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Improving Power System Reliability Calculation Efficiency with EPSO Variants

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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 rely on a biased sampling, induced by an objective function, that focuses 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.**

IndexTerms–**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 emergence of enough computing power in the beginning of the 90's, coupled with the adoption of efficient convergence acceleration techniques. The two basic advantages of MCS were: a) allowing simulation of realistic characteristics of systems, even those not necessarily reducible to formal mathematical models, and b) allowing the calculation of distributions and not only of mean values (in its simplest form, allowing the estimation of variance). Non-chronological models became successful then.

However, as it is usual in such cases, the growth in computer power opened the way to the desire to perform chronological simulations and this became demanding of increased computing power. At the same time, even non-chronological models became more complex because of the availability of computing power at desktop level. As it happened in many other cases in the development of science and technology, the moment one has at his/her disposal more computing power, it becomes almost at once insufficient for the new and more complex models one wishes to run.

Recently, an alternative to MCS started to emerge: *population based* 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, population-based (PB) methods are those that search only for the meaningful subset of the state space and 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 may count, for instance, evolutionary algorithms (EA) – evolutionary programming or genetic algorithms (GA) – and particle swarm optimization algorithms (PSO). They were all traditionally developed to be an optimization tool, 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 kept, 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 – EPSO, Evolutionary Particle Swarm optimization, over Monte Carlo to calculate reliability indices in a Power System. The results obtained will be compared with the results from other researchers and conclusions drawn from the experiments designed.

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II. Population Based Methods

Population based (PB) methods are enumeration methods, which count different states in the state spaces such as proposed in [1]. PB methods are not statistical methods and, therefore, they do not allow the calculation of an interval of confidence to 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 a narrow enough neighborhood of the real value and the search for more states is stopped. If the search process is effective, this will typically happen long before any acceptable confidence interval may be calculated by a Monte Carlo simulation (counting in terms of iterations or visited states): this is the practical value they offer. 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 obtained by:

$$\hat{F} = \sum_{i \in D} p_i \times F_i \ , \qquad (1)$$

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

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 acceptable for a state i whose probability is very small (unless the value of F_i becomes unusually large). If the search process is adequately conducted, this will be assured in practice. Moreover, the truncation of the state space was an accepted fact in the past, when analytical models prevailed. Besides that, a Monte Carlo process does not guarantee an exact value, anyway.

The proposal of PB methods as a competitor to MCS 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

$$\underset{i \in D_f}{Max}\ p = p_i \ , \qquad (2)$$

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 in such states. This means that the evolution of 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, which would lead to states of equal probability, in order 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 $EPNS_j$ of state i to system power not supplied (EPNS):

$$EPNS_i = p_i L_i \ , \qquad (3)$$

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

$$\underset{i \in D_f}{Max}\ EPNS = EPNS_i \ , \qquad (4)$$

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 Eq. (2) and by Eq. (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 by interruption cost.

In [7], a particle swarm method was applied to a bi-objective formulation with two points of attraction (Max L and 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. Moreover, the same approach has proved utility on other areas [11].

In contrast to MCS, the 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. By 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 a MCS process. For instance, if one is evaluating the EPNS (Expected Power Not Supplied) 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 an algorithm to visit the same states. Because a sort of stochastic exploration of the state space is launched in PB methods, 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 growingly 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 the MCS, 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]-[17]. It is an Evolutionary Algorithm with an adaptive recombination operator inspired in the "movement rule" of PSO (Particle Swarm Optimization). The movement rule of PSO generates a new individual as a weighted combination of parents, which are: a given individual, in the population, the best ancestor of this individual and the best ancestor of the present generation. This may be seen as a form of intermediary recombination. In this type of recombination in evolutionary algorithms, 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 is a 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 non-zero 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 *logN* (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: (a) the type of objective function that induces the algorithm search, and (b) 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 FOR (forced outage rate) 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

$$n_k = \begin{pmatrix} N_{1k} \\ M_{1k} \end{pmatrix} \times \begin{pmatrix} N_{2k} \\ M_{2k} \end{pmatrix} \times \ldots \times \begin{pmatrix} N_{Gk} \\ M_{Gk} \end{pmatrix} \tag{7}$$

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

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

note that p_k is the probability of any of the states contained 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 a rounding process 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.

B. Type of objective function

The objective is to conduct a biased search in the state space, identifying states that have L_i positive. Examining Eq. (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.

