Cyclonic Converging Particle Swarm Optimization Technique – CCPSO for Optimal Penetration of Distributed Generator – A Test Simulation

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***Abstract*—*Unprecedented & Catastrophic expansion of power system has given significant impetus to penetration of Distribution Generator. Enhancement in reliability, power quality, performance and efficiency are the advantages, offered by DG penetration; however significance of offered advantage greatly depends upon penetration parameters of DG integration. DG's size and location are of great concern in this context. Number of optimization techniques had been adopted due to stochastic nature of objective. In our research article, we have suggested a newly developed optimization technique named as CCPSO, that is, Cyclonic Converging Particle Swarm Optimization. CCPSO is hybrid technique of Cyclonic Convergence and Particle Swarm Optimization. CCPSO has been implemented on IEEE-33 & IEEE-69 Bus radial distribution system. Loss Sensitivity Factors, Power Loss Reduction Index, Multi-objective Function, System Constraints & DG Capacities is elaborated in context of test simulation in MATLAB Software.*

Index Terms— DG Penetration, Loss Sensitivity Factors, Power Loss Reduction Index, Multi-objective Function

I. INTRODUCTION

Optimization Technique can be defined as the process of finding the greatest value, least value or most suitable values of mathematical complex nonlinear function, which is known as objective function [1], from a set of predefined range of discrete or continues values of variable or variables; committing predefined constrains and conditions, which must be true regardless of the solution and are considered to be most suitable solution [2]. In other words, optimization finds the most suitable value for a function within a given domain. Techniques are commonly used to solve complex non linear objective function, integrating multiples multidirectional linear or nonlinear variables for best possible combination of solution for a set of objective variable within a predefined specific range of variable following multiple terms and conditions. Number of the real world problems and theoretical problems may be modeled in the general framework of an optimization process. Power system is one of the extremely complex domains in electrical engineering field, where optimization [3] plays a vital role. Few of the basic most concerning problems of power system are Optimal Power Flow (OPF), Economic Load Dispatch (ELD), Unit Commitment (UC) and optimal penetration of distribution generator in power grid [4]. In past few years, heuristic methods are widely used for solving complex problems. Stochastic optimization techniques shown in Figure-1 can perform better than classical methods of optimization, when applied to difficult real world problems.

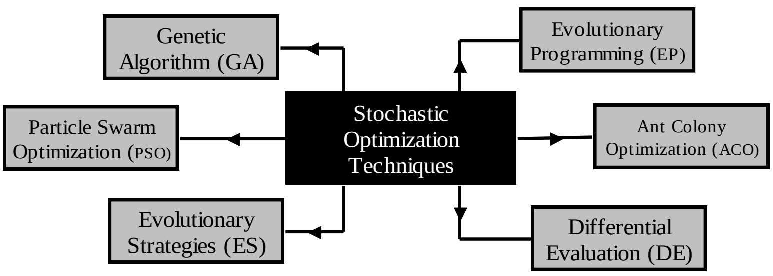


Figure-1. Commonly Use Stochastic Techniques

These methods, though efficient, but are time consuming because of more number of iterative calculations and multidirectional constraints and variables. Various evolutionary techniques like Genetic Algorithm (GA), Evolutionary Programming (EP), Evolutionary Strategies (ES), Differential Evaluation (DE) & Particle Swarm Optimization (PSO) have been applied to power system optimization problems [5]. Variable in the objective function, constraint of the system and range of variable of the objective function plays an important role on the convergence, accuracy and optimal solution of the technique.

II. OPTIMIZATION TECHNIQUE: LITERATURE REVIEW

An investigative review of related literature is carried in the field of distribution generation in context of penetration of DG effects. Forth coming text summarizes the outcomes of the investigation.

Ryuto Shigenobu and Ahmad Noorzad [6] proposed the application of combinatorial multi-objective optimization (MOO) in an electrical power distribution system. Conventional electrical power systems do not consider reverse power flow, in which the power flows towards the feeder in the distribution system. A new MOO method is developed to determine the optimal placement of control devices while retaining operation diversity. Each optimization method is compared with numerical simulation and the advantages are summarized from the simulation results.

Soon-Jeong Lee and Chul-Hwan Kim [7], studied the optimal location and size of a BESS for voltage regulation in a distribution system while increasing the lifespan of the battery. Various factors that affect the lifespan of a battery are considered and modeled. The problem is formulated as a multi-objective optimization problem with two-objective functions. The first objective function calculates the energy losses in the system, whereas the second objective function represents the total investment cost of the distributed generator and BESS installations.

Tarek Masaud et al., [8] proposed a methodology to determine the optimal size and allocate the DG in distribution system with an objective function to improve the voltage profile considering numerous technical and economic constraints. The performance of the proposed DG configuration is compared with DGs that utilize SCIG with parallel reactive power compensation. IEEE 30-bus test system is used to demonstrate the effectiveness of the proposed methodology.

Xueqing Huang et al. [9] investigated the optimization of smart grid-enabled mobile networks, in which green energy is generated in individual BSs and can be shared among the BSs. In order to minimize the on-grid power consumption of this network, we propose to jointly optimize the BS operation and the power distribution. The joint BS operation and power distribution optimization (BPO) problem is challenging due to the complex coupling of the optimization of mobile networks and that of the power grid. We propose an approximate solution that decomposes the BPO problem into two sub problems and solves the BPO by addressing these sub problems. The simulation results show that by jointly optimizing the BS operation and the power distribution, the network achieves about 18% on-grid power savings.

D. K. Dheer and Josep M. Guerrero [10] developed a complete dynamic model of an islanded micro grid. From stability analysis, the study reports that location of DGs and choice of droop coefficient has a significant effect on small signal stability, transient response of the system and network losses. The trade-off associated with the network loss and stability margin is further investigated by identifying the Pareto fronts for modified IEEE 13 bus, IEEE 33 and practical 22-bus radial distribution network with application of Reference point based Non-dominated Sorting Genetic Algorithm (R-NSGA). Results were validated by time domain simulations using MATLAB.

We can conclude that there is still a huge space to carry out further research in concerning field.

III. HYBRID OPTIMIZATION TECHNIQUE

Previously listed commonly used technique offers specific advantages & disadvantages depending of the mathematical modeling of application, contains definition and type of application. In this scenario, few of the research scholars had compiled two techniques simultaneously for the same optimization problem. The implementation of two or more technique is known as hybrid optimization [11]. Hybrid optimization assumes that one has implemented two or more algorithms for the same optimization. A hybrid optimization uses a heuristic to choose the best of these algorithms to apply in a given situation. A hybrid optimization will reduce compilation effort and uses an efficient algorithm most of the time. The hybrid systems [12] can be a hybrid among the classical methods between the classical methods and artificial intelligence based methods or among the artificial intelligence based methods. It provides the opportunity for practitioners to hand their complicated real world issues by using hybrid optimization methodologies and for researchers to realize the significant contribution to the body of the knowledge and look into future directions. Figure 2 depicts the concept of two optimization technique to get final hybrid optimization technique.

