Application of Modified Clonal PSO in Distributed Generator Placement for Enhancement of Efficiency and Voltage Stability in Distribution System

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1 Introduction

Nowadays, living standard of people has increased, which increases the power demand. Industrialization is also one of the main reasons for the rise in power demand. This rise in power demand has created an unbalance in the generation and demand. To fulfil this gap, installation of DG may be one of the solutions. Several advantages of DG have motivated utility, government and researchers towards this solution. Installation of DG has encouraging effects only if optimal capacity of DG is installed at optimal location in a distribution network. Various types of DG technologies are available in literature. A few DG and their effects in the distribution network are summarized [1, 2]. The effect of DG may be broadly categorized into three groups: technical, economical and operational [3]. These effects of DG on the system mainly depend on the location and capacity of it in distribution system. If it is installed at any bus of distribution network, then it may result in the worst effects also. Due to this reason, some optimization technique has to apply for best assignment of DG in distribution system [4]. Authors have discussed different conventional and other advanced techniques for the best possible assignment of DG with single and multi-objective function. These techniques are categorized as analytical, numerical, heuristic and hybrid [5].

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Optimization methods discussed in the literature have considered different objective functions and different test systems [6–8]. Modified clonal particle swarm optimization (MCPSO) algorithm is applied in this paper for optimum placement of DG in IEEE 30-bus and IEEE 14-bus distribution system. The objectives of the optimization problem are curtailment of cost involved in the power generation and power losses and enhancement of voltage profile of the system. Main contributions of the article are:

a. Formulation of a multi-objective function including generation cost, power losses and equivalent voltage profile index.
b. Incorporate the AIS conception in traditional PSO to make a proficient algorithm.

In this article, Sect. 1 discusses a brief introduction and literature review related to the optimum placement of DG. Section 2 is devoted to the formulation of objective function which is formed considering different indices. Different forms of PSO are discussed in Sect. 3. Results of the MCPSO are discussed and compared in Sect. 4. Conclusion of the paper is given in Sect. 5.

2 Formulation of Objective Function

Every optimization process has an objective function. It may be single or multi-objective. A multi-objective function is developed in this paper. It consists of generation cost, bus voltage and line losses. These three parameters are used to indices, considered as cost index (C_i), power loss index (P_i) and voltage profile Index (V_i). Detailed discussion of these indices follows:

2.1 Cost Index (C_i)

Augment in the percentage of the DG in a distribution network has created a challenge to power system planners to reduce capital expenditure (CAPEX) and operational expenditure (OPEX) of DG [9]. This reduction should consider different equality and inequality constraints also. The fixed cost and maintenance cost of DG are the main factors to fix the electricity tariff. These costs are the main factors in determination of the proficiency of the DG. The total cost of power plant consists of three parts: INSCO, MAINCO and RUNCO.

INSCO incorporates the cost included common developments, cost of various types of gear of the plant and other cost identified with instrumentation and control. With increase in the capacity of DG, INSCO also increases. MAINCO included the expenses engaged in the care of equipment of power plant and DG. It incorporates the yearly upkeep cost, wages to the persons involved in the operation of the plant and other different expenses. MAINCO is straightforwardly corresponding to the capacity and uptime of the generating plant. RUNCO incorporates the expense of consumed fuel and other material required for the generation, expenses involved in waste management, the pay of the personal involved in the running of the plant. It relies upon the energy production and the operational long stretches of DG. By consolidating every one of these costs, a single cost index can be formed, which can be written as (1).

$$TC = N_{\text{DG}} \times \left[\sum_{p=1}^{\text{cap}} \text{INSCO} + \sum_{t=1}^{T} \sum_{p=1}^{\text{cap}} \text{MAINCO} + \sum_{t=1}^{T} \sum_{p=1}^{\text{cap}} \text{RUNCO} \right] \tag{1}$$

where TC: overall cost; INSCO, MAINCO and RUNCO: installation cost, maintenance cost and operational cost per unit capacity, respectively; N_{DG}: total number of DGs; T: uptime of DG. Generally cost function of a thermal power plant is quadratic in nature and can be given by Eq. (2) [10].

$$C_k = a + bP_{dgk} + cP_{dgk}^2 \tag{2}$$

In this equation, k = serial number of generators; C_k = expenses involved in operation of kth generator; P_{dgk} = output power of kth generator; a, b and c = fuel cost coefficients of kth generator.

