Modified Artificial Bee Colony Algorithm for Optimal Distributed Generation Sizing and Allocation in Distribution Systems

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***Abstract*-- This paper presents a modification in the neighboring search of the artificial bee colony (ABC) algorithm. The ABC algorithm is a new meta-heuristic population-based optimization technique inspired by the intelligent foraging behavior of honeybee swarms. To verify the validity of the proposed modified ABC algorithm, the problem of determining the optimal size, location and power factor for a distributed generation (DG) to minimize total system real power loss is considered. The IEEE 33-bus and 69-bus feeder systems are examined, and the results obtained by the proposed algorithm are compared with those found using other methods. The outcomes verify that the modified ABC algorithm has excellent solution quality and convergence characteristics. The efficiency of the proposed algorithm lies in the fact that the standard deviation of the attained results for 30 independent runs at every test case is virtually equal to zero.**

***Index Terms*-- Distributed Generation, Power Loss Reduction, Artificial Bee Colony Algorithm.**

I. Introduction

APPLICATION of DG-units has been utilized in some electric power networks. Power loss reduction, environmental friendliness, voltage improvement, postponement system upgrading and improved reliability are some advantages of applying a DG-unit. Practical application of the DG-unit, however, proves difficult.

The DG-unit application is a mixed integer nonlinear optimization problem, which includes maximizing system voltages or minimizing power loss and cost. As more objectives and constraints are considered more data is required, which tends to add difficulty to implementation.

Optimization tools have been employed to solve different DG-unit problems. These include Genetic Algorithm (GA), Evolutionary Programming (EP) and Particle Swarm Optimization (PSO.) Some of those techniques have been modified to enhance their performance or to overcome other limitations.

An approach to evaluate the impact of DG-units on power loss, reliability and voltage profile of distribution networks is presented in reference [1]. The authors represented a DG-unit as a PV bus which is different from what radial distribution feeders are designed for. The authors implied that on-line systems including DG-units can achieve better reliability during power interruption situations to maintain supply continuity The authors stated that the simplest representation of DG-units operating in parallel with the system, especially in radial feeders, is as negative active and reactive power injections, independent of the system voltage at the terminal bus. When using multiple DG-units as PV units, it is unrealistic to manage these DG-units as available for dispatching because they may not be controlled by the main utility.

In reference [2] the optimal size and location of DG-unit (for planning purposes) based on a predetermined power loss reduction level (up to 25%) were proposed. The objective of the method was to reach that level with minimum net DG-unit cost i.e., DG-unit cost subtracted from saving. The maximum number and size of the DG-units found to be two and 40% of peak loads respectively. The solution was achieved using sequential quadratic programming.

Maximizing the voltage support in radial distribution feeders using DG-unit was discussed in [3]. The method used a voltage sensitivity index to determine the DG-unit optimal location. Then, DG-unit active and reactive powers were adjusted to obtain maximum voltage support. The weakest bus was identified using Thevenin's theorem.

Minimizing power loss by finding the optimal size, location and operation point of DG-unit was suggested in [4]. A sensitivity analysis relating the power loss with respect to DG-unit current injection was used to identify the DG-unit size and operation point. The proposed method tested for constant impedance and a constant current model. One of the test systems assumed that loads were uniformly distributed, which is rare in practical feeder systems. The location of the DG-unit was based on the assumption of downstream load buses, which may not be appropriate for different feeder configurations.

The authors of [5] employed the GA for Optimal Power Flow (OPF) to minimize the DG-unit's active and reactive power costs. Two examples of DG-unit optimization cases were considered, with and without reactive power injection. Significant reduction in the search space was attained by eliminating the DG-unit size. However, DG-unit dispatching can cause operational problems in the distribution feeders.

An algorithm was offered in [6] to maximize the reduction of load supply costs as well as operational schedules for all feeder load levels exploiting EP. The optimal solution was selected based on maximum cost reduction, which was

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attained through evaluating the cost of DG-unit supply scenarios based on the base case.

The authors of [7] proposed an analytical method to calculate the optimal DG-unit size. In addition, an approximated loss formula was suggested to identify the optimal DG-unit placement. The method offered was based on the exact loss formula. The power flow was applied twice, without and with DG-unit. The adopted DG-unit injected active power only.

In this paper, a modified artificial bee colony (ABC) algorithm is proposed to solve the DG-unit application problem. The ABC algorithm is a new meta-heuristic approach inspired by the intelligent foraging behavior of honey-bee swarm. Sample feeder systems are examined and the results are compared with those obtained using other methods. The results demonstrate that the proposed modification improves the solution quality and efficiency of the ABC algorithm.