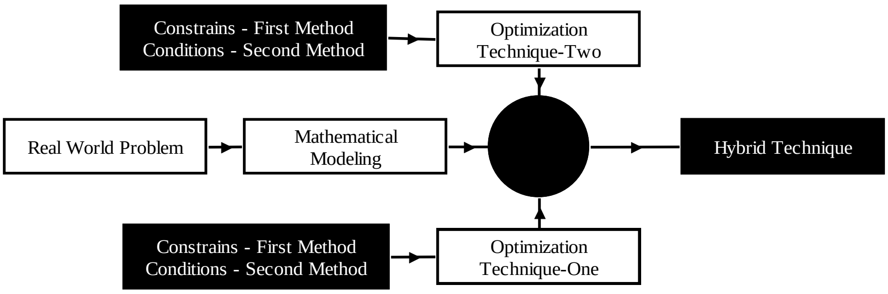


Figure-2. Concept of Hybridization of Two Optimization Technique

III.I. LITERATURE SURVEY ON HYBRIDIZATION CONCEPT

Lagoudakis et al. [13] describes an idea of using features to choose between algorithms for two different problems, order the statistics selection and sorting. The authors used reinforcement learning to choose between different algorithms for each problem. For the order statistics selection problem, the authors choose between Deterministic algorithms which were able to outperform each individual algorithm.

Cavazos et al. [14] described an idea of using supervised learning to control whether or not to apply instruction scheduling. They induced heuristics that used features of a basic block to predict whether scheduling would benefit that block or not.

Monsifrot et al. [15] adopted a classifier based on decision tree learning to determine which loops to unroll. They looked at the performance of compiling Fortran programs from the SPEC benchmark suite using G-77 for two different architectures, an UltraSPARC and an IA64, where their learned scheme showed modest improvement.

Stephenson et al. [16] used genetic programming to tune heuristic priority functions for three compiler optimizations within the Trimaran IMPACT compiler. For two optimizations they achieved significant improvements.

Bernstein et al. [17] described an idea of using three heuristics for choosing the next variable to spill, and choosing the best heuristic with respect to a cost function. This is similar to our idea of using a hybrid allocator to choose which algorithm is best based on properties of the method being optimized.

Study of different research articles of related field reveals that there is lot of space to carry our research in hybridization technique for multiple verticals in real time complex multi objective problems. Numbers of techniques can be framed as per the need of the system under study and its limitations.

IV. CYCLONIC OPTIMIZATION

Optimizing a cyclone is a multi-objective optimization problem where the multiple performance variables, can be optimized simultaneously. In cyclonic optimization, the optimization process requires the evaluation of a large number of objective functions, which can be obtained from experiments, empirical and semi-empirical models, or phenomenological models [18]. In cyclonic convergent optimization, meta-models based on neural network and applied genetic algorithms or the simplex method is used to minimize the incorporating input variables and maximize other function variables. The fitting of meta-models can be carried out using experimental data banks or empirical and semi- empirical models. Discussion concluded that cyclonic converging optimization can be applied when multiple objective function need to be addressed at the same time and these different objective functions incorporates different variables, and these variables may or may not be interdependent. Cyclonic Optimization [19] is composed of following three integrals, these are as listed below:

[1] Computational Fluid Dynamics - CFD
[2] CYCLO-EE$_5$ Code
[3] Box Complex Algorithm

IV.I. COMPUTATIONAL FLUID DYNAMICS - CFD

Computational Fluid Dynamics commonly - CFD; is technique which deals with analysis of turbulence in flows and follows conditions & constrain. CFD is a methodology for obtaining discrete solution of real world problems. Word discrete refers to solution obtained at a finite collection of space points and at discrete time levels. For a reasonably accurate solution, the number of space points that need to be involved is of the order of few millions. Solution is achievable only through modern high speed computers. The result prediction can be achieved in short time. CFD is an efficient, faster, economical method to obtain the results. CFD is a tool for compressing the design and development cycle allowing for rapid prototyping.

IV.II. CYCLO-EE$_5$ CODE

CYCLO-EE$_5$ Code is coded simulator of gas-solid flows in cyclones. CYCLO-EE$_5$ Code is capable of addressing nonlinear objective functions and inequality constraints of any turbulent cyclonic system under consideration. Eulerian-Eulerian six-phase model has been used in cyclones CYCLO-EE$_5$, which composes the dedicated code for the vertical flow into cyclones. CYCLO-EE$_5$ code also incorporates turbulence closure, numerical methods, the initial and the boundary conditions of the system. CYCLO-EE$_5$ Code Offers reliable results, lower cost & higher speed of optimization.

IV.III. BOX COMPLEX ALGORITHM

Box Complex Algorithm [20] is a multi-start optimization method, which gives progressive convergence with significantly small population size compared to other population based evolutionary techniques. But this method has a limitation of getting trapped in local minima. To overcome the large computational efforts with larger population for obtaining global minimum, we propose to combine global search property of PSO; assisted by convergence property of Box-Complex method. One or more new members are created using the current data by using Box-Complex concept on every iteration. New members can be added at every generation by replacing equal number of the inferior members of the population, thereby maintaining the constant population size. Box-Complex algorithm have very high rate of convergence capabilities. A Complex is created by selecting k members from data member, where k = n + 1. The objective function values are evaluated for each vertex of the complex. The vertex, R having the most inferior value of objective function is projected through the centroid of the remaining points that is A and B of complex. The new point is obtained by projecting the worst vertex R through centroid at a distance say alpha times the distance of the centroid from the rejected vertex, after that new member is calculated. Figur-3 shows the concept of Box Complex Algorithm.

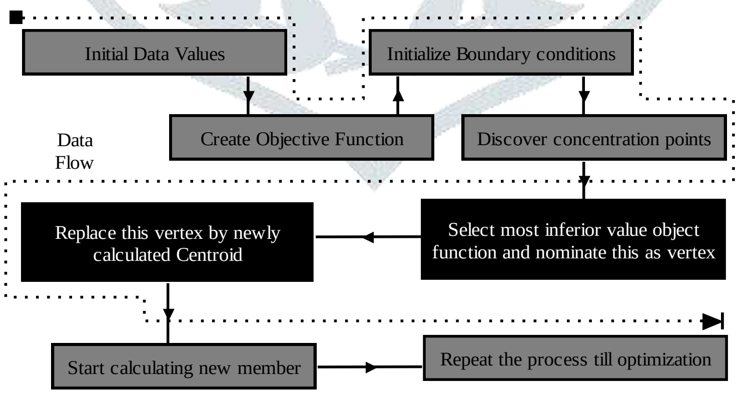


Figure-3. Box Complex Algorithm

V. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization is widely used to find global optimum solution in a complex search space. Particle Swarm Optimization is a novel population-based stochastic search algorithm and an alternative solution to the complex non-linear optimization problem. PSO algorithm basically learned from birds activity or behavior to solve optimization problems [21]. In PSO, each member of the population is narrated as particle and the population is as swarm. Starting with a randomly initialized population and moving in randomly chosen directions, each particle goes through searching space and remembers the best previous positions of itself and its neighbors. Particles of swarm communicate good positions to each other as well as dynamically adjust their own position & velocity derived from best position of all particles. Boundary conditions, convergence speed, discrete valued problems, multi objective real world problems are few challenges we need to address while taking PSO in to account for optimization of real world problem. Narrations used in PSO are indicated in Figure 4.

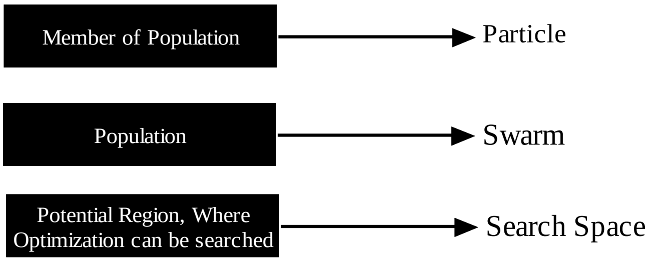


Figure-4. Narration Used in PSO

The PSO can be classified in two classes that is Global Best PSO or gbest PSO and Local Best PSO or lbest PSO.

