SciencePG
Science Publishing Group

A Review of Particle Swarm Optimization (PSO) Algorithms for Optimal Distributed Generation Placement

Musa H., Ibrahim S. B.

Department of Electrical Engineering, Bayero University, Kano, Nigeria

Email address:
harunamusa2@yahoo.co.uk (Musa H.), hmusa.ele@buk.edu.ng (Musa H.), sabkibr@yahoo.com (Ibrahim S. B.)

Abstract: Particle Swarm Optimization (PSO) has became one of the most popular optimization methods in the domain of Swarm Intelligence. Many PSO algorithms have been proposed for distributed generations (DGs) deployed into grids for quality power delivery and reliability to consumers. These can only be achieved by placing the DG units at optimal locations. This made DG planning problem solution to be of two steps namely, finding the optimal placement bus in the distribution system as well as optimal sizing of the DG. This paper reviews some of the PSO and hybrids of PSO Algorithms formulated for DG placement being one of the meta-heuristic optimization methods that fits stochastic optimization problems. The review has shown that PSO Algorithms are very efficient in handling the DG placement and sizing problems.

Keywords: Distributed Generation, Power Losses, Optimization, Placement, Sizing, Objective Function, Power flow, Distribution Networks, Multi-objective

1. Introduction

Distributed generation placement and sizing is an important issue which requires special attention of both planners and system operators. DG installation at non-optimal places can lead to increase in system losses which imply increase in costs and hence having a negative impact opposite to the desired. The selection of the best location and size in large and complex system is a combinatorial optimization problem [1]. Researchers have employed various methods in addressing the placement problems. It has been observed that among all the methods reviewed so far analytical method is found to be the most accurate and more practical technique for placement. However, obtaining a truly optimal solution has presented a challenge as some computational methods do not yield global solution as many local solutions exists.

Due to this problem, deterministic algorithms such as Dynamic programming, NLP, LP, QP and SQP are considered to be the elegant options [2]. However, meta heusutic algorithms such as GA, PSO, EP, Tabu search (TS), simulated annealing (SA) seems to have shared the same dominance as deterministic methods [3]. This is due to the fact that meta heuristic are derivative free problems unlike

the deterministic methods and can be solved without need for convexcity. Apart from that the meta heuristic algorithms are independent of initial solution and can avoid local optima [4]. The techniques are robust and can provide near optimal solution for large and complex systems. The only drawback is the high computational efforts required for good solution. On the other hand, meta heuristic methods have their own drawbacks, such as use of trial and error process during parameter tunning and lack of guarantee of global solution attainment atimes. This is one of the reasons that made researchers to direct a lot of effort towards eliminating such problems by combining more than one algorithms to form a hydrid algorithm. The hybrid algorithms currently utilised are; such as LP – QP, EP – SQP GA – SA and PSO – SQP [5] e.t.c. These efforts have yielded results with a lot of enhancement over the individual algorithms when utilized alone.

Particle swarm optimization (PSO) algorithm is a population based optimization method that has gained much popularity among researchers since after its introduction. The algorithm mimics birds' behavior during flight in space. Each of the bird in the aggregation of the birds called

swarm is represented as a particle. These particles that form the swarm searches for food based on their own experience and that of the other particles within the same swarm. The PSO have been studied by many researchers and several newer versions have been developed for applications in different real-world problems and are found to be robust and fast in solving nonlinear non-differentiable multi-modal problems.

Many survey papers with applications have been presented in literature reviews regarding these studies but it is still in its infancy stage requiring a lot of research work. Authors in [6] presented a method for optimal siting and sizing of multiple distributed generators (DGs) using PSO based approach. Similar multiple DGs placement was also presented in [7] with PSO as an optimization tool for variable power load with non-unity power factor. In another development an improved PSO algorithm was also proposed for optimal placement with an in built mechanism for better search that is capable of escaping local optima in [8]. As part of improvement on initial PSO algorithm, the concept of hybridized PSO was introduced by authors in [9]

in which Genetic Algorithm (GA) was combined with PSO. The GA is made to search for the DG site while the PSO optimizes the DG sizes which resulted in drastic reduction in system losses and improvement in voltage profile.

