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Optimal power flow resolution using artificial bee colony algorithm based grenade explosion method

This paper exposes an Optimal Power Flow (OPF) problem resolution using a recent developed meta-heuristic algorithm called Artificial Bee Colony (ABC) algorithm based Grenade Explosion Method (GEM). From many previous researches, the ABC algorithm has proved its goodness at exploration process in the search space for better solutions, but it is weak at exploitation process. The proposed GEM associated with the ABC algorithm gives more ability to enhance the exploitation process by proposing two modified versions of basic ABC algorithm, which are GABC1 by embedding GEM in the employed bee phase and GABC2 by introducing GEM in the onlooker bee phase. The effectiveness of the two proposed algorithms in the present work is investigated by solving the optimization problems of objective functions for smooth, non-smooth and piecewise quadratic curves of fuel cost function, along with the minimization of voltage magnitude deviation and voltage stability index. The simulation results on IEEE 30 bus and IEEE 57 bus test systems are compared to those of other optimization techniques in literature, showing that the two proposed algorithms are capable to give higher quality solutions efficiently for a complex OPF problem.

Keywords: Artificial bee colony algorithm; Fuel cost; Grenade explosion method; Optimal power flow; Voltage magnitude deviation; Voltage stability index.

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1. Introduction

The Optimal Power Flow (OPF) problem has been widely handled by many researchers through the world, due to its importance for the planners and managers of electrical power systems. Its resolution has attracted more attention and guided the research works of engineers because of its significant impact on the security and economy of power systems. The OPF problem was firstly treated by Dommel et al. in the year of 1968 [1]. Since this year, the research in such area was not ceased to evolve. The main goal of the OPF problem is to determine the optimal settings of control variables related to the control equipments of electrical network to minimize a specified objective function with the satisfaction of equality and inequality constraints.

This optimization problem has been solved using several conventional optimization techniques such as Linear Programming (LP) [2], Quadratic Programming (QP) [3], Interior Point Method (IPM) [4] and Newton based method [5]. All these optimization methods rely on some mathematical assumptions, such as continuity, differentiability and convexity of the objective function and mathematical constraints. Practically, the OPF problem is highly non-linear, non-convex and non-smooth, presenting both continuous and discrete control variables, and discontinuities of the objective function. Therefore, the classical optimization techniques cited above are not suitable to deal with the real OPF problems. In order to

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overcome the drawbacks of conventional optimization methods, a number of Evolutionary Algorithms (EAs) have been suggested for solving the OPF problem such as Genetic Algorithm (GA) [6], Particle Swarm Optimization (PSO) [7], Ant Colony Optimization (ACO) [8], Differential Evolution (DE) [9], Gravitational Search Algorithm (GSA) [10], Biogeography-based Optimization (BBO) [11] and Grey Wolf Optimizer (GWO) algorithm [12]. Such algorithms are inspired from the attitude of insect or animal groups, simulating their collective behavior organization in the real life. For good solutions research, all EAs attempt to reach good balance between exploration and exploitation which are characterized by contradictory mechanisms. In many EAs applications, the lack of the best balance between the two main mechanisms of exploration and exploitation leads to the sufferance of the algorithm from premature convergence in the case of the complex problem resolution. To overcome this drawback, many efforts have been performed to get better performances of EAs, where an important number of their variants has been elaborated.

The Artificial Bee Colony (ABC) algorithm is a recently developed optimization method among EAs which is inspired from the behavior of honeybee groups for finding and exploiting the nectar of flowers [13-14]. In [15], the application results of the ABC algorithm by B. Akay and D. Karaboga were examined and compared to those of recent EAs. Unfortunately, the ABC technique is advantageous at exploration process, but it is weak at exploitation progress [16], where remarkable variants [17-23] developed from ABC base algorithm have been applied in the previous years to ameliorate its performances. For example, [24] introduces the Modified Artificial Bee Colony (MABC) algorithm developed by W.F. Gao et al. and inspired by DE algorithm, proposing a new search process to improve the exploitation capacity. In [25] G. Zhu et al. present Gbest Guided Artificial Bee Colony (Gbest-GABC) algorithm, inspired by PSO algorithm and by introducing the global best (gbest) solution in the investigation equation for the improvement of the exploitation mechanism. For the OPF problem resolution, ABC algorithm is applied in [26] for many cases of optimization and with different objective functions. In [27-28] the (MABC) and (Gbest-GABC) algorithms are proposed to improve the exploitation capacity for solving OPF problems, providing a more effective algorithms than basic ABC algorithm.

A new optimization technique is proposed by Ahrari et al. [29] called Grenade Explosion Method (GEM) in 2009, which is inspired by the mechanism of a grenade explosion. The author in [30] uses a number of standard benchmark functions to prove the efficiency of the presented GEM, the robustness and the simplicity of this method have been justified based on the simulation results. The GEM exhibits fast convergence and effectiveness for solving optimization problems of multimodal functions. In the previous years, the experimental tests on the GEM have attracted the attention of scientific researchers in the field of optimization [31]. Relying on the disadvantages of ABC algorithm and the benefits from GEM, C. Zhang et al. [32] propose two improved versions of ABC algorithm imitated from GEM in the year of 2015, namely GABC1 and GABC2, by embedding GEM in the employed bee phase and in onlooker bee phase, respectively, by attempting to enhance the exploitation capability of the conventional ABC algorithm. The effectiveness of both modified versions of ABC algorithm based GEM is confirmed by the authors in [32] by comprehensive experiments on many benchmark functions.

In this paper, the newly developed meta-heuristic techniques GABC1 and GABC2 are applied for solving OPF problems for many cases of objective functions as total fuel cost corresponding to various fuel cost curves (quadratic, quadratic with valve point loading effects and piecewise quadratic), voltage magnitude deviation and voltage stability index, with the determination of the optimal settings of the OPF control variables. The effectiveness of the two proposed optimization techniques is tested and validated on the IEEE 30 bus and IEEE 57 bus test systems. The simulation results are compared to those of other optimization methods reported in literature for the same test systems, showing the superiority of the solution quality based GABC1 and GABC2 algorithms.

2. Notation

The notation used throughout the paper is stated below.

Indexes:

x	Vector of state variables
u	Vector of control variables
P_{Gi}	Active power generation from unit i
Q_{Gi}	Reactive power generation from unit i
P_{Di}	active power of load demand at node i
Q_{Di}	reactive power of load demand at node i
G_{ij}	real part of the *i-jth* element of the bus admittance matrix
B_{ij}	imaginary part of the *i-jth* element of the bus admittance matrix
δ_{ij}	difference angle between voltage angles of *i-th* and *j-th* nodes
V_{Gi}	voltage magnitude of generator connected to bus i
T_i	tap setting of transformer i
Q_{Ci}	injected VAR power from compensator i
V_{Li}	Voltage magnitude of load bus i
S_{Li}	transmission line loading of line i
N_B	Number of total buses
N_{PQ}	Number of load buses
N_G	number of generators
N_L	number of transmission lines
N_T	number of regulating transformers
N_C	number of VAR compensators

3. Optimal power flow Problem formulation

The main goal for solving the OPF issue is to get the best settings of decision variables, by the minimization of one or more functions as objectives, and satisfying the set of equality and inequality constraints. The mathematical expression based OPF problem can be established as follows:

$$\begin{aligned} &min\ J(x,u) \\ &subject\ to: g(x,u)=0 \\ &\qquad\qquad h(x,u)\le 0 \end{aligned} \tag{1}$$

where J is the optimized function as objective, g is the set of equality constraints, h is the whole inequality constraints relying on the electrical network functioning conditions.
The vector x embodies the state variables, while the vector u contains the control variables.

3.1. State and control variables

The vector x consists of the slack bus active power P_{G1}, load voltages V_L , reactive powers of generators Q_G and transmission line loadings S_L.

$$x=[P_{G1},V_{L1},.....V_{LN_{PQ}},Q_{G1},...Q_{GN_G},S_{L1},....S_{LN_L}]^T \tag{2}$$

where N_{PQ}, N_G and N_L are the number of load buses, the number of generators and the number of transmission lines, respectively.
The vector u consists of active power outputs except at the slack bus, generator voltages V_G, transformer tap settings T and injected VAR powers Q_C.

$$u=[P_{G2}....P_{GN_G},V_{G1}.....V_{GN_G},T_1...T_{N_T},Q_{c1}....Q_{cNc}]^T \tag{3}$$

3.2. Technical constraints

3.2.1. Equality constraints

The equality constraints are the active and reactive power balance equations at all power system nodes, which are expressed in terms of $g(x)$ as follows:

$$P_{Gi}-P_{Di}-V_i\sum_{j=1}^{N_B}V_j(G_{ij}\cos\delta_{ij}+B_{ij}\sin\delta_{ij})=0 \tag{4}$$

$$Q_{Gi}-Q_{Di}-V_i\sum_{j=1}^{N_B}V_j(G_{ij}\sin\delta_{ij}-B_{ij}\cos\delta_{ij})=0 \tag{5}$$

$i=1,2,....N_B$, V_i and V_j are the voltage magnitudes at node i and node j, respectively.