Above cost function and generating capacity of generator are utilized in the formation of a cost index which is formed and can be written as Eq. (3).

$$C_i = \frac{C_k}{P_{dgk}} \tag{3}$$

2.2 Power Loss Index (P_i)

Power losses in every network depend to real and reactive power injection in the system at different buses. A generalized formula in N-bus system can be written as Eq. (4) [10]. This equation is also known as exact loss formula.

$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} \left[\alpha_{ij} \left(P_i P_j + Q_i Q_j \right) + \beta_{ij} \left(Q_i P_j - P_i Q_j \right) \right] \tag{4}$$

where α_{ij} and β_{ij} are given as:

$$\alpha_{ij} = \frac{R_{ij}}{V_i V_j} \cos(\delta_i - \delta_j),$$

$$\beta_{ij} = \frac{R_{ij}}{V_i V_j}\sin(\delta_i - \delta_j),$$

Q_i and P_i are the amount reactive power and active power injection at *i*th node, respectively,

V_i and δ_i are the magnitude and the angle of the voltage at *i*th node, and $Z_{ij} = R_{ij} + jX_{ij}$ is the *ij*th element of $[Z_{\mathrm{BUS}}] = [Y_{\mathrm{BUS}}]^{-1}$.

For formulation of P_i, line losses in the network are determined before and after integration of DG at each node. Mathematically P_i can be expressed as Eq. (5).

$$Pi = \frac{\text{Losses with DG}}{\text{Losses without DG}} \tag{5}$$

2.3 Index of Voltage Profile (VP_i)

Objective of the optimization problem is to get better profile of the bus voltage. For this purpose, a voltage profile index is formed which is written as Eq. (6). Minimum voltage of *i*th bus in proposed objective function supports the voltage profile enhancement.

$$VPi = \frac{\sqrt{(1 - V_{i\,\min})^2}}{V_{i\,\min}} \tag{6}$$

2.4 Objective Function (OF)

The purpose of the optimization process is to reduce production costs, as well as line losses and bus voltage profile improvement. To achieve the preferred goals, an objective function is constructed by mingling $\mathrm{VP}_i C_i$ and $P_{i.}$ Selection of weights x, y and z is done in a manner that their sum is one [11]. Thus, combining all the elements, a multi-objective function can be constructed, which can be written as an Eq. (7).

$$OF = xCi + yPi + zVPi \tag{7}$$

The constraints are stated below:

The bus voltage and active power generation at each bus are limited as mentioned in Eqs. (8) and (9):

$$V_{i\,\min} < V_i < V_{i\,\max} \tag{8}$$

$$P_{\mathrm{DG}}^{\min} \leq P_{\mathrm{DG}} < P_{\mathrm{DG}}^{\max} \tag{9}$$

Reactive power generation is 20% of active power generation:

$$Q_{\mathrm{DG}} = 0.2 P_{\mathrm{DG}} \tag{10}$$

The power balance is given by Eq. (11)

$$\sum P_G + \sum P_{\mathrm{DG}} = P_d + TL \tag{11}$$

3 Evolutionary Algorithms

Evolutionary algorithms belong to set of heuristic algorithms. Nowadays, these meta-heuristic algorithms are becoming very popular due to their advantages over other conventional optimization method. In this article basics of PSO, clonal PSO and modified clonal PSO are discussed.

3.1 Particle Swarm Optimization (PSO)

PSO is good practice that is promoted by the social behaviour of the migration of birds or fish in hunt of the foodstuff. Eberhart and Kennedy developed this algorithm [12]. Food search process by birds or fishes is initiated in group. This group is known as swarm and each bird/fish can be considered as particle. Each member of the swarm has little bit information about location of food. The search process is based on individual data and shared information between group members. Each time the iteration particle examines the gap between its position and the food in relation to the previous location and the excellent herd of the herd closest to the food area.

Initially in PSO random value is assigned to the velocity $v_i(t)$ and position $x_i(t)$. In the next iteration, these particles shift in the search space to search the superlative position. Its movement in next iteration is influenced by the best location of each individual (P_{best}) and its best location in the swarm (G_{best}). During the search process, its position and velocity are given by Eqs. (12) and (13), respectively. The process is repeated till achievement of the target.

$$V_i^n = w \times V_i^{n-1} + c_1 \times R_1 \times \left(P_{\mathrm{best}i}^{n-1} - X_i^{n-1}\right) + c_2 \times R_2 \times \left(G_{\mathrm{best}i}^{n-1} - X_i^{n-1}\right) \tag{12}$$

$$X_i^n = X_i^{n-1} + V_i^n \tag{13}$$

where

w	The inertia weight
c_1 and c_2	Acceleration coefficients
R_1 and R_2	random numbers between 0 and 1
X_i and V_i	Position and velocity of ith particle
$P_{\text{best}i}$	Best position of the ith particle
G_{best}	Achieved best position.

