JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Multi objective PSO Based Network Reconfiguration and DG placement

Rajnesh kumarYadav[1], Naveen Jain[2], Umesh Agrawal[3*], and Manoj Kumawat[4]

[1,2,3] Department of Electrical Engineering, College of Technology and Engineering, Udaipur, Rajasthan, India

[4]Department of Electrical and Electronics Engineering, National Institute of Technology Delhi, Delhi

[1*]Corresponding Author (Mobile No. 9928457221:; Fax: +91 294 2471056; E-mail:yrajnesh@gmail.com)

Abstract- This paper presents a multi objective frame work to configure the radial distribution network considering three objective functions: active power loss, distributed Generator (DG) installation cost, and node closeness. This work proposes a Multi Objective Particle Swarm Optimization (MOPSO) based heuristic approach to obtain Pareto optimal solution. The conflicting nature of these objectives makes them best suitable for multi-objective optimization. Further, a Sensitivity analysis is used for allocation of the DG units. Different scenarios of the DG placement and reconfiguration of network are considered to study the performance of the proposed method. The method has been tested on 33-bus radial distribution system for two different load conditions to demonstrate effectiveness of the proposed method.

Keywords: *DG allocation, multi-objective optimization, Power loss, Reconfiguration.*

I. Introduction

High cost of generating electricity gained the great attention towards the minimization of power losses to save more energy. Therefore, attention of current power system researchers is basically focused on minimization of losses as well as addressing other techno-economic-environmental issues.

In general, a Radial distribution system is used in Distribution network due to its design simplicity and reliable operation. Radial distribution network consists of two types of switches: sectionalize switches and Tie switches. Usually sectionalize switches are normally closed switches and Tie switches are normally open type.

Network reconfiguration is a process to alter the position of these switches to get the optimal network configuration. Network reconfiguration is generally done to get reduction in losses and security enhancement; these problems are solved satisfying all the operating constraints [1].

Obviously, more number of switches, greater the complexity in solving the problem in order to get optimal configuration of network.

In modern era, limitation on fossil fuels and transmission corridors with increasing global warming have forced researchers to pay attention towards renewable based Distributed Generation (DG) units.

These energy sources improve the reliability of power system and limit the green house effects as they are either less polluting or non-polluting. Therefore, the DG penetration in power system has become a dominant choice. Despite of numerous advantages and lots of published research papers on optimal location as well as sizing of the DG, still allocation and sizing of the DG is a major challenge in the distribution system.

The operation of tie switches and sectionalize switches are performed by optimization techniques. Several optimization techniques have been proposed to solve reconfiguration problem considering the minimization of distribution losses and enhancement in reliability [2]-[5]. The location of the DG units is determined by sensitivity analysis [6].

Many papers have been published addressing the issue of network reconfiguration and the DG allocation simultaneously using multi objective optimization techniques [7]-[9. Though, it is difficult to obtain an acceptable solution for conflicting nature of objective functions. The Multi Objective Optimization (MOO) approaches usually provide a set of trade-off solutions, which is known as Pareto optimal solutions (non-dominated solutions).

In literature, numerous computational intelligence based techniques, such as evolutionary computation and swarm intelligence have been employed for solving MOO problems [10]. In power system, Pareto optimal multi objective optimization algorithm was used considering the objective function as minimization in energy loss, DG (installation cost, operating & maintenance cost) and less environmental emission [11]. A stochastic multi-objective distribution system reconfiguration is used to improve the DG profit and minimize investment cost [12].

In [13], a multi-objective particle swarm optimization algorithm based on dynamic crowding distance was proposed. The multi objective particle swarm optimization based Meta heuristic technique was applied in thermal power station to maximize his profit and minimize the risk associated with price forecasting [14].

II. Problem Formulation

Reliable and high efficiency distribution network is to be obtained by reconfiguration and allocation of the DG units to enhance the voltage profile and losses minimization. In the reviewed literature, multi objective optimization is used to improve the system performance, considering power loss, cost, emission control and maximization of profit. These are constraint based approaches with constraints as power flow and voltage.

This paper presents a multi objective particle swarm optimization technique to obtain the better network, considering power loss, DG cost and closeness as the objective functions.