3.2.2. Inequality constraints

Such technical constraints reflect the operating limits of electrical power system devices:

(a) Generation constraints: Real power outputs, reactive power outputs and generator voltages are restricted by the lower and upper limits as follows :

$$P_{Gi,\min}\le P_{Gi}\le P_{Gi,\max}\qquad i=1,...,N_G \tag{6}$$

$$Q_{Gi,\min}\le Q_{Gi}\le Q_{Gi,\max}\qquad i=1,...,N_G \tag{7}$$

$$V_{Gi,\min}\le V_{Gi}\le V_{Gi,\max}\qquad i=1,...,N_G \tag{8}$$

(b) Transformer constraints: Transformer tap settings are restricted by the lower and upper limits :

$$T_{i,\min}\le T_i\le T_{i,\max}\qquad i=1,...,N_T \tag{9}$$

(c) Security constraints: These include the constraints of voltages at load buses and transmission line loadings as follows:

$$V_{Li,\min} \le V_{Li} \le V_{Li,\max} \qquad i=1,\ldots,N_{PQ} \tag{10}$$

$$S_{Li,\min} \le S_{Li} \le S_{Li,\max} \qquad i=1,\ldots,N_{L} \tag{11}$$

(d) VAR sources constraints: these contain switchable VAR sources limits:

$$Q_{Ci,\min} \le Q_{Ci} \le Q_{Ci,\max} \qquad i=1,\ldots,N_{C} \tag{12}$$

3.3. Handling of technical constraints

This issue involves equality and inequality constraints:

3.3.1. Handling of equality constraints

Equality constraints described by (4) and (5) are forced by power flow program execution based Newton–Raphson method. There is no need for incorporating such constraints in the augmented objective function.

3.3.2. Handling of inequality constraints

The most common process to handle inequality constraints is their introduction in the objective function as penalty functions and the original constrained optimization problem becomes an unconstrained one.

To handle the inequality constraints of state variables, including slack bus real and reactive power, load bus voltage magnitudes and transmission line loading, the augmented objective function (fitness function) can be defined as:

$$J_{aug} = J + \lambda_P (P_{G1} - P_{G1}^{\lim})^2 + \lambda_V \sum_{i=1}^{N_{PQ}} (V_{Li} - V_{Li}^{\lim})^2 + \lambda_Q \sum_{i=1}^{N_G} (Q_{Gi} - Q_{Gi}^{\lim})^2 + \lambda_S \sum_{i=1}^{N_L} (S_{li} - S_{li}^{\lim})^2 \tag{13}$$

where λ_P, λ_Q, λ_V and λ_S are the penalty factors, and x^{lim} is the limit value of the state variables x given as :

$$x^{\lim} = \begin{cases} x^{\max} & if \quad x > x^{\max} \\ x^{\min} & if \quad x < x^{\min} \end{cases} \tag{14}$$

4. Artificial bee colony algorithm based GEM

4.1 Overview on artificial bee colony algorithm

The artificial bee colony algorithm is a new optimization technique developed by Karaboga in 2005 [33], inspired from foraging behavior of real bees for treating numerical optimization problems. The honeybee swarm activity is based on the food sources research organized by three genuses of bee: employed bees, onlooker bees and scout bees [34]. Each genus of bees takes care of a well defined task. The research process starts by sending employed bees to the food sources; such bees must share information about the identified food sources with onlooker bees waiting in the hive. In the ABC algorithm, each food source position represents a proposed solution to the optimization problem in the area of research, and the amount of nectar in the food source reflects the fitness value $fitness_i$ of the *i-th* food source locality. The number of food sources (*SN*) in the search space is equal to the number of employed bees and to the number of onlooker bees. The onlooker bees borrow the information about food sources, through famous dances received from employed bees and known as waggle dances. The onlooker bees select the fit food sources based on the informations collected from employed bees, resulting from the probability p_i of the *i-th* food source to be selected indicated in (15):

$$p_i = \frac{fitness_i}{\sum_{j=1}^{SN} fitness_j} \tag{15}$$

The ABC algorithm consists of four stages: initialization, employed bee phase, onlooker bee phase and scout bee phase. One cycle corresponds to last three phases, where the algorithm is limited to a Maximum Cycle Number (MCN).
In the phase of initialization, *SN* number of food sources is generated randomly on *D*-dimensional vector of search space. The initial position of the *i-th* food source can be evaluated by the expression (16):

$$x_{ij} = x_{j,\min} + rand(0,1).(x_{j,\max} - x_{j,\min}) \tag{16}$$

where x_{ij} is the *j-th* component of the *i-th* initial solution; $x_{j,min}$, $x_{j,max}$ are the minimum and maximum ranges of the *j-th* component $(j=1,2,....D)$ of X_i vector $(i=1,2,...SN)$; $rand(0,1)$ is uniformly distributed random number in the interval of (0,1).
After the phase of initialization, each solution is evaluated employing the objective function $F(X_i)=F_i$. The fitness function is given by:

$$fitness_i = \begin{cases} \dfrac{1}{1+F(X_i)} & if\ F(X_i) \geq 0 \\ 1+abs(F(X_i) & if\ F(X_i) < 0 \end{cases} \tag{17}$$

In employed bee or onlooker bee phase, further to an employed bee discovery or onlooker bee selection of food source X_i, both bee types exploit a neighboring food source V_i, by changing one parameter among *D* components of the solution X_i and updating the position using the relation (18):

$$v_{ij} = x_{ij} + \Phi_{ij}.(x_{ij} - x_{kj}) \tag{18}$$

Where x_{ij}, v_{ij} indicate the old and the new position of the *i-th* food source for the *j-th* component respectively, $i=1,2,...SN;\ j=1,2,....D$ and x_{kj} is the *k-th* randomly chosen food source solution for the *j-th* index $(k=1,2,...SN)$ where $k \neq i$. Φ_{ij} is an uniformly distributed random number in the interval of [-1,1].
The new food source V_i is compared with the old one X_i and each bee remembers the new food source if it is better than old one, otherwise the old position is preserved in the memory (greedy selection mechanism) [33, 34].
A Trial Counter (TC) is assigned to each food source, which is set to zero if the new food source is better than old one in both employed and onlooker bee phases, otherwise this TC is incremented by 1.

In the scout bee phase, if a food source quality cannot be enhanced after a predetermined number of trials called *Limit*, the corresponding food source is abandoned and replaced with new food source discovered by scout bee. The new position of the food source is generated by random process by applying the relation (16).
The main steps of the ABC algorithm are showed as below:

Step 1: Preselect the algorithm parameters: *D*, *SN*, *Limit* and *MCN*
Step 2: Initializing the food source positions using (16)
Step 3: Evaluating the quality of food sources by applying (17)
Step 4: Preset cycle=1
Step 5: create new food sources by employed bees and the evaluation is assigned to each one, then a greedy selection rule is applied (employed bee phase)
for i=1 to SN
    create a new food source V_i with respect to old food source X_i (founded on X_k, $i \neq k$) using (18)
    evaluate the fitness of the new food source V_i by applying (17)
    implement the greedy selection between V_i and X_i
end for
Step 6: assign the probability value for each food source accomplished by (15)
Step 7: A new food source is produced by each onlooker bee based on the probability of the corresponding old food source (onlooker bee phase)
for i=1 to SN
    if $rand\ (0,1) < p_i$
    create a new food source V_i with respect to old food source X_i (founded on X_k, $i \neq k$) using (18)
    evaluate the fitness of the new food source V_i by applying (17)
    implement the greedy selection between V_i and X_i
    end if
end for
Step 8: Discover the food source which is abandoned based on its TC and replace it with a new food source
    created randomly by scout bee (scout bee phase) using (16)
for i=1 to SN
    if $TC(X_i) > Limit$
    create a new food source X_i based on (16)
    end if
end for
Step 9: the global best food source obtained so far is memorized
Step 10: if the number of cycles reach MCN then end, otherwise cycle=cycle+1 and go to the step 5

4.2 Grenade explosion method

The algorithm of GEM [29] is inspired by the mechanism of a grenade explosion, where objects in neighborhood of radius Re are affected by shrapnel hits. Damage induced by the piece of shrapnel hitting an object is evaluated. A considerable evaluation of damage for each piece in an area signifies the existence of valuable objects in such area. To increase the damage, the next grenade must be thrown in the proximity of the greatest damage. This process will lead to find the best place for throwing the grenade. Although the objects located in the vicinity of the current location of the grenade are more qualified to be damaged, the most far away objects are endowed to be affected based on the selection of the higher value of R_e. This process can provide the best location to throw grenades, even if the chips can not discover this location in the first iterations. All the damage produced by the coup is given by the "fitness" related to the solution, the whole search domain is covered by radius of explosion where the regions to be explored are exploited for finding the global minimum. At each iteration and after the throwing of shrapnel in perpendicular directions, the collected informations are analyzed and the probable optimal direction to examine for finding a best solution is indicated. The rest of shrapnel are then thrown along biased random directions, which mean these directions are biased towards the Optimal Search Direction (OSD) [30].

