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A Hybrid PGSA-SaHDE algorithm for Network Reconfiguration of Unbalanced Distribution System

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ABSTRACT

Network reconfiguration is the process of changing the topology of distribution system by altering the open/closed status of switches to find a radial operating structure that minimizes the system real power loss while satisfying operating constraints. This paper proposes an efficient algorithm based on Plant Growth Simulation Algorithm (PGSA) and Self Adaptive Hybrid Differential Evolution (SaHDE). The optimization approach based on PGSA provides detailed description on switch states for calculation. The inclusion of SaHDE improves the efficiency of optimization by reducing the number of load flow execution. With the use of proposed algorithm, the system loss has been reduced convincingly, composes proper loading at the branches and make up buses voltage within the limit and which provides solution under different conditions such as normal and abnormal conditions of the system. Furthermore, the solution algorithm is implemented through J2EE (Java 2 Enterprise Edition) architecture to reduce software couplings and to achieve software reusability. The effectiveness of the proposed approach is demonstrated by employing the feeder switching operation scheme to unbalanced standard 25- bus distribution system and modified IEEE-125 bus distribution system.

Key words: distribution network reconfiguration, PGSA, hybrid differential evolution, loss reduction, switching operation

Introduction

Feeder reconfiguration is a very important tool to operate the distribution system at minimum cost and improve the system reliability and security. The reconfiguration of a distribution system is a process, which alters the feeder topological structure by changing the open/close status of the switches in the distribution system. The presence of high number of switching elements in a radial distribution system makes the network reconfiguration a highly complex combinatorial, non-differentiable and constrained non-linear mixed integer optimization problem. Also, the number of variables varies with respect to the size of the system. The distribution system with ‘n’ switches will have ‘n’ variables. The demand for a radial operation also makes the mathematical model more difficult to represent efficiently and codification of a solution becomes difficult when metaheuristic techniques are employed.

The feeder reconfiguration problem has been dealt with in various papers. Civanlar et al. (1988) conducted the early work on feeder reconfiguration for loss reduction. In (Baran ME and Wu FF, 1989), Baran et al. defined the problem of loss reduction and load balancing as an integer programming problem. Aoki et al. (1988) developed a method for load transfer, in which the load indices were used for load balancing. In Shir Mohammadi and Hong (1989), the solution method starts with a meshed distribution system obtained by considering all switches closed. Then, the switches are opened successively to eliminate the loops. Many other methods, such as mathematical programming techniques (Goswami, S.K and Basu, S.K., 1992; Ying-Yi .H and Saw-Yu .H, 2006; L. Whei-Min and C. Hong-Chan, 1998), expert systems (H. Kim, et al., 1993; H. Salazar, et al., 2006; Liu CC, et al., 1988; H.C. Cheng and C.C. Ko, 1994) and optimization algorithm (B. Venkatesh, et al., 2004) have been proposed in recent years. In (S. Thiruvenkadam, et al., 2008) and (K. Huang and H. Chin, 2002), the solution procedures employing heuristic rules and fuzzy multi-objective approach are developed to solve the network reconfiguration problem.

In (Y.H. Song, et al., 1997; C. B. Delbem, et al., 2005), evolutionary computation techniques are employed for optimizing distribution network. The above methods have been successful in solving the problem of distribution network optimization, but the complexity involved in terms of number of variables is more. In addition to the above,
the identification of suitable values of cross over rate, mutation and population size are made by trial and error, which also causes computational difficulty. An efficient and faster differential evolution, Hybrid Differential Evolution (HDE) has also been employed for network reconfiguration (T. Su and C. S. Lee, 2003). In order to avoid the expensive computational costs spent on tuning the control parameters, Self-Adaptive HDE (SaHDE) has been introduced to gradually self-adapt the control parameters by learning from their previous experiences in generating promising solutions (K. Qin and P. N. 2005).

The plant growth simulation algorithm (PGSA) is employed to optimize the network configuration of the distribution system (Wang and H.Z. Cheng, 2008; S. Thiruvenkad, 2009; 2009). The PGSA provides a detailed description on switch state and decision variables, which greatly contracts the search space and hence reduces computation effort. Though it reduces the computational effort, the constraint handling was not effective. For unbalanced distribution network reconfiguration problem, simple reconfiguration approaches had been practiced in (Borazan, V., et al., 1997; Wang.J.C, et al., 1996).