The velocity Eq. (12) has three mathematical terms. The first term in velocity equation is the local particle speed, the second and third terms are cognitive and social component, respectively. Particle velocity is affected by the inertia weight (w) [11] which is kept in the range of 0.4–0.95.

Usually speed of PSO is fast but sometimes it may be trapped locally in complex optimization process. Reasons for the local trapping can be explained as follows:

a. Initialization of inertia weight affects the particle speed throughout the optimization process. This inertia weight has to be selected very carefully. If value of inertia weight is low, then optimization problem may trap in local optimum solution, and if inertia weight is high, then it will result in faster movement of particles and this can lead to skipping the global solution.
b. Social component velocity is responsible for sharing information of G_{best} to all particles in the swarm which decides the movement of the swarm. This results in a decline in swarm diversity.

The PSO directs the herd to find a single result to the optimization process through particle position information. The position of the G_{best} particle serves as a guide for other particles. However, the identification of this G_{best} particle is problematic. This problem will only get worse if the search space has too many local optimum solutions. This may be evaded by inserting AIS's clonal selection policy into the PSO. This leads to better interactions within particles trying to reach global optima as the chances of finding a global solution are much higher for G_{best} particles compared to all other search sites. Therefore, the chances of being caught around a small area are very low. Therefore, the CPSO speeds up the process of efficiency and avoid any premature mergers.

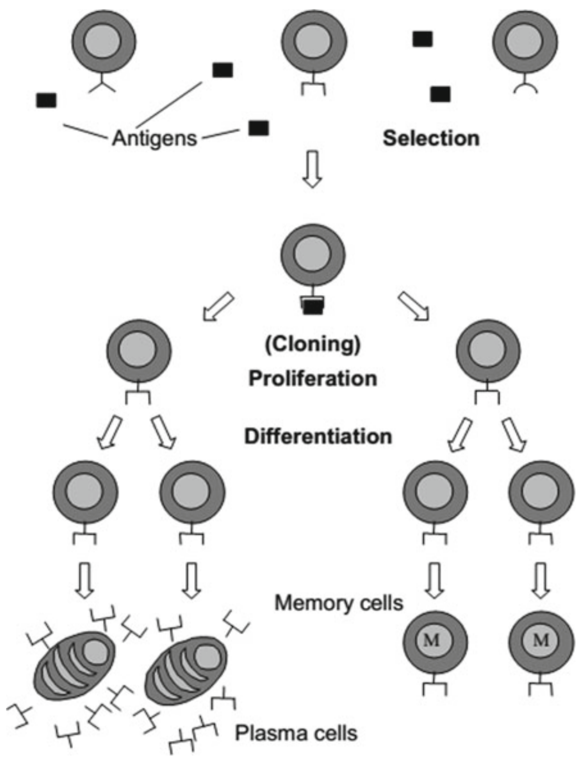
In general, the PSO is self-improving but can be caught around the local optima while the clonal selection process protects that problem. Therefore, the integration of AIS and PSO will give better investigate potential.

3.2 Clonal Particle Swarm Optimization (CPSO)

In PSO, G_{best} works as a guide for all particles in swarm, though it may be located far away from different particles. In each iteration, movement of all particles is towards the G_{best}. There are some particles in the swarm, which will never achieve the position of G_{best}. This may result in wastage of computational asset. Such issues can be kept away by consolidating correlative highlights of clonal selection principle and PSO. CPSO is a combination of the idea of logical hypothesis of immune system and the PSO. Hypothesis of the immune system clarifies the reaction cycle of antibodies during any disease. As per the hypothesis, lymphocytes existing in the body are delicate to a unique sort of antigen. If antigen ties with the lymphocyte, then this phenomenon results in formation of plasma and memory cells. Plasma cells stay for very short duration but memory cells will stay alive for expanded time frame fully expecting future attacking of same antigen. This cycle of clonal determination can be clarified by Fig. 1 [13].