V.I. GBEST PSO

The global best PSO or commonly refer as gbest PSO is a method where the position of each particle is influenced by the best-fit particle in the entire swarm. It uses a star social network topology where the social information obtained from all particles is in the entire swarm.

V.II. LBEST PSO

The local best PSO or lbest PSO method only allows each particle to be influenced by the best-fit particle chosen from its neighborhood, and it reflects a ring social topology. Here this social information exchanged within the neighborhood of the particle, denoting local knowledge of the environment.

V.III. PSO ALGORITHM PARAMETERS

Numbers of parameters are integrated in PSO. Few of them have great influence on final optimized result and few have less influence on result but affects the performance of overall system. These parameters are (1) Swarm Size (2) Iteration Numbers (3) Velocity Components (4) Acceleration coefficients.

V.IV. DISADVANTAGES OF PSO

PSO algorithm suffers from the partial optimism, which degrades the regulation of its speed and direction. PSO can be improved by using velocity clamping, inertia weight or constriction coefficient technique for better and more accurate results.

Existing research yet suffers from several vulnerabilities and limitations. Much can still be done with new optimization algorithms to improve already existing techniqus.

VI. CYCLONIC CONVERGING PARTICLE SWARM OPTIMIZATION TECHNIQUE - CCPSO

We have come up with a new hybrid optimization technique, which is fusion of cyclonic convergence optimization and particle swarm optimization & named as Cyclonic Converging Particle Swarm Optimization Technique as indicated in Figure 5. CCPSO is fusion of Cyclonic convergence and PSO Technique.

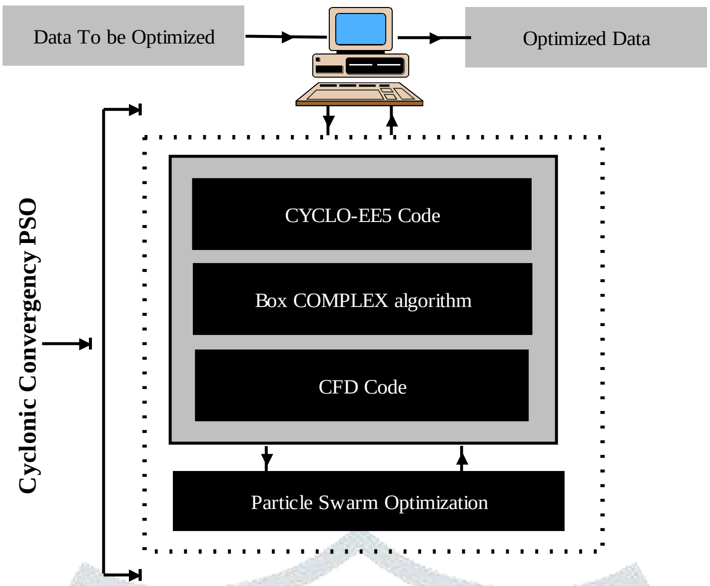


Figure-5. Cyclonic Converging Particle Swarm Optimization Technique

Cyclonic optimization and Particle Swarm Optimization both offer numbers of advantages, but inherit disadvantages and suffer many vulnerabilities. These disadvantages and vulnerabilities adversely affect the performance of the optimization technique and the results obtained from individual optimization are not up to the expectation. These weakness of both the techniques had inspire us, to come up with a new optimization technique which must have capability to compensate disadvantages and vulnerabilities of above discussed techniques and couple the advantages of both the techniques. The suggested technique will have following data processing strategy as show in Figure-6.

Consider the objective of our research, that the location and size of DG in power grid, this is mandatory to address multiple objectives, which are integrating multiple variables, and some of them are interdependent and few are independent. The majority of the proposed algorithms emphasize real power losses only in their formulations. They ignore the reactive power losses which are the key to the operation of the power systems. Hence, there is an urgent need for an approach that will incorporate reactive power and voltage profile in the optimization process, such that the effect of high power losses and poor voltage profile can be mitigated. The newly suggested algorithm reduces the search space for the search process, increases its rate of convergence and also eliminates the possibility of being trapped in local minima. Figure-6 depicts the strategy for CCPSO.

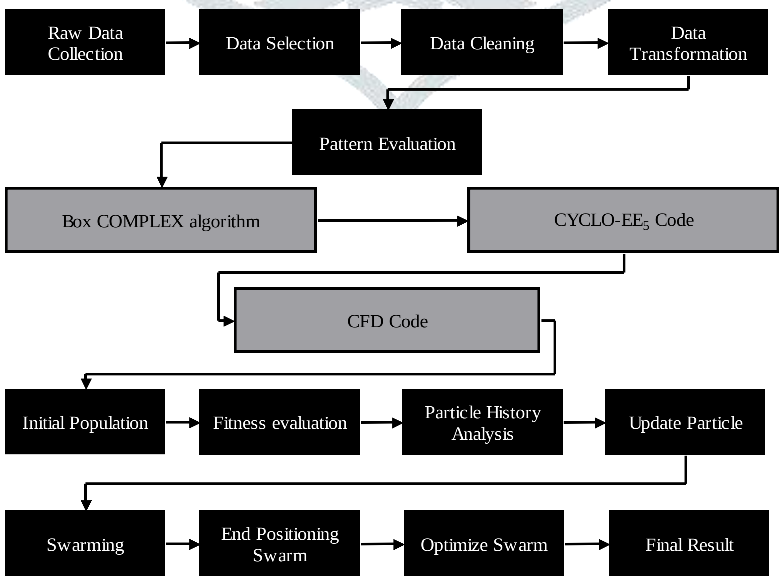


Figure-6. Cyclonic Convergent Particle Swarm Optimization Steps: CCPSO

The raw data from real words problem is first collected from data collection department. Selection is done from the raw data to pick target search space. Selected data is then clean to obtain operational data. The selected operational data then transformed so as to fit data in the optimization algorithm at first stage. Pattern of the data is observed to create mathematical equation to run optimization algorithm. In our proposed optimization technique Box COMPLEX algorithm is used which is already discussed in previous section of the paper. Box COMPLEX algorithm incorporates CYCLO-EE_5 Code, which is optimization code response of CFD optimization hypothesis. The objective behind first stage of optimization to reduce search space for PSO, so that search time can be reduced and committed result can be searched.

In the second phase Particle Swarm Optimization Technique is implemented. First initial population is finalized; which is search space for optimization technique. After this step, fitness function is modeled in the search space. The fitness function formulated is used in PSO to find optimal solution. Particle history is analyzed and followed to practical position in the space. At every step, the position of particle is updated. Boundary conditions of objective functions are redefined and are strictly followed during particle positioning. Particle positions are simultaneously subjected to constrain also during updating process. Swarming is done at every stage so as to reach optimization point in search space. All constraints and conditions are followed on every iteration to avoid struck condition of optimization process. As we reach near optimization value, stopping conditions are need to check to ensure reach of optimization value. The algorithm is terminated when a maximum number of iterations or function evaluations (FEs) have been reached. Or else, the algorithm is terminated when there is no significant improvement over a number of iterations. Or the algorithm is terminated when the normalized swarm radius is approximately zero.