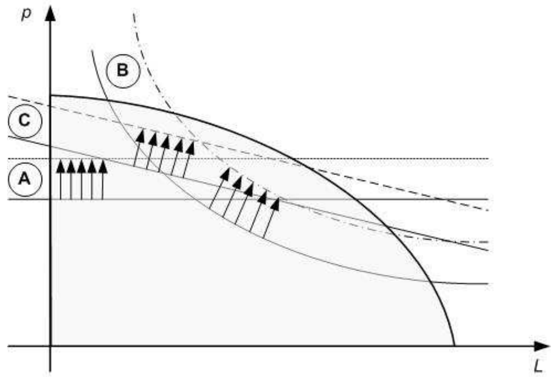

Fig. 1. Illustration of the effect of different objective functions in the way they push the search in the attribute space of *p* and *L*: (A) Maximizing *p*; (B) Maximizing $p{\times}L$; (C) Maximizing a weighted sum of *p* and *L*.

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 *EPSN* 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. *The 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, 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 Eq. (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 **P** and another particle **Q** is below a pre-specified radius
    Then
    Calculate (**P-Q**)
    If (**P-Q**) is close to 0
      Then generate a random (**P-Q**)
    Apply a spreading function Sp to (**P-Q**)
    Apply a squashing function Sq() to (**P-Q**)
    Add Sq(Sp(**P-Q**)) to Eq. (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:

$$Cfit_{ik}=\frac{Fit_i-Fit_k}{\left\|C_i-C_k\right\|},$$

  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 Eq. (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.

TABLE I
IEEE RTS - GENERATING CAPACITY RELIABILITY INDICES

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

TABLE II
IEEE RTS - 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

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:

$$\alpha_1(t) = \left|\sin(2\pi t/T)\right|, \quad \alpha_2(t) = 1 - \alpha_1(t).$$

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, called Dynamic Weight Aggregation (DWA), and Type W were, 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

A set of tests were carried out with the generating system of the IEEE-RTS [20] to assess the reliability indices. The choice of this system is justified by two reasons: (a) It is the same system used in other publications, therefore allowing comparison of results; (b) the exact result is known, which allows the assessment of the accuracy of the reliability results achieved [21] – see Table I.

Table II shows that from a total of 32 units, there are 9 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 τ = 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.

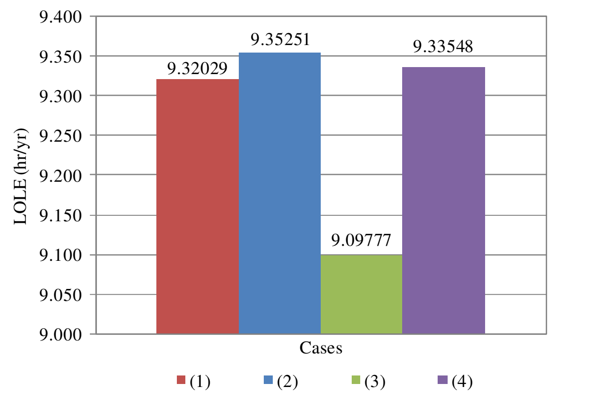

Fig. 2. LOLE estimation with different objective functions and hybrid spreading strategy. (1) A2/XYZ; (2) B2/XYZ; (3) C1/XYZW; (4) C2/XYZW.

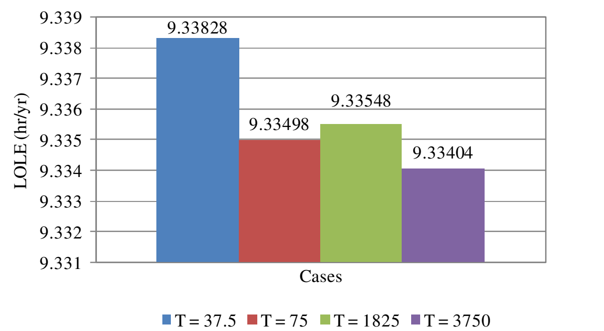

Fig. 3. Comparison of efficacy in LOLE estimation for different oscillation periods T in strategy C2/XYZW.

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.

Figure 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 the corresponding results are shown in Fig. 3. As it can be observed, 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 (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 reliability index used was the EPNS (expected power not supplied, calculated as $EPNS = \sum pL$, for all states or $EPNS = \sum npL$, for all cases. To gauge these comparisons, a run was also made with the classical EPSO algorithm. Figure 4 shows a sensitivity study on a B2/X strategy.