The closeness of a node is defined as the sum of its entire closest path available in the network. The proposed MOPSO algorithm provides a Pareto optimal solution, where trade-off can be obtained. The problem is formulated considering these three conflicting objective functions. The following are the objective functions.

$$Min\ [P_{Loss}(Z)] = \sum_{i=1}^{Nbr} R_i \times \left(\frac{P_i^2 + Q_i^2}{V_i^2}\right) \quad (1)$$

$$Min\ SC_{DG} = \sum_j^{ndg}(IC_j . P_{int-j}) \quad (2)$$

$$Min\ [C_c(m)] = \sum_{n=1}^{N} d_{mk} = \sum_{k=1}^{N}\sum_{n=1}^{N}\frac{P_{nm}(k)}{P_{nm\ max}} \quad (3)$$

Subject to the following constraints

$$P_i^{min} \le P_i^{loss} \le P_i^{max} \quad (4)$$

$$V_i^{min} \le V_i \le V_i^{max} \quad (5)$$

$$P_{DG}^{min} < P_{DG}^{i} < P_{DG}^{max} \quad (6)$$

$$Q_{DG}^{min} < Q_{DG}^{i} < Q_{DG}^{max} \quad (7)$$

Radial Constraints,

$det\ (Y_i) = 1$ or -1 for Radial System

$det\ (Y_i) = 0$ for non radial System

where, Z= Position of the Tie switches

Nbr= Number of branches

R_i= Resistance ofith branch

P_i and Q_i = Active and Reactive power respectively.

V_i = Node voltages

SC_j = One-time installation cost of DG, P_{int-j} = Size of DG

III. Particle Swarm Optimization Technique

Particle Swarm Optimization (PSO) technique is a heuristic technique, which is inspired by social behavior of birds flocking and fish schooling. This technique was introduced in year 1995 by Kennedy and Eberhart for solving non -linear optimization problems. Over the time several modifications has been made and now it is a powerful optimizer to handle linear, nonlinear and complex problems in the field of engineering and science. This algorithm is used to solve many complex problems in the power system.

The convergence characteristic of the PSO is far better than many other heuristic approaches due to absence of genetic operator. The Idea behind this algorithm is the social behavior of birds flocking and fish schooling, where birds are moved in the certain direction in searching of the food and update their own position according to their own and other member's experience in the group to get its best position, which is recorded as local best (p_i) and global best (p_g). Here, particle is represented as a swarm.

The new velocity and new position is represented by V_i^{t+1} and X_i^{t+1}, respectively and can be found using following equation.

$$V_i^{t+1} = V_i^t + c_1.r_1\left(p_i^t - X_i^t\right) + c_2.r_2\left(p_g^t - X_i^t\right) \quad (8)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (9)$$

The velocity and position of each particle are updated in iterations using (8) and (9).

Where, V_i^t= Velocity of Particle i in iteration count t, X_i^t = Position of Particle i in iteration t, c_1 and c_2= real constants, r_1 and r_2 = random numbers between 0-1.

3.1 Multi objective optimization (MOPSO)

Multi-objective PSO was developed in 2004 by Coello-Coello. The MOPSO is capable in easy handling of conflicting constraints of discrete nature. In multi-objective problems, a Pareto ranking scheme is added to the PSO algorithm. The main difference among the single and multi-objective optimization problems is that two solutions compared in single-objective optimization and all non-dominated solutions are compared among each other in multi objective optimization. Implementing of this technique requires a random set of particles, which are initialized in decision space. Further, a position and velocity are assigned to each particle in decision space. These particles change their position on their personal experience. Moreover, they move towards the best solution updating their positions as illustrated in last section. The non-dominated solutions are kept in the archive. The archive is an external repository where all non-dominated solutions are kept stored. Each solution of the MOPSO is compared with the external archive non dominated solution after iteration [15]. It is important to know that the repository size can be adjusted as per the requirements. In the initial stage, the external archive is empty. The current solution is accepted first. The solution stored in archive is dominant to the current solution then the new solution is discarded. In case, the solution present in the archive is non-dominated to the new solution then saves the new solution in the archive. The particles keep on changing their positions during entire iterations until a termination criterion is achieved. Then a Pareto optimal solution is obtained among all possible solutions, which is described in next section (Pareto optimality) in detail.