4.3 Two modified ABC algorithms inspired by GEM

In [32] the author et al. incorporate GEM mechanism into ABC algorithm by releasing two optimization techniques named GABC1and GABC2. The two techniques avoid to choose a random direction among all dimensions of solution but the selection is based on the OSD in the employed or onlooker bee phase in the wish that the movement is collective towards the optimal position. It is noted that the quantity of explored shells per grenade must be considerable sufficiently so that the far away solution zones are examined by exploring the new fittest intervals, and therefore the algorithm can escape from the local optimum. In the interest of a simplified algorithm, the adjustment of GEM parameters is ignored and the choice of only one grenade and D pieces of shell in one cycle of GABC1 or GABC2 is considered [32].
In employed bee phase or onlooker bee phase of GABC1 or GABC2, D (number of dimensions) pieces of shrapnel must be launched in all directions (i.e. by exploiting one dimension by only one shell), in the goal to collect informations in the proximity of the currently adopted grenade location (old food source), meantime, the evaluation of each candidate food source is accomplished by an employed bee or onlooker bee based on the induced damages (fitness) from the throw of shrapnel on a direction (dimension), then a decision is made on a new candidate food source related to the most intensive damage (choose the highest fitness) and that for all dimensions, this process can lead the algorithm with the selection of the OSD to converge more quickly to the global or near global solution.
Therefore, in either of algorithms GABC1 or GABC2, a new proposed solution relying on the OSD for an employed bee or onlooker bee is created based on:

$$\begin{cases} v_{iOSD} = x_{iOSD} + \Phi_{iOSD}.(x_{iOSD} - x_{kOSD}) \\ s.\ t\ fit(V_{iOSD}) = \max\ \{fit(V_{it})\ \mid\ t = 1,2,....,D\} \end{cases} \tag{19}$$

where $k \in \{1,2,\ldots,SN\}$ is a random index selected for $k \neq i$; $OSD \in \{1,2,\ldots,D\}$ indicates the optimal search dimension; Φ_{iOSD} is randomly opted number in the interval [-1, 1]; V_{it} represents a new candidate food source V_i produced by just modifying the variable of old food source X_i in dimension t, namely $v_{it} \neq x_{it}$, while the rest of V_{it} keep the same value as X_{it}; V_{iOSD} has a similar meaning as V_{it} and also indicates V_i obtains the maximum fitness in dimension OSD instead of other dimensions. The dimension OSD may be different from or the same as j shown in (18). For example, assuming $SN=3$, $D=3$, $i=1$ and $k=3$. Hence $X_1=\{x_{11}, x_{12}, x_{13}\}$, $fit(V_{1OSD})=max\{fit(V_{11}), fit(V_{12}), fit(V_{13})\}$, where $V_{11}=\{v_{11},x_{12},x_{13}\}$, $V_{12}=\{x_{11},v_{12},x_{13}\}$, $V_{13}=\{x_{11},x_{12},v_{13}\}$, compute v_{11}, v_{12} and v_{13} using (18) and corresponding $fit(V_{11})$, $fit(V_{12})$ and $fit(V_{13})$, using (17) respectively; if $fit(V_{11})$ is the maximum among the three fitness values, then OSD=1 and $V_{1OSD}=V_{11}$, otherwise OSD=2 and $V_{1OSD}=V_{12}$ or OSD=3 and $V_{1OSD}=V_{13}$ [32]. In the same manner as in the basic ABC algorithm, after the determination of the new candidate solution (food source) in the proximity of its currently associated food source using (17) and (19) (in GABC1 or in GABC2), a greedy selection process is performed between the old food source and the new one. All steps of GABC1 and GABC2 stay the same except for step 5 and step 7 respectively (the main differences from ABC are highlighted in bold):

Step5: **Each food source associated to each employed bee is examined by producing and evaluating new food sources and that for all dimensions, the OSD is then determined with the fittest new competitive food source using (17) and (19)**, the greedy selection mechanism is then applied {employed bees' phase}:

for i=1 to SN
    for t=1 to D
        Produce a new food source V_{it} from X_i (based on X_k, $i \neq k$) using (16)
        Calculate the fitness of a food source V_{it} using (15)
        if t=1
            $V_{iOSD}=V_{i1}$
            $fit(V_{iOSD})=fit(V_{i1})$
            OSD=1
        else
            if $fit(V_{it})>fit(V_{iOSD})$
                $V_{iOSD}=V_{it}$
                $fit(V_{iOSD})=fit(V_{it})$
                OSD=t
            end if
        end if
    end for
    apply the greedy selection between the new food source and old one
end for

Step7: **Each food source associated to each onlooker bee is examined by producing and evaluating new food sources and that for all dimensions, the OSD is then determined with the fittest new competitive food source using (17) and (19)**, the greedy selection mechanism is then applied {onlooker bees' phase}:

for i=1 to SN
    if rand (0,1) < p_i
        for t=1 to D
        Produce a new food source V_{it} from X_i (based on X_k, $i \neq k$) using (16)
        Calculate the fitness of a food source V_{it} using (15)
            if t=1
                $V_{iOSD}=V_{i1}$
                $fit(V_{iOSD})=fit(V_{i1})$
                OSD=1
            else
                if $fit(V_{it})>fit(V_{iOSD})$
                    $V_{iOSD}=V_{it}$
                    $fit(V_{iOSD})=fit(V_{it})$
                    OSD=t
                end if
            end if
        end for
    apply the greedy selection between the new food source and old one
    end if
end for

The framework of ABC algorithm based GEM is depicted in Fig.1.a, while the flowchart is shown in Fig. 1.b for both GABC1 and GABC2 algorithms [32].

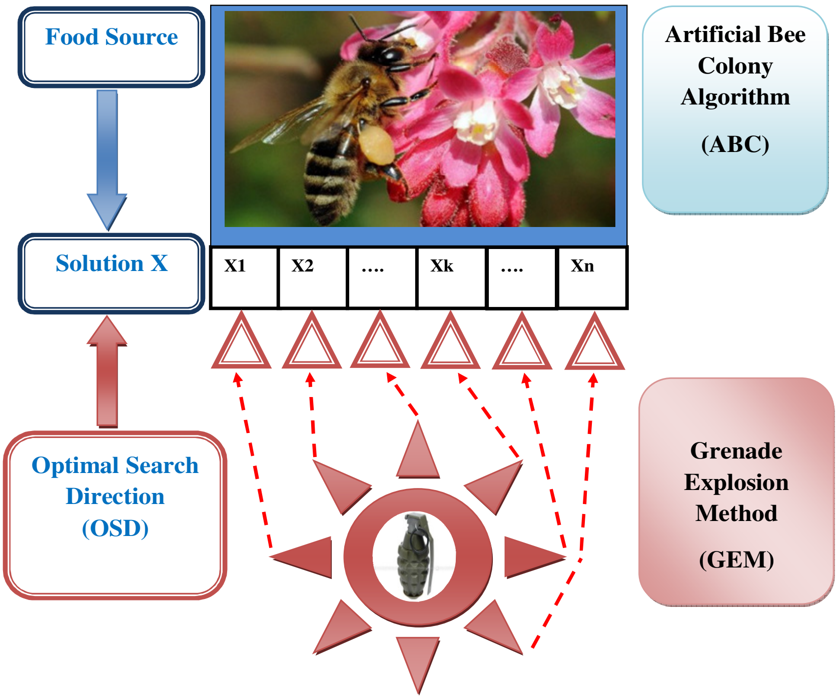

Fig.1.a Concept of ABC algorithm based GEM

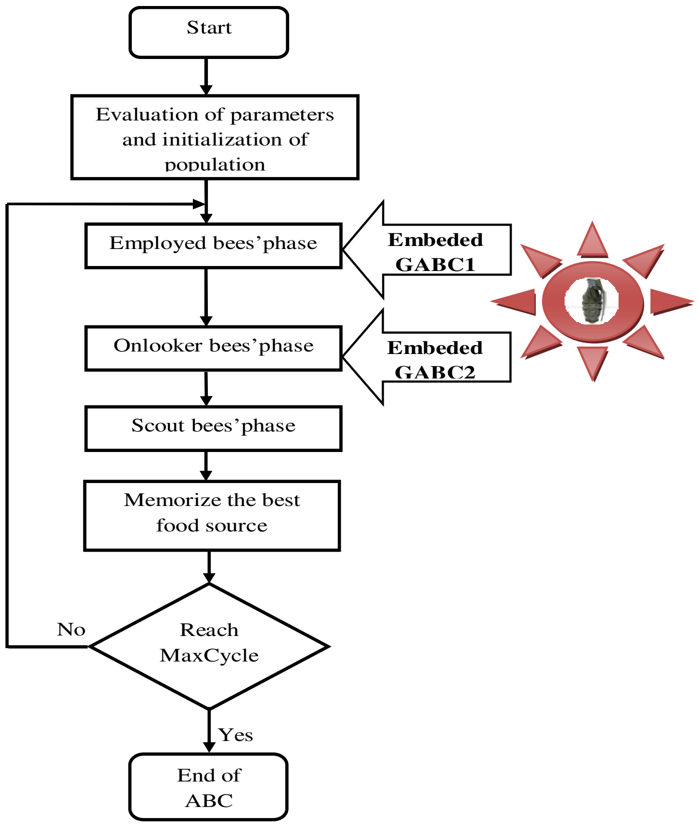

Fig.1.b Flowchart of ABC algorithm based GEM

5. Artificial bee colony algorithm based GEM applied to the OPF problem

This section discus the application of the ABC algorithm based GEM to the OPF problem on the modified IEEE 30-bus and IEEE 57-bus test systems for many cases of study. The MATLAB 7.9 software is used to develop and to implement the proposed algorithms.

