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Solution of Multi-objective Optimal Power Flow using Earthworm Optimization Algorithm

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Abstract—Now-a-days economy of electricity generation, quality of the generated and supplied electricity and emission of greenhouse gases from power plants are the main concern in power system operation. Good quality of electricity is to be produced with reduced cost and emission of greenhouse gases is to be controlled at the same time. These objectives can be achieved through solution of optimal power flow (OPF) problem. This paper applies a newly developed method called the earthworm optimization algorithm (EWA) to solve single-objective and multi-objective OPF problems. The performance of EWA in solving OPF problems has been tested on IEEE-30 bus, IEEE-57 bus and IEEE-118 bus test system. Different objectives such as fuel cost minimization, voltage profile improvement, emission reduction have been taken into account. Separate practical cases have been considered for multi-fuels and valve-point effect while calculating fuel cost. Superiority of the proposed algorithm over other well-known optimization algorithms has been established.

Index Terms— Earthworm optimization algorithm, Equality constraint, Evolutionary algorithm, Inequality constraint, Meta-heuristic, Optimal power flow, Valve-point effect.

1 Introduction

With increasing load demand and ever expanding power generation, transmission and distribution network, the main concern is to minimize fuel cost as well as maintain the system efficiency simultaneously. In consideration of several equality and inequality constraints an optimal power flow (OPF) problem needs to be resolved to meet various objectives like fuel cost reduction, voltage profile improvement, emission reduction or others. This can be achieved by adjusting the control variables like active power generations, generator bus voltages, tap changing transformer ratios, shunt capacitor outputs.Here the equality and inequality constraints are power flow balance, generation and transmission limit, voltage profile maintenance and may include any other limit factors to improve the efficiency of the power system.

The OPF problem was first introduced by Carpentier in 1962 and since then different optimization methods were formulated to deal with multi-objective optimization problem. These methods can be broadly categorized into two techniques, namely the classical (deterministic) method and the metaheuristic (population based) method.

Most of the classical methods need an initial point close to solution and the quality of the solution becomes immensely dependent on this initial setting as the number of control parameters of the problem increases. These classical methods can easily calculate local optimum but cannot always reach global optimum. They lack in continuity calculations, objective function differentiation and discrete variable adaptability. To overcome these shortcomings metaheuristic or population based algorithms evolved lately and gradually helped to resolve complex OPF computational problems. The development of computer technologies over few decades aided the advancement of the metaheuristic algorithms and established better results for complex OPF problem resolution.

Most common classical methods used in OPF problem resolution are linear programming (LP) [1], [2], Newton-based method [3], [4], interior point methods (IPMs) [5], reduced gradient method [6], dynamic programming and many others. These traditional methods suffered from difficulties in solving optimization problems fast and efficiently as they are based on formal logics and mathematical programming.

The meta-heuristic or population based optimization techniques emerged lately and is influenced by the biological evolution phenomenon or physical or swarm foraging process and the strategy focuses on searching for the optimal solution in the state space of the optimal solutions and hence quite effective in solving complicated power system calculation issues. These newly evolved metaheuristic methods use the random transition rules and have the ability of coping with large scale nonlinear problems without getting stuck in the local optimum. Swarm based algorithms are based on collective behaviours of animals which include particle swarm optimization (PSO) [7], ant colony optimization (ACO) [8], artificial bee colony (ABC) [9] and many others. PSO relies on the phenomenon of bird flocking when searching for the food. ACO is based on the fact that ants are able to remember the past paths by pheromone secretion. Many of these swarm based intelligent algorithms have been used in OPF problem resolution successfully. On the other hand, evolutionary algorithms (EA) are based on genetic evolution process and generally make use of different crossover operators. Some of the EAs include genetic algorithm (GA) [10], differential evolution (DE) [11] and biogeography based optimization (BBO) [12].

In recent years, Reddy and Rathnam solved multi-objective OPF problems using glowworm swarm optimization algorithm (GSO) [13]. Abaci and Yamacli proposed a bio-inspired metaheuristic based on differential search algorithm (DSA) [14] to solve OPF problems in power systems. A day ahead Price based optimal reactive power dispatch (PORPD) problem is proposed by Malakar et al.which is solved by cuckoo search (CS) algorithm [15]. Rajan and Malakar also proposed exchange market algorithm based optimum reactive power dispatch [16]. An improved strength pareto evolutionary algorithm to solve multi-objective OPF problem is introduced by Yuan et al. [17]. Some other recently developed algorithms which has been applied to OPF problem or economic load dispatch problem solution include moth swarm algorithm (MSA) [18], improved artificial bee colony optimization algorithm (IABC) based on orthogonal learning [19], improved colliding bodies optimization algorithm [20], partitioning flower pollination algorithm [21], oppositional krill herd algorithm [22], grey wolf optimization [23], backtracking search optimization algorithm (BSA) [24] etc.