By and large in CPSO fundamental administrator of clonal determination, cloning, mutation and reselection are combined in PSO. PSO is performed to refresh speed and places of particles after cloning, transformation and reselection. All particles are chosen for cloning and all clones will be transformed which creates new population in search space. During reselection liking is assessed and arranged in rising request. Low proclivity particles are supplanted by the new randomly produced particles for keeping up assorted variety in the populace. Because of this, an appropriate correspondence stays between particles in a multitude, which helps in their development towards the G_{best}. Consequently, fuse of clonal determination supplements the local

Fig. 1 Clonal selection principle [13]



trapping of PSO and henceforth making CPSO a superior a proficient method than PSO.

3.3 Modified Clonal Particle Swarm Optimization (MCPSO)

For improvement of the performance of CPSO, some modification is done in MCPSO. In CPSO, all particles are selected for cloning at their individual positions. In modified version of CPSO, a slight modification is done in this procedure, and consequently, particle having G_{best} location in the swarm is selected for cloning. After cloning of this particle 'n' new particles will be created at G_{best} location in search space. After this, movement of cloned particle will be towards the ideal situation.

During the movement, all particles will move with their individual speeds from the location of G_{best}. For MCPSO, values for velocity and position are given by Eqs. (14) and (15).

$$V_i^{n'} = w \times V_i^{n'-1} \tag{14}$$

$$X_i^{n'} = X_i^{n'-1} + V_i^{n'} \tag{15}$$

In velocity Eq. (14), inertia weight is a significant factor. In this condition, new velocity can be obtained by multiplying the inertia weight. It implies that there will be direct increment or reduction in velocity which is relying upon the estimation of inertia weight. CPSO proposed by [14] utilized inertia weight which is changing with time. If this type of inertia weight is used, then due to continuous decrease in the velocity, towards the convergence of the optimization problem the particles velocity will be very low. This low speed of particles restricts the convergence of the optimization problem during dynamics. To keep away from such incidences, inertia weight ought to be chosen cautiously. To beat the disadvantage of the CPSO, another modified clonal particle swarm optimization is proposed by making some alteration in the inertia weight of the speed of the particles. Various strategies for determination of inertia weight are available in literature. Fifteen distinctive inertia weight methodology evaluation concludes that random inertia weight procedure has better efficiency [15]. Hence, this feature is incorporated in clonal PSO and a modified clonal PSO is proposed which beat the disadvantage of CPSO. Random inertia weight is given by equation (16).

$$w = 0.5 + \frac{\text{Rand()}}{2} \tag{16}$$

Above condition produces an irregular weight somewhere in the range of 0.5 and 1 with a mean estimation of 0.75. This evades the issue of constantly diminishing velocity. Steps of MCPSO are similar to the PSO except position update equation. Detailed description of steps is given below:

1. Input the framework information (bus, line, load and generation data, etc.).
2. Determine power losses using power flow analysis without DG.
3. Find the value of objective function.
4. Initialize parameters of MCPSO randomly for size and location of DG.
5. *for* bus=2 to n (exclude the slack bus).
6. Start iteration.
7. Update particle speed and position as Eqs. (14) and (15) individually and check for limits.
8. Determine the fitness of all particles positions by considering multi-objective function.
9. Do comparison of P_{best} and G_{best} in complete population.
10. Calculate the best value of the fitness function.
11. Check termination criteria, otherwise go to step 3.
12. Record all information and print optimum result.

4 Results and Discussion

Outcomes of the MCPSO strategy are authenticated by comparing results of some existing techniques for two test systems. These two test networks are IEEE-30 bus and IEEE 14-bus distribution systems. Based on two test systems, two different cases are considered: IEEE 30-bus system (Case-I) and IEEE 14-bus distribution system (case-II). IEEE 30-bus system consists of six synchronous generators, four transformers. Load of 283.4 MW and 126.2 MVAR is divided into 21 load points. The information for the test system is taken from [16]. Generator coefficients are considered from [17]. Total active and reactive losses in the system are 17.594 MW and 22.233 MVAR, respectively.

