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A Comparative Study of Optimization Methods for 33kV Distribution Network Feeder Reconfiguration

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Abstract

Distribution Network Reconfiguration (DNR) has been a part of importance strategies in order to reduce the power losses in the electrical network system. Due to the increase of demand for the electricity and high cost maintenance, feeder reconfiguration has become more popular issue to discuss. In this paper, a comparative study has been made by using several optimization methods which are Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The objectives of this study are to compare the performance in terms of Power Losses Reduction (PLR), percentage of Voltage Profile Improvement (VPI), and Convergence Time (CT) while select the best method as a suggestion for future research. The programming has been simulated in MATLAB environment and IEEE 33-bus system is used for real testing. ABC method has shown the superior results in the analysis of two objectives function. The suggestion has been concluded and it is hoped to help the power system engineer in deciding a better feeder arrangement in the future.

Keywords: Distribution network reconfiguration, artificial bee colony, particle swarm optimization, genetic algorithm, power losses reduction, voltage profile improvement, convergence time.

Introduction

In a distribution network which connects all electricity from generation and transmission unit, the quality of the power is an important element due to achieve excellent work without wasting any cost. According to the statistic in the literature review, there is reported that 70% of the total losses occur in the primary and secondary distribution system, while transmission and sub-transmission lines account for only 30% of the total losses [1]. The Power Losses Reduction (PLR) and Voltage Profile Improvement (VPI) are the major aspect measurement for an efficient power distribution network system.

In order to achieve the stability and fewer losses in the distribution network, there is desired of Distribution Network Reconfiguration (DNR). The DNR is realized by changing the status of open/closed switches with the intention of reducing feeder power losses while improving the voltage profile. There are many existing methods for feeder configuration to get better PLR. A variety approach has been presented to show how far they can get the optimal solution in order to search for best open/closed switches with lower losses. On behalf of feeder reconfiguration, there are many researchers have applied the optimization methods in DNR such as in [2] has applied the Network Partitioning Theory, Ant Colony System (ACS) in [3] and the authors in [4], has presented the Hopfield Neural Network (HNN). Moreover, an improvement of Ant Colony System Algorithm (ACSA) has been proposed in solving the distribution network reconfiguration problem. This ACSA has simplified the searching space of the distribution network structure and also improved information update strategy in reducing the power losses [5]. The objective in minimizing the loss by using the artificial algorithm has been continued. This new Fuzzy multi criteria decision making algorithm is introduced to emphasize the power losses reduction in a network reconfiguration [6].

A Tabu Search (TS) approach that is suitable in solving complex optimization problem network reconfiguration for power losses reduction has been proposed in [7]. Meanwhile, an Enhanced Genetic Algorithm (EGA) is proposed in order to change the open and closed switches status in the network structure of distribution feeder. Due to the EGA, the power losses are minimized and the current constraints are also minimized [8].

In addition, the DNRC distribution network reconfiguration which is based on comprehensive approach has been proposed in the pass research for minimizing the system power losses. The DNRC consists of modified heuristic method and rule base. The rule has been used in selection the optimal reconfiguration network which is come from operations experience. This method is applied in Guiyang South Power Supply Bureau [9].

There are numerous optimization methods in solving distribution network reconfiguration considering PLR and VPI. But, it is infrequent to a comparative study between these algorithm performances while also considering Convergence Time

(CT). Due to that reason, this work will discuss on comparative study of three common optimization methods which are Artificial Bee Colony (ABC), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). These methods have performed the excellence result in solving the complex parameters due to their process of finding the optimal results which are almost the same but different in CT. Their performance will be investigated and analyzed in order to select the greatest search engine as the suggestion for an automotive DNR in the future.

Mathematical Formulation and Constraints

The objective of the feeder reconfiguration is to minimize the total power losses. Therefore, the objective function of this study is:

$$P_{losses} = \sum_{i=1}^{n} \left| I_{ai}^{2} \right| R_{i} \tag{1}$$

Where:

i = Number of lines in the system.