In this paper an introduction of PSO concepts and its algorithm is presented and survey of existing work follows based on objectives, methods and contributions of the work towards finding of optimal solutions to placement and sizing problems.

2. DG Placement and Sizing

The DG placement optimization problem has not been assessed thoroughly as done in many optimization problems. The review in this paper differs from previous reviews in the sense that all work done is going to be categorized based on optimization algorithms employed. Figure 1.0 shows the published research work done on placement and sizing based on IEEE Explore Digital library data base. The analysis shows significant improvement in papers published.
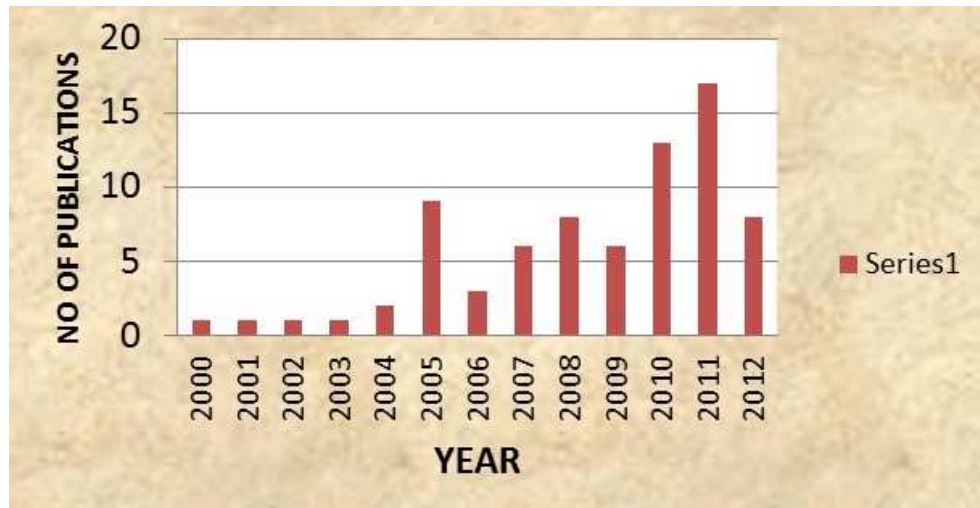

Fig. 1.0. Distributionof papers publsihed on DG placement and sizing

The gradual increase in published papers is a clear indication of growing interest of researchers willing to find solution to DG placement problems.

Many researchers have used various methods to tackle the placement and sizing problems. Methods of optimal placements and sizing of the DGs within networks always depend on the objectives and solution techniques employed. There are three basic models for DG optimization problems that are currently in use which are:

i) Objective function model
ii) Constraints model
iii) Optimization algorithms model

Objective functions are optimized subject to operating constraints by using different techniques. The objective function can be single or multiple for the purpose of achieving maximum benefits of the DG without violating the equality and inequality constraints of the entire power system. The most popular objective is the minimization of

power losses [10]. Among other objectives considered by many researchers includes minimization of real and reactive power loss, maximization of DG capacity, maximization of profit and social welfare to mention a few [11-14]. Other objectives handled by many authors are the technical issues; environmental issues and voltage limit [15-16].

The constraints are state variable limits that are placed on operating conditions. Constraints are basically categorized into equality and inequality which must be satisfied by the objective functions either single or multi-objectives. The common constraints generally in DG placement includes but not limited to the following; line thermal limit, short circuit ratio limit, voltage step limit, phase angle limit, power generation limit, DG power generation limit, number of DG limit, power flow equality constraint, voltage profile limits, short circuit level limit, total line loss limit, substation transformer capacity limit, tap position limit, and power factor limit [12, 14, 17-23].

Many researchers proposed different methods such as analytic as well as deterministic and heuristic methods to solve placements problems. Out of these methods metaheuristic is the only method that has proven their effectiveness in solving optimization problems with appreciable feasible search space [4]. They can also be modified easily to become a hybrid of more than one algorithm to cope with different elements commonly used in most studies.