3.2 Formulation of Multi objective Optimization

Multi objective problem having n objectives can be formulated as follows.

$$\text{Minimize } y = F(x) = [f_1\ (x), f_2\ (x), \ldots \ldots \ldots \ldots \ldots \ldots \ldots . f_n\ (x)] \quad (10)$$

Subject to

$$g_i\ (x) \leq 0, \quad i = 1,2 \ldots \ldots \ldots \ldots \ldots, k \quad (11)$$

where, $x = (x_1, x_2, \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . . x_n)$ is decision vector, and $y = F(x) =$ objective vector, g_i = Constraints. If n=1, problem becomes single optimization problem and global optimal solution can be found clearly.

However, where $n > 1$, a single solution for the problem may not exists as individual objective functions are of conflicting nature. Hence, non dominated set of solutions in form of "trade- off" among the decision variables would be obtained.

3.3 Pareto Optimality

A set of non-dominated solutions in form of 'trade-off' considering all objective functions is known as Pareto front. The concept of Pareto optimality was introduced by Francis Ysidro and later on generalized by Vilfredo Pareto. The Pareto front is a set of solutions, where no other improvement in solution for any of objective is possible without degrading other objective (s). A decision vector w, $w = [w_1, w_2 \ldots \ldots \ldots \ldots \ldots \ldots w_n]$ is said to Pareto dominance,

The decision vector v, $v = [v_1, v_2 \ldots \ldots \ldots \ldots \ldots v_n]$ if only if

$\forall\, i \in (1,2 \ldots \ldots \ldots \ldots . n), f_i\ (w) \leq\ f_i\ (v)$ and $\exists\, j \in (1,2 \ldots \ldots \ldots \ldots . . n): f_j\ (w\,) < f_j(v)$ in minimization context.

That means $f(w)$ is better than $f(v)$ for all objectives and it exists for at least one objective $f(w)$ is superior than $f(v)$.

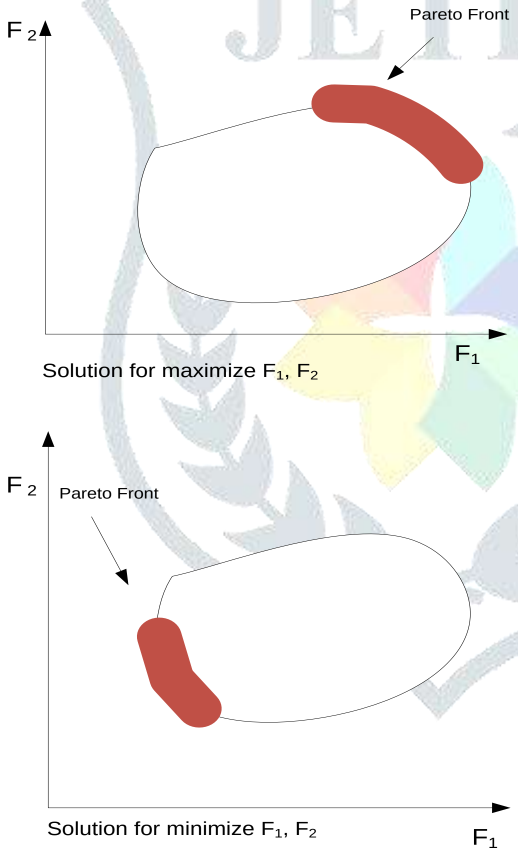

Fig. 1. Pareto optimality for two objective functions

The Pareto set concept for two objective functions for minimization and maximization problems are shown clearly in Fig. 1.

Pseudo Code

Initialize the size of population

Initialize non-dominated solution in the archive

Randomly generate the particles for population and its velocity

Non-dominated solution

Iteration start

while iteration< maximum iteration

for each particle

Select non dominated particle

Update the best position of Swarm

Calculate the best fitness value of the objective function

Update the global best solution

end

Update the global best value in external achieve

Find the non-dominated optimal solution

Iteration=iteration+1

end while

Store the results in external achieve

end

IV Discussion and Results

The proposed multi-objective PSO algorithm has been tested on the IEEE-33 radial standard bus system network. The network consists of 32 sectionalize (NC) and 5 tie switches. The NC (sectionalize) switches are connected from 1 to 32, and 5 tie switches are numbered from 33 to 37 as per diagram shown in Fig. 2. The load flow analysis was carried out to obtain the distribution losses for base network first, which was found 603.43 kW for heavy load conditions, and the lowest per-unit voltage is 0.83 pu.