VI.I. CCPSO Advantages

CCPSO algorithm suggested in this paper offers number of advantages in comparison with the commonly used old optimization technique. CCPSO algorithm eliminates partial optimism, which degrades the regulation of its speed and direction. In CCPSO, non coordinate system problem had been removed; such conditions are generally encountered in energy field without optimization. CCPSO is multi objective optimization where the multiple performance variables, can be optimized simultaneously. CCPSO minimizes the incorporating input variables and maximizes other function variables. Suggested CCPSO algorithm is free of derivative constraints. It is easy to implement, so it can be applied both in scientific research and engineering problems. Number of parameters has been significantly decreased by the application of Cyclonic convergence optimization. The impact of parameters to the solutions is small in CCPSO as compared to other optimization techniques. In CCPSO, the convergence has been ensured and the optimum value of the problem calculates easily within a short time. CCPSO is independent of initial population, as population is already optimized using cyclonic convergent optimization at initial stage.

VI.II. CCPSO Limitations

The algorithm is complex as dual optimization needs to be implemented, which prolonged overall time consumption and creates complexity. Pacific mathematical modeling is required to ensure coupling and systematic data transmission between algorithms. Further investigation is needed on performance analysis of CCPSO for exact response of CCPSO.

VII. TEST SIMULATION

The objective of the research article is to determine optimal size and location of DG penetration so as to fully exploit the system resources following strictly the boundary condition and system constrains. The mentioned objective is needed to be achieved by the implementation of CCPSO. The problem definition clearly illustrates the presence of more the one objective, that this is a multi objective problem. Also, the participating constraints are multidimensional and multi disciplinary. In test simulation first we modeled the power system application in mathematical expression. Constraints are specified and values are finalized. Boundary condition are determined for search domains. An objective function is fabricated with the mathematical model on which the CCPSO is implemented. CCPSO is run with defined objective and optimal size along with location is determined.

VII.I. System Specification

We have taken two IEEE Bus Systems as test system; these are IEEE-33 Bus SRDS & IEEE-69 Bus SRDS [22]. The specification of IEEE-33 and 69 bus is given in Table 1 and 2 respectively. Cyclonic Converging PSO has been implemented on both of these IEEE standard systems. In the article, optimization system variables such as Loss Sensitivity Factor, Power Loss Reduction Index, Multi-Objective Function, Equality Constraints and Inequality Constraints are also elaborated up to significant level.

Table-1. Specification IEEE 33-Bus Standard Radial Distribution Systems

No	Title	Value
1	Number of Buses	33
2	Number of Branches	32
3	Total Load Capacity	3715 kW & 2300 kVAR
4	System Power factor	0.8502
5	Real Power Loss	211 kW
6	Reactive Power Losses	143.11kVAR
7	Minimum Voltage Limit	0.9048 p.u.
8	Maximum Voltage Limit	0.9982 p.u.
9	Apparent Load	4369.35 kVA(S)

Table-2. Specification IEEE 69-Bus Standard Radial Distribution Systems

No	Title	Value
1	Number of Buses	69
2	Number of Branches	68
3	Total Load Capacity	3802 kW & 2694 kVAR
4	System Power Factor	0.8159
5	Real Power Loss	225 kW
6	**Reactive Power Losses**	**102.12 1kVAR**
7	Minimum Voltage Limit	0.9048 p.u.
8	Maximum Voltage Limit	0.9982 p.u.
9	Apparent Load	4659.67 kVA(S)

VII.II OBJECTIVE FUNCTION

Considering N bus radial distribution system [24], minimization of loss in distribution system problem may be formulated as indicated below which is objective function for system:

$$Minimize\ (f_{loss}) = P_{loss} = \sum_{i=1}^{N} \frac{P_i^2 + Q_i^2}{|V_i|^2} \times (R) \cdots\cdots\cdots\cdots\cdots\cdots \textbf{Equation 1}$$

In the above equation the variables used are described as below:

N = Total number of buses, P_{LOSS} = Real Power Loss in System, P_i = Active Power Flow through ***i^th*** Branch, Q_i = Reactive Power Flow through ***i^th*** Branch, R_i = Resistance of ***i^th*** Branch, $|V_i|$ = Voltage Magnitude at the ***i^th*** Branch

The above described equation is subjected to following constrains:

Constrain 1: Voltage limit constraint at each bus must be satisfied following condition:
$V_{min} \leq V_i \leq V_{max}$ where ***i = 1, 2, 3, 4 . . . . upto n***

Constrain 2: Line current constraint must be satisfied $I_i \leq I_i^{rated}$ Where I_i^{rated} is current limit for branch within safe temperature.

Constrain 3: Power balance constraint is satisfied $\sum_{i=1}^{N_{SC}} P_{DGi} = \sum_{i=1}^{N_{SC}} P_{Di} + P_{LOSS}$ and $\sum_{i=1}^{N_{SC}} Q_{DGi} = \sum_{i=1}^{N_{SC}} Q_{Di} + Q_{LOSS}$, N_{SC} = Total Number of Sections, P_{DGi} = Active Power Generation at bus ***I,*** Q_{DGi} = Reactive Power Generation at bus ***i*** , P_{Di} = Active Power Demand at bus ***I,*** Q_{Di} = Reactive Power Demand at bus ***i***

Constrain 4: Radial structure of the network constraint is satisfied

$B = N_{BUS} - N_s$, B = Number of Branches, N_{BUS} = Number of Nodes, N_s = Number of Sources, $B = N_{BUS} - N_S$

VII.III SIMULATION RESULTS

The algorithm for solving the problem of optimal size and location is analyzed on 33 bus and 69 bus radial distribution system. The optimization has been carried out in MATLAB version 2012a on an Intel core i-5 processor with 2.20-GHz speed and 4 GB RAM. To evaluate the effectiveness of the proposed method the performances of the systems are compared with conventional and intelligent techniques. The voltage profile obtained when DG is inserted in both systems is also compared with [16, 22].

The base case was run using by backward forward sweep method to obtain bus voltage magnitude, real & reactive power loss respectively. After the load flow analysis, optimum size of DG for each bus was identified and the approximate loss for each bus was found using power loss equation by placing DG at the corresponding location with the optimum sizing obtained [25] from above analysis. The optimum location at which the loss is minimum after DG placement is obtained.

Implementation of CCPSO:

The fitness function for proposed method is the power loss as in eq. (1). For solving the problem of optimal location and size of DG, CCPSO approach is used as shown in Figure 6. Parameters used for CCPSO is given in Table 3.

Table-3. Parameter for CCPSO

No	Parameter	Value
1	Population Size	**100**
2	Maximum Iteration	**80**
3	Cognitive and social coefficients $\mathbf{c_1}$	**2**
4	Cognitive and social coefficients $\mathbf{c_2}$	**2**
5	Random Numbers $\mathbf{r_1}$	**0-1**
6	Random Numbers $\mathbf{r_2}$	**0-1**
7	Updating Weights $\mathbf{w_1}$	**0.9**
8	Updating Weights $\mathbf{w_2}$	**0.4**

The following steps are performed to obtain the solution:

Step-1: The load flow analysis is performed by using backward- forward sweep method.

Step-2: The objective function is evaluated on both the IEEE bus test system without the placement of DG.

Step-3: The particles are randomly generated with the population size S, the position and velocities of these particles is also randomly generated and are ranged within the limits of size and location of the DG respectively. If there are M DG units, the i^{th} particle is given as

$$P_i = P_{i1}, P_{i2}, P_{i3}, P_{i4}, P_{i5} \cdots\cdots\cdots P_{iM} \cdots\cdots\cdots\cdots\cdots\cdots \textbf{Equation 2}$$

Step-4: The particle's performance is evaluated by using the fitness function individually. The fitness function is formulated in such a manner that the power loss is minimized in the distribution system within permissible limits.