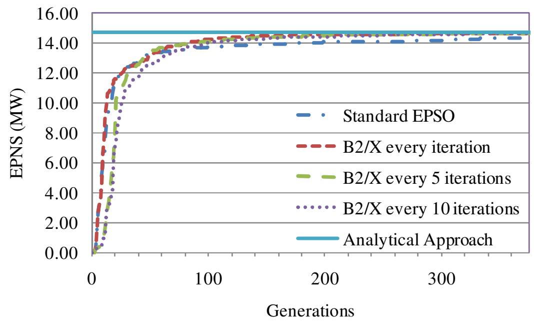

Fig. 4. Progress of the calculated EPNS with different B2/X strategies and comparison with standard EPSO, in 375 generations, 40 particles.

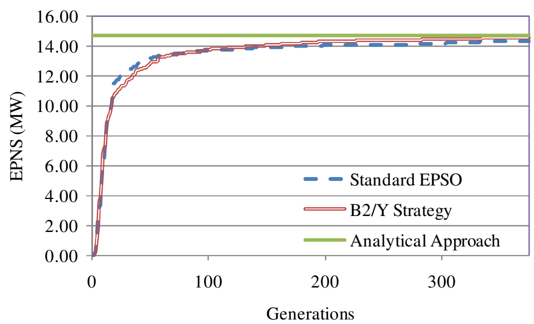

Fig. 5. Progress of the calculated EPSN with a B2/Y strategy and comparison with standard EPSO, in 375 generations, 40 particles.

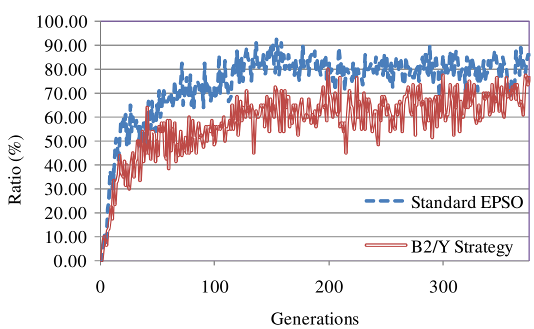

Fig. 6. Calculating EPNS with a B2/Y strategy and comparison with standard EPSO, in 375 generations, 40 particles: evolution of the ratio of case repetitions in percentage of the total number of case visited in each generation

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. Figure 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 finally confirms that strategy -/Z is also beneficial in contributing to building up the EPNS index.

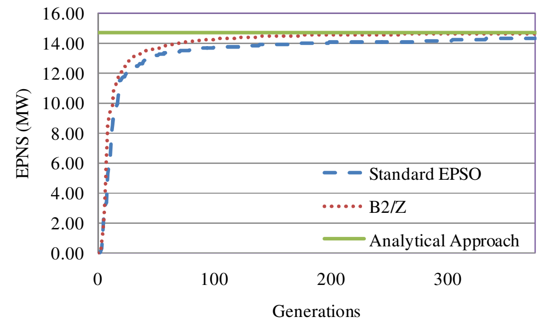

Fig 7. Progress of the calculated EPSN with a B2/Z strategy and comparison with standard EPSO, in 375 generations, 40 particles.

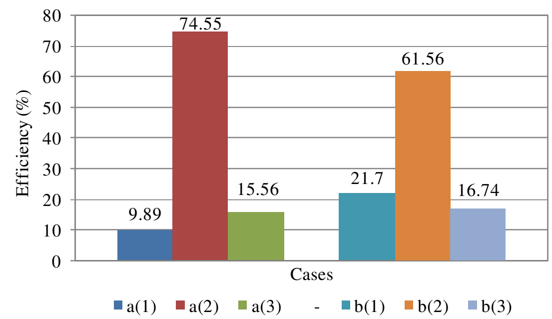

Fig 8. Efficiency ratios, in percentage of the total number of cases visited, comparing a B2/Z strategy (right, b) with standard EPSO (left, a), in 375 generations, 40 particles – (1) Significant cases counted; (2) Repeated visits; (3) Cases visited below threshold limit.

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, 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 the double of 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.

Figure 9 gives another perspective of the quality of the search. One may see that strategy B2/XYZ leads to a better coverage of the set of interesting cases (with higher probability) than the standard EPSO – and this is why the count in significant cases is higher, as seen in Fig. 8.