II. Problem Formulation

An advantage of deploying DG-units in distribution networks is to minimize the total system real power loss while satisfying certain operating constraints. The power flow algorithm offered in [8] is applied in this paper. Consider, as shown in Fig. 1, a sample two bus system including DG-unit.

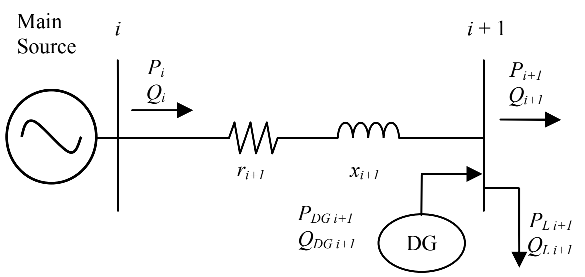

Fig. 1. Single line diagram of a two-bus system.

The mathematical formulation of the mixed integer nonlinear optimization problem for the DG-unit application is as follows:

- The objective function is minimizing the total system real power loss as follows:

$$Obj.Fun. = min \sum_{i=0}^{n} \left[\left(\frac{P_i^2 + Q_i^2}{V_i^2} \right) \times r_{i+1} \right] \tag{1}$$

- The equality constraints are the three nonlinear recursive power flow equations describing the system [8]:

$$P_i - \left(\frac{(P_i^2 + Q_i^2)}{V_i^2} r_{i+1} \right) - P_{L_{i+1}} + \mu_P \, AP_{i+1} - P_{i+1} = 0 \tag{2}$$

$$Q_i - \left(\frac{(P_i^2 + Q_i^2)}{V_i^2} x_{i+1} \right) - Q_{L_{i+1}} + \mu_Q \, RP_{i+1} - Q_{i+1} = 0 \tag{3}$$

$$V_{i+1}^2 = V_i^2 - 2(r_{i+1} \, P_i + x_{i+1} \, Q_i) + (r_{i+1}^2 + x_{i+1}^2) \frac{(P_i^2 + Q_i^2)}{V_i^2} \tag{4}$$

where,

μ_P Real power multiplier set to zero when there is no active power source or set to 1 when there is an active power source

μ_Q Reactive power multiplier set to zero when there is no reactive power source or set to ± 1 when there is a reactive power source

AP_{i+1} Active power magnitude injected at bus $i+1$.

RP_{i+1} Reactive power magnitude injected at bus $i+1$.

- The inequality constraints are the system's voltage limits i.e., ±5% of the nominal voltage value.

$$\left|V_{min}^{spec}\right| \le \left|V_i^{sys}\right| \le \left|V_{max}^{spec}\right| \qquad i = 0, 1, 2, \ldots, n \tag{5}$$

- In addition, the thermal capacity limits of the network's feeder lines are treated as inequality constraints:

$$S_{i,i+1}^{sys} \le S_{i,i+1}^{rated} \ge S_{i+1,i}^{sys} \qquad i = 0, 1, 2, \ldots, n \tag{6}$$

- The boundary (discrete) inequality constraints are the DG-unit' size (kVA) and power factor as follows:

$$\left|S_{DG}^{min}\right| \le \left|S_{DG}\right| \le \left|S_{DG}^{max}\right| \tag{7}$$

$$p.f._{DG}^{min} \le p.f._{DG} \le p.f._{DG}^{max} \tag{8}$$

Practical concerns in terms of DG-unit sizes and power factors are considered. Since the rounding-off issues of the DG-unit's size or p.f. are treated initially in the proposed method, the accuracy of the results is guaranteed. The preselected (discretized) DG-unit sizes are from 10-80% of system demands $\left(\sum_{i=0}^{n}\left|S_{L_{i+1}}\right|\right)$, approximated to integer values with a 100-step interval between sizes.

The DG-unit's p.f. sets to operate at practical values [9] i.e., unity, 0.95, 0.90 and 0.85 towards the optimal result. Moreover, the operating DG-unit's p.f. (i.e., lagging or leading) must be dissimilar to the bus's load p.f. at which the DG-unit is placed [10]. Consequently, the net total of both active and reactive powers of that bus (where DG-unit is placed) will decrease.

III. Artificial Bee Colony (ABC) Algorithm

The artificial bee colony (ABC) algorithm was introduced in 2005 by Karaboga [11]. Initially, it was proposed for unconstrained optimization problems. Then, an extended version of the ABC algorithm was offered to handle constrained optimization problems [12]. Furthermore, the performance of the ABC algorithm was compared with those of some other well-known population-based optimization algorithms, and the results and the quality of the solutions were outperformed or matched those obtained using other methods [12-17].