Step-5: The particles at initial stage are assigned as values corresponding to the computation of fitness function obtained in step 4. The global best that is ***gbest*** is taken from the value among all ***pbest***.

Step-6: Generate cyclonic velocity vectors.

Step-7: The velocity of particle is restricted between - and + in order to avoid excessive roaming of particles. Here was set between 5% and 10%. Maximum velocity limit for particle is given by

$$V_j^{max} = \frac{(P_{jmax} - P_{imax})}{R} \cdots\cdots\cdots\cdots\cdots\cdots \textbf{Equation 3}$$

Step-8: The particle position vector is modified using equation-4 as shown below

$$X_{in}^{(k+1)} = X_{in}^{(k)} + V_{in}^{(k+1)} \cdots\cdots\cdots\cdots\cdots\cdots \textbf{Equation 4}$$

The values of fitness function are evaluated for updated positions of the particles. If the new value is better than previous $pbest$, new value is updated to $pbest$. Similarly, value of $gbest$ is also modified.

33- Bus Radial Distribution System

The 33 bus system shows minimum power loss of 109.12kW when Type-I DG of capacity 3.15MW is inserted at 6th bus in distribution system. Reduction in loss is 48.28%. Similarly, when Type-III DG of capacity 3.1MVA, 0.85leading power factor is placed at 6th bus, real power loss is reduced from 211kW to 66.31kW. Figure 7 indicates the voltage profile of 33 test system when Type-III DG is inserted in the system. It is found that the voltage profile is improved with the insertion of DG.

For Type-I and Type -III DG placement the optimal bus for 33 bus system is 6$^{th\ bus}$. This bus has lagging power factor load. Optimal location for one unit of DG is given in Table 4 and test simulation results in IEEE 33 bus RDS is indicated in Table 5.

Table-4. Summary of Optimal Location for one unit of DG

Test System	Optimal Location	Optimal Size (MW)	Power Loss (kW) Without DC	With DG	% Loss Reduction
33 Bus	Bus – 6	2.49	211.20	99.96	52.6%
	Bus - 7	2.12	211.20	109.95	47.9%

Table-5. Test Simulation Results in IEEE-33 bus Radial Distribution System

Citation	Base Case	Type –I (pf unity)	Type –III (pf 0.85 lead)	Type –III (pf 0.85 lag)
ΣPloss (kW)	211	109.12	66.31	114
% Ploss Reduction	-	48.28	68.57	45.97
ΣQloss (kVAr)	143.11	75.50	48.79	87.29
% Qloss reduction	-	47.50	65.90	39.00
Size and Location of DG	-	3156 kVA at bus 6	3.158 kVA at bus 6	3.243 kVA at bus 6
Best power loss	-	109.12	66.31	114
Average Power loss	-	109.76	66.42	114
Worst power loss	-	110.41	67.23	114
Standard deviation	-	0.000003	0.00001	0.00001
Vmin.	0.9048	0.951	0.9326	0.9364
Vmax.	0.9982	1.004	1.0004	1.0003

Analysis shows that with placement of DG at 6th bus, maximum reduction in active power loss is 68.57% when Type-III DG at 0.85 (leading) power factor is operated in comparison to Type- I DG at u.p.f and Type-III at 0.85 (lagging) power factor for 33-bus system. Also result indicates that losses are increased when DGs of higher capacity are placed near the slack bus and if small size DGs are located at the consumer end, losses are reduced.

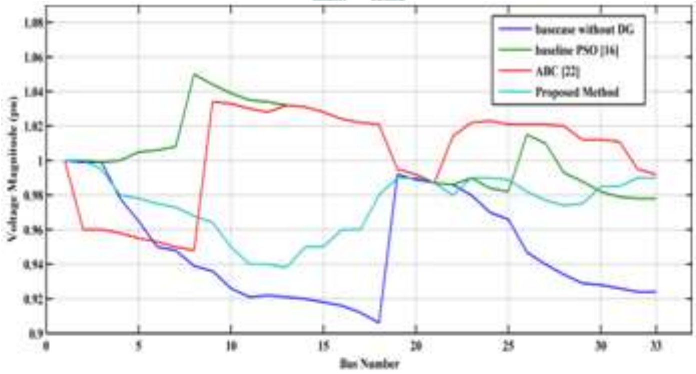


Figure-7. Voltage profile of 33 bus system using Type-III DG

The minimum voltage of magnitude 0.93 p.u is obtained at 14th bus and maximum voltage 1.0 p.u at slack bus. Figure 8 shows the capacities of Type-I and Type-III DGs at each bus for loss minimization and Figure 9 is a plot between the real power loss and bus number when different types of DG are placed. It is observed that percentage of loss reduction is more when Type III is inserted as compared to Type I DG even location is same for both types of DG.

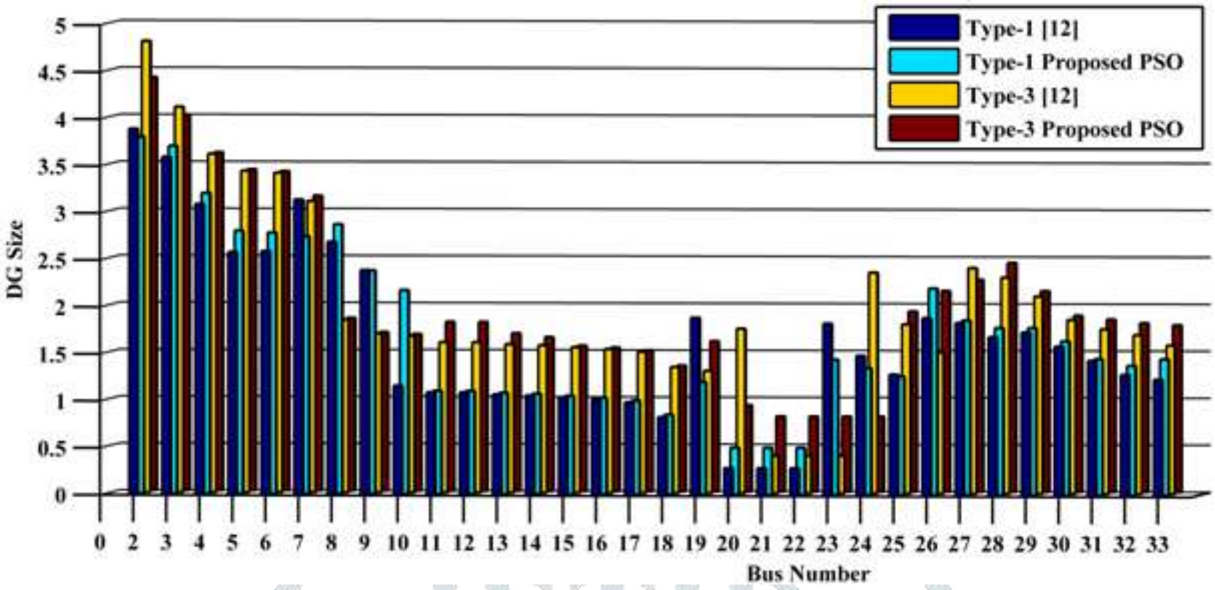
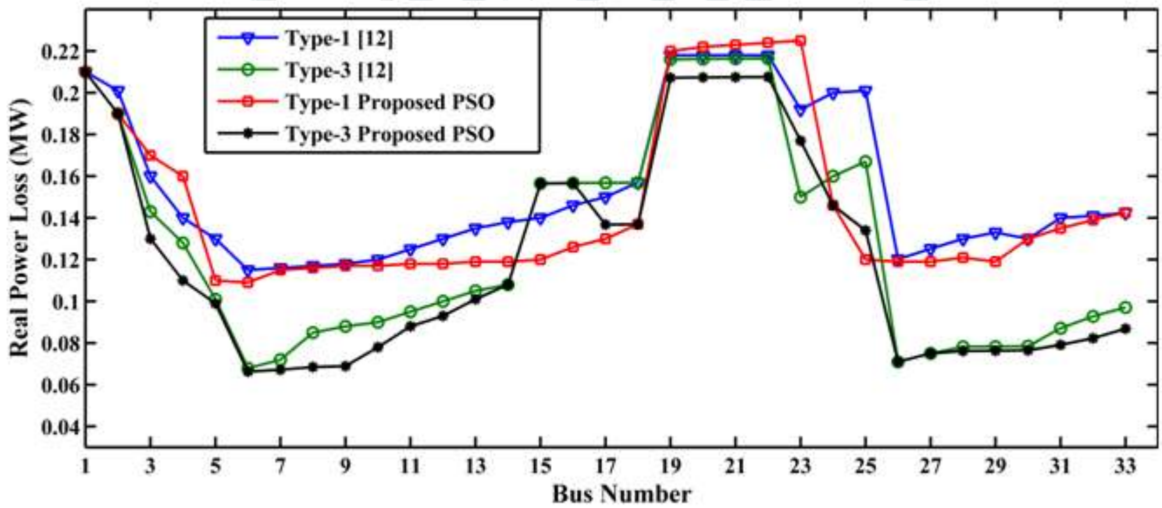


