A Comparative Analysis of SPSO and BPSO for Power Loss Minimization in Distribution System Using Network Reconfiguration

Ankush Tandon*, D. Saxena**
Department of Electrical Engineering
Malaviya National Institute of Technology Jaipur
Jaipur, India
Email: eeankush.1986@gmail.com*, dsaxena.ee@mnit.ac.in**

Abstract— **This paper presents an effective methodology, to solve the Distribution Network Reconfiguration (DNR) problem using Selective Particle Swarm Optimization (SPSO) algorithm which aims at finding the best radial operating configuration that minimizes the power losses of the system while satisfying the imposed operating constraints. The algorithm is a simple modification of Binary Particle Swarm Optimization (BPSO) where the search space is selective. To demonstrate the performance and effectiveness of the proposed method a comparative analysis of SPSO with BPSO for network reconfiguration, under four different load levels, namely base, light, medium and heavy, on 33-bus and 69-bus radial distribution system is presented. Test results have shown that SPSO can effectively ensure loss minimization with better convergence characteristics and improved voltage profile as compared to BPSO.**

Keywords— ***Binary Particle Swarm Optimization (BPSO), Distribution Networks Reconfiguration (DNR), Selective Particle Swarm Optimization (SPSO)***

I. INTRODUCTION

In the modern power system network most of the electrical distribution network normally configured in radial configuration because of simple design, low cost, effective coordination of protective devices and lower short circuit current in medium voltage distribution network. A power distribution network has two types of switches, normally closed sectionalized switches and normally open tie switches. By altering the close/open status of sectionalized and tie switches, the topological configuration of the system is changed while maintaining radial structure of the electrical distribution network and the process is called Network Reconfiguration (NR) [1]. Several objectives can be achieved by network reconfiguration such as minimization of real power losses, number of switching operations, feeder load unbalancing, node voltage constraint violation, branch current constraint violation, improvement in reliability and service restoration after fault occurrence. Reconfiguration of distribution system for the minimization of real power loss was first proposed by Merlin and Back [1]. The branch and bound method was proposed to determine the operating spanning tree configuration of a distribution system with minimum power loss. High computation time and consideration of only real component of current for power calculation are some of the limitations of the proposed method in [1]. Civanlar *et al*. [2] proposed a novel method for evaluating the change in real power losses due to the exchange of load from one feeder to another in the distribution system. Minimum loss switching configuration can be determined rapidly but the reconfiguration of the network was dependant on the initial status of switches. Shirmohammadi and Hong proposed a heuristic algorithm based on power flow method to determine the minimum loss radial distribution system configuration [3].The limitation of the method proposed in [3], is that the search strategy is inefficient and the global optimized solution is not guaranteed. The problem is addressed by various researchers through heuristic algorithms. Nara *et al*. have implemented minimum loss configuration using genetic algorithm [4]. Power loss minimization and load balancing problem is modeled as integer programming problem in [5]. Gosami and Basu [6] proposed a power-flow - minimum heuristic algorithm , where the system is kept radial by complimenting closing of any switch with opening another switch during network reconfiguration, the method is suitable for small systems and results in huge computation for large systems. Simulated annealing [7-9] is also proposed for network reconfiguration problem with loss minimization but the method is again mathematically burdened and involves a large computation time. A fuzzy multi objective approach is proposed by Das [10] combining the optimization techniques with heuristic rules and fuzzy logic. The results are found to be encouraging but no criteria is suggested to select a membership function. Authors in [11] presented a fuzzy mutated genetic algorithm for optimal reconfiguration of radial distribution systems. A number of other artificial intelligence based approaches have been proposed such as expert system [12], refined genetic algorithm [13] and adaptive genetic algorithm [14], to solve the problem of loss minimization by reconfiguring distribution system. In [15] an interval based multi objective evolutionary algorithm is proposed for robust network reconfiguration. A novel and efficient meta-heuristics based fire works algorithm is proposed for loss minimization in radial distribution system [16]. Most of the methods mentioned above suffer from high computation time for larger systems that may be a limitation for a real time operation. In this paper, Selective Particle Swarm Optimization (SPSO) algorithm is proposed to minimize the real power losses in distribution system by network reconfiguration. The proposed method is tested on 33 bus and 69 bus system, under four different loading conditions.