3. The Concept of PSO Algorithm

The search process is similar to the social behaviour of flying birds when searching for food. The individual bird called particles or swarm flies in the optimization problem hyperspace to search for optimal food location. The position and velocity of the particles is always changing and adjusted according to the cooperative communication among the particles and each individual's own experience simultaneously. Therefore the particle changes position by balancing its social and individual experience. Each particle is assigned a velocity V_i as well as position vector x_i

For a swarm of m-particle in hyperspace, the position and velocity vectors are [24];

$$S_i = \left[x_1^i, x_2^i - - - x_n^i\right] \quad i = 1,2 - -, m \quad (1)$$

$$V = [v_1, v_2 - - - - - - - - - v_n] \quad (2)$$

where i is the particle index, V is the swarm velocity and n is the optimization problem dimension. The particle's new position is;

$$S_i^{(k+1)} = S_i^{(k)} + v_i^{(k+1)} \quad (3)$$

where

$S_i^{(k+1)}$ is particle i new position at iteration $k+1$

$S_i^{(k)}$ is particle i old position at iteration k

$v_i^{(k+1)}$ is particle i new velocity at iteration $k+1$

Equation (3) is the updated position equation. The updated velocity vector for particle i is

$$v_i^{(k+1)} = wv_i^{(k)} + c_1 r_1 \left(p_{besti}^{(k)} - s_i^{(k)}\right) + c_2 r_2 \left(g_{best}^{(k)} - s_i^{(k)}\right) \quad (4)$$

where

$V_i^{(k)}$ is the previous velocity of particle i

w is the inertia weight

c_1, c_2 are the individual and social acceleration positive constants.

r_1, r_2 are the random values in the range [0, 1], sampled from a uniform distribution

P_{besti} is the personal best position associated with particle i own experience

g_{besti} is the global best position associated with the whole neighbourhood experience

3.1. Updated Velocity

The updated velocity as given by equation (4) has three major components consisting of the following;
1. The first component is related to particle's immediate previous velocity, and it consists of two variables. The variables are particle i last velocity $V_i^{(k)}$ and inertia weight w.
2. The second component is the cognitive component, which shows the individual's own experience.
3. The last term is the third components that represent the intelligent exchange of information between particle i and the swarm.

In the absence of the second and third terms of the velocity formula the particle will continue to fly in the same direction with a speed proportional to its inertia weight until it hits one of the solution space boundaries.

Therefore solution can never be obtained unless the solution lies in the same path of the previous velocity in such a case. The change in direction towards the solution is achievable with the help of second and third term of the equation. Those three components of the velocity update are responsible for the optimization process.

Versions of PSO algorithms have been proposed since after Kennedy and Eberhart which are the local best PSO and the global best PSO. The two models differ in the social component of the velocity update formula. In the case of the local best PSO the swarm is divided into several neighborhoods and the g_{best} of particle i is its neighborhood's global value. Whereas the global best model considers the swarm as one entity, and therefore the PSO particle's g_{best} is the best value for the whole swarm. Generally, the global model is more popular version since it needs less work to achieve result.

3.2. Previous Velocity Components

The component is given by the product of previous velocity of particle $V_i^{(k)}$ and the inertia weight w. This term connects the particle in the existing iteration with immediate past iteration which serves as the particle's memory. It is important as it prevented the particle from sudden change in its direction, and also allows the particle's own knowledge of its previous flight information to influence its newer course.

The first version of PSO has no inertia weight as was assumed to be unity. It was in subsequent versions that inertia weight was introduced in order to control the contribution of the particle's previous velocity in the current velocity decision making and this lead to a significant improvement in the PSO algorithm [25]. The implication of making its value too large is the broadening of the exploration mission of the particle, and if the value is small the exploration will be localized. Several dynamic inertia weights were proposed in literatures. The formulations of the literatures have expressed inertia weight as follows;

$$w^{(k)} = c_1 r_1^{(k)} + c_2 r_2^{(k)} \qquad (5)$$

$$w^{(k)} = w^{(n_k)} + \left(w^{(1)} - w^{(n,d)}\right)\left(\frac{n_k - k}{n_k}\right) \quad (6)$$

$$w^{(k+1)} = \frac{w^{(k)} - w^{(n_k)}(n_k - k)}{n_k + w^{(n_k)}} \qquad (7)$$

Where $w^{(k)}$ is the inertia weight value at iteration k

n_k is maximum number of iterations

$w^{(n}{}_k)$ is the inertia weight value at the last iteration n_k

Some authors in [26] have proposed using 0.9 and 0.4 as the initial and final weight values respectively.