Even though, the above methods gained encouraging results, the speed for searching optimal configuration was moderate. In order to utilize the advantages of PGSA and SaHDE, and to overcome the aforementioned disadvantages, a hybrid technique based on PGSA and SaHDE has been proposed in this paper. The advantages of the proposed approach concerning previously published algorithms are that it evades heavy numerical computing, the solution procedure is very simple, easy to adapt to any kind of radial distribution network, unambiguous definitions on reconfiguration procedure and most importantly it provides solution under different system conditions such as normal, single fault case and multiple fault case. The effectiveness of the proposed approach is demonstrated by employing the feeder switching operation scheme to 25 bus and modified IEEE-125 bus Distribution systems.

**Problem Formulation:**

In this paper, the objective is to minimize the system power loss under a certain load pattern through network optimization while electrical and operational constraints are met, that is the process of altering the topological structures of distribution network by changing the open/close status of switches so as to minimize total system real power loss. The objective function of the problem is,

\[
\text{min } F = \text{min}(P_{T,Loss})
\]

where,

\[
P_{T,Loss} \text{ is the total real power loss of the system considering all the phases.}
\]

The apparent power transported by the branch must satisfy the branch’s capacity. The voltage magnitude at each bus must be maintained within limits. These constraints are expressed as follows:

\[
S_i \leq S_{i,\text{max}}
\]

\[
V_{i,\text{min}} \leq V_i \leq V_{i,\text{max}}
\]

where,

\[
S_i, S_{i,\text{max}} \text{ are apparent power and maximum capacity limit of branch } i;
\]

\[
V_i \text{ is voltage magnitude of bus } i;
\]

\[
V_{i,\text{min}} \text{ and } V_{i,\text{max}} \text{ are minimum and maximum voltage limits of bus.}
\]

Furthermore, the radial structure of network must be maintained, and all loads must be served.

**Fig. 1:** Single-line diagram of a main feeder

A set of feeder line flow formulations is employed. Considering the single-line diagram in Fig 1, the following set of recursive equations is used to compute power flow:
where, 
$P_i$ and $Q_i$ are the real and reactive powers that flow out of bus $i$; 
$P_{Li}$ and $Q_{Li}$ are the real and reactive load powers in bus $i$.

The resistance and reactance of the line section between buses $i$ and $i+1$ are denoted by $R_{i,i+1}$ and $X_{i,i+1}$ respectively.

$V_{i}^{2} = V_{i}^{2} - 2(R_{i,i+1}P_{i} + X_{i,i+1}Q_{i}) + (R_{i,i+1}^{2} + X_{i,i+1}^{2}) \frac{P_{i}^{2} + Q_{i}^{2}}{V_{i}^{2}}$  \hspace{1cm} (6)

$\frac{V_{i}}{2}$ is the shunt capacitor connected at bus $i$

**Fig. 2:** Single line diagram of a node with two sub feeders

In case of a node with two or more sub feeders as shown in Fig 2, the load flow equations will reflect bus powers including branch powers as given in equations (7) and (8),

\[ P_{i} = P_{i} + P_{j} + P_{k} \]  \hspace{1cm} (7)

\[ Q_{i} = Q_{i} + Q_{j} + Q_{k} \]  \hspace{1cm} (8)

The power loss $P_{Loss}(i,i+1)$ of the line section that connects buses $i$ and $i+1$ is,

\[ P_{Loss}(i,i+1) = R_{i,i+1} \frac{P_{i}^{2} + Q_{i}^{2}}{V_{i}^{2}} \]  \hspace{1cm} (9)

The power loss $P_{F,Loss}$ of the feeder may be determined by summing the losses of all line sections of the feeder, given by,

\[ P_{F,Loss} = \sum P_{Loss}(i,i+1) \]  \hspace{1cm} (10)

The total system power loss $P_{T,Loss}$ is the sum of power losses of all feeders in the system. In the model, the control variables are the states of all switches in the system. The minimization of total system real power loss is obtained by altering the open/closed status of switches.

**Hybrid Technology:**

3.1. Search Strategy through Hybrid Differential Evolution (HDE)

The general HDE solution process involves following steps.