5.1 IEEE 30 bus test system

In order to test the efficiency and robustness of the two proposed algorithms GABC1 and GABC2, the examination of several objective functions is accomplished from case1 to case5 in the conventional OPF problem state for IEEE 30 bus test system. The parameters of the proposed algorithm are tuned as follows: *SN*=10, *Limit*=80 and *MCN*=100. The number of parameters of the problem to be optimized *D* is adjusted based on the number on control variables related to the test system. This test system contains six generators at buses 1, 2, 5, 8, 11 and 13, four transformers with off-nominal tap ratio at branches 6–9, 6–10, 4–12 and 28–27 and shunt VAR compensators located in buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 with lower and upper injected reactive power 0 and 5 MVAR respectively [35]. The total system demand is (2.834+j1.262) p.u at 100 MVA base. The maximum and minimum voltage magnitudes of all generation buses are considered to be 1.10 – 0.95 in p.u. The lower and upper limits of all transformer taps are respectively set to 0.9 and 1.1 p.u, respectively. For each case of optimization problem, each proposed approach has been applied to solve the OPF problem for 30 independent test runs.
The considered cases are as follows:

5.1.1 Quadratic fuel cost minimization (case1):

In this case of study, the total fuel cost minimization is considered for the objective function *J* taking a quadratic aspect in the following form:

$$J = \sum_{i=1}^{N_G} F_i(P_{Gi}) = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \tag{20}$$

where a_i, b_i and c_i are the cost coefficients of the *i-th* generator, The values of these coefficients are given in Table 1 [36]. The active and reactive power limits for IEEE 30 bus test system are presented in the same table cited previously.

Table 1 Power generation limits and cost coefficients for IEEE 30 bus test system

Generation Bus	Pg^{min} (MW)	Pg^{max} (MW)	Qg^{min} (MVAR)	Qg^{max} (MVAR)	a ($/hr)	b ($/MW.hr)	c.10-4 ($/MW².hr)
1	50	200	-20	200	0	2.00	37.5
2	20	80	-20	100	0	1.75	175.0
5	15	50	-15	80	0	1.00	625.0
8	10	35	-15	60	0	3.25	83.0
11	10	30	-10	50	0	3.00	250.0
13	12	40	-15	60	0	3.00	250.0

The fast convergence of objective function (total fuel cost) for this case obtained by the proposed GABC1 and GABC2 algorithms is shown in Fig. 2. The best optimal total fuel cost is assigned to GABC1 algorithm even GABC2 algorithm starts with an excellent initial value of objective function. The optimal control variables by applying GABC1 (best results than GABC2) are illustrated in Table 2.

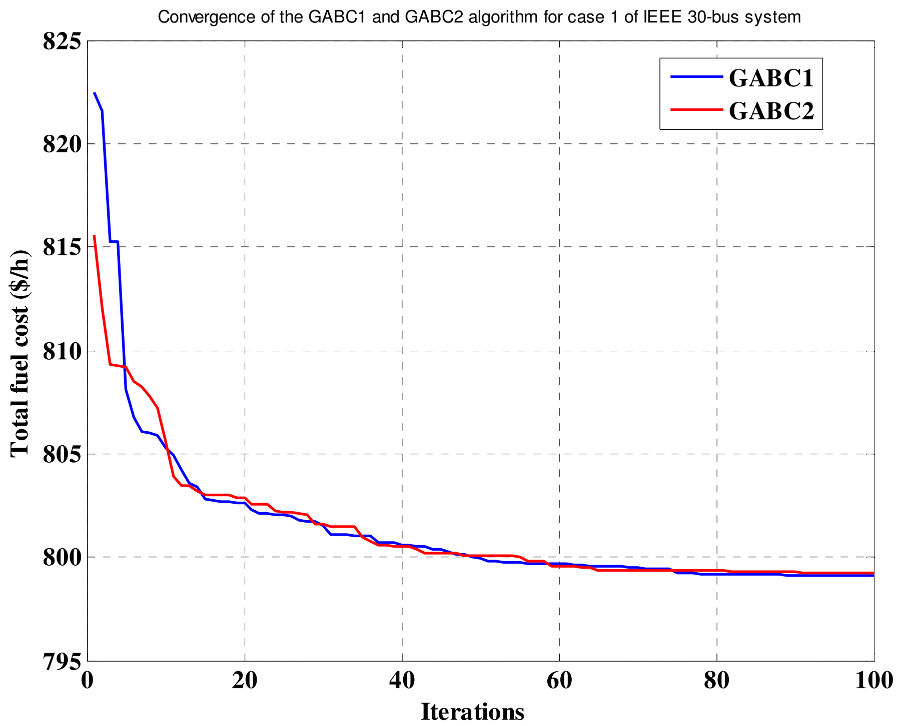

Fig. 2 Convergence of GABC1 and GABC2 algorithms for Case1

To evaluate the effectiveness of the proposed algorithms, the minimum, average and maximum of optimal total fuel cost using GABC1 and GABC2 (for 30 runs) is compared to other results given by several methods in literature and summarized in Table 3. The GABC1 algorithm provides a minimum fuel cost 799.0927 $/h, which is less than the results given by the remarkable algorithms given by Biogeography Based Optimization (BBO) [38], PSO-Nelder–Mead algorithm (PSO–NM) [40] and DE [9]. While GABC2 algorithm gives 799.1559 $/h, which is less by comparison to the result of the conventional ABC [37], Adaptive Real Coded Biogeography-Based Optimization (ARCBBO) [39], Real Coded BBO (RC-BBO) [39], Gbest-ABC [41] and Improved Evolutionary Programming (IEP) [41] algorithms. The best solution corresponding to GSA method [35] 798.675143 $/h is an infeasible solution because the reactive power generation limits of generators at buses 2 and 8 are violated (are found to be, respectively, -58.9227 MVAr and 101.0024 MVAr, the corresponding limits are -20 and 50 MVAr). The solution related to Hybrid Fuzzy Particle Swarm Optimization and Nelder–Mead (HFPSO-NM) algorithm 794.9545 $/h is infeasible describing limit violations for reactive power generated in slack bus -53.36 MVAr (limited to -20 MVAr), reactive power injected by VAR compensators in buses 20, 21 and 24 (5.44, 8.72 and 5.30 MVAr, respectively, with Q_{cmax}=5 MVAr) and voltage magnitude in generation buses 8 and 11 (1.11 p.u). The voltage profile in the optimal state for this case of study is represented in Fig. 3.

5.1.2 Voltage profile improvement with fuel cost minimization (case2)

The voltage magnitude is an indicator of service quality and security, which is considered in this case of study. The objective function J is a combination of the total fuel cost and the voltage deviation function of load buses from 1 per unit. The overall objective function can be expressed as [35]:

$$J = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) + K_{pv} . \sum_{k=1}^{N_{PQ}} \left| V_{Lk} - 1 \right| \tag{21}$$

where K_{pv} is the weighting factor which is set to 100 to balance two objectives without dominance of one objective in relation to another. Both objectives are minimized considering all constraints described by (6)-(12). The optimal setting of control variables and objectives are illustrated in Table 2 for case2 reserved to GABC1 algorithm which dominate GABC2 algorithm due to its solution quality.