I_{ai} = Line real active current.

Ri = Line resistance.

The second consideration of this study is VPI. So that, the voltage bus constraint has been set as follow:

$$V_{\min} \le V_{bus} \le V_{\max} \tag{2}$$

The voltage for each bus should operate within the acceptable limit which is in between1.05 and 0.95 (± 5).

The simple constraint of radial configuration is an importance element for feeder reconfiguration. The configuration must be in radial to avoid excess current flow in the system. Therefore, in order to ensure the radial network is maintained, several constraints must be taken into account. Several standard rules have been adopted for selection of switches. Those switches that do not belong to any loop, connected to the sources and contributed to a meshed network have to be closed.

In this work, the particles consist of the tie switches *(S)* has been considered as set particles as shown in Equation (3).

$$X_{particle} = \{ S_1, S_2, \ldots S_\beta \} \tag{3}$$

Where β is the number of tie line switches. Only the particles that satisfy all the constraints above will be considered as the initial population.

The Implementation of Optimization Methods in Feeder Reconfiguration

Artificial Bee Colony Method

Artificial Bee Colony (ABC) is based on intelligent of bee behavior foraging. In ABC is included:

Initialization Phase

The one-line input data is read and the MNC (Maximum Iteration Count) is initialize and base case as the best solution.

The population of solutions is initialized as each bee is formed by open switches in the configuration and number of employed bees equal with onlooker bees.

Employed Bees Phase

Evaluate as follow:

$$f_{fitness} = \frac{1}{1+P_{losses}} \tag{4}$$

If cycle = 1, repeat.

New population v_{ij} in the neighborhood of x_{ij} for employed bees using Equation (5) is generated and evaluated.

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}) \tag{5}$$

The greedy selection process is applied to x_i and v_i. Calculate the probability P_i for the solutions x_i by means of their fitness values by using Equation (6).

$$P_i = \frac{f_{iti}}{\sum_{i=1}^{SN} f_{iti}} \tag{6}$$

Where;

$$f_{iti} = \begin{cases} \frac{1}{1+f_i} \ if \ f_i \geq 0 \\ 1 + abs(f_i) \ if \ f_i < 0 \end{cases} \tag{7}$$

Where f_i is cost value of objective function.

Onlooker bees phase

Apply the greedy selection process for the onlookers between x_i and v_i.

Scout Bee Phase

Determine the abandoned solution (source), if exists, and replace it with a new randomly produced solution x_i for the scout by using Equation (8) :

$$x_{ij} = x_{minj} + rand(0,1) * (x_{maxj} - x_{minj}) \tag{8}$$

Memorized the best food source position (solution) achieved so far.

For cycle = cycle + 1 until
cycle = Maximum Cycle Number (MCN)

Particle Swarm Optimization Method

The PSO has been developed based on the behavior of social animals which live and move in group such as fish and bird. The birds or fish usually move in a group at a certain speed and position. Their design of movement is depending on their experience as well as the experience of others in the group (P_{best} and G_{best}). The new velocity, V_m^{t+1} and the new position, X_m^{t+1} for the fish or birds are obtained using Equations (9) and (10).

$$V_m^{t+1} = \omega \times V_m^t + wf_1 \times ran_1 \times (P_{bm}^t - X_m^t) + wf_2 \times ran_2 \times (G_b^t - X_m^t) \quad (9)$$

$$X_m^{t+1} = X_m^t + V_m^{t+1} \quad (10)$$

Where V_m^t is the velocity of particle *m* in iteration *t,* X_m^t is the position of particle *m* in iteration *t, ran₁*and *ran₂* are the random numbers between 0 and 1 [10]. P_{bm}^t is the best value of the fitness function that has been achieved by particle *m* before iteration *t.* G_b^t is the best value of the fitness function that has been achieved so far by any particle. Constants $wf_1$and wf_2areweighting factors of the random acceleration terms, which attract each particle towards P_{best} and G_{best} positions. Lower values of fitness function allow particles to move farther from the target region before they return. The inertia weight $\omega_i$is typically set according to the following equation:

$$\omega_i(n+1) = \omega_i^{\max} - \frac{\omega_i^{\max} - \omega_i^{\min}}{n_{\max}} \times n \quad (11)$$