**Step 1: Initialization**

The decision variables for the radial distribution system reconfiguration are the number of loops. The initial population of $N_p$ individuals is randomly selected based on uniform probability distribution for all variables to cover the entire search space uniformly. The initial population is expressed as,

\[ Z^{0}_{j} = Z^{min}_{j} + \rho \left( Z^{max}_{j} - Z^{min}_{j} \right) \]  \hspace{1cm} (11)
Step 2: Mutation

Differential evolution generates new parameter vectors by adding the weighted difference vector between two population members to a third member. The essential ingredient of mutation operation is the difference vector. A perturbed individual is therefore generated on the basis of the parent individual in the mutation process by

\[
\mathbf{Z}_i^{G+1} = \mathbf{Z}_i^G + F \times (\mathbf{Z}_j^G - \mathbf{Z}_k^G)
\]

(12)

where \( F \) is a scaling factor and \( j \) and \( k \) are randomly selected. The scaling factor \( F \in [0, 1] \) ensures the fastest possible convergence.

Step 3: Crossover

In order to extend the diversity of the new individuals in the next generation, the perturbed individual and the current individual are selected by a binomial distribution to perform the crossover operation. In this crossover operation, the gene of an individual at the next generation is produced from the perturbed individual and the present individual

\[
\mathbf{Z}_i^{G+1} = \begin{cases} 
\mathbf{Z}_j^G, & \text{if a random number } > CR \\
\mathbf{Z}_k^G, & \text{otherwise}
\end{cases}
\]

(13)

where \( i = 1, 2, \ldots, N_p \), \( j = 1, \ldots, n \) and the crossover factor \( CR \in [0,1] \) is assigned by user.

Step 4: Evaluation and Selection

In the evaluation process an offspring competes one-to-one with the parent. The parent is replaced by its offspring if the fitness of the offspring is better than that of its parent. Contrarily, the parent is retained in next generation if the fitness of offspring is worse than the parent. The two steps involved are one-to-one competition and selection of best individual in the population and is expressed by

\[
\mathbf{Z}_i^{G+1} = \arg \min \left\{ \psi(\mathbf{Z}_i^G), \psi(\mathbf{Z}_i^{G+1}) \right\}
\]

(14)

\[
\mathbf{Z}_b^{G+1} = \arg \min \left\{ \psi(\mathbf{Z}_i^{G+1}), i = 1, \ldots, N_p \right\}
\]

(15)

Step 5: Acceleration Operation

If the best fitness at the present generation is not further improved by the mutation and crossover operations, then the present best individual is pushed towards a better point. Thus, the accelerated phase is represented as:

\[
\mathbf{Z}_b^{G+1} = \begin{cases} 
\mathbf{Z}_b^G, & \text{if } \psi(\mathbf{Z}_b^{G+1}) < \psi(\mathbf{Z}_b^G) \\
\mathbf{Z}_b^G - \alpha \nabla \psi, & \text{otherwise}
\end{cases}
\]

(16)

where \( \mathbf{Z}_b^{G+1} \) is the best individual. The gradient of the objective function can be calculated with finite variation. The step size \( \alpha \in [0,1] \) is determined by the descent property. Initially \( \alpha \), is set to a value of one to obtain the new individual \( \mathbf{Z}_b^N \). If the descent property is satisfied,

i.e. \( \psi(\mathbf{Z}_b^N) < \psi(\mathbf{Z}_b^{G+1}) \)

(17)

then \( \mathbf{Z}_b^N \) becomes a candidate in the next generation and is added to this population replacing the worst individual. If the descent property is not satisfied, then step size is lowered a little. The descent method is repeated to search \( \mathbf{Z}_b^N \) until \( \alpha \nabla \psi \) is sufficiently small or a specified number of iterations are performed.

Step 6: Migration Operation

A migration phase is introduced to regenerate a newly diverse population of individuals to enhance the investigation over the search space, and thus, reduce the pressure of selection from a small population. The new populations are obtained based on the best individual. The \( h_b \) gene of the \( i_b \) individual is regenerated as
\[
Z_{h_b}^{G+1} = \begin{cases} 
Z_{h_{b_i}}^{G+1} + \delta_{h_i} \left( Z_{h_{\min}}^{G+1} - Z_{h_{b_i}}^{G+1} \right), & \text{if } \delta_{h_i} < \frac{Z_{h_{b_i}}^{G+1} - Z_{h_{\min}}^{G+1}}{Z_{h_{\max}}^{G-1} - Z_{h_{\min}}^{G-1}} \\
Z_{h_{b_i}}^{G+1} + \delta_{h_i} \left( Z_{h_{\max}}^{G+1} - Z_{h_{b_i}}^{G+1} \right), & \text{otherwise}
\end{cases}
\]

where \( \delta \) and \( \delta' \) denote uniformly distributed random numbers. This diversified population is then used as the initial decision parameters to escape the local optimum points. The migration operation is performed only if the population diversity \( \rho \) is smaller than the desired tolerance of population diversity \( \epsilon_1 \),

\[
\rho = \frac{\sum_{i=1}^{N_p} \sum_{h=1}^{n} \eta_Z}{n(N_p - 1)} < \epsilon_1
\]

where,

\[
\eta_Z = \begin{cases} 
1, & \text{if } \frac{Z_{h_{\max}}^{G+1} - Z_{h_{b_i}}^{G+1}}{Z_{h_{b_i}}^{G+1}} > \epsilon_2 \\
0, & \text{otherwise}
\end{cases}
\]

