

A Particle Swarm Based Method for Composite System Reliability Analysis

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Abstract—This paper presents a new method of assessing composite power system reliability. This method is based on the Particle Swarm Optimization Technique, which is fundamentally an optimization method. In this work, the technique has been used as a search method for identifying the loss of load states while the ‘particles’ move towards the optimum. The objective of the ‘particles’ is to move towards the position with the best fitness value. During the dynamics of the particles, they visit various states. These states are tested for acceptability and reliability indices are collected accordingly. This paper presents a formulation and implementation of the method for application in the reliability area, and reports the results of testing this implementation on a simple 4-bus system.

I. INTRODUCTION

Many methods have been developed for reliability analysis of composite (generation and transmission) power systems. These methods can be classified into two categories: (a) analytical techniques such as contingency ranking [1], [2], capacity assistance [3], [4], decomposition [5], [6], [7]; and (b) simulation-based techniques.

Simulation-based methods afford very high modeling flexibility, and in some cases, for large and complex systems, simulation is often the only viable option. Most such methods are based on Monte Carlo simulation. Techniques like accelerated Monte Carlo methods [8], [9], [10] have also been developed. Other simulation methods that have been devised are based on ‘evolutionary methods’ such as “Genetic Algorithms” (GA) [11], [12]. The above approaches have attempted to preserve accurate modeling while improving the process of searching for failure states.

In spite of the availability of many powerful methods of composite system reliability evaluation, the need for even more powerful and efficient tools continues to exist, because of the increasing complexity of present day systems. The authors have identified Particle Swarm Optimization (PSO) as a potentially powerful tool for this kind of analysis. Very recently, this method has found applications in many power systems areas such as distribution state estimation [13], dynamic security assessment [14] and optimization of AGC [15].

This paper develops a formulation and an implementation of the PSO method that is applicable to the composite system reliability assessment area. Here, PSO is used for identifying loss of load states in the composite reliability study of a power system. The results shown are basic and the only index computed is the Loss of Load Probability (LOLP).

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The basis of PSO is to simulate the flocking of birds in search of food. Classically the simulation is performed on a two dimensional grid (representing an area of land, where food is supposed to be located). The birds set out in search of food, the location of which is unknown to them. They follow certain dynamics (described in Sec. II) and concur upon the position where the food is located. Now, in the process they visit other positions as well. In our application, we use these visits to collect reliability data. This is discussed in Sec. III. As a simple test case, this method was applied to a 4-bus system with different generation and load scenarios. The results obtained were compared with results obtained by enumeration for validation.

II. THE PARTICLE SWARM OPTIMIZATION TECHNIQUE

The particle swarm optimization technique was developed as a result of simulating movement of birds flocking in search of food and also as a result of simulating social behavior. In this paradigm, the particles (birds) traverse (fly over) the state space (an area of land) in search of the optimum (food). Each point in the space has a fitness value (a sense of distance from the location of the food). The motion of the particles is governed by three aspects: one, inertia, i.e. they continue to move in the direction in which they had been moving; two, local optima: they tend to move towards the position that gives their personal best fitness value, and three, the group optima: they tend to move towards the position that gives the best fitness within the same group. The interaction of these three factors gives the particles new positions and in due course of time they settle upon the position that gives the best fitness value (a zero distance from the food). This simple concept can be implemented using a small computer program and is computationally inexpensive as this uses only primitive mathematical operators. The basic equation describing the dynamics for any 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.

On the right hand side of the equation, $v[\cdot]$ incorporates momentum of the particles in the dynamics. This term is used in order to prevent the particles from getting stuck at a local optimum. There are some variations on this which can be found in [16]. The second term represents the tendency to move towards the position giving their personal best, while the last term denotes motion towards the group best.

After the velocities are computed, they are added to the positions of the particles to give the new positions in the space.

$$\text{present}x[\cdot] \leftarrow \text{present}x[\cdot] + v[\cdot] \quad (2)$$

This method is similar to many evolutionary techniques such as GA. However, a fundamental difference between PSO and other evolutionary methods is that evolutionary methods simulate evolution: the population evolves based on competition and survival of the fittest, while PSO stems from simulating social behavior: the particles move according to cooperation and competition among individual elements. This method has several distinct advantages over methods like genetic algorithms. This method is very fast because the interactions among the particles is minimum: each particle communicates with only the particle at the location giving the $g\text{best}$, unlike in GA, where each particle must interact with each other. Storage requirement is also much less. The only data we need to store is the current positions of the particles and the positions giving their personal best.

