is reached

Then

Reset the memory of the best particle b_g and update its position according to the fitness of the particles in the current population

Else

Update the best particle b_g position according to the traditional EPSO rule.

For all particles in the population

If the case represented by particle i under evaluation has already been saved

Then

Erase particle i memory b_i by assigning to its fitness a negative value (maximization process)

Until the convergence criterion is verified.

TYPE Y:

Do for each particle in every iteration

Calculate the Euclidean distance to all particles

If the distance between the current particle $\mathbf{P}$ and another particle $\mathbf{Q}$ is below a pre-specified radius

Then

Calculate $(\mathbf{P}-\mathbf{Q})$

If $(\mathbf{P}-\mathbf{Q})$ is close to 0

Then generate a random $(\mathbf{P}-\mathbf{Q})$

Apply a spreading function Sp to $(\mathbf{P}-\mathbf{Q})$

Apply a squashing function $Sq()$ to $(\mathbf{P}-\mathbf{Q})$

Add $Sq(Sp(\mathbf{P}-\mathbf{Q}))$ to (6)

Until the convergence criteria is verified.

The spreading function $Sp()$ can be any function, such as the inverse of the distance, that will cause a separation of particles that are close to one another. The squashing function $Sq()$ can be any function that places bounds on the value of the vector term to be added to the velocity of a particle.

TYPE Z:

Do for each particle i in every iteration

Calculate the value of $Cfit_{ik}$ given by: $Cfit_{ik} = Fit_i - Fit_k/\|C_i - C_k\|$,

Select as *Best Neighbor* $bn_i = X_i$ of particle k the particle i that has a value of Max $Cfit_{ik}$

Add to the movement (6) of particle k the term $w_5(bn_i - X_k)$

Until the convergence criterion is verified.

Fit_i represents the fitness of particle i and bn constitutes a new attractor inserted in the movement equation, while w_5 is a weight of the neighbor term which is added to the set of weights.

TYPE W: (only for objectives of type C)

Do in each iteration

Calculate the fitness of each particle by using the weights α given by: $\alpha_1(t) = |\sin(2\pi t/TT)|, \alpha_2(t) = 1 - \alpha_1(t)$.

Until the convergence criterion is verified.

In this process, T is the weight changing period. The calculation of a good value for T unfortunately requires a fair number of trial and error experiments. Type X technique was tried in [7], and Type W called dynamic weight aggregation (DWA) was, in part, tried in [18] both applied in PSO algorithms searching for the Pareto-optimal border of a two-objective problem. Type Z was the core technique in [19].

V. Tests on the IEEE-RTS-79

Tests were carried out with the IEEE-RTS-79 [20] generating system. Its choice is justified by two reasons: 1) It is the same system used in other publications, therefore allowing comparison of results; 2) the exact results using the full load model with 8736 h is known [21], which allow the assessment of the accuracy of the achieved reliability results—see Table I, for the results with an analytical model (ANA) for the IEEE-RTS-79. Four reliability indices are showed: loss of load expectation

TABLE I
IEEE RTS-24—GENERATING CAPACITY RELIABILITY INDICES

Adequacy Reliability Indices	Values [21]
LOLE (hour/year)	9.394179
LOLF (occurrence/year)	2.019717
LOLD (hour/occurrence)	4.651236
EENS (MWh/year)	1176.3

TABLE II
IEEE RTS-24—GENERATING SYSTEM DATA

Unit type	Unit size (MW)	FOR	Number of units
1	12	0.02	5
2	20	0.10	4
3	50	0.01	6
4	76	0.02	4
5	100	0.04	3
6	155	0.04	4
7	197	0.05	3
8	350	0.08	1
9	400	0.12	2

(LOLE); loss of load frequency (LOLF); loss of load duration (LOLD); and expected energy not supplied (EENS).

Table II shows that from a total of 32 units, there are nine distinct cases of equal generators. This allowed the chromosome coding for the EPSO algorithms to have a dimension of 9. All runs were done using a swarm of 40 particles, with a learning parameter of $\tau = 0.3$ and a communication probability of $p = 0.6$. The maximum number of iterations was 375, meaning that 30 000 fitness function evaluations were done and, so, 30 000 states visited.

