

A New Intelligent Search Method for Composite System Reliability Analysis

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Abstract—This paper presents a new method for composite power system reliability analysis. This method is based on an adaptation of the Particle Swarm Optimization (PSO) technique. The adaptation consists of applying swarm intelligence not to search for an optimum, but to search the state space preferentially for failure states so that system reliability indices can be determined. Another aspect of the adaptation consists of using multiple objectives to exercise better control over the particle dynamics. This new formulation, called Multi-Objective Particle Swarm (MOPS), is shown to be very effective in its intelligent search for system loss of load states. This paper develops the MOPS formulation, describes its implementation and demonstrates it on the Modified IEEE Reliability Test System.

I. INTRODUCTION

As interconnected power systems continue to grow in size, diversity of technology, and complexity of operating policies, tools for planning and analysis must also evolve in sophistication and capability in handling larger and more complex system models. Considerable research has been conducted for determining reliability indices for composite (generation and transmission) systems. Some of the traditional approaches are based on analytical techniques such as contingency ranking [1], [2], capacity assistance [3], [4], and decomposition [5]–[7]; others are based on Monte Carlo simulation. Simulation techniques provide more flexibility when complex system conditions have to be taken into consideration. Most of these techniques are based on the Monte Carlo method. The underlying principle of Monte Carlo methods is to sample states based on the probabilities of their occurrence. However, this also means that for highly reliable systems, the probability of encountering failure states is very low. Hence, the simulation takes a very long time to converge depending on the size of the system. Much work [8]–[10] has been done on improving the performance of Monte Carlo simulation.

Although the advances mentioned above have been significant, research has continued beyond this to develop intelligent search methods that selectively seek out failure states as opposed to the random search that is inherent in Monte Carlo methods. In the last few years, other techniques for selectively searching states have been explored and implemented. ‘Evolutionary methods’ such as ‘Genetic Algorithms’ [11], [12], ‘PSO’ [13] have emerged as promising techniques.

In recent years, PSO [14] has found applications in power system areas [15] like distribution state estimation [16], dynamic security assessment [17] and optimization of AGC [18]. It has also been used as a search tool for identifying the loss of load states for evaluation of reliability indices [13]. In their previous work [13], the authors used a single objective function to control the dynamics of the particles. This formulation was found to have several deficiencies which was later addressed by the formulation of a multi-objective function approach.

Multiple objectives have been used in power systems problems using PSO [17], [19]. However, the above references have used PSO as an optimization technique. In our approach, PSO has been used as a search technique, and therefore our formulation is significantly different from the above. Multiple-objectives enhance the performance of the search method. This paper describes the development and implementation of the Multi-Objective Particle Swarm (MOPS) method as an intelligent search technique for composite system reliability analysis. Intelligent search techniques have been identified as promising alternatives to Monte Carlo techniques, particularly for large and complex systems because of their ability to selectively search for failure states. This paper presents the formulation and implementation of MOPS method.

II. THE PARTICLE SWARM OPTIMIZATION TECHNIQUE

The particle swarm optimization technique was developed as a result of simulating the social behavior and the flocking of birds [14]. Birds flock in search of food on a plot of land. The location of the food is initially unknown to them. At each location the birds have a sense of distance from the location of food. They share this information among themselves and their motion is governed by this sharing of information. Eventually, all the birds finally settle down at the location of the food. In this technique, the birds are represented by a more generic entity called ‘particles’. These particles search for the optimum (the location of food) in the problem space (the plot of land). Each point in the state space has a fitness value (a sense or measure of distance from the location of food) according to an objective function defined by the user. Particles move in the state space in search of the optimal point. In this process

each particle remembers the best position it has ever visited. The dynamics of the particles is governed by three aspects: (a) inertia: the particles continue to move in the same direction as they were previously moving; (b) personal best: the particles tend to move towards a position which has the best personal fitness so far; and (c) group best: particles try to move towards the position which gives the best fitness value in the group. The combination of the above factors give a new direction of motion to each particle. The basic equation governing the dynamics of the particle is:

$$v[\cdot] \leftarrow v[\cdot] + \text{rand}() \times c_1 \times (pbestx[\cdot] - presentx[\cdot]) + \text{rand}() \times c_2 \times (pbestx[gbest] - presentx[\cdot]) \quad (1)$$

where,

$v[\cdot]$ is a vector of velocities in each direction in an

N -dimensional space where the particles are free to move. $pbestx[\cdot]$ is the vector of co-ordinates (or the point in the space) which gives the personal best the particle has encountered so far.

$presentx[\cdot]$ is the present position of the particle.

$pbestx[gbest]$ is the position which gives the best fitness value among all the particles in the group. This is also referred to as group-best.

$\text{rand}()$ is a uniformly distributed random number between 0 and 1, which accounts for randomness in the social behavior or bird flocking.

c_1 and c_2 are parameters that need to be carefully chosen for each application. This requires a careful study of the dynamics of the particle.

In the above equation, the first term in the right hand side represents the momentum of the particle. This term prevents the particles from getting stuck in the local optima. The second term drives the particle towards its personal best. The third term drives it towards group best. These velocities are then used for computing the next position of the particles as follows.

$$presentx[\cdot] \leftarrow presentx[\cdot] + v[\cdot] \quad (2)$$

III. MULTI-OBJECTIVE PARTICLE SWARM

The classical PSO formulation had a single objective function [14]. An initial application of this formulation produced promising results. It was observed that in order to achieve a good approximation of the reliability indices, the particles had to visit already visited states repeatedly. Further, many non-loss of load states were also being visited. This motivated to devise a mechanism that would enable the particles to visit as less non-loss of load states as possible and also minimize multiple visits to already visited states.

In the classical formulation, there was a single objective point or center of attraction, which was the location that resulted in the maximum load curtailment, the particles moved towards the point with maximum curtailment (the origin of the state space where none of the generators are available). A major drawback of the above is that the particles are continually being driven towards the state where all the generators are

unavailable. In this direction, i.e., with increasing loss of load, the exact state probability is decreasing. So, if a particle, by chance missed a significantly contributing loss of load state somewhere away from the objective point, it would never reverse its direction and possibly visit that state. Therefore dual-objectives were formulated. In this formulation, we have two objective functions: one, maximizing the curtailment of the loss of load state (state with all generators unavailable); two, maximizing the probability of the loss of load state. In this case, the particles are acted upon by two opposite forces. During the movement towards one center of attraction (say, the point which gives the most load curtailment), even if the particles miss a state, the velocity vector which points towards the other center of attraction (the one with a high exact state probability) will try to pull the particles towards itself, thereby increasing the chances of encountering the missed state. Corresponding to each objective we have a personal best for each particle and one group best. The modified equation governing the velocity of the particles is now:

$$v[\cdot] \leftarrow v[\cdot] + \text{rand}() \times c_1 \times (pbest1x[\cdot] - presentx[\cdot]) + \text{rand}() \times c_2 \times (pbest1x[gbest] - presentx[\cdot]) + \text{rand}() \times c_3 \times (pbest2x[\cdot] - presentx[\cdot]) + \text{rand}() \times c_4 \times (pbest2x[gbest] - presentx[\cdot]) \quad (3)$$

where,

$v[\cdot]$ is vector of velocities in different directions in N - dimensional state space.

$pbest1x[\cdot]$ is vector of coordinates which gives personal best fitness value for the first objective function the particle has visited so far.

$presentx[\cdot]$ is present position of the particle.

$pbest1x[gbest]$ is the position which gives the best fitness value for the first objective function among all the particles in the group. This is also called as group best1.

$pbest2x[\cdot]$ is vector of coordinates which gives personal best fitness value for the second objective function the particle has visited so far.