Table 2 Optimal settings of the control variables and objectives for cases 1-5

Control variables & Objectives	Case1 (GABC1)	Case2 (GABC1)	Case3 (GABC2)	Case4 (GABC1)	Case 5 (GABC2)
P_{G1} (MW)	177.3376	175.6217	140.0000	175.7193	199.5984
P_{G2} (MW)	48.6060	49.0279	55.0000	49.9298	20.0000
P_{G5} (MW)	21.2689	21.9877	24.2242	20.8879	23.0680
P_{G8} (MW)	21.1075	21.5189	35.0000	21.4058	26.2224
P_{G11} (MW)	11.6481	12.1063	18.1102	11.6032	12.0096
P_{G13} (MW)	12.0797	12.9697	17.9697	12.8324	12.0000
V_{G1} (p.u)	1.1000	1.0395	1.0759	1.0845	1.1000
V_{G2} (p.u)	1.0888	1.0210	1.0601	1.0690	1.0796
V_{G5} (p.u)	1.0614	1.0109	1.0328	1.0474	1.0554
V_{G8} (p.u)	1.0680	0.9936	1.0414	1.0469	1.0677
V_{G11} (p.u)	1.1000	1.0828	1.1000	1.1000	1.0988
V_{G13} (p.u)	1.1000	0.9918	1.0616	1.0495	1.0711
T_1	1.0247	1.1000	1.0175	1.1000	0.9701
T_2	0.9000	0.9000	0.9051	0.9179	1.0680
T_3	0.9859	0.9533	0.9836	0.9810	1.0269
T_4	0.9614	0.9703	0.9612	0.9481	0.9872
$Q_{c\,10}$ (MVAR)	1.5029	3.4249	--	5.0000	--
$Q_{c\,12}$ (MVAR)	4.6766	3.6167	--	5.0000	--
$Q_{c\,15}$ (MVAR)	2.8670	5.0000	--	5.0000	--
$Q_{c\,17}$ (MVAR)	5.0000	2.3510	--	5.0000	--
$Q_{c\,20}$ (MVAR)	5.0000	5.0000	--	4.7734	--
$Q_{c\,21}$ (MVAR)	4.4287	4.2156	--	5.0000	--
$Q_{c\,23}$ (MVAR)	4.5794	3.9902	--	5.0000	--
$Q_{c\,24}$ (MVAR)	5.0000	5.0000	--	4.7694	--
$Q_{c\,29}$ (MVAR)	1.7787	3.1867	--	4.3685	--
Fuel cost ($/h)	**799.0927**	**803.8679**	**647.0794**	**800.5694**	**918.4351**
Power losses (MW)	8.6478	9.8321	6.9041	8.9784	9.4985
Voltage deviations	1.8732	**0.1045**	0.7786	1.2751	0.7527
L_{max}	0.2243	0.2730	0.2077	**0.1179**	0.2401

Table 3 Comparison of GABC1 and GABC2 with several optimization methods for case1

Methods	Fuel cost ($/h)			*Limit violations of variables for infeasible solutions
	Min	Average	Max	
GABC1	**799.0927**	799.5541	800.4296	
GABC2	799.1559	799.6531	800.8867	
ABC [37]	800.6600	800.8715	801.8674	
GSA [35]	798.675143[a]	798.913128	799.028419	*Reactive power Q_{G2} and Q_{G8}
BBO [38]	799.1116	799.1985	799.2042	
ARCBBO [39]	800.5159	800.6412	800.9262	
RCBBO [39]	800.8703	802.02	802.9431	
PSO-NM [40]	799.1030	NA	NA	
HFPSO-NM [40]	794.9545 [a]	NA	NA	*Reactive power : generation Q_{G1} and injection in buses 20 and 24, Voltage magnitude : in buses 8 and 11
Gbest-ABC[41]	800.0963	800.1526	800.3420	
IEP [41]	800.41	NA	NA	
DE [9]	799.2891	NA	NA	

a: infeasible solution

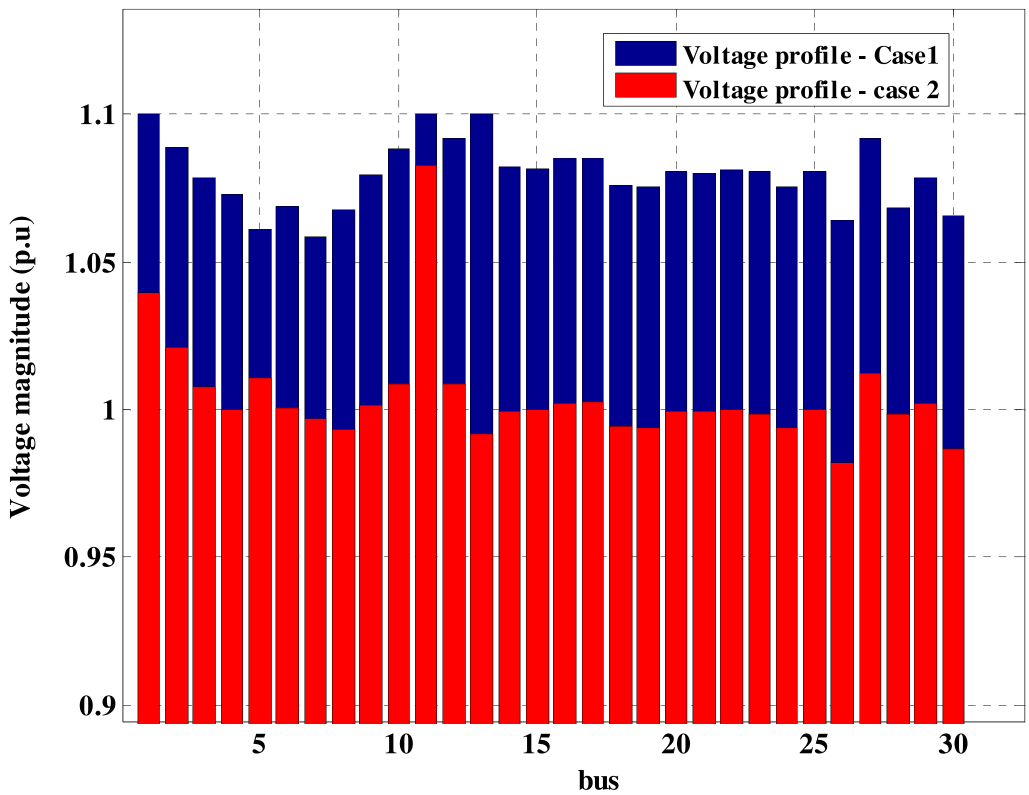

Fig. 3 Voltage profile for both cases 1 and 2 – IEEE30 bus test system

The results provided by both algorithms GABC1 and GABC2 have been compared with those of other methods indicated in Table 4. It is clear from the results that the total fuel cost has been reduced to 803.8679 \$/h for GABC1 (803.4827 \$/h for GABC2) and voltage deviation has been reduced to 0.1045 p.u (0.1131 p.u for GABC2), where the best results have been noticed than those of DE [9] as shown in Table 4. The voltage deviations 0.0932 p.u, 0.1020 p.u, 0.0891 and 0.0920 p.u, obtained respectively by GSA [35], BBO [38], PSO [7] and ARCBBO [39] are reported to be less than the obtained values of the proposed methods but on the other hand their fuel costs obtained are respectively 804.3150 \$/h, 804.9980 \$/h, 806.38 \$/h and 806.3264 \$/h which are greater than costs 803.8679 \$/h and 803.4827 \$/h found respectively by GABC1 and GABC2 algorithms. It may be seen that the best total fuel cost related to PSO-NM [40] or Gbest-ABC [41] is lower than the optimal solution signalized by GABC1 optimization technique (but greater than total fuel cost given by GABC2). Although, HFPSO–NM [40] gives better results but the reactive power compensation at buses 15, 20 and 21 exceeds 5 MVAr limits (VAr shunt power compensator is limited to 0–5 MVAr). The lower voltage deviation for case 2 is reflected by the voltage profile indicated in Fig. 3, where the voltage magnitude at all load buses is near 1 p.u, the comparison with case1 is performed in the same previous figure.

Table 4 Comparison of GABC1 and GABC2 to other optimization methods – Case2

Method	Fuel cost(\$/h)	Voltage deviation
GABC1	803.8679	0.1045
GABC2	803.4827	0.1131
GSA [35]	804.3150	0.0932
BBO [38]	804.9980	0.1020
ARCBBO [39]	806.3264	0.0920
PSO [7]	806.3800	0.0891
PSO-NM [40]	803.8615	0.0976
HFPSO-NM [40]	803.5278[a]	0.0859[a]
Gbest-ABC[41]	803.5790	0.1007
DE [9]	805.2620	0.1357

a: infeasible solution

5.1.3 Piecewise quadratic fuel cost functions (case3)

The thermal units in the power system can be supplied by multiple fuel sources reflecting a specific quadratic fuel cost function for each fuel source. For this case of study, the generators connected to buses 1 and 2 have multiple fuel option. Each generator has a fuel cost function with different fuel cost coefficients for two operating regions. The fuel cost coefficients of these generators are given in Table 5 [36]. The other generating units have the same values as in the case1. The fuel cost function depicting piecewise quadratic form is given in (22) as follows:

$$F(P_{Gi}) = \begin{cases} a_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 & P_{Gi}^{\min} \le P_{Gi} \le P_{Gi1} \\ a_{i2} + b_{i2}P_{Gi} + c_{i2}P_{Gi}^2 & P_{Gi1} \le P_{Gi} \le P_{Gi2} \\ \dots\dots\dots\dots & \\ a_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2 & P_{Gik-1} \le P_{Gi} \le P_{Gi}^{\max} \end{cases} \tag{22}$$

where a_{ik}, b_{ik} and c_{ik} signified the cost coefficients of the *i-th* generator for fuel type *k*.