Optimal locations of the DG units are determined using sensitivity analysis method. Further, potential buses are configured and 06 DG units are installed on 2, 3, 4, 5, 6 and 8 buses.

Now, network is reconfigured using MOPSO technique, where optimal (reconfigured) network is shown in Fig.2. The initial parameters of the proposed MOPSO algorithm are listed in Table1. The population size for algorithm, maximum iteration and inertia weight (w) are 20, 50 and 0.12, respectively. The scenario of the DG unit installation and network reconfiguration problem simultaneously have been analyzed considering two load level conditions viz. heavy load level and normal load level. The results are tabulated in Table 2 and shown in Fig. 3-7.

Table 1: MOPSO parameters

Iteration	50
Swarm population	20
External repository size	10
Inertia weight (W)	0.12
Individual coefficient factor (C_1)	0.1
Swarm Confidence factor (C_2)	1.2

Optimal network after simultaneous reconfiguration and DG installation is shown in Fig.2, the tie switches are reconfigured and change their position from (33, 34, 35, 36), 37 to (7, 13, 28, 35, 36). The initial power loss for standard system is 603.43 kW with lowest voltage 0.83602 pu at bus no. 18. After MOPSO based network reconfiguration technique, these power losses are reduced to 245.2249 after reconfiguration and DG placement which is 48.86% lesser than base (standard IEEE 33 bus system) case losses and voltage level of bus no. 18 has improved to 0.9743 pu and lowest voltage level is also improved to 0.9545 at bus no.28 as shown in Fig.5.

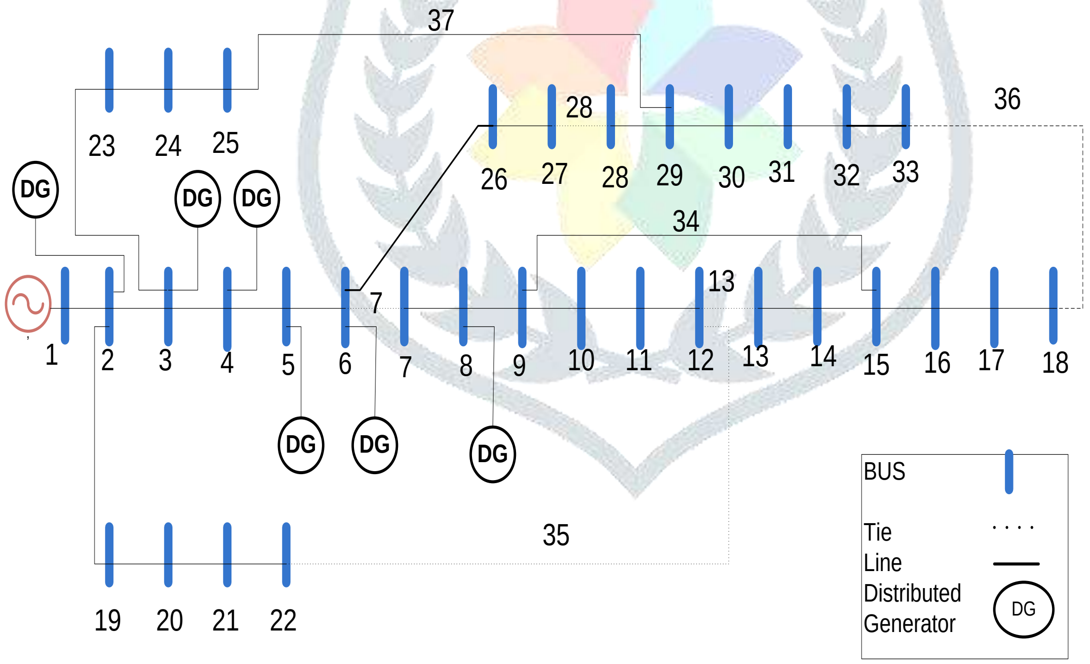

Fig. 2: optimal network structure after simultaneous reconfiguration and DG installation.

The multi-objective approach consisting three objective functions as the DG installation cost, active power loss, and closeness of nodes are optimized with the MOPSO technique. Fig.3 shows the convergence trend for the proposed MOPSO, where dominated and non-dominated solutions are shown. Solution stored in external repository is also represented by red mark in each iterations.