The colony of artificial bees consists of three groups of bees: employed, onlookers and scout bees. The employed bees are those which randomly search for food-source positions (solutions.) Then, by dancing, they share the information about that food source i.e., nectars' amounts (solutions' qualities), with the bees waiting in the dance area at the hive. Onlookers are those bees waiting in the hive's dance area. The duration of a dance is proportional to the nectar's content (fitness value) of the food source currently being exploited by the employed bee. Hence, onlooker bees watch various dances before choosing a food-source position according to the probability proportional to the quality of that food source. Consequently, a good food-source position (solution) attracts more bees than an inferior one. Onlookers and scout bees, once they discover a new food-source position (solution), may change their status to become employed bees. Furthermore, when the food-source position (solution) has been visited (tested) fully, the employed bee associated with it abandons it, and may once more become a scout or onlooker bee. In a robust search process, exploration and exploitation processes must be carried out simultaneously [11], [18]. In the ABC algorithm, onlookers and employed bees perform the exploitation process in the search space, while on the other hand, scouts control the exploration process. Inspired by the aforementioned intelligent foraging behaviour of the honey bee [11], the ABC algorithm was introduced.

The first half of the colony size of the ABC algorithm represents the number of employed bees, and the second half stands for the number of onlooker bees. For every food-source's position, only one employed bee is assigned. In other words, the number of food-source positions (possible solutions) surrounding the hive is equal to the number of employed bees. The scout initiates its search cycle once the employed bee has exhausted its food-source position (solution.) The number of trials for the food source to be called "exhausted" is controlled by the $limit$ value of ABC algorithm's parameter. Each cycle of the ABC algorithm comprises three steps: first, sending the employed bee to the possible food-sources' positions (solutions) and measuring their foods' nectar amounts (fitness values); second, onlookers selecting a food source after sharing the information from the employed bees in the previous step; third, determining the scout bees and then sending them into entirely new food-source positions.

The ABC algorithm creates a randomly distributed initial population of i solutions $(i = 1,2,..,E_b)$, where i signifies the size of population and E_b is the number of employed bees. Each solution x_i is a D-dimensional vector, where D is the number of parameters to be optimized. The position of a food-source, in the ABC algorithm, represents a possible solution to the optimization problem, and the nectar amount of a food source corresponds to the quality (fitness value) of the associated solution. After initialization, the population of the positions (solutions) is subjected to repeated cycles of the search processes for the employed, onlooker and scout bees $(cycle = 1,2,\dots,MCN)$, where MCN is the maximum cycle number of the search process. Then, an employed bee modifies the position (solution) in her memory depending on the local information (visual information) and tests the nectar amount (fitness value) of the new position (modified solution.) If the nectar amount of the new one is higher than that of the previous one, the bee memorizes the new position and forgets the old one. Otherwise, she keeps the position of the previous one in her memory. After all employed bees complete the search process, they share the nectar information of the food sources and their position information with the onlooker bees waiting in the dance area. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability related to its nectar amount. The same procedure of position modification and selection criterion used by the employed bees is applied to onlooker bees.

The greedy-selection process is suitable for unconstrained optimization problems. However, to overcome the greedy-selection limitation specifically in a constrained optimization problem [11], the Deb's constrained handling method [19] is adopted. It employs a tournament selection operator, where two solutions are compared at a time when the following conditions are imposed: 1) any feasible solution is preferred over an infeasible one, 2) among two feasible solutions, the one with better objective function value is preferred and 3) among two infeasible solutions, the one having the smaller constraint violation is preferred.

The probability of selecting a food-source p_i by onlooker bees is calculated as follows:

$$p_i = \frac{fitness_i}{\sum_{i=1}^{E_b} fitness_i} \tag{9}$$

where, $fitness_i$ is the fitness value of a solution i, and E_b is the total number of food-source positions (solutions) or, in other words, half of the colony size. Clearly, resulting from using eq. (9), a good food source (solution) will attract more onlooker bees than a bad one. Subsequent to onlookers selecting their preferred food-source, they produce a neighbour food-source position $i + 1$ to the selected one i, and compare the nectar amount (fitness value) of that neighbour $i + 1$ position with the old i position. The same selection criterion used by the employed bees is applied to onlooker bees as well. This sequence is repeated until all onlookers are distributed. Furthermore, if a solution i does not improve for a specified number of times (*limit*), the employed bee associated with this solution abandons it, and she becomes a scout and searches for a new random food-source position. Once the new position is determined, another ABC algorithm cycle (MCN) starts. The same procedures are repeated until the stopping criteria are met.