4.1 Case-I

For IEEE 30-bus system, parameters of MCPSO are: swarm size: 25 and number of iterations: 50. Results for the case-I are compared with the analytical [8], Modified Differential Evolution (MDE) [18] and PSO [19] techniques and shown in Table 1. Comparison shows that except MDE and PSO all techniques consider real and reactive power injection both and value of injected reactive power is 0.2 times of injected active power while MDE and PSO consider only active power injection. In analytical technique and MDE, objective function of the optimization problem considers active losses and cost of DG, in PSO only active losses are considered as objective function. CPSO and proposed MCPSO are applied to reduce active losses, cost of DG and voltage profile enhancement. The obtained results confirm that the

Table 1 Results and comparison of MCPSO in case-I

Name of technique	OF	Capacity of DG (MW)	Bus No.	Losses (MW)	DG power injection
Analytical [8]	Active losses and cost of DG	35	11	13.61	P_{inj} and $Q_{inj} = 0.2 * P_{inj}$
MDE [18]	Active losses and cost of DG	49.96	5	13.32	P_{inj}
PSO [19]	Active losses	14.80	6	15.519	P_{inj}
CPSO	Active losses, cost of DG and VPI	45	21	12.982	P_{inj} and $Q_{inj} = 0.2 * P_{inj}$
MCPSO	Active losses, cost of DG and VPI	46.95	23	12.93	P_{inj} and $Q_{inj} = 0.2 * P_{inj}$

proposed size by the MCPSO gives maximum loss reduction. In compared methods, although size proposed by the PSO is less but losses in that case are maximum as 15.519 MW. Proposed MCPSO method suggests higher size with minimum losses in the system. In case of MCPSO size is 46.95 MW and this size gives minimum losses of 12.93 MW. This size is less than that of MDE with lesser losses. Although analytical and CPSO gives lesser size than that of MCPSO as 35 and 45 MW, respectively, but in these cases, losses are more than that of MCPSO. Active and reactive line loss comparison of base case and optimum results with MCPSO are demonstrated in Figs. 2 and 3, respectively. These figures also show that the optimal placement of DG reduces the line losses in the system.

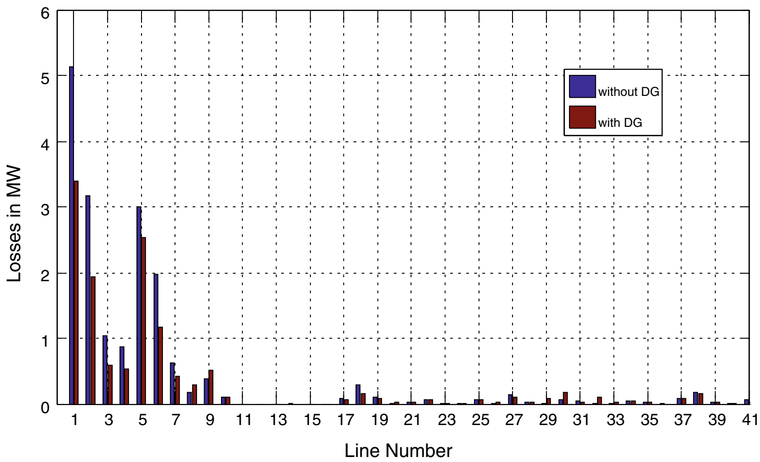


Fig. 2 Active line losses comparison in case-I

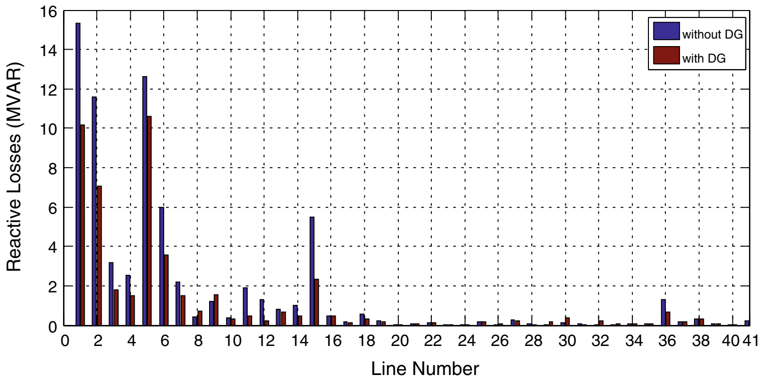


Fig. 3 Reactive line losses comparison in case-I

Table 2 Variation in different indices in case-I

	C_i	VP_i	P_i	OF
Base case	–	0.0266	4.066	–
CPSO	2.168	0.0221	2.7488	1.6301
MCPSO	2.1761	0.0229	2.7211	1.6236

Variation in different indices in case-I with CPSO and MCPSO is shown in Table 2. Table shows that C_i and VP_i in case of MCPSO are slightly higher than that of the CPSO but MCPSO results in minimum objective function. Due to minimum objective function, it can be concluded that MCPSO results in optimum size DG for multi-objective optimization. With the first test system the voltage profile in base case and with optimally placed DG is shown in Fig. 4. Voltage profile is compared for the base case and for the best case as suggested by MCPSO. Figure 4 shows that