Parameter \( \epsilon_2 \) expresses the gene diversity with respect to the best individual. \( \eta_Z \) is the scale index. With the members of the next generation thus selected, the cycle repeats until there is no improvement in the best individual.

### 3.7. Self Adaptive Hybrid Differential Evolution Strategy (SaHDE):

To achieve the most satisfactory optimization performance by applying the conventional HDE to a given problem, it is common to perform a trial-and-error search for the most appropriate fine-tune its associated control parameter values, i.e., the values of F, CR, and NP. Obviously, it may expend a huge amount of computational costs. Moreover, during different stages of evolution, control parameter adaptation schemes can be more effective than others.

In the conventional HDE, the choice of numerical values for the three control parameters F, CR, and NP highly depends on the problem under consideration. In the proposed SaHDE algorithm, NP has been left as a user-specified parameter because it highly replies on the complexity of a given problem. In fact, the population size NP does not need to be fine-tuned and just a few typical values can be tried according to the preestimated complexity of the given problem. Between other two parameters, CR is usually more sensitive to problems with different characteristics, e.g., the unimodality and multimodality, while F is closely related to the convergence speed. In SaDE algorithm, the parameter F is approximated by a normal distribution with mean value 0.5 and standard deviation 0.3, denoted by \( N(0.5, 0.3) \). A set of F values are randomly sampled from such normal distribution and applied to each target vector in the current population. It is easy to verify that values of F must fall into the range \([-0.4, 1.4]\] with the probability of 0.997. By doing so, we attempt to maintain both exploitation (with small F values) and exploration (with large F values) power throughout the entire evolution process.

As demonstrated by a suite of extensive experiments in (Borazan V., et al., 1997) and (Wang J.C., et al., 1996), the proper choice of CR can lead to successful optimization performance while a wrong choice may deteriorate the performance. In fact, good values of CR generally fall into a small range for a given problem, with which the algorithm can perform consistently well. Therefore, we consider gradually adjusting the range of CR values for a given problem according to previous CR values that have generated trial vectors successfully entering the next generation. Specifically, we assume that CR obeys a normal distribution with mean value CRm and standard deviation Std=0.1, denoted by \( N(CRm, Std) \) where CRm is initialized as 0.5. The Std should be set as a small value to guarantee that most CR values generated by \( N(CRm, Std) \) are between \([0, 1]\). Hence, the value of Std is set as 0.1. The minor changes to the Std of the Gaussian distribution do not influence the performance of SaDE significantly.

A set of CR values are randomly generated according to \( N(CRm, 0.1) \) and then applied to those target vectors to the strategy. To adapt the crossover rate CR, we establish memories named CRMemory to store those CR values with respect to the strategy that have generated trial vectors successfully entering the next generation within the previous LP generations. Specifically, during the first LP generations, CR values with respect to the strategy are generated by \( N(CRm, 0.1) \). At each generation after LP generations, the median value stored in CRMemory will be calculated to overwrite CRm. Then, CR values can be generated according to \( N(CRm, 0.1) \) when applying the strategy. After evaluating the newly generated trial vectors, CR values in CRMemory that correspond to earlier generations will be replaced by promising CR values obtained at the current generation with respect to the strategy. By incorporating the aforementioned control parameter adaptation scheme into the conventional HDE framework, a
SaHDE algorithm is developed. The SaHDE algorithm, control parameter values are gradually self-adapted by learning their previous experiences of generating promising solutions.

The earlier works addressed for reconfiguration by DE in (Y. H. Song, et al., 1997; C.B. Delbem, 2005; T. Su and C.S. Lee, 2003), individual switches present in the distribution system are considered as variables. The number of variables varies with respect to the size of the system. The distribution system with 'n' switches will have 'n' variables. Therefore the complexity involved by means of number of variables becomes more. This complexity has been reduced by the introduction of the concept of PGSA (Wang and H.Z. Cheng, 2008).