In order to determine a neighbouring food-source position (solution) to the old one in memory, the ABC algorithm alters one randomly chosen parameter and keeps the remaining parameters unchanged. In other words, by adding to the current chosen parameter value the product of the uniform variant [-1,1] and the difference between the chosen parameter value and other "random" solution parameter value, the neighbour food-source position is created according to the following expression:

$$x_{ij}^{new} = x_{ij}^{old} + u\left(x_{ij}^{old} - x_{kj}\right) \tag{10}$$

where, $k \neq i$ and both $\in \{1, 2, .., E_b\}$. The multiplier u is a random number between [-1,1] and $j \in \{1, 2, \dots, D\}$. When the food-source position has been abandoned, the employed bee associated with it becomes a scout. The scout produces a completely new food-source position as follows:

$$x_i^{j\,(new)} = min\, x_i^j + u\left(max\, x_i^j - min\, x_i^j\right) \tag{11}$$

where, eq. (11) applies for all j parameters and u is a random number between [-1,1]. If a parameter value produced using (10) and/or (11) exceeds its predetermined limit, the parameter can be set to an acceptable value [11]. In this paper, the value of the parameter exceeding its limit is forced to the nearest (discrete) boundary limit value associated with it. Furthermore, the random multiplier number u is set to be between [0, 1] instead of [-1,1].

It is clear from the preceding discussion that the ABC algorithm has the following control parameters: 1) the colony size CS, that consists of employed bees E_b plus onlooker bees O_b, 2) the *limit* value, which is the number of trails for a food-source position (solution) to be abandoned and 3) the maximum cycle number MCN.

IV. ABC Algorithm for DG-Unit Application Problem

The flowchart of the ABC algorithm is illustrated in Fig. 2. The solution steps of the proposed ABC algorithm for DG-unit application are described as follows:

1. Initialize the food-source positions x_i (solutions population), where $i = 1,2, \dots, E_b$.
2. Calculate the nectar amount of the population by means of their fitness values using:

$$fitness_i = 1/(1 + Obj.Fun._i) \tag{12}$$

   where, $Obj.Fun._i$ represents the response of eq. (1) at solution i.
3. Produce neighbour solutions x_{ij}^{new} for the employed bees by using eq. (10) and evaluate them as indicated in step 2.
4. Apply the selection process.
5. If all onlooker bees are distributed, go to step 9. Otherwise, go to the next step.
6. Calculate the probability values p_i for the solutions x_i using eq. (9)
7. Produce neighbour solutions x_{ij}^{new} for the selected onlooker bee, depending on the p_i value, using eq. (10) and evaluate them as step 2 indicates.
8. Follow step 4.
9. Determine the abandoned solution for the scout bees, if it exists, and replace it with a completely new solution $x_i^{j\,(new)}$ using eq. (11) and evaluate them as indicated in step 2.
10. Memorize the best solution attained so far.
11. If $cycle = MCN$, stop and print result. Otherwise follow step 3.

Clearly, employed and onlooker bees select new food sources in the neighbourhood of the previous one in their memory depending on visual information. Visual information is based on the comparison of food-source positions [14]. On the other hand, scout bees, without any guidance, while looking for a food-source position, explore a completely new food-source position.