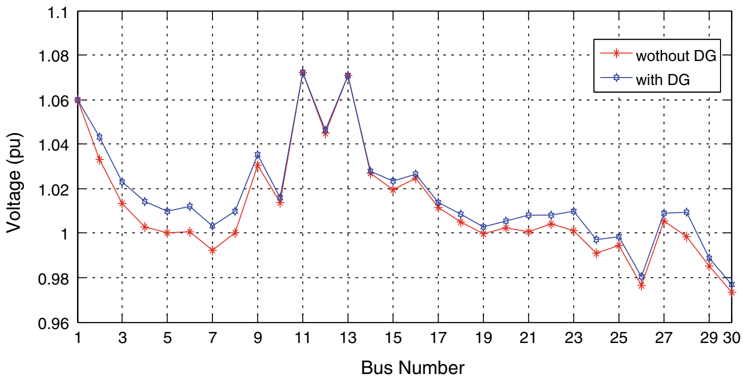


Fig. 4 Voltage profile comparison in case-I

if optimal size DG (46.95 MW) is installed at optimum location (bus #23) then it also supports profile bus voltage.

4.2 Case-II

In case-II, IEEE 14-bus network is considered. In this the proposed MCPSO is judged against other existing approach as analytical [8] and MDE [18], PSO and CPSO. For PSO, CPSO and MCPSO number of particles are 12 and number of iterations are 25. Comparative results of MCPSO with other methods in case-II are shown in Table 3. For optimization using PSO, CPSO and MCPSO a objective function is considered as given in Eq. 7, whereas analytical and MDE techniques consider bi-objective function. Bi-objective function takes the real losses and cost of DG and multi-objective function is a combination of the real losses, cost of DG and voltage profile index. Except MDE, in all other techniques, DG may provide both active and reactive power support. The reactive power provided by DG is related to the active power capacity and is only 20%. According to analytical method, most suitable place for the DG is 8th bus and optimal capacity is 16 MW. With installation of it at bus no. 8, losses in the system are 11.70 MW. According to the MDE, a DG with a capacity of 34.12 MW should be installed at bus number 3. This installation generated losses of 11.54 MW. In the same system with same conditions PSO, CPSO and proposed MCPSO are also applied.

According to PSO, size of DG is 32.45 MW and its place is 6th bus. In this approach, loss is 10.914 MW. This loss is lesser than that of MDE. CPSO suggests the 33.95 MW DG 6th bus. This size results loss of 10.811 MW and these losses are lesser than that of PSO. Size suggested by the MCPSO is in the order of as proposed

Table 3 Results and comparison of MCPSO in case-II

Name of technique	OF	Capacity of DG (MW)	Bus No.	Losses (MW)	DG power injection
Analytical [8]	Active losses and cost of DG	16	8	11.70	P_{inj} and $Q_{inj} = 0.2 * P_{inj}$
MDE [18]	Active losses and cost of DG	34.12	3	11.54	P_{inj}
PSO	Active losses, cost of DG and VPI	32.45	6	10.914	P_{inj} and $Q_{inj} = 0.2 * P_{inj}$
CPSO	Active losses, cost of DG and VPI	33.95	6	10.811	P_{inj} and $Q_{inj} = 0.2 * P_{inj}$
MCPSO	Active losses, cost of DG and VPI	34	14	10.093	P_{inj} and $Q_{inj} = 0.2 * P_{inj}$

Table 4 Variation in different indices in case-II

	C_i	VP_i	P_i	OF
Base case	–	0.01	4.3054	–
PSO	2.1217	0.01	3.2051	1.5058
CPSO	2.1273	0.01	3.1639	1.4974
MCPSO	2.1275	0.01	3.0143	1.4600

by the CPSO but this size results in the maximum loss reduction in IEEE 14-bus system. According to MCPSO optimal capacity of DG is 34 MW at bus number 14. This installation results in 10.093 MW losses only. These losses are least among the compared techniques. Although size suggested by MCPSO is higher than analytical and approximately equal to MDE and CPSO but this size gives minimum losses in the system. These results show that results of the MCPSO are best among the compared methodologies. Variation in different indices in case-II for PSO, CPSO and MCPSO is shown in Table 4. This tables shows that CI is increased in case of size suggested by the MCPSO but overall objective function is lowest in case of MCPSO.