Figure-8. Different types of DG sizes at different locations for 33 bus radial distribution system



Figur-.9. Total real power loss of 33bus radial distribution system using different types of DG

69 Bus radial distribution system

The voltage profile, total real and reactive power losses obtained by Backward forward sweep method is given in Table 2. Minimum voltage is 0.9048p.u and total active and reactive power losses are 225kW and 102.12 kVAR respectively. It's observed that voltage magnitude varies within the permissible limits as indicated in Figure 10. It is 1.0 p.u. at the slack bus and 0.97p.u. at 61bus when the different types of DG is placed.

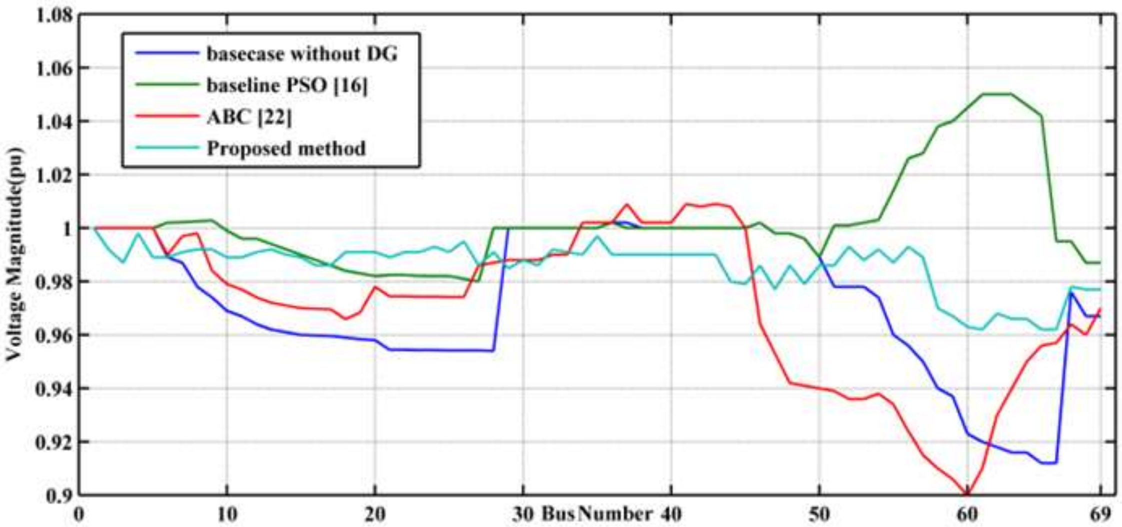


Figure-10. Voltage profile of 69 bus system using Type-III DG

Table-6. Distribution systems with DG for 69 Bus radial distribution system

Citation	Base Case	Type 1 (PF unity)	Type 3 (PF0.82lead)	Type 3 (PF0.82 lag)
ΣPloss (kW)	225	81.31	22.34	110
% Ploss Reduction	-	63.86	90.07	51.11
ΣQloss (kVAr)	102.12	75.50	20.79	85.82
% Qloss reduction	-	26.06	79.64	15.96
Size and Location of DG	-	1816 kVA at bus 61	2244 kVA at bus 61	2247 kVA at bus 61
Best power loss	-	81.31	22.34	110
Average Power loss	-	81.31	22.34	110
Worst power loss	-	81.31	22.34	110
Standard deviation	-	0.000003	0.00001	0.00001
Vmin.	0.9048	0.971	0.9722	0.9742
Vmax.	0.9982	1.002	1.0003	1.0004

The variation of DG capacity on different buses is indicated in Figure 11. It is observed that optimal capacity of Type-I DG is 1.81MW and Type-III is 2.244MVA, 0.82 power factor leading.

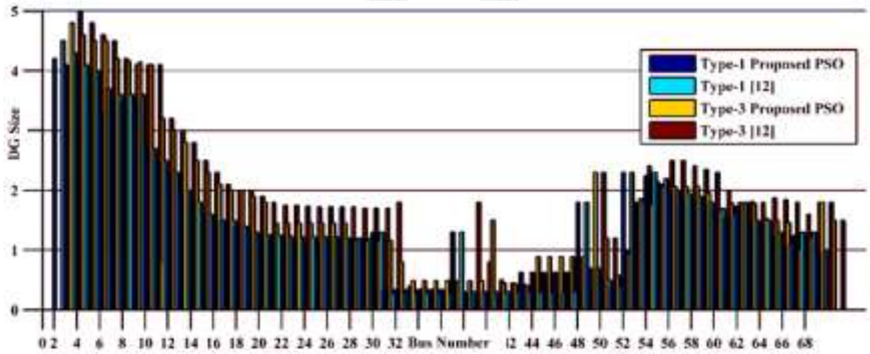


Figure-11. Different types of DG sizes at different locations for 69 bus radial distribution system

The 69 bus system has minimum power loss, when Type I and Type III DGs are placed at 61st bus as shown in Figure 12. It is observed that loss reduction is higher when Type III DG is used in comparison to Type-I DG. Table 6 is indicating the reduction in power loss with the placement of DG in 69 Bus system. The analysis is performed at lagging and leading power factor of Type-III DG. of system. So DG is operated at 0.82 power factor in 33 bus and 69-bus test systems.