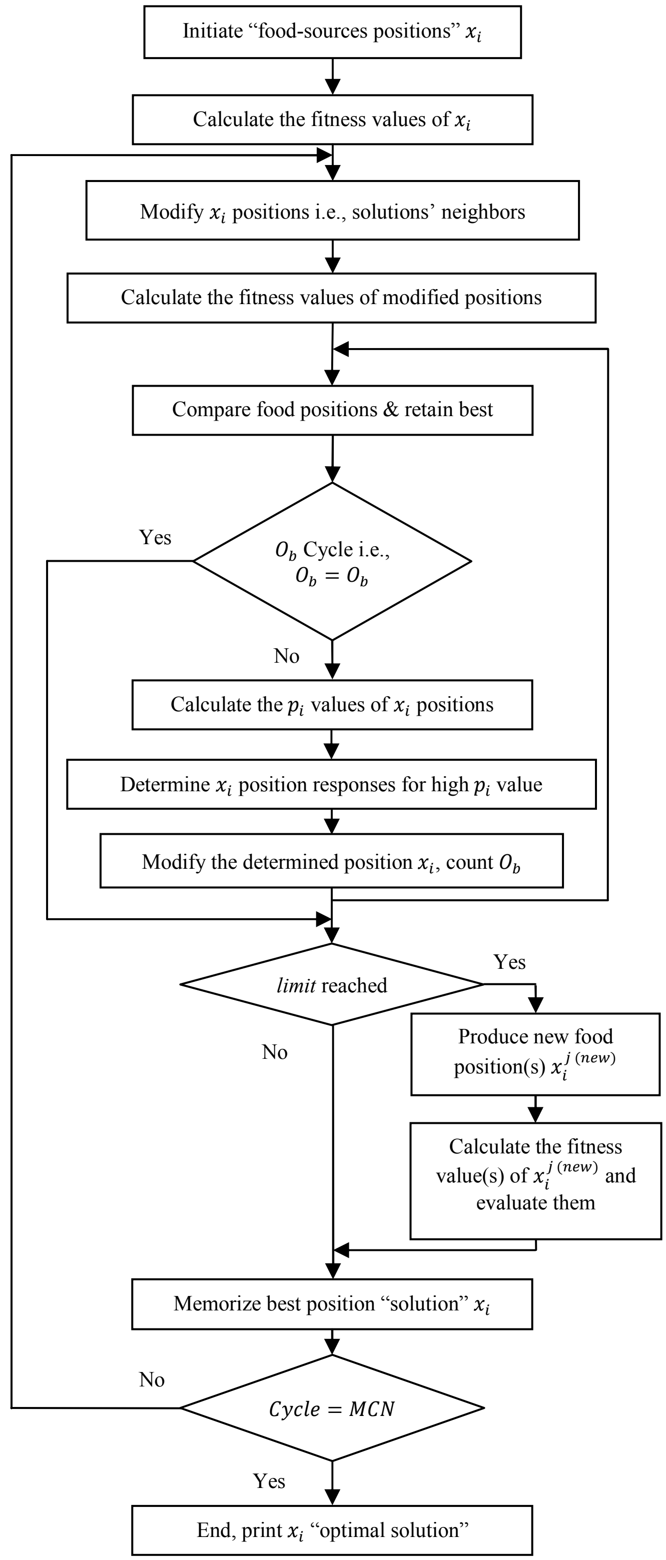

Fig. 2. Flowchart of the ABC algorithm.

Therefore, scouts are characterized, based on their behaviour, by low search costs and a low average in food-source quality. Occasionally, the scouts can be fortunate to discover rich, entirely unknown, food sources. In the case of artificial bees, the artificial scouts could have the fast discovery of the group of feasible solutions as a task [20].

Parameter-tuning, in meta-heuristic optimization algorithms, influences the performance of the algorithm significantly. Divergence, becoming trapped in local extrema and time-consumption are such consequences of setting the parameters improperly. The ABC algorithm, as an advantage, has few controlled parameters. Since initializing a population "randomly" with a feasible region is sometimes cumbersome, the ABC algorithm does not depend on the initial population to be in a feasible region. Instead, its performance directs the population to the feasible region sufficiently [12].

A. The Proposed Modified ABC Algorithm

The proposed neighboring search takes place during the onlooker search cycle. In other words, once the solution with high probability value is determined, all O_b recruit to search positions in the neighbourhood of the selected solution (food source), and then compare these neighbour nectar amounts with the old (selected) one, after that apply the selection process. This search cycle is repeated O_b times. The ABC algorithm in [11-17], [20], on the other hand, sends the onlooker bees one at a time to find a food-source position in the neighborhood of the selected one. The features of the proposed process are as follows: 1) it reduces the MCN and CS with insignificant impact on the solution quality resulting in accelerating the algorithm performance and, 2) it has good potential for problems with large (high-dimensional) decision space.

The controlled parameter (*limit*) is important in the ABC algorithm because it prevents the algorithm from being trapped in local extrema. Therefore, it is suggested in [11] that the $limit$ be taken as $0.5 \times CS \times D$. However, assume that one of the initial solutions was "fortunately" the optimal or near the optimal one, then after a predetermined number of trials this solution, intuitively, will never be improved; consequently the ABC algorithm will abandon this (presumed optimal) solution. To overcome this situation and to guarantee that the optimal solution, if it is discovered, is memorized at least once before releasing it, the proposed $limit$ value is set equal to $1 + O_b{}^2$.

V. Results and Discussion

To check the validity of the proposed ABC algorithm, the 33-bus and 69-bus radial distribution feeder systems were examined. In addition, the results were compared with those obtained using other methods. The substation voltage and load power factors in both tested systems were considered to be 1.0 per unit and lagging p.f. respectively. The proposed ABC algorithm implemented in C, and executed on an Intel® core™ 2 duo PC with 2.66-GHz speed and 4GB RAM.

Furthermore, the proposed ABC algorithm results are obtained after carrying out 30 independent runs for different cases. In other words, the initial population was randomly generated in each run by using different seeds.

To support the conclusion that the proposed ABC algorithm obtains very close results to the exact optimal ones, an exact optimal DG-unit method is created. The exact method provides the optimal result after examining all possible solution combinations and then retained the optimal one. Summary (default case) results of both tested feeder systems are listed in Table I.