Active and reactive line losses comparison for base case and optimum case proposed by MCPSO are shown in Figs. 5 and 6, respectively. These figures also prove that optimum size suggested by the MCPSO is able to reduce active as well as reactive line losses although in objective function only active losses are considered. Voltage profile of the IEEE 14-bus system without DG and with optimum DG is shown in Fig. 7. Figure shows that optimum installation suggested by the proposed MCPSO improves the overall voltage profile of the system.

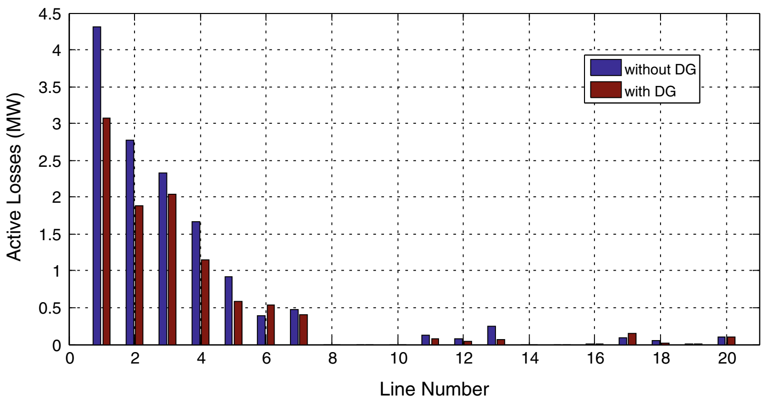


Fig. 5 Active line losses comparison in case-II

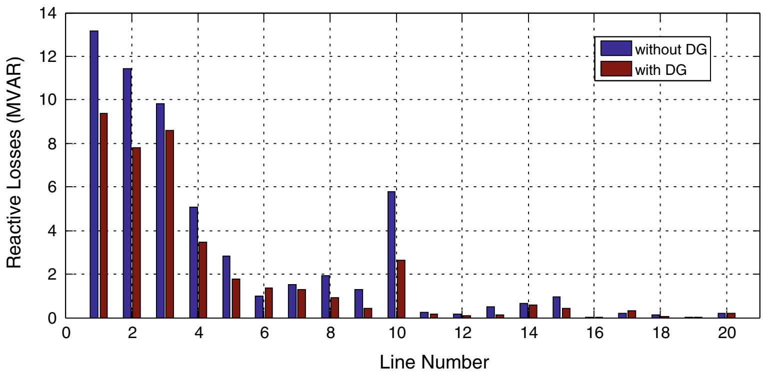


Fig. 6 Reactive line losses comparison in case-II

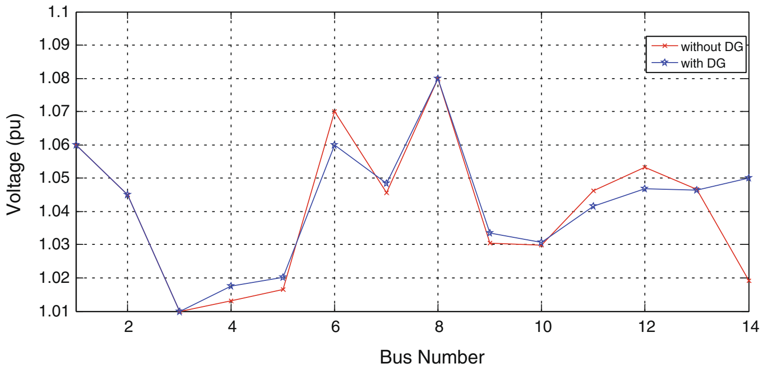


Fig. 7 Voltage profile comparison in case-II

5 Conclusion

In this paper, a principle of clonal selection is combined with the PSO and a new modified clonal PSO is proposed. Selection of inertia weight strategy is also discussed for proposed MCPSO. It also used to optimize a multi-objective function to find the optimal location of DG in IEEE 30-bus and IEEE 14-bus distribution system. Objective of the proposed objective function is to minimization of generation cost and line loss and enhancement of voltage profile. In both cases, results of MCPSO are compared with other existing methodologies. Results are found better than the compared methods in multi-objective optimization.

As a future scope, this MCPSO can be implemented in other types of distribution networks. The proposed work can be extended by considering placement of multiple and different types of DGs. Time varying load can also be considered during optimization.