Table 5 Data characteristics of units 1 and 2 for case 3

Bus	Operating region		Cost coefficients		
	From (MW)	To (MW)	a	b	c
1	50	140	55.0	0.7	0.0050
	140	200	82.5	1.05	0.0075
2	20	55	40.0	0.30	0.0100
	55	80	80.0	0.60	0.0200

The algorithms GABC1 and GABC2 are applied for this case, without considering shunt VAr compensators and with limit voltage magnitude at load buses to 1.05 p.u. The optimal setting of control variables and objectives of GABC2 algorithm (GABC1 presents a lower solution quality) are represented in Table 2. Both presented optimization techniques are compared to other optimization methods in literature via simulation results drawn in Table 6. The minimum fuel cost 647.0794 \$/h to carry away from the application of GABC2 is better slightly than that produced by GABC1 and other optimization methods to perceive from the literature in Table 6, except GSA [35] method which provides 646.8480 \$/h, but with voltage magnitude violations at many load buses below lower limit of 0.95 p.u and reactive power generation violations at generation buses 2 and 8. The convergence characteristic of GABC1 and GABC2 algorithms is demonstrated in Fig. 4.

Table 6 Comparison of GABC1 and GABC2 algorithms to other optimization Techniques – Case3

Methods	Fuel cost (\$/h)			*Limit violations of variables for infeasible solutions
	Min	Average	Max	
GABC1	647.0816	647.2410	647.6300	
GABC2	**647.0794**	647.1987	647.9054	
ABC [37]	649.0855	654.0784	659.7708	
GSA [35]	646.8480[a]	646.8962[a]	646.9381[a]	*Voltage magnitudes *Reactive power Q_{G2} and Q_{G8}
BBO [38]	647.7437	647.7645	647.7928	
PSO [7]	647.69	647.73	647.87	
PSO-NM [40]	647.718	NA	NA	
HFPSO-NM [40]	647.6180	NA	NA	
Gbest-ABC [41]	647.03[a]	647.0767	647.1234	*Voltage magnitudes of $V_3$and V_4
MDE [36]	647.846	NA	NA	
DE [9]	650.8224	NA	NA	

a: infeasible solution

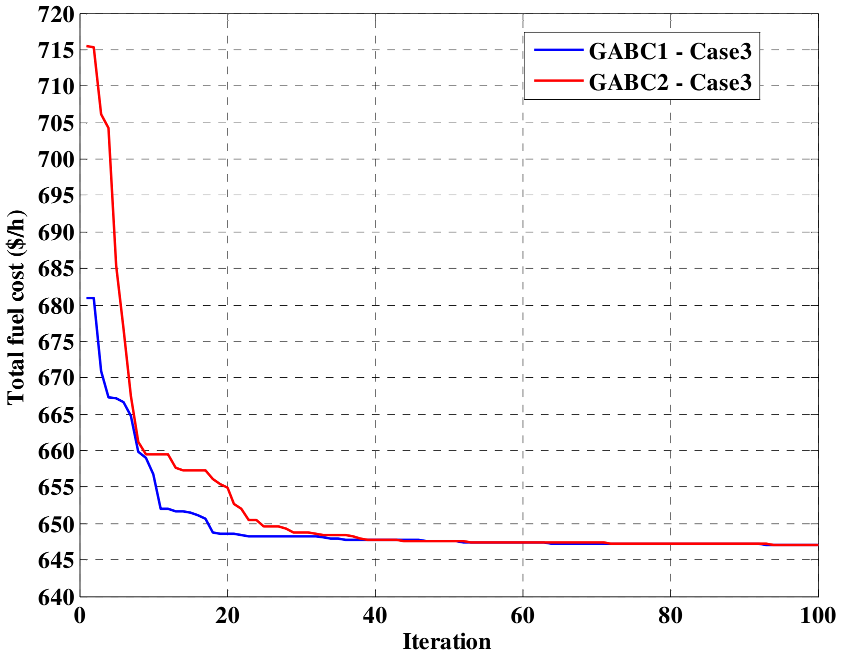

Fig. 4 Convergence of GABC1 and GABC2 algorithms for Case3

5.1.4 Voltage stability enhancement along with cost (Case4)

Static voltage stability analysis is an important tool to determine the critical states of power system in the aim to ovoid the voltage collapse at critical buses. An appropriate index called Voltage Stability Index (VSI) measures the closeness of the system to voltage collapse [38]. The determination of L-index proposed in [42] which is based on load flow analysis presents a fundamental indicator to carry out the static voltage stability studies. The bus with the highest L-index value will be the most vulnerable bus in the system. The L-indices for a given load condition are computed for all load buses and the maximum of L-index (L_{max}) gives the proximity of the system to voltage collapse. For this case of study, the total fuel cost and the maximum of L-index must be minimized simultaneously. The overall objective function is expressed in (23):

$$J = \sum_{i=1}^{N_G} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) + K_{ind}.\max(L_{index}) \tag{23}$$

Among the total number N_B of buses, there is N_{PV} number of PV buses and N_{PQ} number of load buses, where the value of L-index Lj of load bus j can be given as [43]:

$$L_j = \left| 1 - \sum_{i=1}^{N_{PV}} F_{ji} \frac{V_i}{V_j} \right| \quad \text{where } j=1, 2,\dots, N_{PQ} \tag{24}$$

$$F_{ji} = -[Y_1]^{-1}.[Y_2] \tag{25}$$

where Y_1 and Y_2 are the sub-matrices after the arrangement of the admittance matrix in the following manner :

Y_1 joins the vector of injected currents and voltages of load buses.

Y_2 joins the vector of injected currents of load buses and voltages of PV buses.

The L-index value ranges from 0 (no load system) to 1 (voltage collapse) and lower value of L_j reflects more stable system. K_{ind} is the weighting factor with setting value 6000 in such case of study.
The results extracted from the application of GABC1 (GABC2 presents lower solution quality) algorithm are distinguished from the Table 2 for case4, where the obtained optimal settings of control variables and objectives are shown.
To verify the effectiveness of the two proposed algorithms, a comparative study is accomplished and detailed in Table 7.

Table 7 Comparison of GABC1 and GABC2 to other optimization methods – Case4

Methods	Fuel cost($/h)	max (L-index)
GABC1	**800.5694**	0.1179
GABC2	801.3708	0.1196
ABC [41]	801.6650	0.1379
GSA [35]	806.6013 [a]	0.1162 [a]
BBO [38]	805.7252	0.1104
ARCBBO [39]	801.8076	0.1369
PSO [7]	801.7600	0.1246
PSO-NM [40]	804.1137 [a]	0.1051 [a]
HFPSO-NM [40]	801.7488[a]	0.1023[a]
Gbest-ABC [41]	801.5821	0.1370
DE [9]	807.5272	0.1219

a: infeasible solution

According to the obtained simulation results, the minimum total fuel cost obtained from the two proposed algorithms is less than the one of other optimization techniques in literature. The maximum *L-index* of BBO [38] method 0.1104 is small than 0.1179 and 0.1196 of the same index assigned respectively to GABC1 and GABC2 methods, while the minimal total fuel cost of BBO technique 805.7252 $/h is much greater than 800.5694 and 801.3708 $/h of GABC1 and GABC2 methods, respectively. From Table 7, it is seen clearly that the optimal values of both objectives related to conventional ABC [41], ARCBBO [39], PSO [7], Gbest-ABC [41] and DE [9] present lower solution qualities than ones of GABC1 and GABC2 methods. The maximum *L-index* 0.1162 obtained by GSA [35] is better than 0.1179 and 0.1196 of the proposed techniques, but the corresponding solution presents reactive power generation violations at buses 8, 11 and 13 with, respectively, 78.3569, -31.56 and -33.2756 MVAr, violating the reactive power generation limits. Meanwhile, voltage magnitude limits violations occurred in buses 9, 10 and 12 greater than 1.1 p.u. In PSO-NM [40] and HFPSO-NM [40] cases, the corresponding solutions 0.1051 and 0.1023 are better than ones of GABC1 and GABC2 methods, but these solutions present any voltage magnitude limits violations in bus 27 for PSO-NM and in buses 9, 10, 12 and 27 for HFPSO-NM, with a voltage magnitude greater than 1.1 p.u.

5.1.5 Quadratic fuel cost curve with valve point loadings (Case 5)

For this case, a sine component is added to the cost curves of case1 and that for generators connected to buses 1 and 2. This addition of sine function is considered in the aim to simulate the valve point loading effects [36].
The valve point loading effects are reflected by the curve function (26) and the corresponding cost coefficients are given in Table 8.

$$F_i(P_{Gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \times \sin(e_i (P_{Gi}^{\min} - P_{Gi})) \right| \qquad \text{where } i=1,2 \tag{26}$$

where a_i, b_i, c_i, d_i and e_i are the cost coefficients of the *i-th* generating unit.