TABLE I
Tested Systems Default Case Results

Feeder System	33-bus	69-bus
∑kW loss	202.668	224.8
∑kVar loss	135.147	102.157
$\|V_{min}\|$, p.u.	0.913082	0.90919
$\|V_{max}\|$, p.u.	1.0000	1.0000
$\sum\|S_{Load}\|$, kVA	4369.35	4660.2

- *33-bus System*

The total loads of the 33-bus system are 3720 kW and 2300 kVar. Data of this system is given in [21]. After carrying out all possible solution combinations using the exact method, the optimal solution of applying a DG-unit to satisfy the aforementioned objective function and constraints is recorded in Table II. It proved that the total real power loss after placing the optimal DG-unit became 68.88 kW, and the system $|V_{min}|$ improved to be 0.964 per unit. Clearly as Table II shows, the proposed ABC algorithms successfully attained the identical optimal result. Figure 3 illustrates the compensated results in terms of loss reductions and voltage profile improvements due to optimal DG-unit application. Obviously as Table II shows, the proposed modified ABC algorithm outperforms the ABC algorithm in terms of solution quality as well as CPU time. In other words, in every independent run the proposed algorithm reached the optimal solution with an average of 30% reduction in CPU time.

TABLE II
Simulation Results of ABC Algorithms over 30 Independent runs for the 33-bus Feeder System

Optimal*	**2900 kVA** with **0.85 leading p.f.** placed at **bus 25**							
Method	ABC				Modified ABC			
Setting	CS = 20, MCN = 30, $limit$ = 30				CS = 20, MCN = 30, $limit$ = 102			
Solution	2900 kVA with 0.85 leading p.f. placed at bus 25				2900 kVA with 0.85 leading p.f. placed at bus 25			
Stat.	**Best**	Worst	**Mean**	StDev	**Best**	Worst	**Mean**	StDev

Obj.Fun.	**62.88**	64.36	62.93	0.27	**62.88**	62.88	62.88	0.000
CPU (s)	3.3	5.6	**4.2**	---	1.7	3.6	**2.9**	---

* Refers to the optimal solution obtained using the exact method.

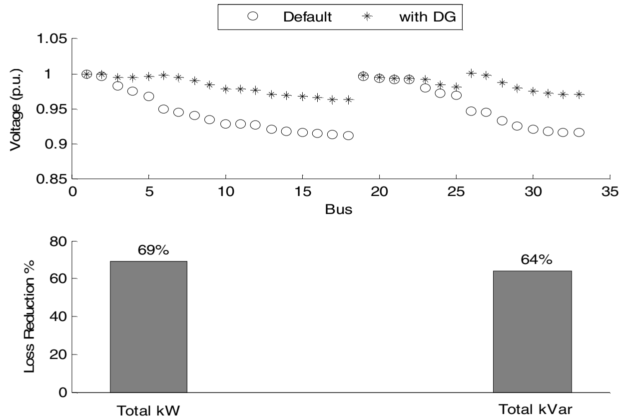

Fig. 3. Compensation results of the 33-bus system.

- *69-bus System*

The system demands are 3802.19 kW and 2694.60 kVar, and the data of the 69-bus system is in [22]. As Table III shows, the results of the proposed ABC algorithms match the one optimally obtained using the exact method. After placing the optimal DG-unit bus 61, the total real power loss became 23.92 kW, and the system $|V_{min}|$ enhanced by 0.0631 per unit. The compensated results in terms of loss reductions and voltage profile improvements due to optimal DG-unit application is demonstrated in Fig. 4. The proposed modified ABC algorithm successfully obtained the optimal solution in each run with an average CPU time reduction of 40% w.r.t. the ABC algorithm.

TABLE III
SIMULATION RESULTS OF ABC ALGORITHMS OVER 30 INDEPENDENT RUNS FOR THE 69-BUS FEEDER SYSTEM

Optimal*	**2200 kVA** with **0.85 leading p.f.** placed at **bus 61**							
Method	ABC				Modified ABC			
Setting	*CS* = 30, *MCN* = 20, *limit* = 45				*CS* = 30, *MCN* = 20, *limit* = 227			
Solution	2200 kVA with 0.85 leading p.f. placed at bus 61				2200 kVA with 0.85 leading p.f. placed at bus 61			
Stat.	**Best**	Worst	**Mean**	StDev	**Best**	Worst	**Mean**	StDev
Obj.Func.	**23.92**	25.82	24.07	0.48	**23.92**	23.92	23.92	0.000
CPU (s)	4.83	6.9	**5.7**	--	2.8	5.4	**3.4**	--

* Refers to the optimal solution obtained using the exact method.

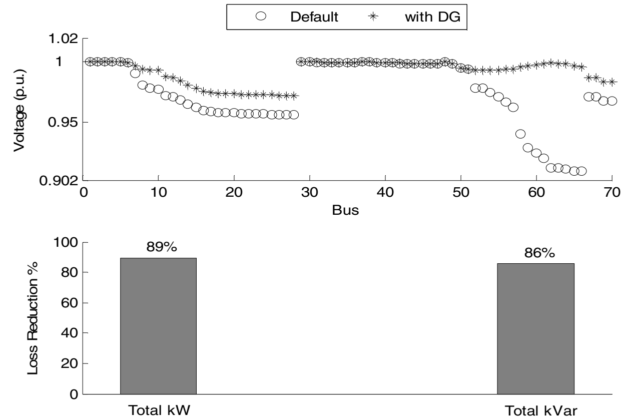

Fig. 4. Compensation results of the 69-bus system.