Another factor introduced that is similar to inertia weight function is the constriction factor (λ) which is used for the balancing of the search mechanism between global and local exploration. Use of this factor improves convergence and the particles velocity is therefore constricted by a factor λ as expressed in the following equation;

$$v_i^{(k+1)} = \lambda\left(v_i^{(k)} + c_1 r_1\left(p_{best}^{(k)} - s_i^{(k)}\right) + c_2 r_2\left(g_{best}^{(k)} - s_i^{(k)}\right)\right) \quad (8)$$

where

$$\lambda = \frac{2}{\left|2 - \emptyset - \emptyset\sqrt{\emptyset^2 - 4\emptyset}\right|} \qquad (9)$$

and

$$\emptyset = c_2 + c_2$$

$$\emptyset \geq 4$$

Hence, the constriction factor is a factor of individual and social acceleration positive constants C_1 and C_2 respectively. This factor is normally considered as a special case of inertia weight PSO algorithm because of the constraints imposed above. The factor λ controls the particle's velocity vector, whiles the inertia weight w controls the contribution of the particle's previous velocity towards calculating the new one velocity. Use of constriction factor eliminates velocity clamping and can safe guards the algorithm against explosion [27].

3.3. Cognitive Component

The cognitive component of the velocity update equation uses P_{best} which is referred to as the particle's best personal position that it has visited so far since the beginning of the PSO iterative process. Each particle in the swarm tries to evaluate its own performance by comparing its own fitness in the current PSO iteration with that evaluated in the proceeding one. The $p_{best_i}^{(k+1)}$ given that its $p_{best_i}^{(k)}$ is the best personal position so far, is defined as;

$$p_{best_i}^{(k+1)} = \begin{cases} p_{best_i}^{(k)} & if\ f(s_i^{(k+1)}) \geq f\left(p_{best_i}^{(k)}\right) \\ s_i^{(k+1)} & if\ f(s_i^{(k+1)}) \geq f\left(p_{best_i}^{(k)}\right) \end{cases} \quad (10)$$

Based on equation (5) each particle is suppose to remember its optimal personal best position achieved for use in the update of velocity for future iteration. This component of velocity update equation diversifies searching process at the same time helps in avoiding possible stagnation.

3.4. Social Component

This represents the social behavior of the PSO particles. The g_{best} term in this component is referred to as the best position achieved among all the swarm particles. Whenever the best solution among the whole population of the swarm is achieved, all the particles are informed. The g_{best} fitness value is the optimal among all the particles during the current PSO iteration as;

$$g_{best}^{(k+1)} = min\left\{f(s_1^{(k)}), f(s_2^{(k)}), - - -, f(s_m^k)\right\} \quad (11)$$

where $f(S_i^k)$ is particle i fitness value at iteration k, and m is the swarm size.

3.5. Cognitive and Social Parameters

These parameters C_1 and C_2 are cognitive and social parameters respectively. They are factors that scaled the P_{best} and g_{best} in the updated velocity equation. The trust of the particle in itself is measured by C_1, while C_2 reflects the confidence it has on its neighbours. If C_1 is 0, the particle's own experience is eliminated during search process for a new solution, while if C_2 is 0 the search is localized and exchange of information between the particles is eliminate. The highest value recommended for the two in most literatures is 2.

r_1 and r_2 are two random numbers in the range of [0, 1] that are sampled from a uniform distribution. The stochastic exploration nature of PSO is due to these random numbers. A typical illustration for velocity and position update for a single PSO particle during iteration is shown in Fig. 2.0 during iteration.
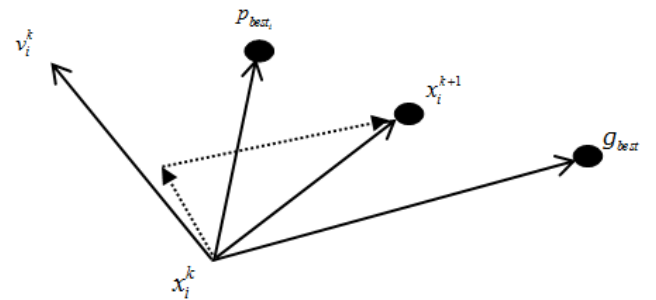