The comparisons among distinct strategies of objective function/spreading technique will be measured in terms of efficiency, as a percentage of the significant cases visited against the total number of cases visited by the particles during the search, and also in terms of efficacy, evaluating the proximity of the achieved value to the exact result.

A. Comparison of Different Objective Functions

This section presents a comparison of results when using different objective functions, for the same mix of spreading techniques. A strategy will be called M/N if it uses objective function type M and spreading technique of type N. Here, all results are for strategies of type -/XYZ or -/XYZW.

Fig. 2 shows that the objective B2 presents the best result for the same computing effort. For strategies C1 and C2, the period $T = 375$ was used. A sensitivity study was conducted on the case C2/XYZW by varying the oscillation period T for several values, and its results are shown in Fig. 3. As it can be observed, a higher frequency of variation in the relative weights in the objective function is beneficial to the process. Nevertheless, the best result (for $T = 37{,}5$) is not as good as the one obtained with strategy B2/XYZ.

B. Effect of the Different Spreading Techniques

Having asserted that objective function B2 $(\mathrm{Max}\ npL)$ leads to the best results, one may inspect if all spreading techniques contribute to this result. The tests were performed considering only the peak load of the system to simplify the analysis. The

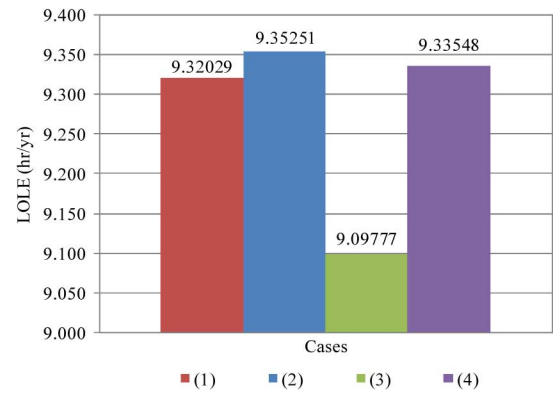

Fig. 2. LOLE estimation with different objective functions and hybrid spreading strategy. (1) A2/XYZ. (2) B2/XYZ. (3) C1/XYZW. (4) C2/XYZW.

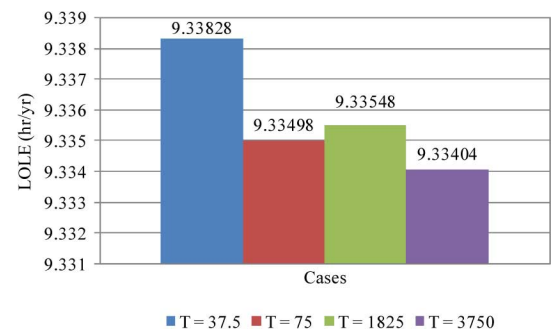

Fig. 3. Comparison of efficacy in LOLE estimation for different oscillation periods T in strategy C2/XYZW.

reliability index used was the EPNS. The analytical result achieved for the EPNS index, considering only the peak load, is 14.69575 MW. To gauge these comparisons run was also made with the classical EPSO algorithm. Fig. 4 shows a sensitivity study on a B2/X strategy. One may see that forgetting the global best b_g from iteration to iteration is the best strategy, and that this spreading technique is advantageous over the use of an EPSO standard optimization algorithm. Fig. 4 also displays the characteristic of population-based methods, i.e., the asymptotic unilateral convergence to the exact value. In Fig. 5, one notices the beneficial effect of a spreading strategy -/Y. This is especially relevant at later stages when new unvisited cases must be discovered. Fig. 6 explains why strategy -/Y is more effective. It shows that this strategy leads to a smaller percentage of visits to cases already visited (and counted) than the standard EPSO.

In Fig. 7, one confirms that strategy -/Z is also beneficial in contributing to building up the EPNS index. An explanation may be found in Fig. 8, where the search efficiency of a standard EPSO is compared to an EPSO modified with a neighbor term added (strategy -/Z). The calculations were made by establishing a limit cut-off threshold of 10^{-15}, for state probability p, in which the case is not counted for index build-up. One may confirm that the EPSO algorithm with added neighbor term manages to visit more than double the significant cases when compared to the standard EPSO. The "quality" of the cases is, however, relevant and not only the quantity. A case may even have a small probability but count for many different combinations, giving, therefore, a significant contribution to the total index.