Table 8 Cost coefficients of units in buses 1 and 2 for case 5

Bus	Cost coefficients				
	a	b	c	d	e
1	150	2.00	0.0016	50.00	0.0630
2	25	2.50	0.0100	40.00	0.0980

The VAR shunt compensators as control variables are not introduced in this case. The optimal setting of control variables and objectives from GABC2 (GABC1 presents lower solution quality) method are illustrated in Table 2 for case 5, with optimal fuel cost 918.4351 \$/h providing a best solution than that of other metaheuristic optimization methods presented in the comparison Table 9 as ABC [37], GSA [35], BBO [38], Gbest-ABC [41] and MDE [36]. For the presented technique in literature PSO-NM [40], the true value of total fuel cost corresponding to the found active power generations is 930.1514 \$/h. In the case of HFPSO-NM [40] method, the corresponding solution gives active power generation limit violations with 4.652 and 7.087 MW in generation buses 8 and 13, respectively, less than lower generation limits. The variation of the total fuel cost with respect to the number of cycles (iterations) for the proposed algorithms GABC1 and GABC2 is shown in Fig. 5.

Table 9 Comparison of GABC1 and GABC2 to other optimization methods – Case5

Methods	Fuel cost (\$/h)		
	Min	Average	Max
GABC1	919.5972	925.8113	956.4276
GABC2	**918.4351**	925.6516	959.7288
ABC [37]	945.4495	960.5647	973.5995
GSA [35]	929.7240472	930.9246338	932.0487291
BBO [38]	919.7647	919.8389	919.8876
PSO-NM [40]	917.4226[a]	NA	NA
HFPSO-NM [40]	912.0229[a]	NA	NA
Gbest-ABC [41]	931.7450	932.5348	933.3246
MDE [36]	930.793	942.501	954.073

a: infeasible solution

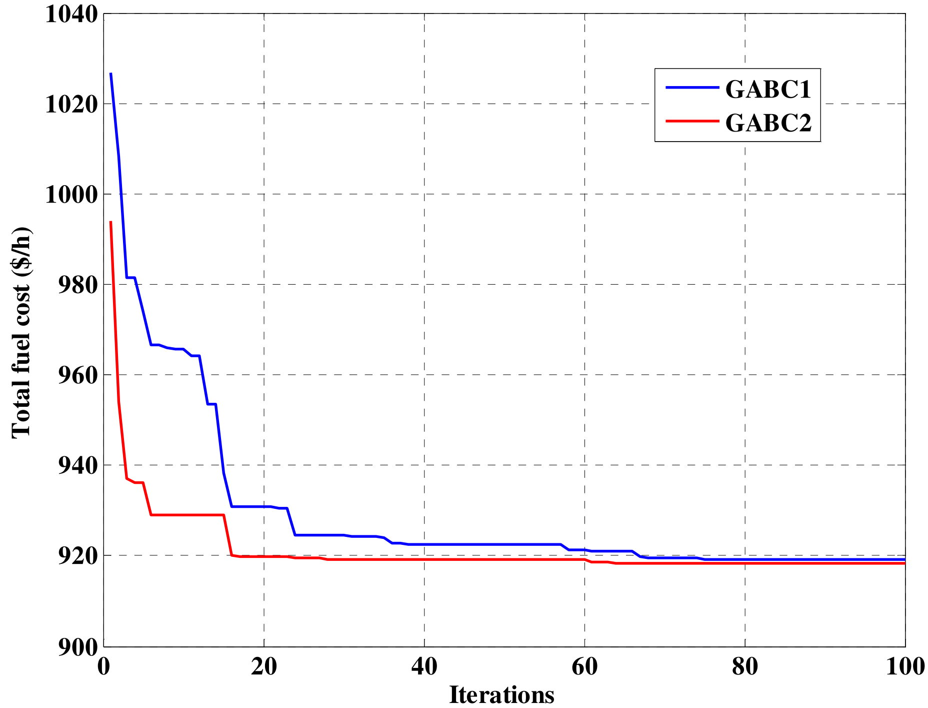

Fig. 5 Convergence of GABC1 and GABC2 algorithms for Case5

5.2 IEEE 57 bus test system

To describe the ability of two proposed GABC1 and GABC2 algorithms in the resolution of the OPF problem for larger electrical network, the standard test system IEEE 57 bus was proposed [44]. Such test system includes seven generating units at buses 1, 2, 3, 6, 8, 9, and 12, eighty branches including seventeen branches contain load tap setting transformers and three adjustable shunt VAR sources at buses 18, 25 and 53. The total power demand of the system is (12.508+j3.364) p.u at 100 MVA base. The cost coefficients, the capacity limits of generating units, the bus data and the lines data are taken from [45]. The voltage magnitudes in generation buses where assumed to be in the range [0.95 1.1] p.u, while the voltage magnitude of load buses is limited from 0.94 to 1.08 in p.u. The transformer-tap settings variations are in the interval [0.9 1.1]. The maximum and minimum of adjustable reactive power injected by VAR shunt sources are respectively 0.3 and 0.0 in p.u. The simulation process is accomplished by minimizing the total fuel cost considered as quadratic function to test the performances of ABC algorithm based GEM. The *SN* and *MCN* parameters are adjusted to be 70 and 200, respectively. The simulation results are performed to get the optimal settings of control variables along with minimal total fuel cost and the total active losses, which are given in Table 10. The results are reported to be elaborated from 30 independent trial runs using GABC1 and GABC2 algorithms. The results of GABC1 algorithm are better than those of GABC2.

To proceed to a comparative study, Table 11 is organized for providing the optimal total fuel cost attributed by other optimization techniques reported in the literature. It is clearly seen that the optimal fuel cost obtained from the proposed GABC1 algorithm is less in comparison to GSA [35], ABC [37], Interior point method (MATPOWER) [39], Evolving Ant Direction Differential Evolution (EADDE) [46] and Multi-Objective Modified Imperialist Competitive (MOMICA) [47] algorithms.

Table 10 The optimal control variables obtained by GABC1 for IEEE 57 bus test system

Control variables		Control variables	
P_{G1}(MW)	141.7952	$T_{24\text{-}25}$	1.1000
P_{G2}(MW)	93.9561	$T_{24\text{-}25}$	0.9765
P_{G3}(MW)	45.8650	$T_{24\text{–}26}$	1.0295
P_{G6}(MW)	69.0545	$T_{7\text{–}29}$	0.9874
P_{G8}(MW)	450.1613	$T_{34\text{–}32}$	0.9705
P_{G9}(MW)	100.0000	$T_{11\text{–}41}$	0.9000
P_{G12}(MW)	364.6701	$T_{15\text{–}45}$	0.9413
V_{G1} (p.u)	1.0305	$T_{14\text{–}46}$	0.9228
V_{G2} (p.u)	1.0316	$T_{10\text{–}51}$	0.9248
V_{G3} (p.u)	1.0345	$T_{13\text{–}49}$	0.9000
V_{G6} (p.u)	1.0543	$T_{11\text{–}43}$	0.9254
V_{G8} (p.u)	1.0687	$T_{40\text{–}56}$	1.0410
V_{G9} (p.u)	1.0325	$T_{39\text{–}57}$	0.9740
V_{G12} (p.u)	1.0190	$T_{9\text{–}55}$	0.9848
$T_{4\text{–}18}$	0.9000	Q_{C18} (MVAR)	24.79
$T_{4\text{–}18}$	1.1000	Q_{C25} (MVAR)	16.44
$T_{21\text{–}20}$	1.0293	Q_{C53} (MVAR)	14.26
Fuel cost ($/h)	**41684.9617**		
Power loss (MW)	14.7021		

Table 11 Comparison of GABC1 and GABC2 to other methods for IEEE 57 bus system

Method	Optimal fuel cost($/h)
GABC1	**41684.9617**
GABC2	41692.490
MATPOWER [45]	41737.79
GSA [35]	41695.87
ABC [37]	41693.95
ARCBBO [39]	41686 [a]
EADDE [46]	41713.62
MOMICA [47]	41886.79

a : infeasible solution

For ARCBBO algorithm [39], the optimal fuel cost obtained is underlined to be 41686 $/h, which is an infeasible solution considering the optimal control variables reported in [39], where the main equality constraint (active power balance) is violated reflecting the sum of the generated powers minus the total active losses greater than the total active power demand. It is declared in [39] that the power generation in slack bus is 142.5804 MW, meanwhile, the true value found of this power is 108.3862 MW and the exact total fuel cost is calculated to be 41819 $/h. For the proposed GABC2 algorithm, it can be observed that the minimum fuel cost solution is 41692.490 $/h and then it is less than other solutions obtained by other methods in literature.

6. Conclusion

This paper proposes ABC algorithm based GEM for solving OPF problem. The two proposed algorithms GABC1 and GABC2 are tested and examined with various types of objective functions including convex and non-convex fuel costs, voltage profile improvement and voltage stability enhancement. The simulation results are obtained considering two test systems IEEE 30 bus and IEEE 57 bus systems. The efficiency and the robustness of the two proposed algorithms GABC1 and GABC2 are justified based on the comparison purpose to other optimization techniques in literature, overcoming the drawbacks of conventional ABC algorithm. The exhibiting results have been analyzed demonstrating the enhancement of the exploitation process ability of the proposed algorithms. The best results provide a suggestion that the proposed algorithms GABC1 and GABC2 can effectively serve as alternatives for solving global optimization problems.