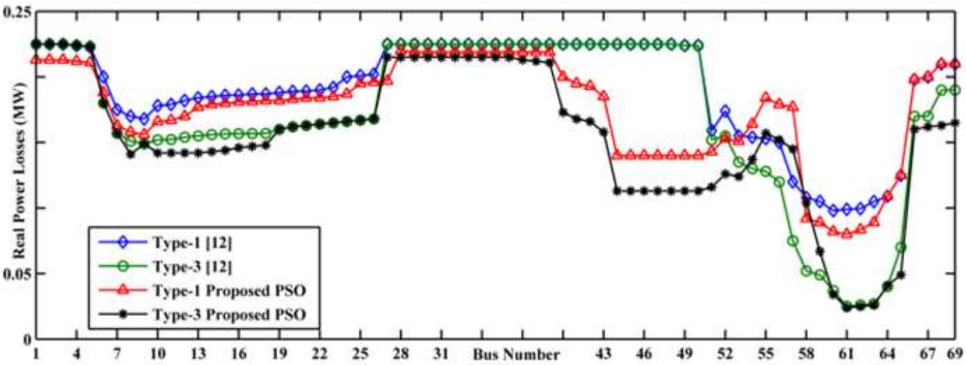


Figure-12. Total real power loss of 69 bus radial distribution system using different types of DG.

Comparison between different approaches

The proposed method is applied to two different test systems and performance evaluation of the proposed method is compared with various approaches like analytical approach , Exhaustive Load flow (ELF) [4], Improved Analytical (IA) [4], Mixed Integer Non-linear Programming (MINLP) [5], Combined Power Loss Sensitivity (CPLS) [6] , Non linear programming (NLP) and Power loss sensitivity (PLS) [8], Analytical method [12], Particle Swarm Optimization (PSO) [12] and Grid Search Algorithm (GSA)

Effect of variation of power factor of Type-III DG

Its analyzed that real power loss of radial distribution varies with the variation of power factor of DG over a wide range when its capacity (MVA rating) is kept constant. This analysis is done when Type III DG is kept at bus number 6 & 61 of 33 & 69 bus system respectively. Its found that minimum losses occurs when DG is operated at power factor is nearly the same as system power factor [26] for DG placement. All the methods are compared in terms of DG size, optimal location of DG, reduction in power loss and voltage profile in both 33 and 69 Bus system which is given below:

33 Bus system with Type-I and Type-III DG

The proposed method is compared with the existing methods as indicated in Table 7. Its observed that the optimal location is same in all the methods except CPLS and PSO methods.

Table-7. Comparison of proposed method with existing methods for Type-I DG in 33bus radial system

Technique	DG Installation		Power Loss		Bus Voltage	
	Capacity (kW)	Bus No.	Value (kW)	Reduction (%)	Min. (p.u.)	Mean (p.u.)
Without DG	-	-	211	-	0.9048	0.9453
ELF[4]	2600	6	111.10	47.39	0.9048	0.9454
IA[4]	2600	6	111.10	47.39	0.9547	0.9715
MINLP[5]	2590	6	111.10	47.38	0.9418	0.9679
CPLS[6]	1800	8	118.12	44.01	0.9449	0.9645
NLP & PLS [8]	2565.56	6	111.00	47.39	0.9048	0.9456
Analytical [12]	3138	6	116.01	45.01	0.9146	0.9426
Base Line PSO [12]	3150	6	115.29	45.36	0.9345	0.9524
Grid [26]	2600.50	6	111.03	47.37	0.9148	0.9354
Proposed CCPSO	3150	6	109.12	48.28	0.9447	0.9715

Table-8. Comparison of proposed method with existing methods for DG Type-III in 33-bus radial system

Technique	DG Installation		Power Loss		Bus Voltage	
	Capacity (kW)	Bus No.	Value (kW)	Reduction (%)	Min. (p.u.)	Mean (p.u.)
Without DG	-	-	210.98	-	0.9038	0.9453
IA[4]	2547.74	6	67.90	67.85	0.9347	0.9715
MINLP[5]	2558	6	67.854	67.84	0.9318	0.9679
CPLS[6]	1890	8	84.472	59.962	0.9349	0.9634
NLP & PLS[8]	2533.266	6	67.8	67.86	0.9038	0.9446
Analytical method [12]	3050	6	68.76	67.41	0.9327	0.9731
PSO [12]	3020	6	67.95	67.79	0.9145	0.9623

Proposed CCPSO	2547.74	6	67.90	67.85	0.9347	0.9715

Table-9. Comparison of proposed method with existing methods for Type-I DG in 69 bus radial system

Technique	DG Installation		Power Loss		Bus Voltage	
	Size (kW)	Bus No.	Value (kW)	Reduction (%)	Min. (p.u.)	Mean (p.u.)
Without DG	-	-	225	-	0.9038	0.9453
ELF[4]	1900	61	81.33	63.85	0.9028	0.9452
IA[4]	1900	61	81.33	63.85	0.9247	0.9715
MINLP[5]	1870	61	83.48	62.89	0.9218	0.9679
CPLS[6]	1850	61	83.15	63.04	0.9249	0.9625
NLP & PLS [8]	1887.767	61	83.15	63.04	0.9028	0.9452
Analytical method [12]	1802	61	83.5	62.88	0.9118	0.9568
PSO [12]	1807.8	61	83.37	62.94	0.9347	0.9613
HPSO [16]	3684.7	61	87.13	61.27	0.9183	0.9504
GSA [26]	1863.03	61	83.22	63.01	0.9418	0.9693
RPSO [27]	1873	61	83.22	63.01	0.9028	0.9452
Proposed CCPSO	1810	61	81.3	63.86	0.9247	0.9715

Table-10. Comparison of proposed method with existing methods for DG Type-III in 69-bus radial system

Technique	DG Installation		Power Loss		Bus Voltage	
	Capacity (kW)	Bus No.	Value (kW)	Decline (%)	Min. (p.u.)	Mean (p.u.)
Without DG	-	-	225	-	0.9038	0.9453
IA[4]	1839	61	22.62	89.94	0.9347	0.9715
MINLP[5]	1828	61	23.31	90.08	0.9312	0.9679
CPLS[6]	1980	61	27.91	87.59	0.9349	0.9635
NLP & PLS [8]	1843.992	61	23.12	89.72	0.9032	0.9453
Analytical method [12]	2238	61	24.02	89.32	0.9322	0.9568
PSO[12]	2243	61	23.18	89.69	0.9224	0.9604
Proposed CCPSO	2244	61	22.34	90.07	0.9347	0.9715

Reduction in power loss is maximum with the proposed approach and minimum with CPLS method. When Type-III DG is placed in 33 bus radial distribution system, following results are tabulated in Table 8. It indicates the comparison between the proposed approach and existing methods. Percentage loss reduction is almost the same location in all the approaches except CPLS approach. Even the optimal location obtained by CPLS is different in comparison to other methods and size is reduced.

69 Bus system with Type-I and Type-III DG: The results of proposed method and existing methods are tabulated in Table 9. Its observed that optimal location of DG unit is same for all methods i.e the 61st bus. The size of DG is least by PSO approach. Percentage loss reduction is slightly high by PSO method. ELF, IA and proposed method gives almost the same percentage loss reduction. However, IA consumes more computational time when compare to proposed method.

A comparison of the existing methods and the proposed method is indicated in Table 10. Results indicate that in CPLS and MNM, percentage loss reduction is almost same but less than other methods. Proposed method gives slightly high percentage loss reduction and also consumes less computational time.

VIII. CONCLUSION

Active and Reactive Power loss is reduced in all the test simulation like IEEE-33 Bus System and in IEEE-69 Bus System. Voltage profile and Proficiency had been improved in CCPSO technique. System performance is improved in multiple contexts. The results comparison under two different load condition shows that CCPSO performs better than other technique. It is also confirmed that DG has the capability to reduce losses and improve the voltage. CCPSO convergence is faster than ordinary PSO or then other optimization technique. CCPSO is not trapped at local minimal unlike PSO. This has been observed that better voltage profile is obtained and the power loss reduces considerably.