$\text{rand}(\cdot)$ is a uniformly distributed random number between 0 and 1.

c_1, c_2, c_3, c_4 are acceleration coefficients which need to be carefully chosen for each application.

In this model we have denoted $pbest1$ as $PPbest[\cdot]$ which is a state which has the maximum probability that particle has ever encountered. $pbest1[gbest]$ is denoted as $PGbest$ which is state which has the maximum probability among all the particles of the group. $pbest2$ is denoted as $CPbest[\cdot]$ which is a state which has the maximum curtailment that the particle has ever encountered. $pbest2[gbest]$ is denoted as $CGbest$ which is a state which has the maximum curtailment among all the particles of the group.

The next positions of the particles are computed using equation (2).

IV. SYSTEM MODELING

Generators: These are modeled as two state devices described by their generating capacities and forced outage rates. Multiple units at the same bus are replaced by a single equivalent multi-state unit described by a capacity outage table at that bus.

Transmission lines: These are treated as two state components described by their capacity and probability of failure. However, multiple circuits between any two buses is replaced by an equivalent transmission line with multiple capacity states.

Load: The load is considered to be at the system co-incident peak.

V. APPLICATION TO RELIABILITY ASSESSMENT

A. The MOPS formulation

The various components of the multi-objective formulation are described below:

State space: The state space is of dimension $(N_g + N_t)$ where N_g is the number of generating buses and N_t is the number of transmission lines (after equivalencing multiple lines between same pair of nodes). Each point in the discrete state space can be denoted by the co-ordinates $(g_1, g_2, \dots, g_{N_g}, t_1, t_2, \dots, t_{N_t})$. Here the component g_i denotes the generating capacity available at the i^{th} generating bus. The component t_i denotes the capacity state of the i^{th} transmission line.

Multiple Objectives: As mentioned earlier, the particles are now subject to conflicting forces from two opposing objectives. The first objective is to move towards that part of the state space that maximizes the probability of occurrence of a system state. The second objective is to move towards that part of the state space that maximizes the load curtailment.

Database: In order to keep track of the states visited by the particles, a dynamic array has been used. Whenever a state is encountered, its decimal equivalent is computed. Then this number is searched in the array. If the number is already present, then it means that this state has already been encountered before. Otherwise, this state is being encountered for the first time, and therefore the decimal equivalent is stored in the array.

B. Algorithm

- 1) Initialize the particles.
- 2) For each particle compute the exact state probability for the system state represented by it. If the probability is less than a threshold, then do not do anything and proceed to the next particle. Otherwise, go to the next step.
- 3) Compute the decimal equivalent and check if it exists in the database.
- 4) If the decimal equivalent exists in the database, then check if that state has already been a personal or group best (both objectives) for any particle. If so, then reset the corresponding 'best value' to a very small number. This is necessary to decrease the likelihood of this state

or location being the personal best or the group best. Then proceed to step (6)

If the decimal equivalent does not exist, then put this number in the database and go to the next step.

- 5) For each particle evaluate the objectives: For the first objective, i.e., for movement towards the state that gives the maximum load curtailment, the minimum load curtailment is evaluated for the state or the co-ordinates the particle is in. This fitness is evaluated using a DC flow model as shown below.

$$\text{Loss of Load} = \text{Min} \sum_{i=1}^{N_b} C_i$$

subject to:

$$\begin{aligned} \hat{B}\theta + G + C &= D \\ G &\leq G^{max} \\ C &\leq D \\ b\hat{A}\theta &\leq F_f^{max} \\ -b\hat{A}\theta &\leq F_r^{max} \\ G, C &\geq 0 \\ \theta &\text{ unrestricted} \end{aligned} \quad (4)$$

where

- N_b = number of buses
- N_t = number of transmission lines
- C = N_b -vector of bus load curtailments
- C_i = i -th element of C , i.e., unsatisfied demand at bus i
- D = N_b -vector of bus demands
- G^{max} = N_b -vector of available generation at buses
- F_f^{max} = N_t -vector of forward flow capacities of transmission lines
- F_r^{max} = N_t -vector of reverse flow capacities of transmission lines
- G = N_b -vector of dispatched generation at buses
- θ = N_b -vector of bus voltage angles
- b = $N_t \times N_t$ primitive (diagonal) matrix of transmission line susceptances
- $\hat{A}$ = $N_t \times N_b$ element-node incidence matrix
- $\hat{B}$ = $N_b \times N_b$ augmented node susceptance matrix
- $\hat{B} = \hat{A}^T b \hat{A}$