The paper is organized as follows: Section II gives the mathematical problem formulation. Section III gives an overview of the proposed SPSO approach and its application to the problem. Section IV presents results of 33 and 69-bus system, and Section V concludes the paper. Finally references are given in section VI.

II. PROBLEM FORMULATION

The prime objective of the distribution network reconfiguration problem is to minimize the real power losses of distribution system P_{Loss} under the operating constraints, which are, system voltage profile, current capacity of the feeder, and the radial structure of the distribution network. To minimize the power loss the objective function is described as

$$\text{Minimise}\, F = \text{Minimum}(P_{Loss}) \tag{1}$$

Subjected to:

$$V_{\min} \le |V_p| \le V_{\max} \tag{2}$$

$$|I_p| \le |I_{p,\max}| \tag{3}$$

$$Det(A) = 1\, or -1 \quad \text{(radial system)} \tag{4}$$

$$Det(A) = 0 \quad \text{(non radial system)} \tag{5}$$

where

P_{Loss} is the total real power loss of the system;

$|V_p|$ is the voltage magnitude of bus p;

$V_{\min}, V_{\max}$ are bus minimum and maximum voltage limit respectively ($V_{\min}$ = 0.9 p.u. and V_{max} = 1.0 p.u.);

$I_p, I_{p,\max}$ is the current magnitude and maximum current limit of branch p respectively;

A is bus incidence matrix;

The power flow equations [17] for the one line diagram shown in Fig. 1. are

$$P_{p+1} = P_p - P_{Lp+1} - R_{p,p+1}\frac{\left(P_p^2 + Q_p^2\right)}{|V_p|^2} \tag{6}$$

$$Q_{p+1} = Q_p - Q_{Lp+1} - X_{p,p+1}\frac{\left(P_p^2 + Q_p^2\right)}{|V_p|^2} \tag{7}$$

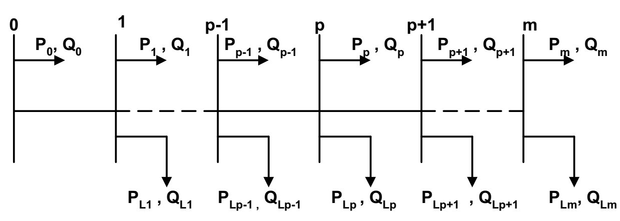

Fig. 1. Single Line Diagram of Main Feeder

$$|V_{p+1}|^2 = |V_p|^2 - 2(R_{p,p+1}P_p + X_{p,p+1}Q_p) + (R_{p,p+1}^2 + X_{p,p+1}^2)\frac{\left(P_p^2 + Q_p^2\right)}{|V_p|^2} \tag{8}$$

P_p is the real line power flowing out of bus p.

Q_p is the reactive line power flowing out of bus p.

P_{Lp} is the real load power at bus p.

Q_{Lp} is the reactive load power at bus p.

$R_{p,p+1}$ is the resistance of the line between bus p and p+1.

$X_{p,p+1}$ is the reactance of the line between bus p and p+1.

The power loss between buses p and p+1 is computed as:

$$P_{L,Loss(p,p+1)} = R_{p,p+1}\frac{\left(P_p^2 + Q_p^2\right)}{|V_p|^2} \tag{9}$$

The total real power loss of the feeder is given by:

$$P_{Loss} = \sum_{p=1}^{m} P_{L,Loss(p,p+1)} \tag{10}$$

where P_{Loss} is the total power loss of the system obtained by summing up the power losses of all line sections of the feeder.

III. SELECTIVE PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a self educating population based algorithm inspired by the collective movement of a flock of birds, a school of fish or a swarm of bees, first introduced by Eberhart and Kennedy [18] in 1995. In this section mathematical frame work of the algorithm is presented.