III. APPLICATION TO RELIABILITY ASSESSMENT

The state space is a G -dimensional space where G is the number of generators in the system. Each particle is a point in this space whose value changes according to the equations in the previous section. So each particle position is denoted by $(x_1, x_2, x_3, x_4, \dots, x_G)$. This denotes a particular generation scenario, i.e., the availability or unavailability of the generators. Each coordinate can assume a value of either 0 or 1. A value of 0 implies the generator is unavailable, while a value of 1 denotes availability. For each point, or in other words, each combination of available or unavailable generators, the fitness value was chosen to be the minimum load curtailment for that generation scenario. So the particles will move to the point which maximizes the load curtailment. Clearly, this point is the origin, (where none of the generators is available). During the movement of the particles towards the origin, they visit other states. Each state is tested for loss of load. If the present state turns out to be a loss of load state, then it is compared against a database to see if this state has been encountered before. If not, then the probability of this state is added to the LOLP. However, for our purpose, the origin was not chosen to be the point with the best objective. This was because in such a case, the particles missed several significantly contributing loss of load states. So a point slightly removed from the origin was

chosen to be the desired culminating point. This is described in the algorithm.

A. Algorithm

- 1) Randomly allocate positions to the particles.
- 2) For each particle compute the fitness function. The fitness function in this formulation is the minimum load curtailment given the generator availabilities, for the given demand, subject to the network constraints. A DC load flow model [7] as shown below is used.

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

subject to:

$$\begin{aligned} \hat{B}\theta + G + C &= D \\ G &\leq G^{max} \\ C &\leq D \\ b\hat{A}\theta &\leq F_f^{max} \\ -b\hat{A}\theta &\leq F_r^{max} \\ G, C &\geq 0 \\ \theta &\text{ unrestricted} \end{aligned} \quad (3)$$

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
 $= \hat{A}^T b \hat{A}$

If the curtailment is not zero, check if that state has been accounted for. This is done by using an array, where the decimal equivalent of the state is used to index a boolean value, which says whether the state was encountered earlier or not. If the state was not encountered earlier, then add the contribution of this state to the LOLP and mark the state as visited.

- 3) The G -vector and C -vector obtained from the solution of equation (3) gives the dispatched generation and the minimized curtailment. The dispatch for each generator is used to compute the next state for each particle as follows:

(a) Compute the velocity as:

$$v[\cdot] = v[\cdot] + \text{rand}() \times (g\text{best}x[\cdot] - \text{present}x[\cdot]) \quad (4)$$

where, $presentx[\cdot]$ is a vector of the actual generator despatches (and not the generator availability states of 0 or 1). The $gbestx[\cdot]$ point is slightly away from the origin, where each component has a value of 40% of the generating capacity of the respective unit. The $gbest$ position was not taken to be the origin because the states near to the origin contribute less to the LOLP. Further, choosing the origin as the desired culminating point makes the particles rush into it, thereby skipping many loss of load of states in between. So a point relatively away was chosen so that when the particles try to move to this point they encounter more loss of load states with higher probabilities. Various fractions of the generating capacity were tried and 40% gave the best results for this test system.

(b) After the computation of the ‘velocity’, add this to the current despatch.

$$presentx[\cdot] \leftarrow presentx[\cdot] + v[\cdot] \quad (5)$$

(c) Now, reduce the particle positions to their binary states using the following criteria: if the computed generation is less than 50% of the capacity, the generator goes to the down state. In other words, that component of the particle position transits to 0.

It is noteworthy that the generator despatches do not bear any temporal relationship to the actual generation schedule of a generating unit, and that there is no relationship between any two consecutive states. The transition of one state to another merely constitutes a sampling of the state space.

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

$$\frac{\sum_k \Delta LOLP}{LOLP} \leq \epsilon \quad (6)$$

where, $\sum_k \Delta LOLP$ is the total change in the obtained LOLP estimate over k consecutive iterations, k being a predetermined integer, and ϵ a predetermined tolerance. This is equivalent to occurrence of either of the following two conditions:

- Condition 1 is true if the index stabilizes after a sufficiently large number of samples, i.e., it ceases to undergo significant relative change. This condition is dominant in large sample spaces.
- Condition 2 is true if previously visited loss of load states are encountered consecutively for a set number of times. This condition is dominant in small sample spaces, where in order for the index to stabilize, the particles would have to keep on revisiting loss of load states for a much longer time than necessary.