The fitness for second objective, i.e., movement towards that part of the state space that maximizes the occurrence of the state, is nothing but the exact state probability of that state.

Now, based on these two fitness values, we have two sets of pbest and gbest. During the simulation the pbest and gbest locations are updated using the respective fitness values.

- 6) Compute velocity and next position.
- 7) If all particles have been processed, then go to next step, otherwise go to step (2).

- 8) Test for the convergence of the index. The simulation stops when the index stabilizes. This is said to be true if the relative change in the index stays below a threshold for a consecutive number of iterations:

$$\frac{\sum_k \Delta \text{LOLP}}{\text{LOLP}} \leq \epsilon \quad (5)$$

Where, $\sum_k \Delta \text{LOLP}$ is the total change in the obtained LOLP estimate over k consecutive iterations, k being a predetermined integer, and ϵ a predetermined threshold.

Inclusion of Multiple Load States and Scheduled Maintenance:

In this framework, multiple load states are accommodated using a cluster load model as described in [21].

Scheduled Maintenance: Planned outages are accommodated as follows. Based on the maintenance schedules, the study period is divided into intervals such that one or more components are taken out for maintenance or brought back from maintenance only at the beginning or end of an interval. In other words, the only outages that occur within an interval are forced outages, not planned outages. Based on the relative durations of the maintenance intervals, a discrete probability distribution function is constructed over all the maintenance intervals. Within each interval, appropriate generation and transmission capacity distributions and cluster load models are constructed, and reliability indices are determined using MOPS. After this is done for all the maintenance intervals, each annualized index is obtained from the weighted sum of the corresponding index over each maintenance interval, the weights being the probabilities of the corresponding intervals.

VI. METHOD DEMONSTRATION AND ANALYSIS OF BEHAVIOR

In this section, the outcome of applying the MOPS method to a test system is described. The values of the parameters used in the implementation are also described. Finally, the convergence behavior of the MOPS algorithm is discussed.

A. Test System, Conditions and Results

The MOPS method described above was applied to the Modified IEEE Reliability Test System (MRTS) [20]. The MRTS has 24 buses, 32 generators and 38 transmission lines. It has a peak load of 5130 MW and generating capacity of 6810 MW.

In applying the MOPS method, the system load was assumed to remain constant at 5130 MW. The generator forced outages were taken into account. The transmission line contingencies along with line capacity constraints were duly considered. Transmission line capacity constraints were modeled as described in section V.

In equation (3), there are four constants that affect the dynamics of the particles, and the selection of these constants affects the rate of convergence of the algorithm. After some trials, the following values of these constants were found to provide satisfactory results: $c_1 = 0.1$, $c_2 = 0.1$, $c_3 = 0.01$ and $c_4 = 0.01$.

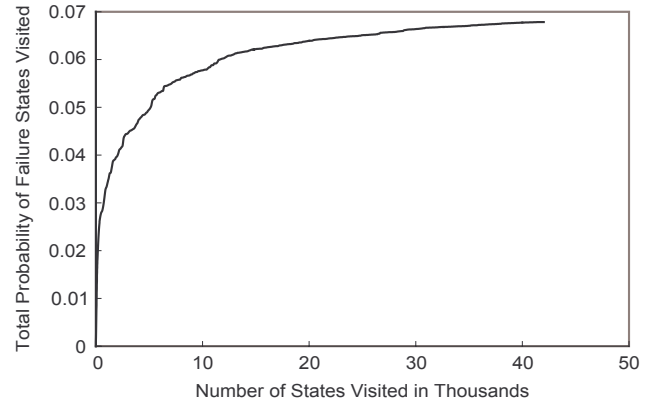


Fig. 1. Convergence behaviour for the test system.