In Equation (10), $n_{\max}$ is the maximum number of iterations and *n*is the current iteration number. $\omega_{i\max}$ and $\omega_{i\min}$ are maximum and minimum of the inertia weights, respectively. The summary process of implementation of PSO algorithm is as follows:

Step A- Initialization- generate randomly all particles.
Step B- Evaluate the fitness function.
Step C- Determine P_{best} and G_{best} for all populations.
Step D- Evaluate the new speed for each population.
Step E- Update the existing position to a new position.
Step F- Update the existing speed to the new speed.
Step G- Check the stopping criteria –otherwise go to Step B.

Genetic Algorithm Method

Problem Formulation for GA has been set and explained as follow:

Genetic Operations

In this part, it has three important parts which are crossover, mutation and reproduction [10].

- Crossover: two crossover points are considered and selected randomly.
- Mutation: identified digit is changed to a number excludes the element of leaf nodes to avoid local optimum.
- Reproduction: the elitist strategy is employed to select a portion of individuals with best fitness value. The roulette wheel approach is used.

Algorithmic Steps

A criterion depends on performances of the system for an operator in determining the switch status in network system and is formulated as:

$$PM\ (V, \theta, x) = 0 \tag{12}$$

$$QM\ (V, \theta, x) = 0 \tag{13}$$

$$V_i^{min} \leq V_i \leq V_i^{max}, i = 1, \dots., N \tag{14}$$

$$I_\ell^{min} \leq I_\ell \leq I_\ell^{max}, \ell = 1, \dots., L \tag{15}$$

Where,

$c_0(V, \theta, x)$: MW loss in the systems

$PM\ (V, \theta, x) = 0$: vector of the MW power flow balance equations

$QM\ (V, \theta, x) = 0$: vector of the MVAR power flow balance equations

V_i : bus voltage magnitude at bus I, i=1, ….N

I_ℓ : line flow at line ℓ, ℓ = 1, …., L

N : number of system busses

L : number of system lines

x : vector of switch statuses

In solving the network reconfiguration problem in distribution system to minimize real power losses the steps are taken:

Step 1- Read the bus data, line data, and switch data, etc.

Step 2- The population size, crossover rate, and mutation rate for GA is estimated. Initial chromosomes are encoded by Prufer number randomly selected. The radial structure is reasonable.

Step 3- solve (12) and (13) to obtain system bus voltages for each chromosome.

Step 4- The line flows (14) for each chromosomes compute.

Step 5- If (14) or (15) is violated, penalty function is augmented to the fitness function (the negative objective for maximization).

Step 6- The roulette wheel approach is used to reproduce new chromosomes (offspring).
Step 7- Convergent step. Stop if all new chromosomes are the same.
Step 8- Perform crossover and mutation operations in GA.
Step 9- Go to Step 3.

The Simulation and Test System

The case study used the test system which consists of 33-bus radial distribution system as shown in Figure 1. The system contains of a feeder, 32 normally closed tie switches and 5 normally open tie switches at 33, 34, 35, 36 and 37. The system load is assumed to be constant and Sbase is approximately 100MVA.The total load on the system is 3715kW and 2300kVAr. The minimum and maximum voltages are set at 0.95 and 1.05p.u. respectively [12]. All calculations for this method are carried out in the per-unit system. The convergence value is taken as 0.0001.