II. Variable selection through PGSA:

The PGSA, which characterizes the growth mechanism of plant phototropism, is a bionic random algorithm. It looks at the feasible region of integer programming as the growth environment of a plant and determines the probabilities to grow a new branch on different nodes of a plant according to the change of the objective function. The developed model simulates the growth process of a plant, which rapidly grows towards the light source and reaches global optimum solution. The concept of PGSA has been introduced by Wang and Cheng (2008).

1: Decision Variables:

In distribution network optimization, the switch is usually selected as the decision variable. It can be assigned either a value 0 (zero) or 1, which means open switch or closed switch respectively. Two problems exist during selection of switches, i) the number of possible network states grows exponentially with the number of switches, making the exhaustive search techniques totally unsuitable for the large scale problem; ii) a lot of unfeasible solutions will appear in the iterative procedure, which dramatically decreases the efficiency of calculation and sometimes may not obtain the optimal solution.

Therefore, more sophisticated techniques are required for the selection of decision variable. In a distribution system, the number of independent loops is the same as the number of tie switches. The problem of network optimization is identical to the problem of selection of an appropriate open switch for each independent loop so that the system active power loss can be minimized. So, we can employ independent loops rather than switches as decision variables, which can greatly reduce the dimension of the variables in the solved model and lead to a marked decrease of unfeasible solutions in the iterative procedure.

The basic procedure for designing the new decision variable is:

i. Radial distribution system is constructed with open and closed switches.
ii. The open switch of the nth loop is closed to form nth independent loop.
iii. It is assumed that the decision variable of loop n as Ln, and the switches are numbered in loop n using consecutive integers, the numbers of all switches in loop n constitute the possible solution set of Ln.

2: Switch State:

The dimension of decision variables is greatly decreased, when independent loops are taken as decision variables. However, it cannot avoid the unfeasible solutions in the iterative procedure. The switches are described in four states so as to reduce the chances of unfeasible solutions in the iterative procedure and to further improve the efficiency of calculation.

i. Open state: a switch is open in a feasible solution.
ii. Closed state: a switch is closed in a feasible solution.
iii. Permanent closed state: a switch is closed in all feasible solutions.
iv. Temporary closed state: switches that have been considered in an earlier loop should be treated as closed switch for the loop under considerations.

After the depiction of the states of all switches, the permanently closed switches can be eliminated from the possible solution sets of the decision variables. Similarly we can monetarily delete the temporarily closed switches.

PGSA reduces the number of control variables by means of selecting individual loops as control variables rather than selecting individual switches. With the introduction of switch state selection by PGSA, unnecessary selection of few switches for optimization also has been avoided. Further the radiality constraint is very well handled within PGSA. Thus with the influence of PGSA, the complexity has been greatly reduced and produces good response for SaHDE for reconfiguration.

The complete flow of operation for reconfiguration through the co-ordination of PGSA and SaHDE has been revealed by the flowcharts shown in Figure 3.

Results and Discussion

The effectiveness of the algorithm has been validated through two test distribution systems; Test System I and Test System II.
4.1. Test System I:

The test system I (Borazan. V., et al., 1997) is an unbalanced distribution system with base of 4.16KV and 25 Nodes. The initial condition of the system is identified by the open switches S25, S26, S27; the closed switches S1 to S24. The corresponding power loss is 450.38kW. As per the PGSA, decision variables are designed for the Test System I. As per the proposed approach all the switches of the loops are considered as closed. Test System I with decision variables is shown in the Fig. 4.

![Flowchart](image-url)
The possible solution sets are,
\[
\{ \{ S_1, S_2, S_3, S_4, S_6 \} \}
\]
\[
\{ \{ S_1, S_2, S_3, S_4, S_6, S_7, S_8 \} \}
\]
\[
\{ \{ S_1, S_2, S_3, S_4, S_6, S_7, S_8, S_9, S_{10}, S_{11}, S_{12}, S_{13}, S_{14}, S_{15}, S_{16}, S_{17}, S_{18}, S_{19}, S_{20}, S_{21}, S_{22}, S_{23}, S_{24}, S_{25}, S_{26}, S_{27}, S_{28}, S_{29}, S_{30} \} \}
\]