Fig. 9 gives another perspective of the quality of the search. One may see that strategy B2/XYZ leads to a better coverage of

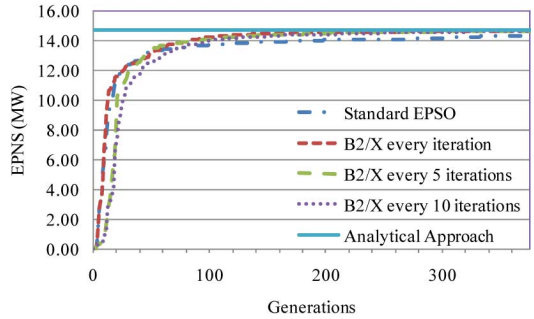

Fig. 4. Progress of the calculated EPNS with different B2/X strategies and comparison with standard EPSO, in 375 generations, 40 particles.

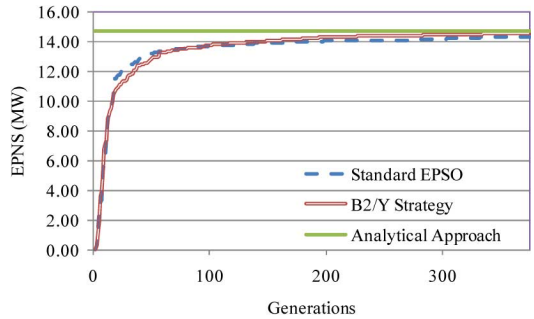

Fig. 5. Progress of the calculated EPSN with a B2/Y strategy and comparison with standard EPSO, in 375 generations, 40 particles.

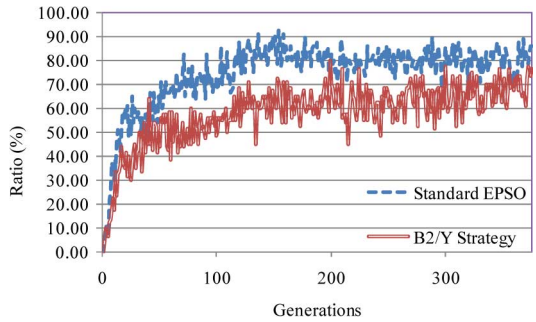

Fig. 6. Calculating EPNS with a B2/Y strategy and comparison with standard EPSO, in 375 generations, 40 particles: evolution of the ratio of case repetitions in percentage of the total number of case visited in each generation.

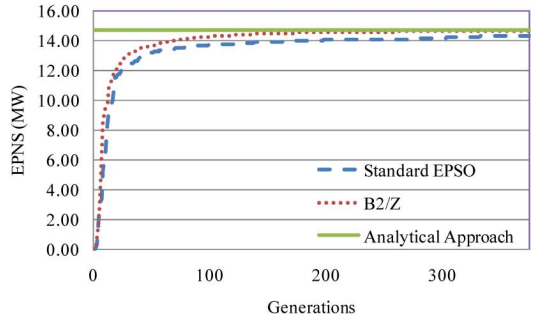

Fig. 7. Progress of the calculated EPSN with a B2/Z strategy and comparison with standard EPSO, in 375 generations, 40 particles.

the set of interesting cases than the standard EPSO and this is why the count in significant cases is higher, as seen in Fig. 8.

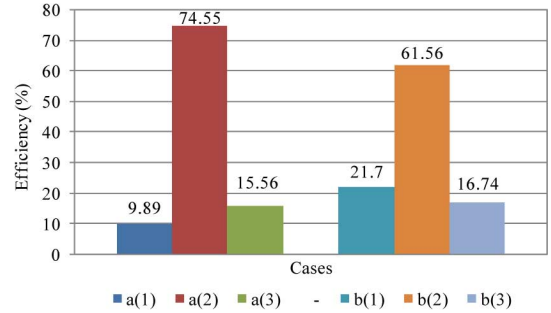

Fig. 8. Efficiency ratios, in percentage of the total number of cases visited, comparing a B2/Z strategy (right, b) with standard EPSO (left, a), in 375 generations, 40 particles. (1) Significant cases counted. (2) Repeated visits. (3) Cases visited below threshold limit.