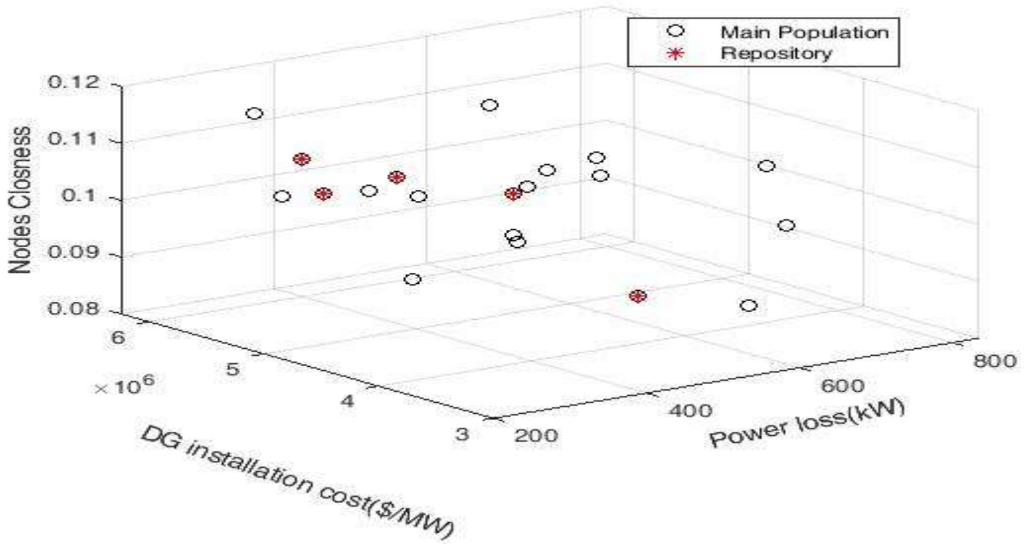

Fig. 3: Convergence characteristics of MOPSO.

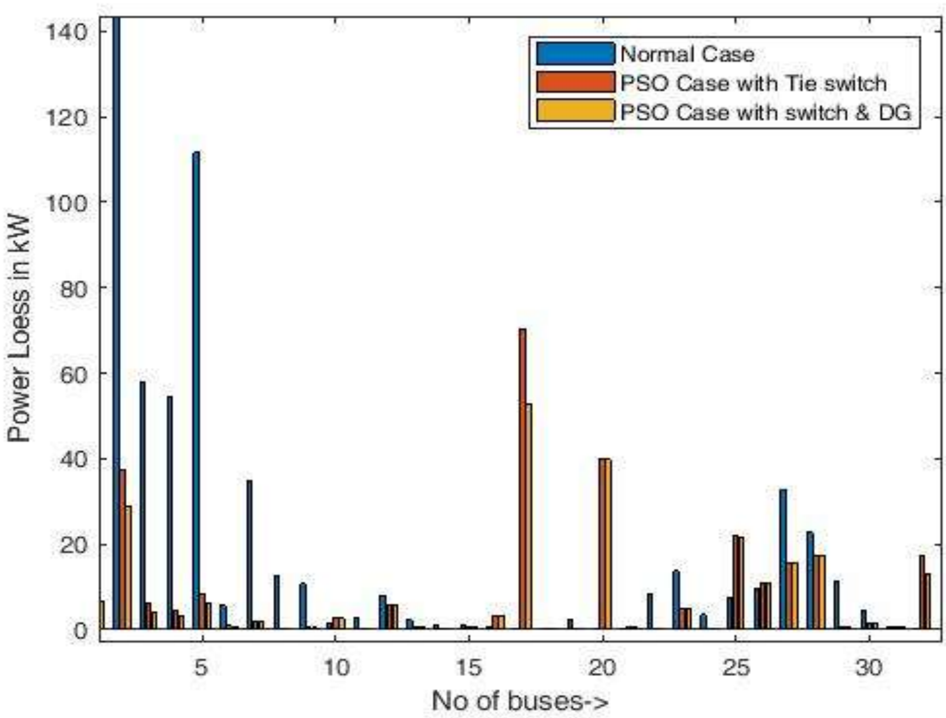

Fig. 4: Active power for normal load condition

Active power losses at each bus are shown in Fig. 4. It can be seen that losses at each bus has been reduced in a significant amount after reconfiguration.