References

[1] H.W. Dommel, W.F. Tinney, Optimal power flow solutions, *IEEE Transactions on Power Apparatus and* Systems, *87*, 1866–1876, 1968

[2] B. Stott & E. Hobson, Power system security control calculation using linear programming, *IEEE Trans Power Appar. Syst.*, 97, 1713-31, 1978.

[3] G. E Reid & L. Hasdorf, Economic dispatch using quadratic programming. *IEEE Trans. Power Appar. Syst.*, 92, 2015-23, 1973.

[4] J. A Momoh & J. Z. Zhu, Improved interior point method for OPF problems. *IEEE Trans. Power Syst.*, 14, 1114-20, 1999.

[5] D. I Sun, B. Ashley, B. Brewer, A. Hughes & W. F Tinney, Optimal power flow by Newton approach, *IEEE Trans. Power Syst.*, 103,2864-80, 1998.

[6] L.L. Lai & J.T. Ma. Improved genetic algorithms for optimal power flow under both normal and contingent operation states. *Electrical Power and Energy Systems*, 19, 287-292, 1997.

[7] M. A. Abido, Optimal power flow using particle swarm optimization, *Electrical Power and Energy Systems*, 24, 563-571, 2002.

[8] T. Bouktir & L. Slimani, Optimal Power Flow of the Algerian Electrical Network using an Ant Colony Optimization Method, *Leonardo Journal of Sciences*, 7, 43-54, 2005

[9] A. A. Abou El Elaa, M.A. Abido & S.R. Spea, Optimal power flow using differential evolution algorithm, *Electric Power Systems Research*, 80, 878–885, 2010.

[10] S. Duman, U. Guvenc, Y. Sonmez & N. Yorukeren, Optimal power flow using gravitational search algorithm, *Energy Conversion and Management*, 59,86–95, 2012.

[11] A. Bhattacharya & PK. Chattopadhyay, Application of biogeography-based optimisation to solve different optimal power flow problems, *IET Generation, Transmission and Distribution*, 5(1), 70–80, 2011.

[12] S. Mohd Herwan, M. Zuriani, M. Mohd Rusllim & O. Aliman, Using the gray wolf optimizer for solving optimal reactive power dispatch problem, *Applied Soft Computing*, 32, 286–292, 2015.

[13] D. Karaboga & B. Akay, A comparative study of artificial bee colony algorithm, *Applied Mathematics and Computation*, 214, 108–132, 2009.

[14] W. Gao & S. Liu, Improved artificial bee colony algorithm for global optimization, *Information Processing Letters,* 111, 871–88, 2011.

[15] B. Akay, D. Karaboga. A modified Artificial Bee Colony algorithm for real-parameter optimization. Information sciences 2012; 192:120-142

[16] Z. Xian, J. Xie & Y. Wang, Representative Artificial Bee Colony Algorithms: A Survey, *In: Proceedings of 2nd International Conference on Logistics, Informatics and service Science*, 1419-1424, 2013.

[17] D. C. Secui, A new modified artificial bee colony algorithm for the economic dispatch problem, *Energy Conversion and Management*, 89, 43-62, 2015.

[18] S. Özyön & D. Aydin, Incremental artificial bee colony with local search to economic dispatch problem with ramp rate limits and prohibited operating zones, *Energy Conversion and Management*, 65, 397-407, 2013.
[19] A. Banharnsakun, B. Sirinaovakul & T. Achalakul, The best-so-far ABC with multiple patrilines for clustering problems, *Neurocomputing*, 116, 355–366, 2013
[20] G. Li, P. Niu &X. Xiao, Development and investigation of efficient artificial bee colony algorithm for numerical function optimization, *Applied Soft Computing*, 12, 320–332, 2012.
[21] W. Gao, S. Liu & L. Huang, A global best artificial bee colony algorithm for global optimization, *Computational and Applied Mathematics*, 236 (11), 2741–2753, 2012.
[22] S-M. Chen, A. Sarosh & Y-F. Dong, Simulated annealing based artificial bee colony algorithm for global numerical optimization, *Applied Mathematics and Computation*, 219(8), 3575–3589, 2012.
[23] N. Imanian, M. E. Shiri & P. Moradi, Velocity based artificial bee colony algorithm for high dimensional continuous optimization problems, *Engineering Applications of Artificial Intelligence*, 36, 148–163, 2014.
[24] W.F. Gao & S.Y. Liu, A modified artificial bee colony algorithm, *Computers and Operations Research*, 39, 687–697, 2012.
[25] G. Zhu, S. Kwong, Gbest-guided artificial bee colony algorithm for numerical function optimization, *Applied Mathematics and Computation*, 217, 3166–3173, 2010.
[26] M. Rezaei Adaryani & A. Karami, Artificial bee colony algorithm for solving multi-objective optimal power flow problem, *Electrical Power and Energy Systems*, 53, 219–230, 2013.
[27] A. Khorsandi, S. H. Hosseinian & A. Ghazanfari, Modified artificial bee colony algorithm based on fuzzy multi-objective technique for optimal power flow problem, *Electric Power Systems Research*, 95, 206– 213, 2013.
[28] H.T. Jadhav & R. Roy, Gbest guided artificial bee colony algorithm for environmental/economic dispatch considering wind power, *Expert Systems with Applications*, 40(16), 6385–6399, 2013.
[29] A. Ahrari & M. Shariat-Panahi & A. A. Atai, GEM: A novel evolutionary optimization method with improved neighborhood search, *Applied Mathematics and Computation*, 210, 376–386, 2009.
[30] A. Ahrari & A. A. Atai, Grenade Explosion Method - a novel tool for optimization of multi modal functions, *Applied Soft Computing*, 10, 1132–1140, 2010.
[31] R. Rajabioun, Cuckoo optimization algorithm, *Applied Soft Computing*, 11, 5508–5518, 2011.
[32] C. Zhang, J. Zheng & Y. Zhou, Two modified Artificial Bee Colony algorithms inspired by Grenade Explosion Method, *Neurocomputing*, 151, 1198–1207, 2015.
[33] D. Karaboga & B. Basturk, On The performance of Artificial Bee Colony (ABC) algorithm, *Applied Soft Computing*, 8(1), 687-697, 2008.
[34] D. Karaboga & C. Ozturk, A novel clustering approach: Artificial Bee Colony (ABC) algorithm, *Applied Soft Computing*, 11,652-657, 2011.
[35] S. Duman, U. Guvenc, Y. Sonmez & N. Yorukeren, Optimal power flow using gravitational search algorithm, *Energy Conversion and Management*, 59, 86–95, 2012.
[36] S. Sayah & K. Zehar, Modified differential evolution algorithm for optimal power flow with non-smooth cost functions, *Energy Conversion and Management*, 49, 3036–3042, 2008.
[37] M. Rezaei Adaryani & A. Karami, Artificial bee colony algorithm for solving multi-objective optimal power flow problem, *Electrical Power and Energy Systems*, 53,219–230, 2013.
[38] A. Bhattacharya & PK. Chattopadhyay, Application of biogeography-based optimisation to solve different optimal power flow problems, *IET Generation, Transmission and Distribution*, 5(1), 70–80, 2011.
[39] A. Ramesh Kumar & L. Premalatha, Optimal power flow for a deregulated power system using adaptive real coded biogeography-based optimization, *Electrical Power and Energy Systems*, 73,393–399, 2015.
[40] M. Joorabian & E. Afzalan, Optimal power flow under both normal and contingent operation conditions using the hybrid fuzzy particle swarm optimisation and Nelder–Mead algorithm (HFPSO–NM), *Applied Soft Computing*, 14, 623–633, 2014.
[41] R. Roy & H.T. Jadhav, Optimal power flow solution of power system incorporating stochastic wind power using Gbest guided artificial bee colony algorithm, *Electrical Power and Energy Systems*, 64, 562–578, 2015.
[42] P. Kessel & H. Glavitsh, Estimating the voltage stability of power systems, *IEEE Trans. Power Syst.*, 1(3), 346–54, 1986.
[43] J. Preetha Roselyn, D. Devaraj & S. Sekhar Dash, Multi Objective Differential Evolution approach for voltage stability constrained reactive power planning problem, *Electrical Power and Energy Systems*, 59, 155–165, 2014.
[44] The IEEE 57-Bus Test System. <http://www.ee.washington.edu/research/pstca/pf57/pg_tca57bus.htm>
[45] A MATLAB Power system Simulation Package (MATPOWER); http://www.pserc.cornell.edu//matpower/; Sep 17, 2015.
[46] K. Vaisakh & LR Srinivas, Evolving ant direction differential evolution for OPF with non-smooth cost functions, *Eng. Appl. Artificial Intelligence*, 24, 426–36, 2011.
[47] M. Ghasemi , S. Ghavidel, M. M. Ghanbarian, M. haribzadeh & A. A. Vahed, Multi-objective optimal power flow considering the cost, emission, voltage deviation and power losses using multi-objective modified imperialist competitive algorithm, *Energy* 78, 276–289, 2014.