The position and velocity vectors of the i^{th} particle in a D dimensional search space can be represented as $X_i = (x_{i1}, x_{i2}, \ldots.., x_{iD})$, $V_i = (v_{i1}, v_{i2}, \ldots.., v_{iD})$ respectively. The best previous position of the particle is recorded and represented as $p_{best\,i} = (p_{i1,}\, p_{i2,\ldots..,}\, p_{iD})$ .If the g^{th} particle is the best among all particles in the group so far, it is represented as $g_{best} = p_{bestg}(p_{g1,}\, p_{g2,\ldots..,}\, p_{gD})$. The velocity and position of the particle are updated as

$$v_{iD}^{k+1} = wv_{iD}^{k} + c_1 r_1\left(p_{bestiD}^{\,k} - x_{iD}^{k}\right) + c_2 r_2\left(g_{bestiD}^{\,k} - x_{iD}^{k}\right) \tag{11}$$

$$x_{iD}^{k+1} = x_{iD}^{k} + v_{iD}^{k+1} \tag{12}$$

where

i = 1,2,3………….m;

w is the inertia weight;

c_1 and c_2 are the acceleration constants;

r_1 and r_2 are the random values in the range [0,1];

Weighting function is calculated as:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} * iter \quad (13)$$

$w_{\max}, w_{\min}$ are the initial weight value and the final weight of value respectively;

$iter_{\max}$ are the maximum number of iterations;

$iter$ is the current iteration number;

In binary PSO [19] the sigmoid transformation is applied to the velocity components to limit the velocities in the range and [0,1] and force the locations of particles to be either 0 and 1.

$$sig\left(v_{iD}^{k+1}\right) = \frac{1}{1+\exp(-v_{iD}^{k+1})} \quad (14)$$

$$x_{iD}^{k+1} = \begin{cases} 1, if \ \sigma < sig\left(v_{iD}^{k+1}\right) \\ 0, if \ \sigma \geq sig\left(v_{iD}^{k+1}\right) \end{cases} \quad (15)$$

A simple modification to binary PSO was proposed by Khalil and Gorpinich [20] by confining the search in the selected search space. The search space in SPSO, at each D dimension $S_D = [S_{D1}, S_{D2}, ..., S_{DN}]$ is a set of DN positions where, DN is the number of selected positions in dimension D. As in the conventional PSO, a fitness function is defined, in SPSO it maps at each D dimension from DN positions of the selective space S_D which leads to alter the position of each particle from being in real-valued space to be a point in the selective space, thereby changing the sigmoid transformation as per (16)

$$sig\left(v_{iD}^{k+1}\right) = DN\frac{1}{1+\exp(-v_{iD}^{k+1})} \quad (16)$$

$$x_{iD}^{k+1} = \begin{cases} S_{D1} \ if \ sig\left(v_{iD}^{k+1}\right) < 1 \\ S_{D2} \ if \ sig\left(v_{iD}^{k+1}\right) < 2 \\ .... \\ S_{DN} \ if \ sig\left(v_{iD}^{k+1}\right) \leq DN \end{cases} \quad (17)$$

Velocities of the particles are restricted to some minimum and maximum values $[v_{\min}, v_{\max}]$ using (18)

$$v_{iD}^{k+1} = \begin{cases} v_{\max} \ if \ v_{iD}^{k+1} > v_{\max} \\ v_{iD}^{k+1} \ if \ \left|v_{iD}^{k+1}\right| \leq v_{\max} \\ v_{\min} \ if \ v_{iD}^{k+1} \leq v_{\min} \end{cases} \quad (18)$$

The invariability of the value of i^{th} particle velocity in a D dimension at the maximum or minimum values is avoided using (19)

$$v_{iD}^{k+1} = \begin{cases} rand * v_{iD}^{k+1} \quad if \ \left|v_{iD}^{k+1}\right| = \left|v_{iD}^{k}\right| \\ v_{iD}^{k+1} \quad otherwise \end{cases} \quad (19)$$

The numbers of dimensions in a distributed network are equal to the number of loops formed on closing all the tie switches. The search space for a particular dimension consists of the branches of the loop represented by this dimension. The branches of the network which do not belong to any loop are not in any search space and hence not considered in the optimization algorithm. The branches which are common to the loops and hence in the dimensions, should appear only in one dimension at a time which can be done randomly. Once the dimensions and the search space for each dimension are specified the SPSO can be applied to find the optimal solution.

IV. Simulation And Results

The proposed method is tested on IEEE 33 bus and 69 bus radial distribution system [5, 22]. Comparative analysis of SPSO with BPSO for network reconfiguration, under four different load levels, namely base, light, medium and heavy, is carried out to evaluate the effectiveness of the proposed method. Light, medium and heavy load levels are considered where all loads observe -5%, +5% and 10% increment from the base case respectively. The comparative analysis is established on the basis of distribution losses, convergence characteristics, voltage profile of the network, change in position of tie switches (from the base case) and time elapsed to run the optimization process. Table II gives the parameters used in SPSO and BPSO in simulation of network for 33 bus and 69 bus system. The algorithms are developed in MATLAB, and the simulations were done on a computer with Pentium IV, 3.5GHz, 2 GB RAM.