If the stopping criterion is met, i.e., either of the two conditions is true, stop; else repeat steps 2 through 4.

B. Test System

The above procedure was applied to the 4-bus system shown in Fig. 1:

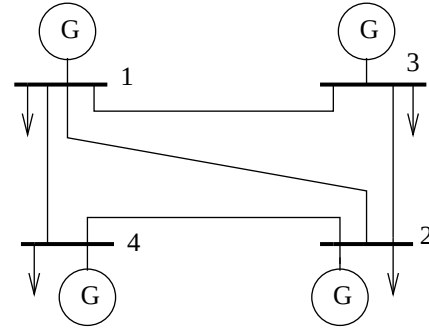


Fig. 1. Four Bus Test System.

Four cases were generated by varying the generating capacities, loads and the transmission line capacities. These are presented below:

1) *Case I:* The generating capacities and the loads are tabulated in Table I.

TABLE I
CASE I: GENERATION AND LOAD

Bus	Generating Capacity (MW)	Load (MW)
1	100	70
2	200	70
3	150	70
4	50	70

The transmission line capacities are tabulated in Table II.

TABLE II
CASE I: LINE CAPACITIES

From Bus	To Bus	Capacity (MW)
1	3	20
1	4	20
4	2	50
2	3	50
1	2	20

For this scenario the different generator states along with the minimum curtailment (fitness) and exact state probabilities are tabulated in Table III.

The algorithm could identify the following loss of load states: 1001, 1000, 0000, 0100, 0111, 0011, 0001, 0101, 1011, 1010, 1110.

Thus, the LOLP was found to be 0.0324. The LOLP computed by enumeration was 0.0326.

Number of loss of load states identified: 11 out of 14.

2) *Case II:* The generating capacities and the loads are tabulated in Table IV.

The transmission line capacities are tabulated in Table V.

For this scenario the different generator states along with the minimum curtailment (fitness) and exact state probabilities are tabulated in Table VI.

The algorithm could identify the following loss of load states: 0100, 0000, 1010, 1011, 0011, 0111, 0010, 0101, 0110, 1100, 0001.

Thus, the LOLP was found to be 0.0219. The LOLP computed by enumeration was 0.0220.

Number of loss of load states identified: 11 out of 13.

TABLE III

CASE I: MINIMUM CURTAILMENT FOR VARIOUS GENERATOR STATES

State	Curtailment (MW)	State Probability
0000	280	1.464×10^{-8}
0001	230	1.316×10^{-6}
0010	146	1.316×10^{-6}
0011	93.75	1.118×10^{-4}
0100	103.33	1.316×10^{-6}
0101	66.66	1.183×10^{-4}
0110	53.33	1.180×10^{-4}
0111	26.66	1.060×10^{-2}
1000	180	1.316×10^{-6}
1001	130	1.183×10^{-4}
1010	52.85	1.830×10^{-4}
1011	2.857	1.060×10^{-2}
1100	9.99	1.183×10^{-4}
1101	0	1.060×10^{-2}
1110	3.32	1.060×10^{-2}
1111	0	0.95672

TABLE IV

CASE II: GENERATION AND LOAD

Bus	Generating Capacity (MW)	Load (MW)
1	200	110
2	50	70
3	250	50
4	100	40

TABLE V

CASE II: LINE CAPACITIES

From Bus	To Bus	Capacity (MW)
1	3	50
1	4	50
4	2	20
2	3	20
1	2	30

TABLE VI

CASE II: MINIMUM CURTAILMENT FOR VARIOUS GENERATOR STATES

State	Curtailment (MW)	State Probability
0000	270	1.464×10^{-8}
0001	176.67	1.316×10^{-6}
0010	156	1.316×10^{-6}
0011	50	1.118×10^{-4}
0100	220.77	1.316×10^{-6}
0101	120	1.183×10^{-4}
0110	100	1.180×10^{-4}
0111	2.727	1.060×10^{-2}
1000	70	1.316×10^{-6}
1001	24.28	1.183×10^{-4}
1010	29.09	1.830×10^{-4}
1011	4×10^{-4}	1.060×10^{-2}
1100	20	1.183×10^{-4}
1101	0	1.060×10^{-2}
1110	0	1.060×10^{-2}
1111	0	0.95672

3) *Case III*: The generating capacities and the loads are tabulated in Table VII.