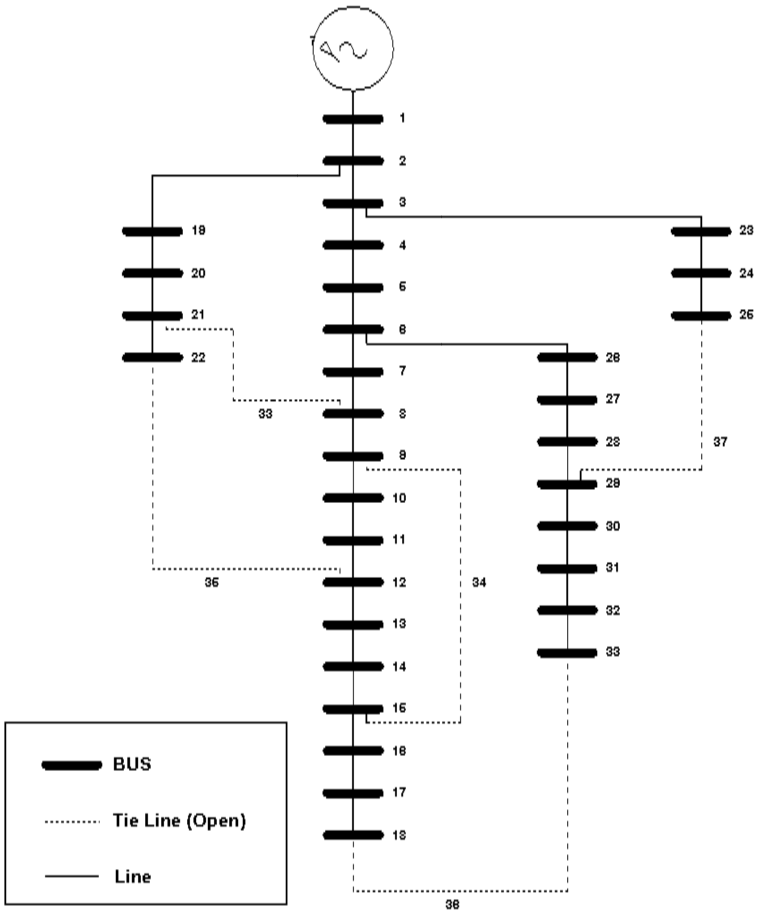

Figure 1. Initial configuration of the 33-bus radial distribution system

Three cases have been executed in determining their reliability of having ABC, PSO and GA in the test system to achieve the best configuration.

In this first case
The system follows the original network distribution of 33-bus without any alteration done. All the tie switches in the network remains as they are.

In this second case
The reconfiguration strategy is applied in the system is based on ABC method.

In this third case
The reconfiguration strategy is applied in the system is based on PSO method.

In this fourth case
The reconfiguration strategy is applied in the system is based on GA method.

Results and Analysis

The analysis of the reconfiguration is done by using ABC, PSO and GA methods. Tie switches and sectionalizing switches are considered as the main control variables. The optimal power losses depend on the flexibility of the switches. The programming is running randomly and takes approximately 100 times by using MATLAB software and the minimum power losses with the voltage profile of each busses is selected. The results are presented consists of five opened switches, total power losses and voltage profile value. Three important parts will be discussed; for part A and part B, the analyses of the results are mainly focused on the PLR and VPI while part C focuses on CT for the cases 2, 3 and 4 accordingly.

Part A: Power Losses Reduction (PLR)

Table 1 shows the result obtain after distribution network reconfiguration for case 2, case 3 and case 4. The parameters that has been considered are switches opened, total power losses, power loss reduction and percentage of loss reduction.