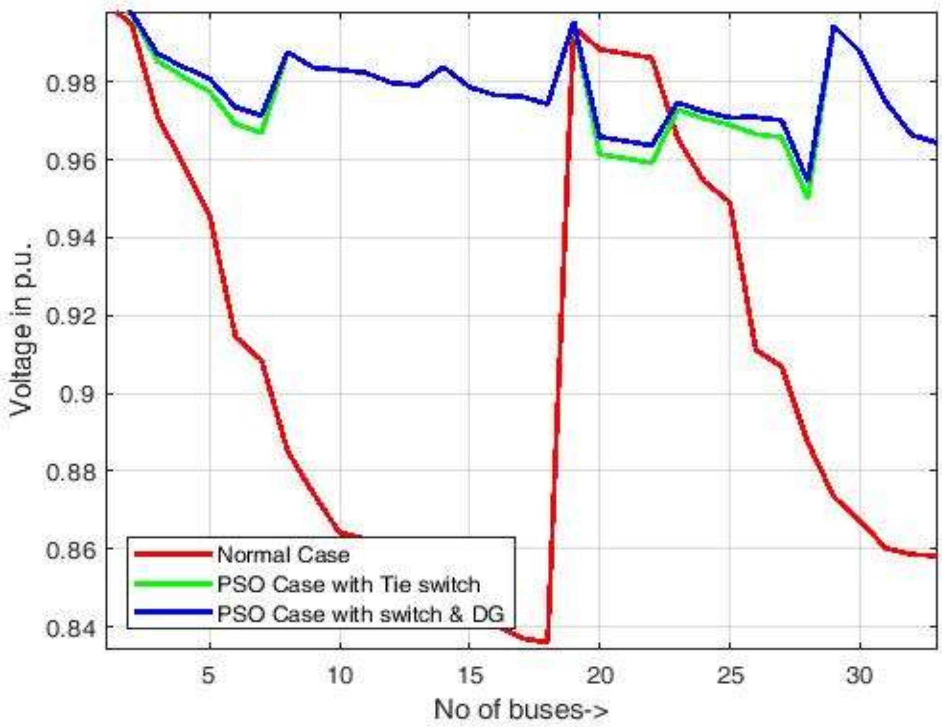

Fig. 5: Voltage profile for heavy load condition

Fig. 5 shows the voltage profile before reconfiguration and after reconfiguration. The minimum node voltage before reconfiguration is 0.83602 pu (heavy load condition). After reconfiguration, it is improved to 0.9545pu (heavy load condition).