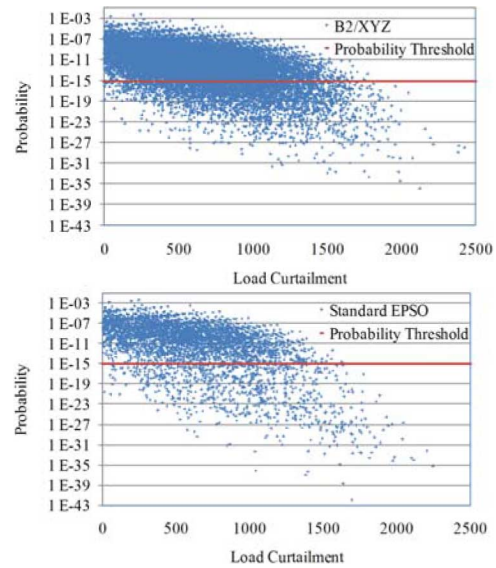

Fig. 9. Charts depicting load curtailment L versus case probability p, in logarithmic scale (the cut-off value of 10^{-15} is marked)—standard EPSO (below) versus EPSO with B2/XYZ (above).

Finally, a comparison of results is made with those published in [4] with the approach named MSGA. This work used a GA with a population of 40 and running for 750 generations. This makes a fair comparison with the EPSO algorithm running for 375 generations because both come to perform about the same number of 30 000 fitness function evaluations. Also, the same cut-off threshold value is used. The EPSO algorithm followed a B2/XYZ strategy that has been proven to lead to the best results, as shown above. Table III presents the results of the comparison in three reliability indices in absolute values and in errors, of a single run of EPSO and of MSGA [4] relative to the known exact result from [21]. To confirm the robustness of the EPSO approach, a series of 250 runs of the algorithm have been made, in the same conditions as previously referred, and the results are in Table IV. The result from MSGA [4] is below the 95% confidence interval (two standard deviations) for the value obtained from EPSO, meaning that one has 95% confidence that an EPSO run will give a better result than the result reported in [4].

VI. Comparison With Monte Carlo

In this section, one compares the performance of the EPSO PB-based technique with a Monte Carlo simulation. For this, it

TABLE III
COMPARISON IN THREE RELIABILITY INDICES (VALUE AND ERROR) OF THE RESULTS OF MSGA[4] WITH EPSO B2/XYZ

Indices	MSGA	EPSO B2/XYZ
LOLE (h/year)	9.324000	9.352507
LOLE Error (%)	0.75	0.44
LOLF (occ./year)	2.003700	2.010145
LOLF Error (%)	0.79	0.47
EENS (MWh/year)	1163.00	1169.18
EENS Error (%)	1.13	0.61

TABLE IV
RESULTS OF 250 REPEATED RUNS OF EPSO B2/XYZ

Indices	Mean	Standard Deviation
LOLE (hour/year)	9.337799	0.013395
LOLF (occ./year)	2.007116	0.002742
EENS (MWh/year)	1166.38	1.93
No. of Signif. Cases Found	10699	94

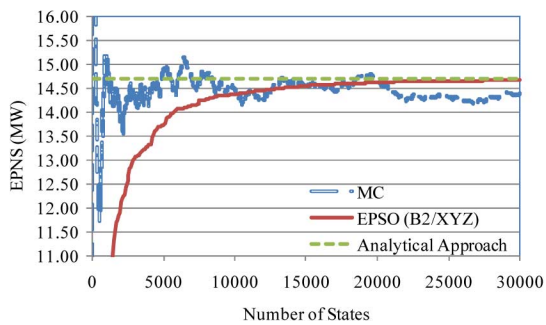

Fig. 10. IEEE RTS-79: Evolution of estimated EPNS (y-axis) with the number of states visited (x-axis): MC results (dashed curve oscillating around the real value) versus EPSO results (line converging "asymptotically" to the exact result).