Fig. 2.0. Velocity and position updates for a single particle during iteration k

3.6. Pretty Features of PSO

The advantages associated with PSO are many just like other optimization algorithm. The main advantages are clearly distinct when compared to deterministic methods that

are gradient based techniques and have no flexibility of dealing with objective functions that are not continuous or differentiable naturally. The search process for PSO does not involve use of derivative function; instead it uses the fitness function value as a guide for finding optimal solution in problem space. This concept of fitness function employed in PSO helps in eliminating the approximations and assumptions usually adapted on objective functions and constraints as in conventional optimization methods. For this reason PSO is considered as a stochastic optimization method and found to be very efficient in handling problems that their

objective functions are time varying or stochastic in nature. Above all the solutions from PSO are not dependant on the initial solutions unlike the deterministic method.

4. Studies on PSO Algorithms for DG Placements and Sizing

This section deals with all the studies done on PSO and hybridized PSO Algorithms for DG placements and sizing. All the literature surveyed are summarized in table 4.1

Table 4.1. *Some Published Works on PSO Algorithms*

S/NO.	Ref.	Objectives	Optimization method	Contributions
1.	Haruna M. [28]	Minimization of power losses and voltage stability index (VSI)	PSO	Optimal DG Placement model for better search and improved (VSI)
2.	El-Zonkoly [7]	Multi-objective for short circuit level and other technical parameters	PSO	Determination of voltage collapse point for variable load
3	Nabavi, S.M.H[29]	Reduce network congestion and minimize locational marginal price (LMP)	PSO	congestion management and social welfare in placement/sizing
4	Amanifar, O. [30]	Minimization of investment cost of DGs and power losses	A PSO algorithm integrated in harmonic power flow algorithm	Investiment cost justifies DG placement for increase in power transfer capability
5	Dias, B.H [31]	Minimization of power losses	PSO in Nonlinear Optimal Power Flow (OPF)	Reduction in search space and improvement convergence
6	Gomez-Gonzadez [32]	Minimization of cost	PSO in Optimal power flow	ODGP model using discrete PSO and OPF
7	Wong, L.Y. [33]	Minimization of power losses	Pso in Newton –Raphson power flow	Effective solutions and improved voltage profile
8	Nguyen Cong Hien [34]	Maximizes reactive power flow	PSO	Enhancement of loadability of the primary distribution feeder

The PSO algorithms allow the system planner to find not only a single optimum point, but a family of near-optimum planning alternatives. This feature of PSO has become very useful in DG allocation because distribution network operators usually have little or no control on the DG integration and different planning alternatives can be necessary to face uncertainties and minimize risks.

Numerous publications and wide spread implementation of PSO algorithms has been conducted, a lot of barriers to proper implementation of these researchers by network operators is still lacking. Although the algorithm has many advantages over other meta-heuristic methods, the main challenge associated PSO is that of lack of solid mathematical background like many heuristic methods. It's solution method is problem dependent and for every solution parameters have to be tuned and adjusted for better solution. The conventional PSO introduced by Kennedy and Eberhart in 1995 and even those that had under gone modifications, are still dependent on a number of parameters that are externally set or arbitrary selected by the user [24]. This setting or selection by the user is a very delicate operation

involving a lot of trials and errors before a reasonable tuning can be achieved especially in practical problems that require defining of inertia weight at each iteration step. Apart from that the usual initial assumption that inertia term is eliminated at an early stage of the optimization process, can cause the algorithm to be trapped at some local minimum. As a solution to this problem some authors have proposed some procedures of "re-seeding" the search by generating new particles at distinct places of the search space [35]. Other shortcoming of PSO is the random operation involved that a particle is initialized randomly and its location in the search space is updated during each iteration in the PSO algorithm. The problem is that when the particle initialization is not well done the issue of local minimum trapping can also arise or convergence can be prolonged as sharing of information between particles is not properly coordinated.

These challenges made researchers to direct a lot of effort towards eliminating such problems by combining more than one algorithms to form a hybrid algorithms. The efforts have yielded results with a lot of enhancement over the individual algorithms when utilized alone as indicated in table 4.2.