After describing the switches in four states, the chance for the unfeasible solutions in the iterative procedure have been eliminated. By closing some switches permanently closed, the search space was reduced as follows,
\[
L_3 = \{ S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9, S_{10}, S_{11}, S_{12}, S_{13}, S_{14}, S_{15}, S_{16}, S_{17}, S_{18}, S_{19}, S_{20}, S_{21}, S_{22} \}
\]

Then the inclusion of the concept of temporary closed state avoids finding the unfeasible solutions due to the interrelation of some switches. As a result, the possible solution sets shown in equation (21) and (22) were reduced. The search space reduced to,
\[
\{ \{ S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8 \} \}
\]
\[
\{ \{ S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9, S_{10}, S_{11}, S_{12}, S_{13}, S_{14}, S_{15} \} \}
\]

From the above equation, it is clear that the Test system 1 has three control variables (L1, L2, and L3) and those variables has ranges from 1 to 5, 6, and 8 respectively. For an instance for control variable L1, by the control strategy “DE/current-to-rand/1” the value generated is 3 then S11 is the switch assumed as opened in the loop 1 and the same process is continued for the rest of the variables.

The initial population and their respective losses were calculated and stored. With the initial values of F_Mean=0.5, F_Variance=0.1, CR_Mean=0.5 and CR_Variance the new chromosomes were generated and their respective losses were calculated and stored. The CRMemory has been created, which stores only the CR_Mean values of the best new chromosomes. The mean of the CRMemory has been considered as CR_Mean for the next iteration.

The best solution and its respective configuration have been stored at the end of each iteration. The same process has been repeated for the fixed number of iterations. The loss has been reduced to 400.47kW from its initial configuration loss. The identified switches to be opened are S15, S17 and S22. The final configuration bus voltages and branch currents are maintained within the limit.

For the same test system, PGSA has been incorporated with DE and HDE and applied for reconfiguration. The proposed hybrid PGSA-SaHDE self tunes crossover rate and mutation values. The speed of convergence of the proposed hybrid PGSA-SaHDE is comparatively good with the PGSA-DE and PGSA-HDE.

4.2. Test System II:
The IEEE 123 node system shown in Fig 5, is an unbalanced distribution system with base kV of 4.16 kV and base MVA of 100 MVA. It is characterized by overhead and underground line segments, four step-type voltage regulator, and shunt capacitors and switching to provide alternate paths of power flow. The initial loading at the phases a, b and c are 331.28A, 207.86A and 313.53A respectively. It consists of 125 lines and 2 loops with 26 and 9 switches in respective loops. For the loops, solution sets are named sequentially from L1 to L2. As per the PGSA, decision variables are designed for the system shown in Figure 5. The maximum current capacity of the branches is 400A. The bus voltage limits are fixed as Vmin=0.9 pu and Vmax=1.02 pu. After applying the proposed methodology, the real power loss is reduced from 87.56 kW to 64.73 kW. The feeder currents and bus voltages are maintained within the limit. The final configuration branch currents and bus voltages are shown in Fig. 6. and Fig. 7. The identified switches to be opened at the final configuration are S2 and S3.

![Fig. 5: IEEE-125 bus unbalanced distribution system (Test System II)](image)

For this test system, the proposed method compared with PGSA-DE and PGSA-HDE. The results are tabulated in Table 1. It shows that out of three optimization algorithms, the hybrid PGSA-SaHDE is the best. The speed of convergence of the proposed hybrid PGSA-SaHDE is comparatively good with the other two methods.

![Table 1: Comparison of optimization methods applied for Test System II](image)

![Fig. 6: Final configuration branch currents of Test System II](image)
Conclusion:

An efficient approach that employs hybrid technology as optimal means has been presented for the reconfiguration of unbalanced radial distribution system, where the objective is loss reduction and subjected under constraints like branch currents limit violation and bus voltages limit violation. The results have shown that reconfiguration has been attained with multi constraints of radial distribution system. Thus the introduction of PGSA reduce dimension of variables. The incorporation of HDE will speed up the searching process. With the inclusion of SaDE tuning of control parameters can be done. The proper use of PGSA and SaHDE improves the efficiency in terms of reduced number of load flow executions, reduced computational executions and removal of unfeasible solutions in the search space.

The results obtained with the present approach, when compared with the previous methods proposed by the authors will show that the introduction of the algorithm with hybrid PGSA-SaHDE has contributed to reduce the number of power flows and has incorporated the network constraints. Hence with the effective introduction of the proposed reconfiguration algorithm, loss reduction was done subjected under constraints such as bus voltage limit and branch current limit. This can be further improved to address minimization of phase currents deviation in future.

References