- *A Comparative Study*

The results of the proposed algorithm were compared with those obtained analytically in [24]. The DG-unit application in [24] was limited to supply real power only. Table IV summarizes the optimal solutions achieved by these methods. Observing Table IV, the compensated results of all algorithms at 69-bus system were virtually identical. However, slight improvements in the loss reduction were achieved by the proposed ABC and modified ABC algorithms.

TABLE IV
COMPARISON RESULTS OF OPTIMAL DG-UNIT APPLICATION

Feeder System	33-bus			69-bus		
Method	[24]	ABC	Modified ABC	[24]	ABC	Modified ABC
Optimal (bus)	6	6	6	61	61	61
DG size (kW)	2490	2400	2400	1810	1900	1900
Loss Reduction	47.3%	48.2%	48.2%	62.9%	63%	63%

To demonstrate the efficiency of the proposed modified ABC algorithm, its performance was compared with the ABC algorithm at different cases. Each case was evaluated after performing 30 independent runs i.e., with different seeds. In addition, each case has a preselected parameter-setting based on best/worst case scenario w.r.t. the modified ABC algorithm. Tables V and VI recorded the parameter-setting for each case applied to the 33-bus and 69-bus feeder system respectively.

TABLE V
CASES FOR PERFORMANCE COMPARISON OF 33-BUS FEEDER SYSTEM

Parameter	CS	MCN	(ABC) $limit$	(Modified ABC) $limit$
Case I	20	30	30	102
Case II	10	30	15	27
Case III	10	20	15	27
Case IV	10	10	15	27

TABLE VI
CASES FOR PERFORMANCE COMPARISON OF 69-BUS FEEDER SYSTEM

Parameter	CS	MCN	(ABC) $limit$	(Modified ABC) $limit$
Case I	40	20	60	402

Case II	30	20	45	227
Case III	20	30	30	102
Case IV	10	40	15	27

The solution quality of the proposed modified ABC outperformed the ABC algorithm by means of standard deviation and CPU time, as shown Fig. 5. Considering the worst case (case IV), the standard deviations of the modified and the ABC algorithms were 0.84 and 2 respectively. In addition, 0.57 second was the average CPU time required at that case. The variation between optimal and local solutions in the ABC algorithm, as Fig. 6 shows, was relatively large. However, the proposed algorithm proves its efficiency by means of the stander deviation and average CPU time at worst case (case IV) i.e., 0.016 and 3.4 second respectively.