Table 4.2. Some Published Works on Hybrid PSO Algorithms

S/No.	Ref	Objective	Method	Contribution
1	Moradi [9]	Multi-objective with weights	Hybrid (GA &PSO)	Optimal DG Planning for placement using GA and sizing using PSO
2.	Sedighizadeh, M [36]	Minimization of power losses and voltage profile improvement	Hybrid (PSO and Clonal Selection)	Better quality of solutions and less number of iterations
3.	Musa, H. [37]	Multi-objective for power loss reduction and voltage stability index improvement	Hybrid (PSO & Evolutionary Programming)	Well-distributed Pareto optimal non-dominated solutions of DG sizes obtained
4.	Afzalan, M [38]	Minimization of power losses	Hybrid (PSO & HBMO)	Voltage profile improvement and branch current reduction
5.	Ziari, I [39]	Minimizes loss and improves system reliability.	Hybrid (Discrete PSO & GA)	Increase in the diversity optimization variables in DPSO not to be trapped in a local minimum
6	Soroudi, A. [40]	Multi-objective for technical constraint dissatisfaction, costs and environmental emissions	Hybrid (Binary PSO-based & Fuzzy)	Better timing of investment for both distributed generation (DG) units and network components obtained
7	Wen S. T.[41]	Multi-objective index-based approach for total real power losses, voltage profile, MVA intake by the grid, number of DG and greenhouse gases emission	Hybrid (PSO & Gravitational Search Algorithm)	Algorithm can provide efficient and robust solution to mixed integer nonlinear optimization problem
8	Haruna Musa[42]	power loss reduction (PLR) value	Hybrid (PSO & Ranked Evolutionary programming)	A simple and effective algorithm for power loss reduction and voltage profile improvement

5. Conclusions

Although there have been numerous publications in the area of the siting and sizing of DG, it is evident that, widespread implementation of the PSO optimizations has not been much. Development of the DG integration strategies and PSO optimization methods requires proper distribution system planning especially with the proliferation of electric vehicle in existing distribution networks. Further challenges that are yet to be tackled for better optimization are the modelling of the distribution networks with all the necessary details needed by network operators.

Acknowledgements

References

[1] Borges, C., Falcao, D., "Optimal DG allocation for reliability, losses, and voltage improvement", International Journal of Electrical power & Energy systems, vol. 28 pp. 413-420. 2006

[2] T. Griffin, K. Tomsovic, D. Secrest, A. Law, " Placement of disperse generation systems for reduced losses", Proceedings of the 33rd Annual Hawaii International Conference on system Science, IEEE , pp. 164–164, Jan. 2000.

[3] M. Gandomkar, M. Vakilian, and M. Ehsan, "A genetic-based tabu search algorithm for optimal DG allocation in distribution networks," *Elect. Power Compon. Syst.*, vol. 33, no. 12, pp. 1351–1362,Aug. 2005

[4] Haruna Musa "A Review of Distributed Generation Resource Types and their Mathematical Models for Power Flow Analysis" International Journal of Science, Technology and Society Doi: 10.11648/j.ijsts.20150304.21, 2015; 3(4): 204-212

[5] G. P. Harrison, A. Piccolo, P. Siano, and A. R. Wallace, "Hybrid GA and OPF evaluation of network capacity for distributed generation connections," *Elect. Power Syst. Res.*, vol. 78, no. 3, pp. 392–398, Mar. 2008

[6] Jain Naveen, Singh SN, Srivastava SC. Particle swarm optimization based method for optimal siting and sizing of multiple distributed generators. In Proc 16th national power systems conference, 15–17th December, 2010. p. 669–74.

[7] A. M. El-Zonkoly, "Optimal placement of multi-distributed generation units including different load models using particle swarm optimisation," *IET Gener., Transm., Distrib.*, vol. 5, no. 7, pp. 760–771, Jul. 2011.

[8] W. Prommee and W. Ongsakul, "Optimal multiple distributed generation placement in microgrid system by improved reinitialized social structures particle swarm optimization," *Euro. Trans. Electr. Power*, vol. 21, no. 1, pp. 489–504, Jan. 2011.