Table 1. Performance analysis of ABC, PSO and GA

Parameters	Case 1: Original Network	Case 2: After Reconfiguration using ABC	Case 3: After Reconfiguration using PSO [12]	Case 4: After Reconfiguration using GA [13]
Switch Open	33, 34, 35, 36, 37	31, 7, 9, 14, 37	7, 10, 14, 28, 32	7, 9, 14, 32, 37
Total Power Loss (kW)	202.7	107.1	126.0	137.0
Power Loss Reduction (kW)	-	95.6	76.7	65.7
Percentage of Loss Reduction (%)	-	47.16	37.83	32.41

From Table 1, there is greatest difference of PLR between these three cases if to be compared with original network. In Case 2, the total power loss is 107.1 kW through 95.6 kW power loss reductions while the percentage of reduction is approximately 47.16 %which is almost half percent of reduction. On the other hand, the total power losses in Case 3 is 126.0 kW while the total loss reduction is 76.7 kW and the percentage is around 37.83 % of reduction. Meanwhile, for the case 4 which is DNR by using GA, the total power loss is 137kW. The PLR for this case is 65.7 kW and the percentage is 32.41%. From the results, it can be concluded that ABC algorithm is better in PLR if to be compared to PSO and GA method with 9.33% and 14.75% improvement respectively. The cooperation method between employed bees, onlooker bees, and scout bees process in ABC show a better result compare to GA method that used only the process of crossover and mutation. In ABC, the higher the fitness value, the lower the power losses in the network system. The Figure 2 reviews the PLR plotted in graph for better analysis while the Figure 3 represents the percentage of PLR.

In getting the optimal value of power losses for these three cases, the sectionalizing switches are contributed in getting the value. The original switches have been opened for original network are at 33, 34, 35, 36 and 37. For Case 2, ABC algorithm after reconfiguration, the sectionalizing switches to be opened are 31, 7, 9, 14, 37 while for PSO technique are 7, 10, 14, 28, 32 and GA techniqueare7, 9, 14, 32, and 37 respectively.