A. Test Case I

The first test case is a 33-bus, 12.66-kV, radial distribution system as shown in Fig. 2. It consists 32 normally closed switches (sectionalizing switches), and 5 normally open switches (tie switches). The normally open switches are 33 to 37. The line data and load data are obtained from [5]. The initial loss of this system is 208.45 kW. The total real and reactive loads on the system are 4300 kW and 2800 kVAr respectively. The minimum voltage is 0.9107 p.u. at node 18 before reconfiguration. The solid lines in the Fig. 2 represent the sectionalizing switches and the dashed lines indicate the tie switches. As it is can be seen from the Fig. 2, five loops are formed on closing the 5 tie switches; therefore the numbers of dimensions for this 33 bus system are 5. Table I gives the respective loops and hence the dimensions and the search space for respective dimension.

TABLE I. The Loops of 33-bus System

Loops	Dimensions	Switches
I	S_{D1}	S8, S9, S10, S11 , S21, S33, S35
II	S_{D2}	S2 , S3 , S4 ,S5 , S6 ,S7 , S18 ,S19 , S20
III	S_{D3}	S12 ,S13, S14, S34
IV	S_{D4}	S15 ,S16, S17, S29, S30, S31, S36, S32
V	S_{D5}	S22, S23, S24, S25, S26, S27, S28, S37

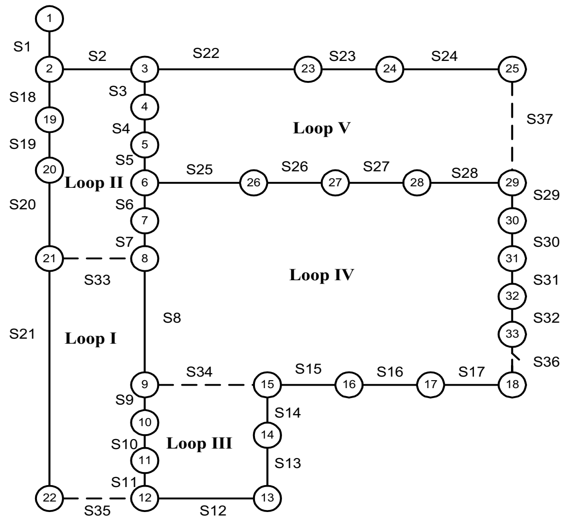

Fig. 2 Simplified Single Line Diagram IEEE 33 Bus System

The switch S1 is not in any loop and therefore it is not considered while finding the optimal solution by SPSO. Table III gives the comparative results for reconfiguration of 33 bus radial distribution system using SPSO and BPSO. As per table III it can be seen that the power loss reduction is more prominent for all the four different loadings when the network reconfiguration is performed through SPSO algorithm. Before reconfiguration the power losses for the base case are 208.45 kW which are reduced by 33.35% after reconfiguration was done with SPSO as compared to 32.05% when BPSO algorithm is used. Thus it can be concluded that SPSO outperformed BPSO as far as the minimization of the losses are concerned.

Significant improvement in voltage profile is observed in all loading levels. Effect of reconfiguration on voltage levels (Base case) using SPSO and BPSO is shown graphically in Fig. 3 & Fig. 4 respectively. The minimum voltage is 0.9107 p.u. at node 18 before reconfiguration. The minimum bus voltage is improved to 0.9423 p.u. (node 32) after reconfiguration. The voltage profile is improved by reconfiguration performed by both the algorithms at all four load levels; however significant increment is observed when reconfiguration is done using SPSO algorithm. As can be seen form table III in SPSO four switches changes its position from the initial configuration of the switches, as compared to five switches in BPSO and the computational time required to run the optimization process using SPSO is less than that required by BPSO under all loading levels.