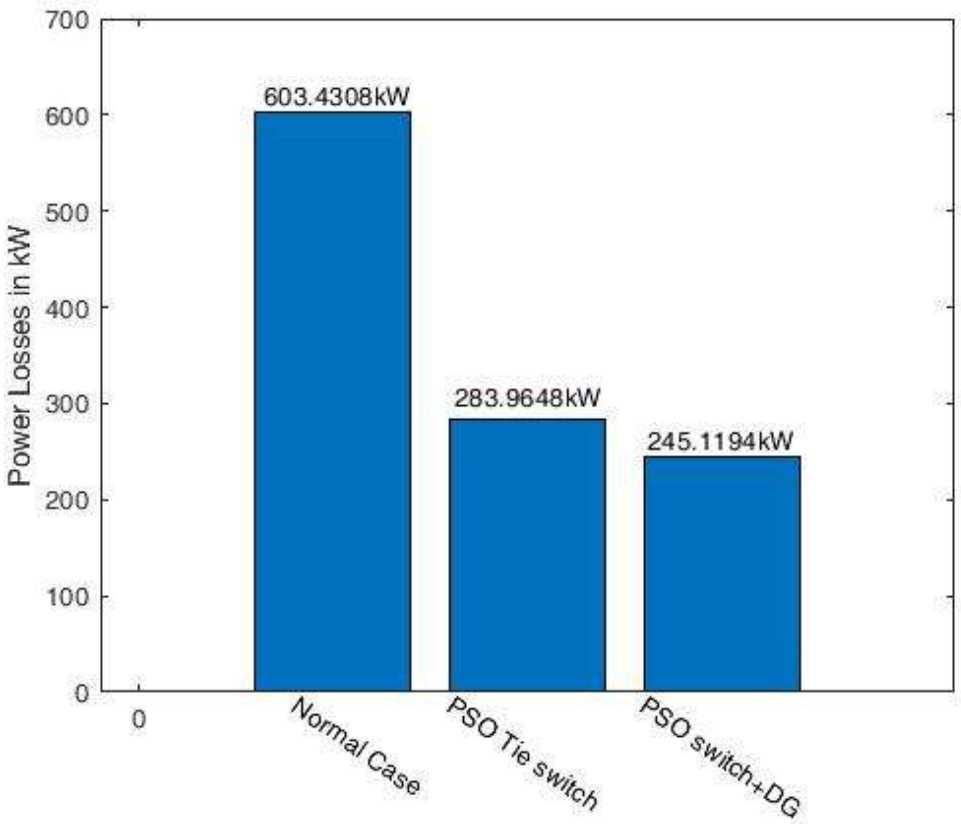

Fig. 6: Power loss comparison for heavy load condition

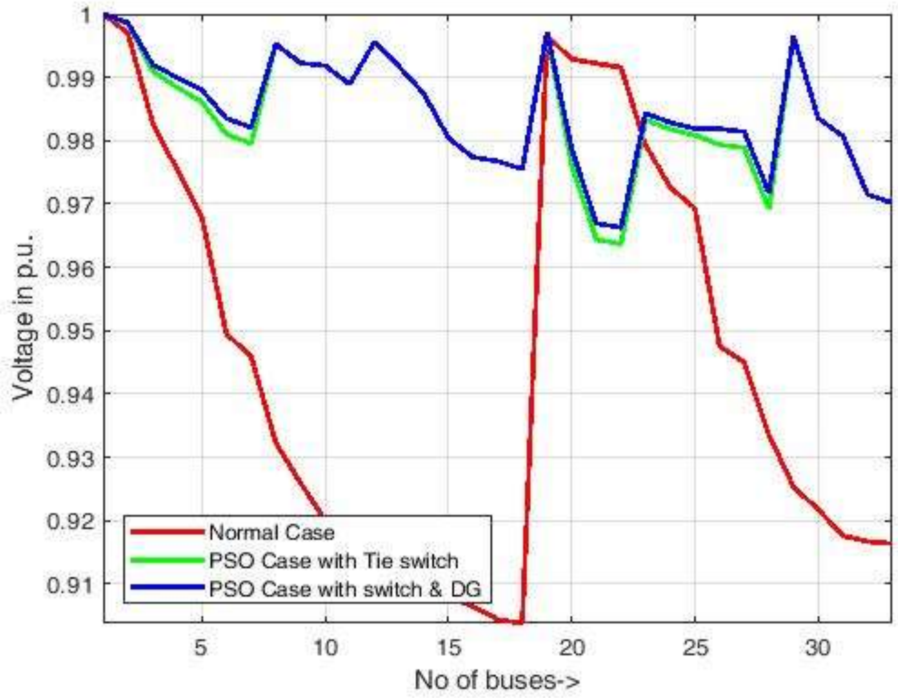

Fig. 7: Voltage profile for normal load condition

Voltage waveform at each bus before and after reconfiguration is shown in Fig.7 (normal load condition). It can be seen that voltage level is maintained in desirable range.

Table 1.2

MOPSO based reconfiguration (i) Tie-switch (ii) Tie switch with DG

Results of 33 Bus system			
Scenario		**Load Level**	
		Normal	**Heavy**
Base Case (Standard IEEE 33 Bus system)	Switches Open	33,34,35,36,37	33,34,35,36,37
	Power Loss (kW)	210.9876	603.4308
	Minimum Voltage (pu)	0.90378 pu	0.83602 pu
Only reconfiguration using MOPSO	Switches open	11,7,34,31,28	35,7,13,36,28
	Power Loss (kW)	206.3491	283.9648
	% Reduction in loss	2.20%	56.22%
	Minimum Voltage (pu)	0.9637	0.9502
MOPSO with DG	Switches Opened	11,7,34,31,28	35,7,13,36,28

	Size of DG in kW (Bus Number)	DG(2)=7.29001 DG(3)= 61.452 DG(4)=75.9465 DG(5)=16.1504 DG(6)=87.9747 DG(8)=32.4066	DG(2)= 43.3915 DG(3)= 80.5647 DG(4)= 36.5189 DG(5)= 50.0857 DG(6)= 61.6196 DG(8)= 58.9368
	Power Loss (kW)	187.0367	245.1194
	% Reduction in loss	11.35%	48.86%
	Minimum Voltage (pu)	0.9663	0.9545

Conclusion

The paper proposed a Multi Objective Particle Swarm Optimization (MOPSO) approach to obtain optimal network reconfiguration combined with the DG allocation in order to minimize three objective functions as Power loss, DG cost and closeness centrality.