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 740 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.

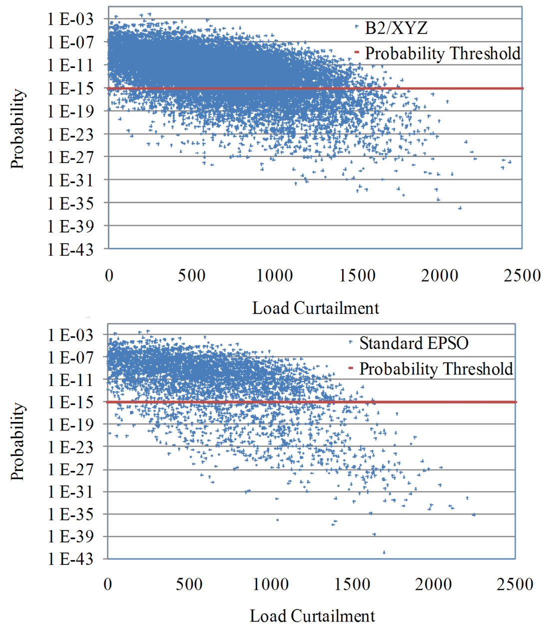

Fig. 9. Charts depicting load curtailment L vs. case probability p, in logarithmic scale (the cut-off value of 10^{-15} is marked) – same number of cases identified by standard EPSO (below) versus EPSO with B2/XYZ (above). The density of points below the probability threshold is much higher in the Standard EPSO case, representing a wasted effort when compared to the B2/XYZ strategy.

TABLE III
COMPARISON IN 3 RELIABILITY INDICES (VALUE AND ERROR) OF THE RESULTS OF MSGA [4] WITH EPSO B2/XYZ

Index	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
LOEE (MWh/year)	1163.00	1169.18
LOEE Error (%)	1.13	0.61

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

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

Table III presents the results of the comparison in three reliability indices (LOLE – Loss of load expectation; LOLF – Loss of load frequency; LOEE – Loss of energy expectation) 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. One can confirm that 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 then the result reported in [4].

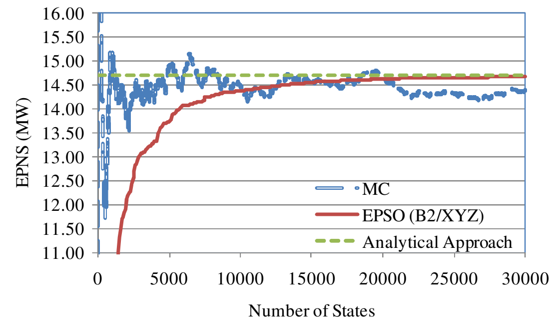

Fig. 10. Evolution of estimated EPNS (y-axis) with the number of states visited (x-axis): MC results (dashed curve oscillating around the real value) vs. EPSO results (line converging "asymptotically" to the exact result).

TABLE V
COMPARISON OF RESULTS FROM ANALYTICAL (ANA), MC AND EPSO

ANA	EPNS (MW)	14.69575			
MC	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

C. Comparison with Monte Carlo

The final comparison to be made is with a non-sequential Monte Carlo simulation run on the same problem. To make the comparison clear and not confuse the analysis with unnecessary model details, a comparison is presented considering the peak load value (see Fig. 10 for EPNS). Table V shows a comparison of performance between MCS and EPSO, for the estimation of EPNS and for different variation coefficients β applied to the MC sampling. Rows 4 and 5 show the limits for the confidence interval at 95% confidence level in each case. Two things should be noted: the value calculated by the EPSO method is in all cases inside the confidence interval obtained for the MCS simulation 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. Finally, the result from EPSO is always a lower bound for the exact value, while nothing can be said about the MCS result.

VI. CONCLUSION

Population-based (PB) methods are a promising alternative approach to Monte Carlo simulation (MCS) in non-chronological power system reliability assessment. They rely on a biased sampling, induced by an objective function that focuses 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.

This paper innovates in the application of PB methods by using an Evolutionary Particle Swarm Optimization (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.

PB methods are not statistical-based approaches and, therefore, no confidence interval can be calculated. However, they can be tuned with MCS and also with fast analytical convolution (FAC) methods to ensure the correct stop criterion. Moreover, PB methods can be considered as excellent competitors to FAC-based methods, and also to MCS-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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