TABLE II. PARAMETERS OF SPSO AND BPSO FOR 33 BUS AND 69 BUS SYSTEM

Parameters	SPSO AND BPSO
w_{max}	0.9
w_{min}	0.4
Maximum number of iterations	100
Acceleration constants	2

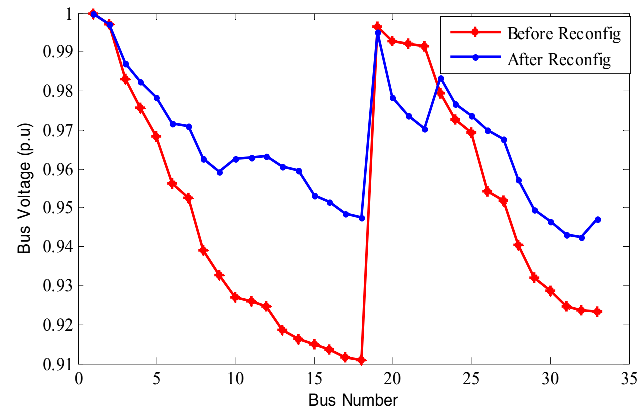

Fig. 3 Effect of Reconfiguration on Voltage Levels using SPSO for 33 Bus System (Base Case).

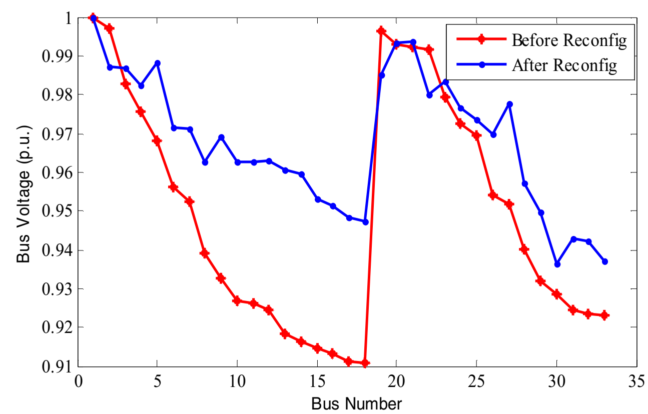

Fig. 4 Effect of Reconfiguration on Voltage Levels using BPSO for 33 Bus System (Base Case).

Fig. 5 shows the convergence characteristics of the proposed SPSO algorithm compared with the BPSO algorithm for 33 bus system. SPSO has a fast convergence rate; SPSO converges in 11 iterations as compared to 13 iterations for BPSO.

To verify the performance of the proposed algorithm, an evaluation is carried out by running the optimization process repeatedly for 100 times. Table IV shows the best and worst values among the best solutions, as well as the average value, standard deviation, and the success rate for the best solutions of these 100 trails of the optimization process. It is concluded from the table IV that the standard deviation is quite smaller for the case when NR problem is solved by SPSO, which indicates that most of the best solutions are close to average It also proves the robustness of the algorithm.

The success rate of the algorithm is defined as how many times the value of objective function is equal to the best losses; in case of 33 bus system the success rate of SPSO is 59 % which is better than the success rate of BPSO which is 54%.The reduction in power loss through network reconfiguration by the SPSO algorithm is found to be lesser than the method proposed in [3, 21] as mentioned in Table V.

TABLE III. RESULTS OF IEEE 33 BUS SYSTEM USING SPSO AND BPSO

Item		Base Case	Medium Loading	Heavy Loading	Light Loading
Initial Configuration	Position of Tie Switches	33,34,35, 36,37	33,34,35, 36,37	33,34,35, 36,37	33,34,35, 36,37
	Losses in (kW)	**208.45**	**231.57**	**256.445**	**186.298**
	Minimum Voltage (p.u.)	0.91075	0.90588	0.903	0.91565
SPSO Reconfiguration	Position of Tie Switches	7,9,14,32, 37	7,9,14, 32,37	7,9,14, 32,37	7,9,14, 32,37
	Losses in (kW)	**138.92**	**157.839**	**169.8848**	**124.5**
	Loss reduction (%)	**33.355**	**31.83**	**33.75**	**33.17**
	Minimum Voltage (p.u.)	0.9423	0.93929	0.936	0.94201
	Elapsed Time(s)	21.35	20.652	20.68	20.32
BPSO Reconfiguration	Position of Tie Switches	7,9,14,28, 32	7,9,14, 28,32	7,9,14, 28,32	7,9,14, 28,32
	Losses in (kW)	**141.6316**	**162.5228**	**175.3543**	**126.686**
	Loss reduction (%)	**32.05**	**29.81**	**32.40**	**31.99**
	Minimum Voltage (p.u.)	0.9364	0.9233	0.92567	0.935
	Elapsed Time(s)	24.34	22.73	22.876	23.01