Due to the variability of the objective function, it cannot be concluded that any specific optimization technique is the best and most efficient among all the metaheuristic methods. Hence the option and necessity for finding out a better approach towards OPF problem resolution and formulating a better algorithm to solve most of the OPF problems still prevail.

The aim of this paper is to apply a new nature inspired evolutionary algorithm called earthworm optimization algorithm (EWA) to solve single-objective and multi-objective OPF problems on IEEE 30-bus, 57-bus and 118-bus test systems. The EWA is proposed by Wang et al. in 2015 [25]. It is an optimization technique based on two kinds of reproduction of the earthworms in nature. The weighted summation of the independently generated offsprings from reproduction 1 and 2 are used to get the earthworm for the next generation. Several improved crossover operators can be used in reproduction 2. Finally Cauchy mutation is applied to make certain earthworm escape from the local optima and improve its search ability.

The remainder of this paper is organized in the following way. Section 2 details about the OPF problem formulation. Section 3 depicts the description, steps and mathematical interpretation of EWA. The results of MATLAB simulation of EWA based OPF problems are listed in section 4 with its performance evaluation in comparison to other popular meta-heuristic algorithms for solving the OPF problems. The conclusions are drawn in section 5.

2 OPF PROBLEM FORMULATION

As mentioned earlier, the solution of OPF problem finds a set of control variables that can optimize predefined power system objectives while maintaining system operating limits [26], [27].

2.1 Mathematical Expression

The OPF problem can be formulated as follows [28], [9].

$$Minimize \quad F(\boldsymbol{x},\boldsymbol{u}) \qquad (1)$$
$$Subject\ to \quad g(\boldsymbol{x},\boldsymbol{u}) = 0 \qquad (2)$$
$$and \quad h(\boldsymbol{x},\boldsymbol{u}) \le 0 \qquad (3)$$

Where u is the vector of independent variables or control variables; x is the vector of dependent variables or state variables; F(x,u) is the objective function; g(x,u) is the set of equality constraints and h(x,u) is the set of inequality constraints.

2.2 Control variables

The solution of OPF problem tries to adjust the set of control variables which consists ofactive power generation at PV buses except the slack bus (Pg), voltage magnitudes at PV busesor generator buses (Vg), tap settings of transformers (TAP) and shunt VAR compensation (Qc).Therefore, u can be expressed as follows.

$$\boldsymbol{u^T} = \left[P_{g2} \dots P_{gNgen}, V_{g1} \dots V_{gNgen}, Q_{c1} \dots Q_{cNcap}, TAP_1 \dots TAP_{Ntrans}\right] \quad (4)$$

Where Ngen is the number of generators; Ncap is number of shunt VAR compensators and Ntrans is number of regulating transformers.

2.3 State variables

The set of state variables consideredin the formulation of OPF problem consists ofactive power generation at the slack bus (Pg1), reactive power output of all generator units (Qg), voltage magnitudes at PQ buses or load buses (VL) and line flow or transmission line loadings (Sl).Therefore, x can be expressed as:

$$\boldsymbol{x^T} = \left[P_{g1}, Q_{g1} \dots Q_{gNgen}, V_{L1} \dots V_{LNload}, S_{l1} \dots S_{lNline}\right] \quad (5).$$

Where Nload is the number of PQ buses and Nline is the number of the transmission lines.

2.4 Equality constraints

The equality constraints are represented by typical load flow equations as follows,

$$P\mathrm{gi} - P\mathrm{loadi} - V\mathrm{i}\sum_{j=1}^{n} V\mathrm{j}\left(G_{ij}cos\delta\mathrm{ij} + B\mathrm{ij}sin\delta\mathrm{ij}\right) = 0 \qquad (6)$$

$$Q\mathrm{gi} - Q\mathrm{loadi} - V\mathrm{i}\sum_{j=1}^{n} V\mathrm{j}(G\mathrm{ij}\,sin\delta\mathrm{ij} - B\mathrm{ij}cos\delta\mathrm{ij}) = 0 \qquad (7)$$

In the above equations, n is the number of buses and i=1, 2,…,n. Usually, Newton Raphson or fast decoupled load flow methods are used for the solution of equality constraints.