IX. FUTURE SCOPE

Multi-Objective function optimization is more complicated then the single objective function in CCPSO, and constrains and boundary conditions are very vast and irregular. A systematic future is needed to defuse this issue to make technique more applicable with little effort. Effort is needed to speed up the convergence speed as space is there in convergence time. Future research can be done to make AI optimization technique to accommodate renewable energy sources. Further research can be done to resolve and to get optimal interfacing methodology with real time application.

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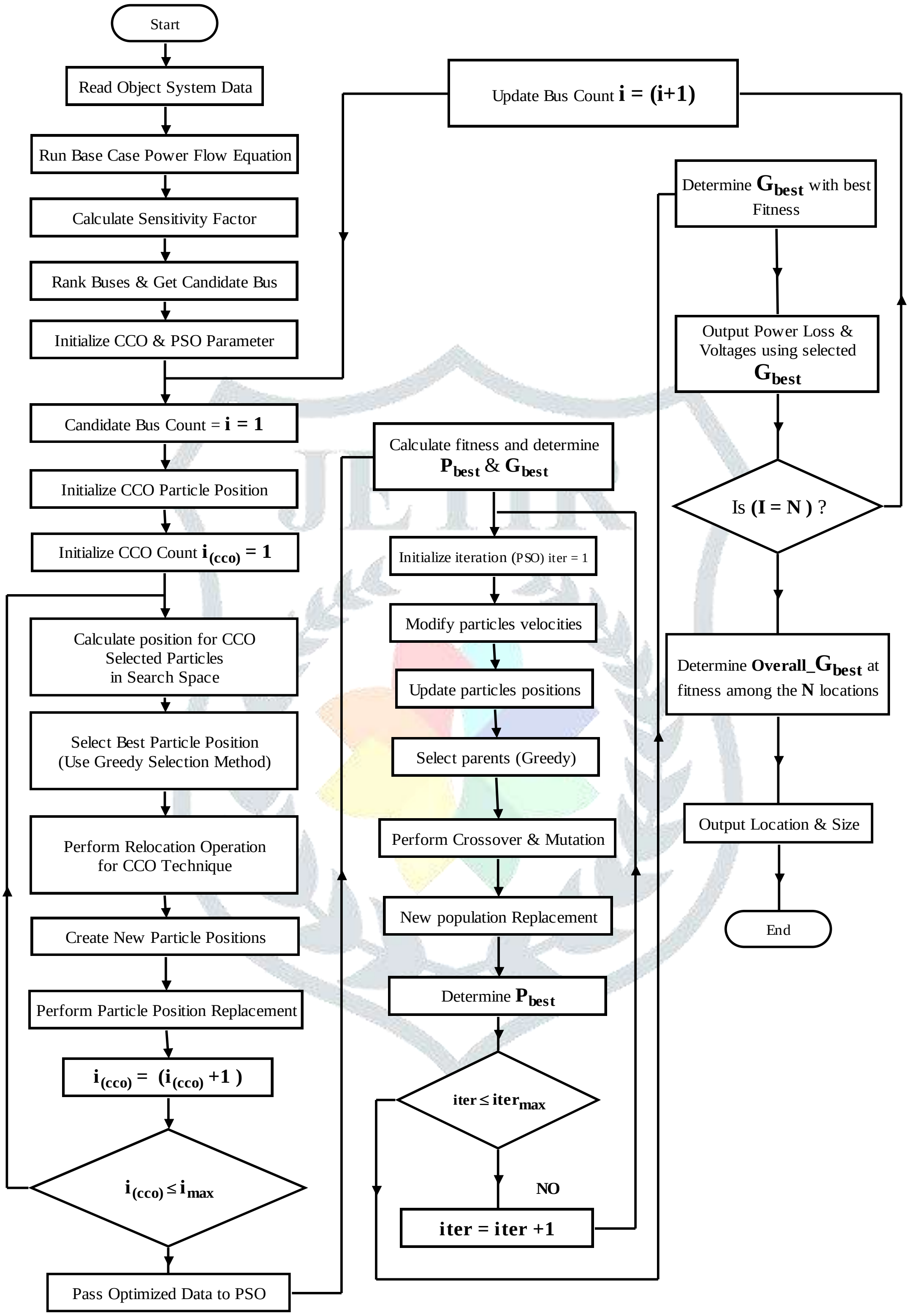
Appendix-A

CCPSO Detailed Flow Chart



Appendix-B

Table - Load data for 33-bus distribution system

Bus No	P_L(kW)	Q_L(kVAR)	Bus No	P_L(kW)	Q_L(kVAR)
2	100	60	18	90	40
3	90	40	19	90	40
4	120	80	20	90	40
5	60	30	21	90	40
6	60	20	22	90	40
7	200	100	23	90	40
8	200	100	24	420	200
9	60	20	25	420	200
10	60	20	26	60	25
11	45	30	27	60	25
12	60	35	28	60	20
13	60	35	29	120	70
14	120	80	30	200	100
15	60	10	31	150	70
16	60	20	32	210	100
17	60	20	33	60	40

Table- Effects of weight factor on System Performance

	$w1$	$w2$	$w3$	Best Fitness
	0.5	0.1	0.4	0.9094
	0.5	0.2	0.3	0.9102
	0.5	0.3	0.2	0.9099
	0.5	0.4	0.1	0.9103
	0.6	0.1	0.3	0.9107
Selected Set →	0.9	0.4	0.2	0.9091
	0.6	0.3	0.1	0.9096
	0.7	0.1	0.2	0.9101
	0.7	0.2	0.1	0.9102
	0.8	0.1	0.1	0.9092

Appendix-C

Table - Branch data for 33-bus distribution system

Branch Number	Sending end bus	Receiving end bus	R (Ω)	X (Ω)
1	1	2	0.0922	0.0470
2	2	3	0.4930	0.2512
3	3	4	0.3661	0.1864
4	4	5	0.3811	0.1941
5	5	6	0.8190	0.7070
6	6	7	0.1872	0.6188
7	7	8	0.7115	0.2351
8	8	9	1.0299	0.7400
9	9	10	1.0440	0.7400
10	10	11	0.1967	0.0651
11	11	12	0.3744	0.1298
12	12	13	1.4680	1.1549
13	13	14	0.5416	0.7129

14	14	15	0.5909	0.5260
15	15	16	0.7462	0.5449
16	16	17	1.2889	1,7210
17	17	18	0.7320	0.5739
18	2	19	0.1640	0.1565
19	19	20	1.5042	1.3555
20	20	21	0.4095	0.4784
21	21	22	0.7089	0.9373
22	3	23	0.4512	0.3084
23	23	24	0.8980	0.7091
24	24	25	0.8959	0.7071
25	6	26	0.2031	0.1034
26	26	27	0.2842	0.1447
27	27	28	1.0589	0.9338
28	28	29	0.8043	0.7006
29	29	30	0.5074	0.2585
30	30	31	0.9745	0.9629
31	31	32	0.3105	0.3619
32	32	33	0.3411	0.5302
34	8	21	2.0000	2.0000
35	9	15	2.0000	2.0000
36	12	22	2.0000	2.0000
37	18	33	0.5000	0.5000
33	25	29	0.5000	0.5000