TABLE IV. SIMULATION RESULTS OF IEEE 33 BUS SYSTEM

Item	Initial Configuration	Optimal Configuration	
		SPSO	**BPSO**
Standard Deviation	-------------	0.95617	1.42016
Minimum losses in kW	208.45	138.92	141.631
Worst losses in kW	-----------	138.77	140.023
Best losses in kW	-----------	138.92	141.631
Loss reduction (Best losses) (%)	----------	33.35	32.05
Average Value (losses in kW)	-----------	139.466	142.258
Average Loss reduction (%)	-----------	33.09	31.75
Success Rate	-----------	59	54
Values less than Best value	-----------	8	11
Value greater than Best value	------------	33	35

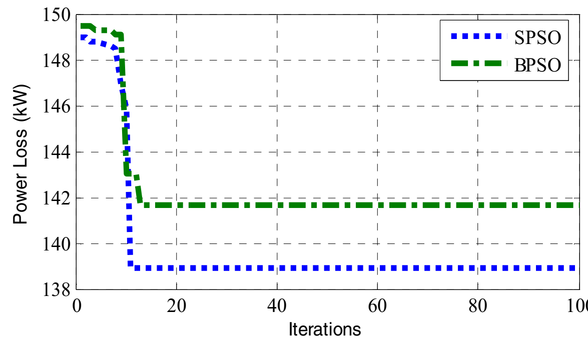

Fig. 5 Convergence Characteristics of SPSO for 33 Bus System

TABLE V. COMPARISON OF POWER LOSS REDUCTION AND MINIMUM VOLTAGE

Methods	Power Loss Reduction (%)	Minimum Voltage (p.u.)
Proposed method (SPSO)	33.35	0.9423
Method proposed in Ref. [21]	31.14	0.9378
Method proposed in Ref. [3]	30.78	0.9378

B. Test Case II

A large scale distribution test system of 69-bus system, is considered to exhibit the applicability of the proposed approach. The single line diagram of the same system is presented in Fig. 6.The line and load data are obtained from [22]. It consists of 68 sectionalizing switches (normally closed) and 5 tie switches (normally open). The tie switches are 69,70,71,72,73. The real power loss before reconfiguration is 224.98 kW. The minimum voltage is 0.90919 p.u. at node 65 before reconfiguration. The final configuration obtained from the proposed algorithm is 14, 56, 61, 69, 70. The real power losses for the base case are reduced to 98.59 kW which amounts an reduction of 56.17% in total power loss. The minimum bus voltage is improved to 0.949 p.u. (node 61) after reconfiguration. Table VI gives the comparative results for reconfiguration of 69 bus radial distribution system using SPSO and BPSO. From the table VI it can be concluded on the SPSO effectively reduces the power loss by reconfiguration of 69 bus radial distribution with better convergence characteristics and improved voltage profile as compared to BPSO.

Table VII shows the best and worst values among the best solutions, as well as the average value, standard deviation, and the success rate for the best solutions of these 100 trails of the optimization process. From the table it can be concluded that SPSO performed better than BPSO in terms of solution quality.