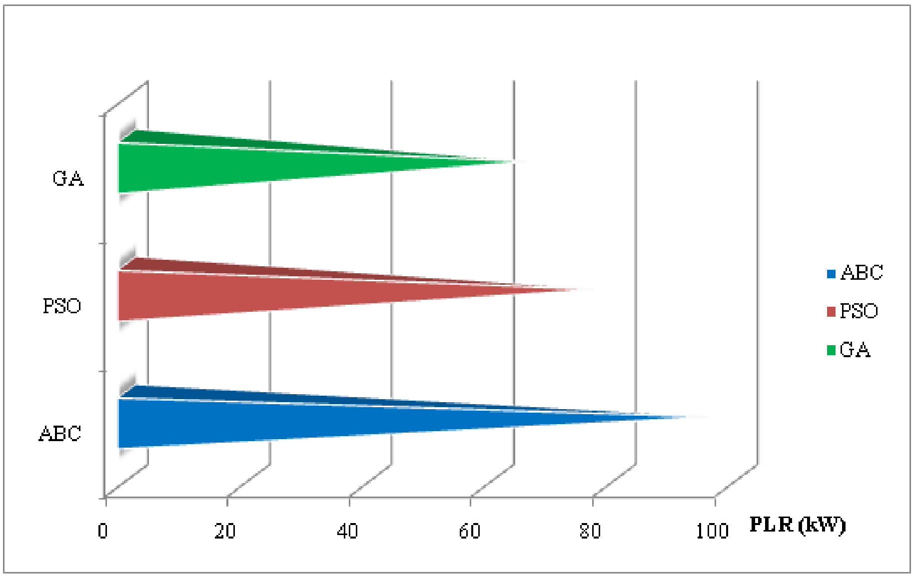

Figure 2.PLR for ABC, PSO and GA

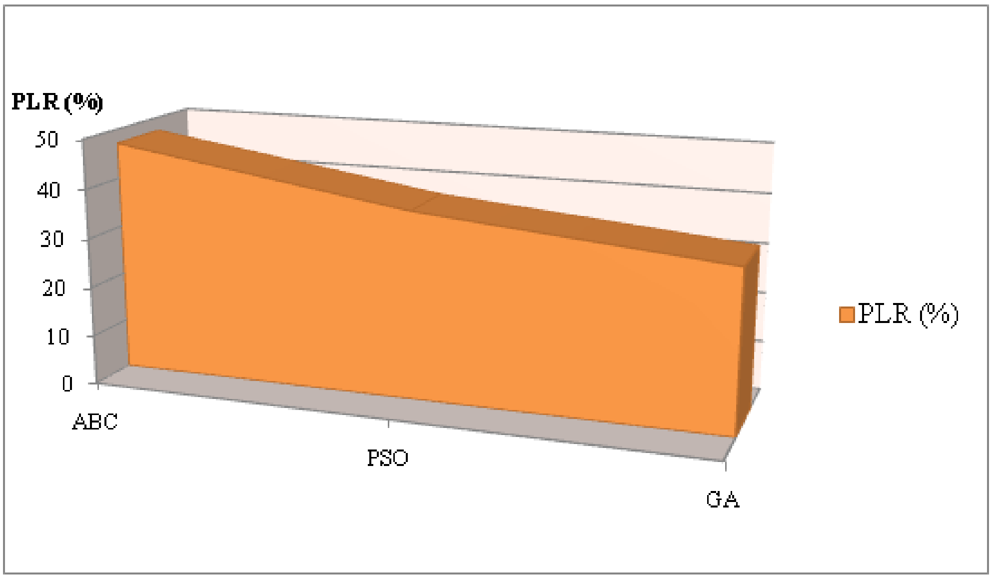

Figure 3. Percentage of PLR for ABC, PSO and GA

Part B: Voltage Profile Improvement (VPI)

Table 2 shows the results obtain for case 2, 3, and 4 respectively. The VPI is considered based on the increment of voltage profile value in p.u unit.

Table 2. Voltage profile improvement for ABC compared to PSO and GA

Bus No.	***Voltage Magnitude in p.u***		
	ABC	*PSO*	*GA*
1	1.000	1.000	1.000
2	1.000	1.000	1.000
3	1.000	1.000	1.000
4	1.000	1.000	1.000
5	1.000	1.000	1.000
6	1.000	1.000	1.000
7	1.000	0.999	0.995
8	1.000	0.999	0.995
9	1.000	0.999	0.995
10	1.000	0.999	0.995
11	1.000	0.999	0.995
12	1.000	0.999	0.995
13	1.000	0.999	0.999
14	1.000	0.999	0.999
15	1.000	0.999	0.999
16	1.000	0.999	0.999
17	1.000	0.999	0.999
18	1.000	0.999	0.999
19	1.000	1.000	1.000
20	1.000	1.000	1.000
21	1.000	0.999	0.982
22	1.000	0.999	0.982
23	0.999	1.000	0.982
24	0.999	1.000	0.982
25	0.999	0.999	1.000
26	1.000	1.000	1.000
27	0.999	1.000	0.999
28	0.999	0.999	0.999
29	0.999	0.999	0.999
30	0.999	1.000	1.000
31	0.999	0.999	0.999
32	0.999	0.999	0.999
33	1.000	0.999	0.999

From the Table 2, the results of VPI show that ABC method has a better value when it is compared to PSO and GA method. Regarding to the data at bus number 7 until 18, ABC algorithm has an improvement value from 0.999 to 1.000 if to be compared to PSO results. For the comparison between ABC and PSO, the increment can also be seen at the bus number 21, 22, 31, 32, and also 33 instantaneously. The significant improvement of voltage profile also can be seen at the bus number 21 until 24 for ABC when it is compared to GA method. The plotted graph in Figure 4 shows the VPI between ABC, PSO and GA techniques. As in ABC, the tie switches represents the position of food sources which is contributed to optimization problem solution. The onlookers bees process in ABC are contributed to voltage profile improvement which in GA applied crossover and mutation did not overall contribute to better voltage profile.