The proposed MOPSO method is tested on standard IEEE 33 bus system for two different load scenarios (heavy load and normal load). In the proposed work, the configuration has been addressed by altering the position of switches using the MOPSO algorithm. Further, the DG installation cost and closeness of branch nodes are also minimized by providing a Pareto optimal solution, which provides a trade- off between all the three objectives. The MOPSO reduced the power losses by 11.351% (normal load) and 48.86% (heavy load) with significant improvement in the voltage for both cases.

.Reference

1. Azizivahed, Ali, Ali Arefi, Sahand Ghavidel Jirsaraie, MiadrezaShafie-khah, Li Li, Jiangfeng Zhang, and Joao PS Catalao. "Energy management strategy in dynamic distribution network reconfiguration considering renewable energy resources and storage." IEEE Transactions on Sustainable Energy (2019).
2. R. M. Vitorino, L. P. Neves and H. M. Jorge.“Network reconfiguration to improve reliability and efficiency in distribution system” IEEE buharest Power Tech conference, (2009).
3. R.M. vitorino, H.M. Jorge and L.P. Nevese, “Loss and reliability optimization for power distribution system operation.” Electric power system research, 96 (2013): 177-184.
4. Abdollah Kavousi-Fard, Taher Niknam, “Multi objective stochastic distribution feeder reconfiguration from the reliability point of view.” Energy 64(2014): 342-354.
5. Romeu M. V. Vitorino, Humberto M. M. Jorge and Luís M. P. Neves. “Network reconfiguration using a genetic approach for loss and reliability optimization in distribution system.” Powergen (2009):84-89.
6. Liu, Ke-yan, Wanxing Sheng, Yongmei Liu, and Xiaoli Meng. "A network reconfiguration method considering data uncertainties in smart distribution networks." Energies 10, no. 5 (2017): 618.
7. D.P. Bernardon, A.P.C. Mello, L.L. Pfitscher, L.N. Canha, A.R. Abaide, A.A.B. Ferreria. “Electric Power System Research 107 (2014): 59-67.
8. Fazel Abbasi and Seyed Mehdi Hosseini, “Optimal DG allocation and Sizing in presence of storage system considering network configuration effects in Distribution System.” IET Generation, Transmission & Distribution (2015):1-8.

9. Ola Badran, Saad Mekhilef, Hazlie Mokhlis and Wardiah Dahalan,"Optimal reconfiguration of distribution system connected with distributed generation: A review of different methodologies." Renewable and Sustainable Energy Reviews 73 (2017):854-867.
10. Komail Nekooei, Malihe M. Farsangi, Hossein Nezamabadi-Pour, and Kwang Y. Lee, "An Improved Multi-Objective Harmony Search for Optimal Placement of DGs in Distribution Systems." IEEE Transactions on Smart Grid, Vol. 4, (2013):557-567.
11. Aboelsood Zidan, Mostafa F. Shaaban, Ehab F. El-Saadany, "Long term multi objective distribution network planning by DG allocation and feeder's reconfiguration." Electric Power System Research 105 (2013): 95-104.
12. Nikkhah, Saman, and Abbas Rabiee. "Multi-objective stochastic model for joint optimal allocation of DG units and network reconfiguration from DG owner's and DisCo's perspectives." Renewable energy 132 (2019): 471-485.
13. Liqin Liu, Xueliang Zhang, Liming Xie and Juan Du. "A Novel Multi- Objective Particle Swarm Optimization based on Dynamic Crowding Distance." Science and Technology R& D project of Shanxi colleges and Universities (2009): 481-486.
14. N. M. Pindoriya and S. N. Singh, "MOPSO based Day-Ahead Optimal Self-Scheduling of generators under Electricity Price Forecast Uncertainity." IEEE Power and Energy Society General Meeting (2009):1-8.
15. Hooshmand, Ehsan, and Abbas Rabiee. "Energy management in distribution systems, considering the impact of reconfiguration, RESs, ESSs and DR: A trade-off between cost and reliability." Renewable energy 139 (2019): 346-358.