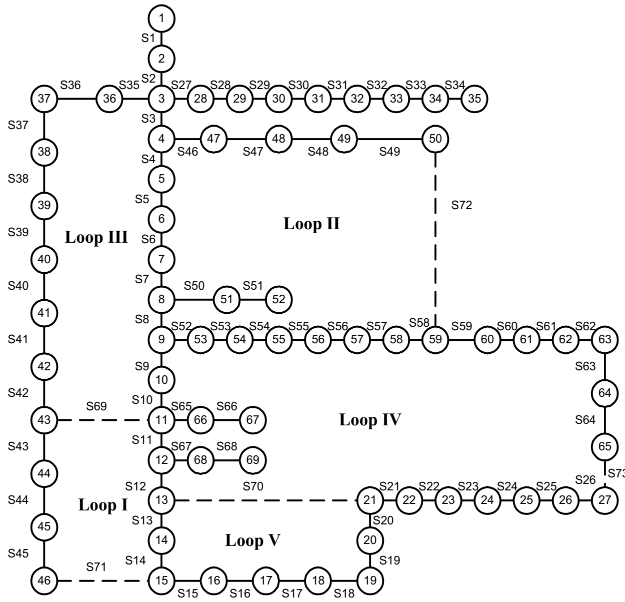

Fig. 6 Simplified Single Line Diagram IEEE 69 Bus System

TABLE VI. RESULTS OF IEEE 69 BUS SYSTEM USING SPSO AND BPSO

Item		Base case	Medium Loading	Heavy Loading	Light Loading
Initial Configuration	Position of Tie Switches	69,70,71, 72,73	69,70,71, 72,73	69,70,71, 72,73	69,70,71, 72,73
	Losses in (kW)	**224.9804**	**250.3786**	**277.4261**	**201.18**
	Minimum Voltage (p.u.)	0.90919	0.90416	0.89907	0.9416
SPSO Reconfiguration	Position of Tie Switches	14,56,61, 69,70	12,56,61, 69,70	14,56,61, 69,70	14,56,61, 69,70
	Losses in (kW)	**98.59**	**109.4**	**120.38**	**88.5862**
	Loss reduction (%)	**56.17**	**56.3**	**56.6**	**55.96**
	Minimum Voltage (p.u.)	0.94947	0.94861	0.94413	0.95212
	Elapsed Time(s)	21.3565	25.557	24.99934	25.564666
BPSO Reconfiguration	Position of Tie Switches	13,20,55, 61,69	13,20,55, 61,69	13,20,55, 60,68	13,20,55, 61,69
	Losses in (kW)	**105.1431**	**116.43**	**128.37**	**94.47**
	Loss reduction (%)	**53.26**	**53.49**	**53.72**	**53.04**
	Minimum Voltage (p.u.)	0.92394	0.91982	0.91567	0.94803
	Elapsed Time(s)	57.35	63.349	67.27	54.41

TABLE VII. SIMULATION RESULTS OF IEEE 69 BUS SYSTEM

Item	Initial Configuration	Optimal Configuration	
		SPSO	BPSO
Standard Deviation	-------------	0.970491	1.512555
Minimum losses in kW	224.9804	98.595	99.14
Worst losses in kW	-----------	103.179	109.724
Best losses in kW	-----------	98.595	105.14
Loss reduction (Best losses) (%)	----------	56.17	53.26
Average Value (losses in kW)	-----------	98.93591	105.2009
Average Loss reduction (%)	-----------	56.02	53.23
Success Rate	-----------	78	67
Values less than Best value	-----------	0	10
Value greater than Best value	------------	22	23

Fig. 7 shows the convergence characteristics of proposed algorithm for 69 bus system. The optimal solution is achieved in 28 iterations for SPSO while in case of BPSO it is obtained in 33 iterations. It shows that SPSO has fast convergence rate with better solution quality to obtain the optimal solution.

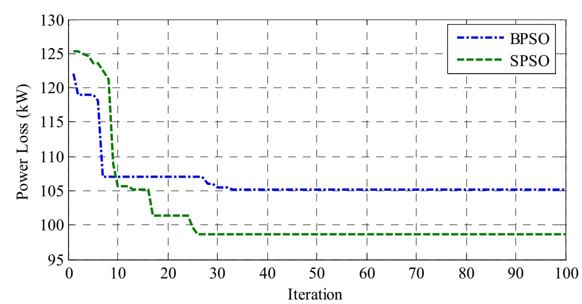

Fig. 7 Convergence Characteristics of SPSO for 69 Bus System

V. CONCLUSION

In this paper, performance of SPSO is compared to that of BPSO, to optimize radial distribution system for minimum real power losses and improved voltage profile, at four different load levels. Simulated results on IEEE 33 bus and IEEE 69 bus system show that for network reconfiguration, SPSO outperformed BPSO with significant reduction of distribution losses, significant improvement in voltage profile and has better convergence characteristics.

VI. REFERENCES

[1] A. Merlin and H. Back, "Search for a minimal-loss operating spanning tree configuration in an urban power distribution system," *Proc. 5th Power Syst. Comput. Conf. (PSCC), Cambridge , UK*, 1975, pp. 1-18.

[2] S. Civanlar, J.J. Grainger, H. Yin, and S.S.H. Lee, "Distribution feeder reconfiguration for loss reduction," *IEEE Trans. Power Del*., vol. 3, no. 3, July 1988, pp.1217-1223.