[9] M. H. Moradi and M. Abedini, "A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 34, no. 1, pp. 66–74, Jan. 2012.

[10] D. Q. Hung and N. Mithulananthan, and R.C. Bansal "An analytical expression for DG allocation in primary distribution networks," *IEEE Trans. Energy Convers.*, vol. 25, no. 3, pp. 814–820, Sept. 2010.

[11] Rau N. S. and Wan Y.-H., "Optimum location of resources in distributed planning". *IEEE Trans. Power Syst.*, vol. 9, pp. 2014– 2020. 1994

[12] A. Keane and M. O'Malley, "Optimal allocation of embedded generation on distribution networks," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1640–1646, Aug. 2005.

[13] D. Gautam and N. Mithulananthan, "Optimal DG placement in deregulated electricity market," *Elect. Power Syst. Res.*, vol. 77, no. 12, pp. 1627–1636, Oct. 2007.

[14] C. J. Dent, L. F. Ochoa, and G. P. Harrison, "Network distributed generation capacity analysis using OPF with voltage step constraints," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 296–304, Feb. 2010.

[15] E. Haesen, J. Driesen, and R. Belmans, "Robust planning methodology for integration of stochastic generators in distribution grids," *IET Renew. Power Gener.*, vol. 1, no. 1, pp. 25–32, Mar. 2007.

[16] Y. M. Atwa and E. F. El-Saadany, "Probabilistic approach for optimal allocation of wind-based distributed generation in distribution systems," *IET Renew. PowerGener.*, vol. 5, no. 1, pp. 79–88, Jan. 2011.

[17] A. Kumar and W. Gao, "Optimal distributed generation location using mixed integer non-linear programming in hybrid electricity markets," *IET Gener. Transm. Distrib.*, vol. 4, no. 2, pp. 281–298, Feb. 2010.

[18] Algarni Ayed A. S. and Bhattacharya Kankar, 2009. Disco operation considering DG units and their goodness factors. IEEE Trans. Power System, vol. 24, no. 4, pp.1831-1840.

[19] D. Singh, D. Singh, and K.-S. Verma, "Multiobjective optimization for DG planning with load models," IEEE Trans. Power Syst., vol. 24, no. 1, pp. 427–436, Feb. 2009.

[20] D. H. Popovic, J. A. Greatbanks, M. Begovic, and A. Pregelj, "Placement of distributed generators and reclosers for distribution network security and reliability," Int. J. Elect. Power Energy Syst., vol. 27, no. 5, pp. 398–408, Jun. 2005.

[21] W. El-Khattam, K. Bhattacharya, Y. Hegazy, and M. M. A. Salama, "Optimal investment planning for distributed generation in a competitive electricity market," *IEEE Trans. Power Syst.*, vol. 19, no. 3, pp. 1674–1684, Aug. 2004.

[22] P. N. Vovos, G. P. Harrison, A. R.Wallace, and J.W. Bialek, "Optimal power flow as a tool for fault level-constrained network capacity analysis," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 734–741, May 2005.

[23] R. A. Jabr and B. C. Pal, "Ordinal optimisation approach for locating and sizing of distributed generation," *IET Gener., Transm., Distrib.*, vol. 3, no. 8, pp. 713–723, Aug. 2009.

[24] Eberhart, R.C., Kennedy, J. " A new optimizer using particle swarm theory", Proceedings of the sixth International symposium on Micro Machine and Human Science, 1995 pp. 39-43

[25] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," *IEEE World Congress on Computational Intelligence,* 1998 pp. 69-73.

[26] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization,"*Proceedings of the 1999 Congress on Evolutionary Computation,* vol. 3, p. -1950, 1999.

[27] R. C. Eberhart and Y. Shi, "Comparing inertia weights and constriction factors inparticle swarm optimization," *Proceedings of the 2000 Congress on Evolutionary Computation,* vol. 1, pp. 84-88, 2000.