The transmission line capacities are tabulated in Table VIII.

For this scenario the different generator states along with the minimum curtailment (fitness) and exact state probabilities are tabulated in Table IX.

TABLE VII

CASE III: GENERATION AND LOAD

Bus	Generating Capacity (MW)	Load (MW)
1	100	40
2	150	120
3	50	50
4	200	60

TABLE VIII

CASE III: LINE CAPACITIES

From Bus	To Bus	Capacity (MW)
1	3	50
1	4	20
4	2	20
2	3	40
1	2	30

TABLE IX

CASE III: MINIMUM CURTAILMENT FOR VARIOUS GENERATOR STATES

State	Curtailment (MW)	State Probability
0000	270	1.464×10^{-8}
0001	170	1.316×10^{-6}
0010	220	1.316×10^{-6}
0011	120	1.118×10^{-4}
0100	120	1.316×10^{-6}
0101	48	1.183×10^{-4}
0110	70	1.180×10^{-4}
0111	0	1.060×10^{-2}
1000	170	1.316×10^{-6}
1001	92	1.183×10^{-4}
1010	120	1.830×10^{-4}
1011	52	1.060×10^{-2}
1100	26	1.183×10^{-4}
1101	0	1.060×10^{-2}
1110	20	1.060×10^{-2}
1111	0	0.95672

The algorithm could identify the following loss of load states: 0100, 0101, 0011, 1011, 1010, 0010, 0110, 1100, 1110, 1001, 0100.

Thus, the LOLP was found to be 0.0220. The LOLP computed by enumeration was 0.0220.

Number of loss of load states identified: 10 out of 13.

4) *Case IV*: The generating capacities and the loads are tabulated in Table X.

TABLE X

CASE IV: GENERATION AND LOAD

Bus	Generating Capacity (MW)	Load (MW)
1	150	80
2	50	60
3	200	120
4	100	40

The transmission line capacities are tabulated in Table XI.

For this scenario the different generator states along with the minimum curtailment (fitness) and exact state probabilities are tabulated in Table XII.

The algorithm could identify the following loss of load states: 0001, 0000, 1101, 0101, 0100, 1010, 1011, 1000, 1001, 0110.

TABLE XI
CASE IV: LINE CAPACITIES

From Bus	To Bus	Capacity (MW)
1	3	30
1	4	40
4	2	20
2	3	30
1	2	50

TABLE XII
CASE IV: MINIMUM CURTAILMENT FOR VARIOUS GENERATOR STATES

State	Curtailement (MW)	State Probability
0000	300	1.464×10^{-8}
0001	206	1.316×10^{-6}
0010	120	1.316×10^{-6}
0011	40	1.118×10^{-4}
0100	250	1.316×10^{-6}
0101	150	1.183×10^{-4}
0110	70	1.180×10^{-4}
0111	0	1.060×10^{-2}
1000	150	1.316×10^{-6}
1001	106	1.183×10^{-4}
1010	13	1.830×10^{-4}
1011	1.7×10^{-15}	1.060×10^{-2}
1100	100	1.183×10^{-4}
1101	73	1.060×10^{-2}
1110	0	1.060×10^{-2}
1111	0	0.95672

Thus, the LOLP was found to be 0.0218. The LOLP computed by enumeration was 0.0220.

Number of loss of load states identified: 10 out of 13.

IV. RESULTS

A summary of the results obtained from the four case studies is presented in Table XIII:

TABLE XIII
SUMMARIZED RESULTS

CASE	# Loss of Load States (Actual)	# Loss of Load States (PSO)	LOLP (Actual)	LOLP (PSO)
I	14	11	0.0326	0.0324
II	13	11	0.0220	0.0219
III	13	10	0.0220	0.0220
IV	13	10	0.0220	0.0218

The results show that the index obtained through the proposed method agrees closely with the results obtained by enumeration. Another aspect of the simulation that needs to be brought out is the number of loss of load states visited. It can be seen that the difference between the actual number of such states and the number visited is very small. The errors introduced due to this could be noticeable for a small system, but with an increasing system size, the error would gradually diminish in magnitude.

V. CONCLUSION

This paper has presented a formulation and implementation of the Particle Swarm Optimization method to the reliability

analysis of composite power systems. The method was validated by applying it to a small 4-bus test system with which the results could be validated manually.