2.5 Inequality constraints

The system operating limits are represented by the inequality constraints. The operating limits for the control variables are taken care while choosing those variables before the load flow is run in each generation. After the execution of the load flow in each generation the state variables are checked to see whether they are in the operating limits or not which determines the feasibility of the solution. The inequality constraints representing the minimum and maximum operating limits for the control and state variables are shown below.

$$P_{gimin} \le P_{gi} \le P_{gimax} \qquad i = [1,2,\dots,N_{gen}] \qquad (8)$$

$$Q_{gimin} \le Q_{gi} \le Q_{gimax} \qquad i = [1,2,\dots,N_{gen}] \qquad (9)$$

$$V_{gimin} \le V_{gi} \le V_{gimax} \qquad i = [1,2,\dots,N_{gen}] \qquad (10)$$

$$TAP_{imin} \le TAP_i \le TAP_{imax} \qquad i = [1,2,\dots,N_{trans}] \qquad (11)$$

$$Q_{cimin} \le Q_{ci} \le Q_{cimax} \qquad i = [1,2,\dots,N_{cap}] \qquad (12)$$

$$V_{Limin} \le V_{Li} \le V_{Limax} \qquad i = [1,2,\dots,N_{load}] \qquad (13)$$

$$S_{li} \le S_{limax} \qquad i = [1,2,\dots,N_{line}] \qquad (14)$$

(8), (9) and (10) represent generator constraints, (11) represents the transformer constraints, (12) represent the shunt capacitor constraints and (13) and (14) represent security constraints.

2.6 Penalty function

The inequality constraints of state variables can be included into the objective function as quadratic penalty terms which is expressed as follows:

$$Penalty = \lambda_P (P_{g1} - P_{g1}^{lim})^2 + \lambda_V \sum_{i=1}^{Nload} (V_{Li} - V_{Li}^{lim})^2 + \lambda_Q \sum_{i=1}^{Ngen} (Q_{gi} - Q_{gi}^{lim})^2 + \lambda_S \sum_{i=1}^{Nline} (S_{li} - S_{li}^{lim})^2 \quad (15)$$

Where λ_P, λ_V, λ_Q and λ_S are penalty factors and the details on selection of penalty factors are given in [29]. x^{lim} is the limiting value of the state variables which can be expressed as follows:

$$x^{lim} = \begin{cases} x^{max}; & x > x^{max} \\ x^{min}; & x < x^{min} \\ x; & x^{min} < x < x^{max} \end{cases} \quad (16)$$

By adding the penalty function of (15) with the objective function any unfeasible solution is declined [30].

2.7 Objective function

Different single and multi-objective functions are used in this paper as listed below.

2.7.1 Cost reduction

This is the base case to minimize the fuel cost of generation which is defined by a quadratic function. So the objective function for fuel cost minimization is:

$$F_1(\boldsymbol{x}, \boldsymbol{u}) = \left(\sum_{i=1}^{Ngen} \alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2\right) + Penalty \quad (17)$$

Where α_i, β_i and γ_i are cost coefficients of the ith generator. The values of the cost coefficients are considered as given in [24].

2.7.2 Cost minimization using numerous fuel sources

Thermal power generation unit may have various fuel sources like coal, natural gas and oil and for them the curve for fuel cost can be represented by the following piecewise quadratic functions [31].

$$f_i = \alpha_{ik} + \beta_{ik} P_{gi} + \gamma_{ik} P_{gi}^2 \quad if \;\; P_{gik}^{min} \le P_{gi} \le P_{gik}^{max} \quad (18)$$

Where k denotes the fuel option. In this study, generators 1 and 2 of IEEE 30 bus test system have two fuel options (k=1, 2) and the values of generator fuel cost coefficients are taken from [24]. Hence the objective function becomes

$$F_2(\boldsymbol{x}, \boldsymbol{u}) = F_{Cost_{g1\ and\ g2}} + F_{Cost_{Remaining\ Generators}} + Penalty \quad (19)$$

Where

$$F_{Cost_{g1\ and\ g2}} = \sum_{i=1}^{2} \alpha_{ik} + \beta_{ik} P_{gi} + \gamma_{ik} P_{gi}^2 \quad if \;\; P_{gik}^{min} \le P_{gi} \le P_{gik}^{max} \quad for\ fuel\ option\ k; k = 1\ and\ 2 \quad (20)$$

$$\boldsymbol{F_{Cost_{Remaining\ Generators}} = \sum_{i=3}^{Ngen} \alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2} \quad (21)$$

2.7.3 Cost minimization giving consideration to valvepoint effect

A ripple-like effect is observed in generating units having multi-valve steam turbines [32]. To consider this valve-point effect, the fuel cost function can be extended by adding a recurring rectifying sinusoidal term to it [33]. Therefore, the objective function being non-continuous can be formulated in the following way [34].

$$F_3(\boldsymbol{x}, \boldsymbol{u}) = \left(\sum_{i=1}^{Ngen} (\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2 + \left|\mu_i \times \sin\left(\omega_i \times \left(P_{gi}^{min} - P_{gi}\right)\right)\right|\right)) + Penalty$$

(22)

Where μ_i and ω_i represents the coefficients of the valve-point effect and their values are taken from [24].