[28] Haruna Musa, Sanusi Sani Adamu "PSO based DG sizing for improvement of voltage stability index in radial distribution systems" Proceedings of the IASTED International Conference Power and Energy Systems and Applications (PESA 2012) Pages 175-180

[29] Nabavi, S.M.H. Hajforoosh, S. ; Masoum, M.A.S., "Placement and sizing of distributed generation units for congestion management and improvement of voltage profile using particle swarm optimization" Innovative Smart Grid Technologies Asia (ISGT), 2011 IEEE PES , pages 1-6

[30] Amanifar, O. , "Optimal distributed generation placement and sizing for loss and thd reduction and voltage profile improvement in distribution systems using particle swarm optimization and sensitivity analysis Electrical Power Distribution Networks (EPDC), 2011 16th Conference on Publication Year: 2011 , Page(s):1-5

[31] Dias, B.H. ; Oliveira, L.W. ; Gomes, F.V. ; Silva, I.C. ; Oliveira, E.J., "Hybrid heuristic optimization approach for optimal Distributed Generation placement and sizing" Power and Energy Society General Meeting, 2012 IEEE Digital Object Identifier: 10.1109/PESGM.2012.6345653

[32] M. Gomez-Gonzalez, A. López, and F. Jurado, "Optimization of distributed generation systems using a new discrete PSO and OPF," *Elect. Power Syst. Res.*, vol. 84, no. 1, pp. 174–180, Mar. 2012.

[33] Wong, L.Y. ; Rahim, S.R.A. ; Sulaiman, M.H. ; Aliman, O. "Distributed generation installation using particle swarm optimization "Power Engineering and Optimization Conference (PEOCO), 2010 4th International , Page(s): 159 – 163

[34] Nguyen Cong Hien ; Mithulananthan, N. ; Bansal, R.C. Location and Sizing of Distributed Generation Units for Loadabilty Enhancement in Primary Feeder Systems Journal, IEEE Volume: 7 , Issue: 4 2013 , Page(s): 797 - 806 Digital Object Identifier: 10.1109/JSYST.2012.2234396

[35] Vladimiro Miranda, Nuno Fonseca, "EPSO Evolutionary self-adapting Particle Swarm optimization", internal report INESC Porto, July 2001

[36] Sedighizadeh, M. ; Fallahnejad, M. ; Alemi, M.R.; Omidvaran, M. ; Arzaghi-haris, D. "Optimal placement of Distributed Generation using combination of PSO and Clonal Algorithm" Power and Energy (PECon), 2010 IEEE International Conference 10.1109/PECON.2010.5697547, Page(s): 1 – 6

[37] Musa, H. ; Adamu, S.S., "Enhanced PSO based multi-objective distributed generation placement and sizing for power loss reduction and voltage stability index improvement" Energytech, 2013 IEEE Conference, pages 1-6

[38] Afzalan, M. ; Taghikhani, M.A. ; Sedighizadeh, M., "Optimal DG placement and sizing with PSO&HBMO algorithms in radial distribution networks" Electrical Power Distribution Networks (EPDC), 2012 Proceedings of 17th Conference on , 2012 , Page(s): 1 – 6.

[39] Ziari, I. ; Ledwich, G. ; Ghosh, A. ; Cornforth, D. ; Wishart, M. , "Optimal allocation and sizing of DGs in distribution networks Power and Energy Society General Meeting, 2010 IEEE Digital Object Identifier: 10.1109/PES.2010.5588114 2010 , Page(s): 1 – 8.

[40] A.Soroudi, M.Afrasiab; "Binary PSO-Based Dynamic Multi-Objective Model for Distributed Generation Planning under Uncertainty", IET Renewable Power Generation, 2012, Vol.6, No. 2, pp. 67 - 78.

[41] Wen Shan Tan, Hassan, M.Y., Rahman, H.A., Abdullah, M.P., Hussin, F. , "Multi-distributed generation planning using hybrid particle swarm optimisation- gravitational search algorithm including voltage rise issue" Generation, Transmission & Distribution, IET Volume: 7 , Issue: 9 , DOI10.1049/iet-gtd.2013.0050 , 2013 , Page(s): 929 – 942.

[42] Haruna Musa, Sanusi Sani Adamu "Optimal Allocation and Sizing of Distributed Generation for Power Loss Reduction using Modified PSO for Radial Distribution Systems" Journal of Energy Technologies and Policy Volume: 3 Issue: 3, 2013 Pages 1-8.