TABLE V
IEEE-RTS 79: COMPARISON OF RESULTS FROM ANALYTICAL, MC AND EPSO

ANA	EPNS (MW)	14.69575			
MCS	No. States	31 019	21 587	7 551	1 865
	β (%)	2.50	3.00	5.00	10.00
	EPNS (MW)	14.42295	14.31442	14.54172	14.04935
	[EPNS×(1-1.96β)	[13.71622	[13.47273	[13.11663	[11.29568
	EPNS×(1+1.96β)]	15.12967]	15.15610]	15.96681]	16.80302]
EPSO	EPNS (MW)	14.66185	14.62527	14.23322	11.84474
	No. States	30 040	21 500	7 500	1 800

is present two experiments: on the IEEE RTS-79 with 32 generating units, considering only a constant (peak) load value of 2850 MW (see Fig. 10 and Table V); and on the IEEE RTS-96 [22] with 96 generating units, a peak load of 8550 MW and a chronological load model based on 8736 h values transformed into a ten equivalent state Markovian model.

Fig. 10 presents the convergence characteristics of MCS and EPSO for a run on the IEEE-RTS-79. The unilateral convergence is well illustrated. Table V compares the performance between MCS and EPSO in the IEEE-RTS-79 for the estimation of EPNS and for different coefficients of variation β applied to the MCS sampling. Rows 4 and 5 show the limits for the confidence interval at 95% confidence level in each case. Two things

TABLE VI
IEEE-RTS 96: COMPARISON OF RESULTS FROM ANALYTICAL, MC, AND EPSO

Indices	**ANA**	**MCS**	**EPSO**
LOLP	1.58694×10^{-5}	1.61081×10^{-5}	1.51430×10^{-5}
LOLE (hr/yr)	0.138635	0.140721	0.132293
EPNS (MW)	0.002777	0.002743	0.002590
EENS (MWh/yr)	24.26002	23.97020	22.62624
LOLF (occ./yr)	0.052875	0.051543	0.050420
No. of States	-	45 567 000	400 200

should be noted: the value calculated by the EPSO method is in all cases inside the confidence interval obtained for the MCS and the value obtained by the EPSO method, at 7500 analyzed states, is already inside the confidence interval only reached by MCS after more than 31 000 states sampled.

Table VI shows the results obtained for the RTS-96. The target coefficient of variation was $\beta = 5\%$ to the EPNS index. The MCS required circa 45 million visits to system states to converge and produce all results while the EPSO-based model required only circa 400 thousand visits to enter the confidence interval defined by the same β. The ANA results in Tables V and VI are included to allow gauging the quality of the results obtained. In fact, several factors can influence on the performance (i.e., accuracy, number of visited states, and CPU time) of all three methods (i.e., ANA, PB, and MCS). Among these factors, the following can be listed: system size, rarity of the failure event, number of different units, unit capacity sizes, and load shape. Some of these factors are interconnected and also related with other ones: for instance, the event rarity is related to failure/repair rates and to other factors previously listed. Moreover, time-dependent sources like wind generation can also be dealt with PB methods (and, obviously, with the MCS), as it was shown in other works [10] with relative success. Clearly, each method will have its best performance under very specific conditions. Undoubtedly, the proposed PB method, the EPSO algorithm, has demonstrated to be a serious challenger of the other two traditional methods.

VII. CONCLUSION

PB methods are a promising alternative approach to MCS in nonchronological power system reliability assessment. This paper innovates in the application of PB methods by using an EPSO algorithm and by systematically adopting a swarm spreading strategy instead of an optimization approach. The beneficial effects of such options are evident in speeding up calculations for the same accuracy or in obtaining a better accuracy for the same computing effort. Comparisons confirming this assertion have been made with previously published results and with a pure optimization strategy. From a theoretical point of view, PB methods can only be efficient when the cardinal of the set of states contributing to an index is not too large (one must remember that it is an additive method). A weaker condition is that, although the cardinal of the set of states contributing to an index is large, a subset of states with significant contributions to the index is not too large (this allows the coexistence of a much larger subset of states only contributing in extremely small amounts to the index under calculation).

When competing with MCS, one can also say that PB methods gain advantage when the set of states contributing to the index is small, relatively to the whole set of possible states—because in these cases, the MCS usually takes more

iterations to converge while the coverage of the set of contributing states is done more efficiently by PB methods.

PB methods are not statistic-based approaches, and therefore, no confidence interval has been calculated. However, they can be tuned with MCS and also with fast analytical convolution (FAC) methods to ensure the correct stopping criterion. Moreover, PB methods can be considered as excellent competitors to FAC-based methods, and also to MC-based methods equipped with variance reduction techniques. Finally, this work helps opening another research frontier to tackle power system reliability assessment.

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