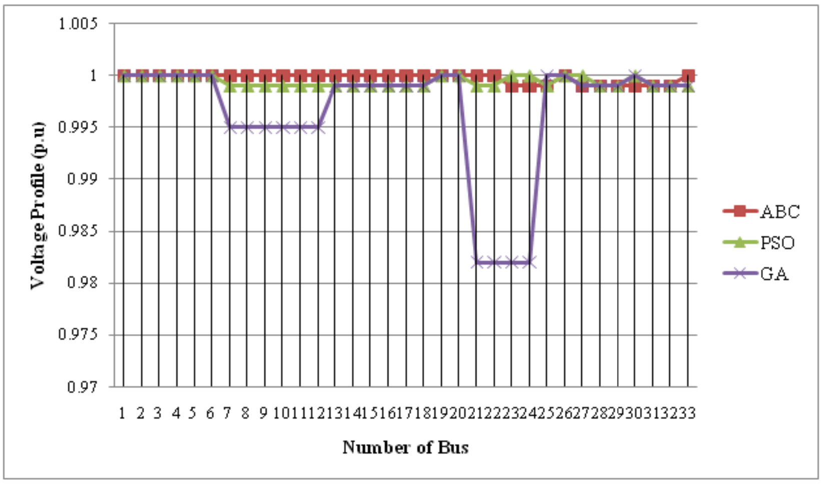

Figure 4. VPI between ABC, PSO and GA methods

Part C: Convergence Time (CT)

CT completed the element of analysis for the comparative study of these three cases. From the Table 3, the computation time for GA is better than ABC in getting the optimal value; it is because of the process genetic, mutation and crossover in GA contributes to converge in 24 seconds by using Intel Core i-5 while ABC algorithm takes 10 minutes to converge by using the same processor. Nevertheless, PSO method shows the superior point for this criterion by 18 seconds in order to achieve the last iteration in the simulation process. The practice of determining the global and local best population in the PSO flow make it fast to solve the complex problem effectively. The Figure 5 represents the graph for CT analysis between three test methods which are ABC, PSO and GA accordingly.

Table 3. Convergence time for ABC, PSO and GA

Technique	ABC	PSO	GA
Computational Time (s)	600	18	24

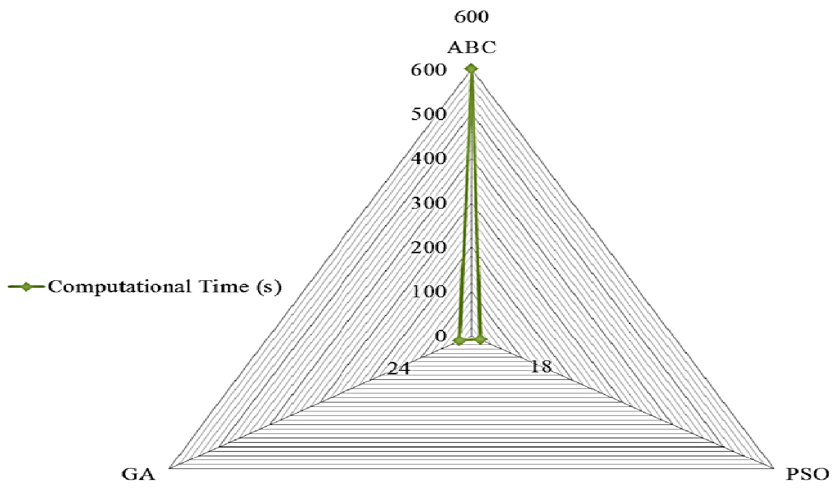

Figure 5. CT between ABC, PSO and GA method

Conclusion

This paper discuses a comparative study of optimization algorithm ABC, PSO and GA by considering Power Losses Reduction, Voltage Profile Improvement and Convergence Time for feeder reconfiguration. The results of the reconfiguration has shown that in comparison between the four cases, ABC gives better result in PLR and VPI which achieving the objective function of the optimization development. Even though, the computational time for ABC is lower if to be compared to PSO and GA technique; this technique can be improved by modifying its process in terms of employed bees, onlooker bees and scouts bees. The superior of ABC technique also can be applied to the huge test system such as 69kV distribution system by also considering distributed generations in the future research.

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