While the framework within which the PSO method has been applied in this research is similar to that of non-sequential Monte Carlo simulation, it was felt that the method has considerable promise, particularly due to its ability to seek out failure states more selectively than Monte Carlo simulation.

As can be seen from the results provided, the method works for the small system. However, both the formulation and the results shown here represent the outcome of preliminary investigations. Further improvement of the method is in progress, and so is testing with larger systems. Progress with this research will be reported in due course.

REFERENCES

- [1] M. P. Bhavaraju, R. Billinton, "Transmission planning using a reliability criterion, Part I," *IEEE Transactions on Power Apparatus & Systems*, vol. 89, no. 1, pp. 28–34, January 1970.
- [2] Electric Power Research Institute, "Composite system reliability evaluation methods," Final Report on Research Project 2473-10, EPRI EL-5178, Electric Power Research Institute, Palo Alto, CA, June 1987.
- [3] C. Singh, G. M. Chintaluri, "Reliability evaluation of interconnected power systems using a multi-parameter gamma distribution," *Electrical Power & Energy Systems*, vol. 17, no. 2, pp. 151–160, April 1995.
- [4] J. Mitra, C. Singh, "Capacity assistance distributions for arbitrarily configured multi-area networks," *IEEE Transactions on Power Systems*, vol. 12, no. 4, pp. 1530–1535, Nov 1997.
- [5] P. Doulliez, E. Jamoulle, "Transportation networks with random arc capacities," *Revue Francaise d'Automatique, informatique et Recherche Operationelle*, vol. 3, pp. 45–66, 1972.
- [6] D. P. Clancy, G. Gross, F. F. Wu, "Probabilistic flows for reliability evaluation of multiarea power system interconnections," *Electrical Power & Energy Systems*, vol. 5, no. 2, pp. 101–114, April 1983.
- [7] J. Mitra, C. Singh, "Incorporating the DC load flow model in the decomposition-simulation method of multi-area reliability evaluation," *IEEE Transactions on Power Systems*, vol. 11, no. 3, pp. 1245–1254, August 1996.
- [8] M. Mazumdar, "Importance sampling in reliability estimation," in *Reliability and Fault Tree Analysis* (R. E. Barlow, J. B. Fussell and N. D. Singpurwalla, editors), ch. 7, pp. 153–163. Philadelphia, PA: Society for Industrial and Applied Mathematics, 1975.
- [9] G. J. Anders, *Probability Concepts in Electric Power Systems*. New York, NY: John Wiley & Sons, 1990.
- [10] J. Mitra, C. Singh, "Pruning and simulation for determination of frequency and duration indices," *IEEE Transactions on Power Systems*, vol. 14, no. 3, pp. 899–905, August 1999.
- [11] N. Samaan, C. Singh, "Adequacy assessment of power system generation using a modified simple genetic algorithm," *IEEE Transactions on Power Systems*, vol. 17, no. 4, pp. 974–981, November 2002.
- [12] N. Samaan, C. Singh, "Assessment of the annual frequency and duration indices in composite system reliability using genetic algorithms," in *Proceedings of the IEEE Power Engineering Society General Meeting, 2003*, vol. 2, July 2003.
- [13] S. Naka, T. Genji, T. Yura, Y. Fukuyama, "A hybrid particle swarm optimization for distribution state estimation," *IEEE Transactions on Power Systems*, vol. 18, no. 1, pp. 60–68, February 2003.
- [14] I. N. Kassabalidis, M. A. El-Sharkawi, R. J. Marks II, L. S. Moulin, A. P. Alves da Silva, "Dynamic security border identification using enhanced particle swarm optimization," *IEEE Transactions on Power Systems*, vol. 17, no. 3, pp. 723–729, August 2002.
- [15] Y. L. Abdel-Magid, M. A. Abido, "AGC tuning of interconnected reheater thermal systems with particle swarm optimization," in *Proceedings of the 10th IEEE International Conference on Electronics, Circuits and Systems, 2003*, vol. 1, pp. 376–379, December 2003.
- [16] V. Miranda, N. Fonseca, "EPSO-evolutionary particle swarm optimization, a new algorithm with applications in power systems," in *Proceedings of IEEE/PES Transmission and Distribution Conference and Exhibition 2002: Asia Pacific*, vol. 2, pp. 745–750, October 2002.