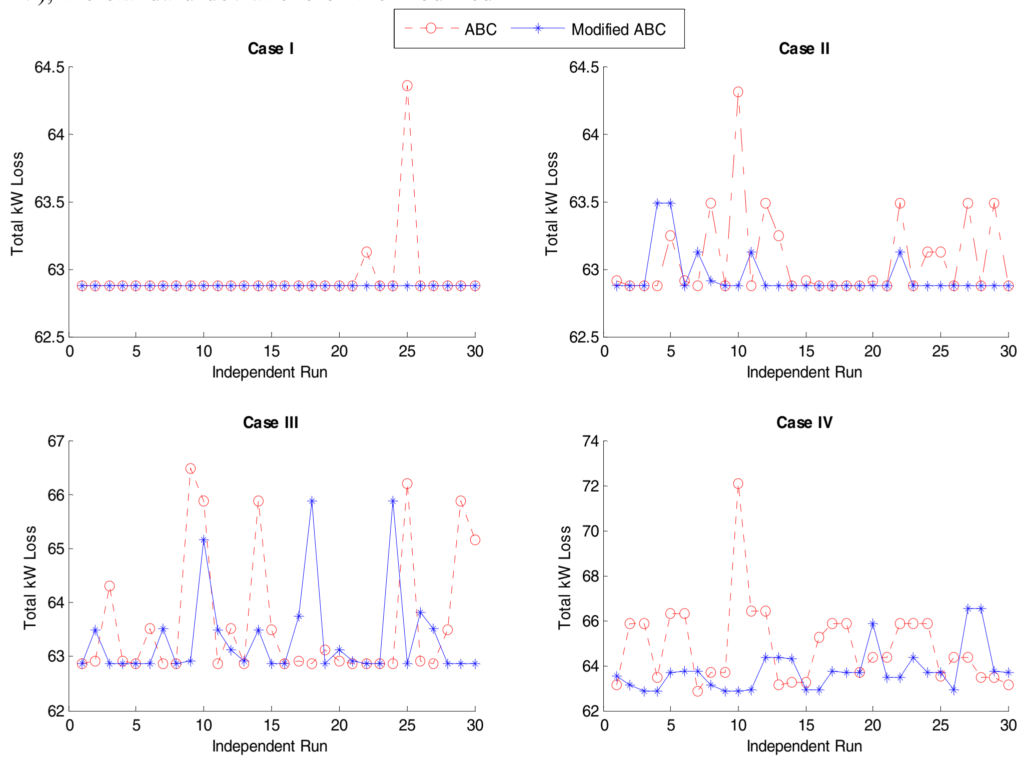

Fig. 5. Convergence characteristic of the 33-bus system due to ABC and modified ABC algorithms at different cases.

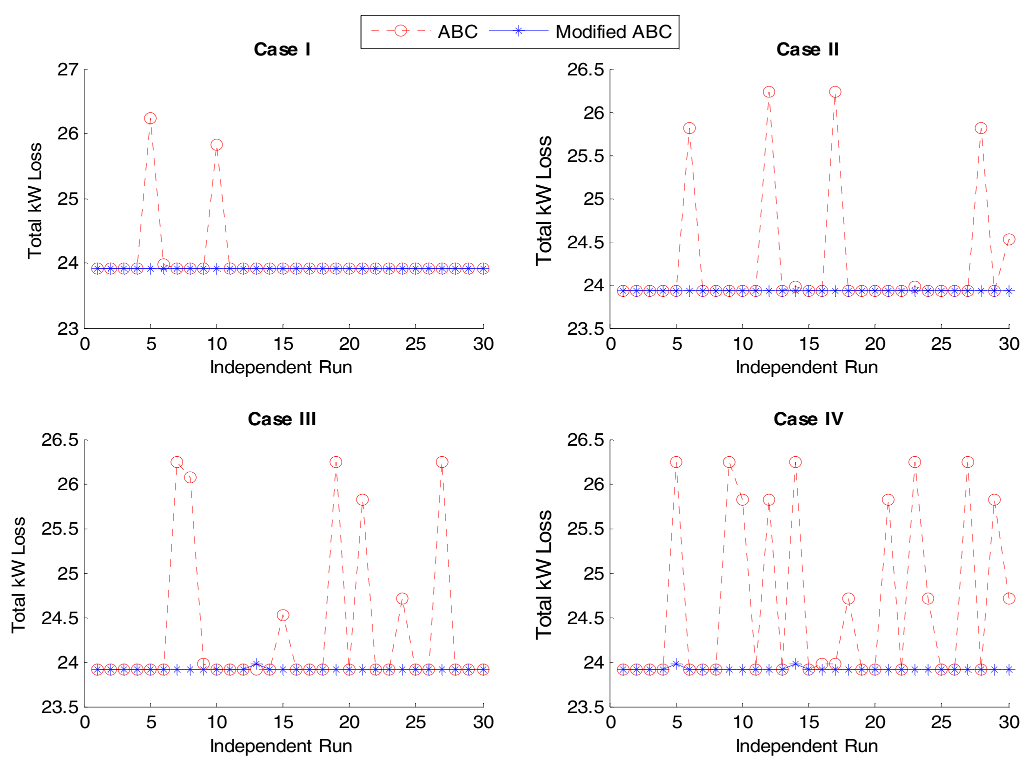

Fig. 6. Convergence characteristic of the 69-bus system due to ABC and modified ABC algorithms at different cases.

VI. CONCLUSION

In this paper, a modification to the new meta-heuristic population-based artificial bee colony algorithm (ABC) has been proposed. The objective function was to minimize the total system real power loss subjected to equality and inequality constraints. In other words, it is a mixed integer nonlinear optimization problem. Simulations were conducted on the IEEE 33-bus and 69-bus radial feeder systems. The proposed modified ABC algorithm successfully achieved the optimal solutions at different cases with advantages of less CPU time-consumption and high solution quality. In addition, the results of the proposed algorithm were either matched or outperformed those attained by other methods. The outcomes of the proposed modified ABC algorithm were encouraging to exploit it in large dimensional optimization problems for future research. The convergence tendency of the modified ABC in all cases shows that the proposed algorithm relatively converges with fewer MCN and CS numbers. Further insight of the solution quality achieved by performing 30 independent runs at different cases. As the statistical results were reported in Tables II and III, the efficiency of the proposed modified algorithm lies in the fact that the standard deviation of the results was equal to zero.

Evidently as Figures 5 and 6 demonstrated, the modified ABC algorithm has excellent solution quality and convergence characteristics. The performance of the proposed algorithm shows its superiority and potential for solving complex power system problems in future publications.

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