TABLE I
RELIABILITY INDICES

Location	EUE (MWh/yr)	LOLE (hr/yr)	Location	EUE (MWh/yr)	LOLE (hr/yr)
System	87522.01	594.27	Bus 9	2413.85	16.72
Bus 1	10050.34	193.52	Bus 10	1524.92	15.56
Bus 2	2940.46	64.23	Bus 13	62.49	0.39
Bus 3	11121.77	57.98	Bus 14	23603.75	251.98
Bus 4	531.56	6.87	Bus 15	1469.39	12.00
Bus 5	4912.18	63.94	Bus 16	3353.46	30.38
Bus 6	6025.78	91.13	Bus 18	989.38	21.06
Bus 7	470.95	37.78	Bus 19	1004.71	12.07
Bus 8	16993.97	171.67	Bus 20	52.97	0.61

The size of the swarm also plays a role in determining the convergence behavior. A swarm of 44 particles was found to perform satisfactorily.

The results are summarized as follows.

The stopping criterion described in equation (5) was applied with $k = 100$ and $\epsilon = 0.1\%$. This criterion was met after the MOPS visited 42001 states. This number compares favorably with the total size of the state space, which comprises over 10^{17} states. The number of states visited also compares favorably with those required by Monte Carlo methods [10].

At convergence, the LOLP as estimated by the MOPS was 0.06784, which corresponds to an LOLE of 594.27 h/y. The convergence behaviour is shown in Fig. 1. The system EUE was found to be 87522.01 MWh/yr. The locational indices are shown in Table I.

B. Convergence Behavior

The MOPS algorithm was found to visit higher probability failure states with much higher frequency in the early part of the simulation. This is consistent with swarm behavior in ‘intelligently’ identifying the ‘more attractive’ regions of the search space. Thereafter, the convergence slows down. The overall convergence pattern is depicted in Fig. 1.

The convergence behavior showed considerable sensitivity to the size of the swarm and to the values of the constants c_1 , c_2 , c_3 and c_4 . However, the values stated in section VI.A provided satisfactory results.

It is noteworthy that the convergence behavior of the MOPS is not, in general, unlike that of another intelligent search technique that has been applied to both generation system reliability analysis and composite system reliability analysis — the Genetic Algorithm (GA) [11]. Both methods (MOPS and GA) estimate indices by aggregating the contribution of the failure states visited and hence these estimates are asymptotically unbiased.

VII. CONCLUSION

This paper described an intelligent search technique for the estimation of composite system reliability indices. The method consisted of an adaptation of the Particle Swarm Optimization technique, which has been found to be extremely effective in search spaces containing multiple local optima. The adaptation was effected by defining multiple and conflicting objectives, so that the particles would never converge upon any one part of the state space and thereby end the search; rather, the conflicting objectives force the particles to continue their selective search for failure states until the estimated indices converge.

There are several reasons for the high effectiveness of the MOPS method. One is the simplicity of the representation of the particle dynamics; this makes it possible to incorporate the swarm intelligence with very little computational effort. The second reason is that the small randomness built into the movement of the particles prevents them from getting stuck in the neighborhood of dominant states. This feature enabled the original PSO method to 'ride out' of local optima. The third reason is the multi-objective formulation; if only one objective (LOLP or EIR) were used, that swarm would settle at one 'corner' of the state space and stop, and this would invariably occur well before the indices converged.

The MOPS method shows considerable promise as an alternative to Monte Carlo simulation, particularly for large and complex systems, because of its intelligent search capability. Further research will attempt to improve the method, as well as to estimate other indices such as frequency and duration indices.

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