References

1. Bhadoria VS, Pal NS, Shrivastava V (2016) Comparison of analytical and heuristic techniques for multiobjective optimization in power system. In: Problem solving and uncertainty modeling through optimization and soft computing, pp 264–291. https://doi.org/10.4018/978-1-4666-9885-7.ch013
2. Ramavat SR, Jaiswal SP, Goel N, Shrivastava V (2019) Optimal location and sizing of DG in distribution system and its cost–benefit analysis. In: Applications of artificial intelligence techniques in engineering. Advances in intelligent systems and computing, vol 698. Springer, Singapore. https://doi.org/10.1007/978-981-13-1819-1_11
3. Bhadoria VS, Pal NS, Shrivastava V (2013) A review on distributed generation definitions and DG impacts on distribution system. In: International conference on advanced computing and communication technologies (ICACCTTM-2013), Panipat, pp 1–7. https://doi.org/10.13140/RG.2.1.4439.4328
4. Bhadoria VS, Pal NS, Shrivastava V (2014) Installation of DG for optimal demand compensation. In: 2014 international conference on issues and challenges in intelligent computing techniques (ICICT). IEEE, pp 816–819. https://doi.org/10.1109/ICICICT.2014.6781385
5. Maurya H, Pal NS, Bhadoria VS (2020) Performance analysis of optimal placement of multiple DGs using PSO. In: Decision analytics applications in industry. Springer, Singapore, pp 239–247. https://doi.org/10.1007/978-981-15-3643-4_18
6. Bhadoria VS, Pal NS, Shrivastava V, Jaiswal SP (2017) Reliability improvement of distribution system by optimal sitting and sizing of disperse generation. Int J Reliab Qual Saf Eng. https://doi.org/10.1142/S021853931740006X
7. Bhadoria VS, Pal NS, Shrivastava V, Jaiswal SP (2018) Optimal sitting and sizing of capacitor using iterative search method for enhancement of reliability of distribution system. Lect Notes Electr Eng 508:123–129. https://doi.org/10.1007/978-981-13-0662-4_11
8. Ghosh S, Ghoshal SP, Ghosh S (2010) Optimal sizing and placement of distributed generation in a network system. Int J Electr Power Energy Syst 32:849–856. https://doi.org/10.1016/j.ijepes.2010.01.029
9. Jaiswal SP, Shrivastava V, Singh S (2019) Economic viability solar PV power plant in distribution system. IOP Conf Ser Mater Sci Eng 594:012010. https://doi.org/10.1088/1757-899X/594/1/012010
10. Elgerd O (1971) Electric energy systems theory: an introduction. McGraw-Hill, New York
11. Maurya H, Bohra VK, Pal NS, Bhadoria VS (2019, August) Effect of inertia weight of PSO on optimal placement of DG. In: IOP Conference Series: Materials Science and Engineering, vol 594, no 1. IOP Publishing, p 012011. https://doi.org/10.1088/1757-899X/594/1/012011
12. Kennedy J, Eberhart R (1995) Particle swarm optimization. In: Proceedings of ICNN'95—international conference on neural networks. IEEE, Perth, WA, Australia, pp 1942–1948. https://doi.org/10.1109/ICNN.1995.488968
13. Castro LND, Zuben FJV (2002) Learning and optimization using the clonal selection principle. IEEE Trans Evol Comput 6:239–251
14. Nanda SJ, Panda G (2009) Artificial immune systems: principle, algorithms and applications
15. Bansal JC, Singh PK, Saraswat M, Verma A, Jadon SS, Abraham A (2011) Inertia weight strategies in particle swarm optimization. In: 2011 third world congress on nature and biologically inspired computing, pp 633–640. IEEE, Salamanca, Spain. https://doi.org/10.1109/NaBIC.2011.6089659
16. Pai MA (2006) Techniques in power system analysis. Tata McGraw-Hill Publishing Company Limited, New Delhi
17. Gautam D, Mithulananthan N (2007) Optimal DG placement in deregulated electricity market. Electr Power Syst Res 77:1627–1636. https://doi.org/10.1016/j.epsr.2006.11.014
18. Kumar S, Pal D, Mandal KK, Chakraborty N (2013) Performance study of a new modified differential evolution technique applied for optimal placement and sizing of distributed generation. In: Lecture notes in computer science (including subseries lecture notes in artificial

intelligence (LNAI) and lecture notes bioinformatics), vol 8297. LNCS, pp 189–198. https://doi.org/10.1007/978-3-319-03753-0_18
19. Haidar AMA (2011) Optimal location of distributed generation using intelligent optimization. In: Proceedings of international conference tools with artificial intelligence ICTAI, pp 891–893. https://doi.org/10.1109/ICTAI.2011.143