[3] D. Shrimohanammadi and H. W. Hong, ”Reconfiguration of electric distribution networks for resistive line losses reduction,” *IEEE Trans. Power Del*., vol.4, No. 2, Apr. 1989, pp. 1492-1498.

[4] K. Nara, A. Shiose, M. Kitagawa, and T. Ishihara, ”Implementation of genitic algorithm for didtribution systems loss mimimum configuration,” *IEEE Trans. Power Syst.* 7(1992), pp. 1044-1051.

[5] M. E. Baran and F. Wu, “ Network reconfiguration in distribution systems for loss reduction and load balancing,” *IEEE Trans. Power Del*., 1989, 4(2), pp. 1401-1407.

[6] S. K. Goswami and S. K. Basu, “A new algorithm for the reconfiguration of distribution feeders for loss minimization,” *IEEE Trans. Power Del*., 1992, 7(3), pp. 1484-1491.

[7] H. D. Chiang and J. J. Rene, “Optimal network reconfiguration in distribution systems: Part 1: Solution algorithms and numerical results,” *IEEE Trans. Power Del*., 1990, 5(4), pp. 1902-8.

[8] H. D. Chiang and J. J. Rene, “Optimal network reconfiguration in distribution systems: Part 2: Solution algorithms and numerical results,” *IEEE Trans. Power Del*., 1990, 5(3), pp. 1568-74.

[9] H. C Chang and C. C. Kuo, “Network reconfiguration in distribution system using simulated annealing,” *Electr. Power Syst. Res.,* 29(1994), pp. 227-238.

[10] D. Das, “A fuzzy multi objective approach for network reconfiguration of distribution systems,” *IEEE Trans. Power Del*., 2006 , 21(1), pp. 202-209.

[11] K. Prasad, R. Ranjan, N. C. Sahoo, and A. Chaturvedi, “Optimal configuration of radial distribution systems using a fuzzy mutated genetic algorithm,” *IEEE Trans. Power Del*., 20(2005), pp. 1211-1213.

[12] C. C. Liu, S. J. Jee, S. S, and Venkata, “An expert system operational aid for restoration and loss allocation of distributed system,” *IEEE Trans. Power Syst.,* 3(1988), pp. 619-629.

[13] Z. Zhu, “Optimal reconfiguration of electrical distributed network using redifined genetic algorithm,” *Electr. Power Syst. Res.,62(2002),* pp. 37-42.

[14] A. Swarnkar, N. Gupta, and K. R. Niazi, “Minimal loss configuration for large scale distribution system using adaptive genetic algorithm,” *16th National Power System Conference*, December 2010.

[15] C. Barbosa, M. Mendes, and J. Vacocelos, “Robust feeder reconfiguration in radial distribution networks,” *Electrical Power and Energy Systems,* 54, 2014, pp. 619-630.

[16] A. Imran and M. Kowsalya, “A new power system reconfiguration scheme for power loss minimization and voltage profile enhancement using fireworks algorithm,” *Electrical Power and Energy Systems,* 62, 2014, pp. 312-322.

[17] S. Ghosh and K. S. Sherpa, “An efficient method for load flow solution of radial distribution networks,” *Int J. Elect. Power Energy Syst. Eng.,* vol.1, no. 2, 2008, pp. 108-115.

[18] J. Kennedy and R. Ebehart, “Particle swarm optimization,” Proc. *IEEE Int. Conf. on Neural Networks*, vol. 4, 1995, pp. 1942-1948.

[19] J. Kennedy and R. Ebehart, “A discrete binary version of the partcle swarm algorithm,” *IEEE Int. Conf. on Systems, Man, and Cybernetics (SMC 97),* vol. 5, 1997, pp. 4140-4109.

[20] T. M. Khalil and A. V. Gorpinich,”Reconfiguration for loss reduction in distribution system using selective particle swarm optimization,” *Int. J. of Multidisciplinary sciences and Eng*., vol. 3, no. 6, 2012, pp,1-4.

[21] T. Niknam, “A new hybrid algorithm based on DPSO and ACO algorithms for multi objective feeder reconfiguration,” *Energy Conversion and Management*, 50(8), 2009, pp. 2074-2082.

[22] J. S. Savier and D. Das, “Loss allocation to consumers before and after reconfiguration of radial distribution networks,” *Electrical Power and Energy Systems,* 33, 2011, pp. 540-549.