2.7.4 Cost minimization and voltage profile enhancement

The voltage profile of any power system is related to the safety and service quality issues. The improvement of voltage profile of the power system means to minimize the voltage deviation from the unity at the load buses. This voltage deviation (VD) can be expressed by the following equation.

$$VD = \left(\sum_{i=1}^{Nload} |V_{Li} - 1|\right) \quad (23)$$

Therefore, the two-fold objective function considering voltage profile improvement and fuel cost reduction is as follows.

$$F_4(\boldsymbol{x}, \boldsymbol{u}) = \left(\sum_{i=1}^{Ngen} \alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2\right) + \lambda_{VD}(VD) + Penalty \quad (24)$$

Where λ_{VD} is a scaling factor which keep balance between the VD term and the cost term giving desired amount of importance to each of them.

2.7.5 Cost minimization using numerous fuel sources and voltage profile enhancement

This instance considers the multi fuel options for the generators and the cost term is described by a piecewise quadratic function as in (19) and voltage deviation is calculated by (23). Therefore the objective function becomes as follows.

$$F_5(\boldsymbol{x}, \boldsymbol{u}) = F_{Cost_{g1\ and\ g2}} + F_{Cost_{Remaining\ Generators}} + \lambda_{VD}(VD) + Penalty \quad (25)$$

$F_{cost\ g1\ and\ g2}$ and $F_{cost\ Remaining\ Generators}$ can be calculated by (20) and (21).

2.7.6 Cost minimization giving consideration to valve-point effect and voltage profile enhancement

This instance takes into account the valve-point effect while calculating the fuel cost. Voltage profile improvement is considered as before. Therefore the objective function can be expressed by the following equation.

$$F_6(\boldsymbol{x}, \boldsymbol{u}) = \left(\sum_{i=1}^{Ngen} (\alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2 + \left|\mu_i \times \sin\left(\omega_i \times Pgimin - Pgi\right)\right)\right) + \lambda VDVD + Penalty$$

(26)

2.7.7 Cost minimization and emission control

One of the most important concern of the modern world is global warming and power industries are very much responsible for that. So emission of the greenhouse gases in the environment is to be controlled. An environment friendly policy namely carbon credit system or CCS motivates the power sector to reduce the emissions of NO_x, SO_x and CO_2gases. The emission dispatch function is expressed as follows.

$$F_{emission} = \sum_{i=1}^{Ngen} 10^{-2}(a_i + b_i P_{gi} + c_i P_{gi}^2) + \left(d_i e^{(h_i P_{gi})}\right) \quad (27)$$

Where a_i, b_i, c_i, d_i and h_i are emission coefficients of the ith generator and their values have been taken from [24].Hence the objective function in this case considering cost reduction and emission control is as follows.

$$F_7(\boldsymbol{x}, \boldsymbol{u}) = \left(\sum_{i=1}^{Ngen} \alpha_i + \beta_i P_{gi} + \gamma_i P_{gi}^2\right) + \lambda_{emission}(F_{emission}) + Penalty \quad (28)$$

Where $\lambda_{emission}$ is a scaling factor to balance between the two objectives of cost reduction and emission control.

3 Optimization technique: Earthworm Optimization Algorithm (EWA)

As mentioned earlier EWA is a nature-inspired evolutionary algorithm based on reproduction procedure of earthworms to solve optimization problems [25]. EWA is based on some basic rules as follows: (A) Each earthworm in the population can reproduce offsprings by two and only two kinds of reproduction. (B) The genes contained by the child earthworm has the same length as that of the parent earthworm. (C) Some earthworm individuals of the previous generation with best fitness pass on directly to the next generation without any change. Following is the brief description of EWA as applied to the OPF problems.

3.1 Reproduction 1

Earthworms are hermaphrodites which mean each earthworm carries both male and female sex organs. Therefore, a single parent earthworm can generate a child earthworm by itself. The mathematical expression for reproduction 1 is as follows.

$$u_{i1,j} = u_{max,j} + u_{min,j} - \alpha u_{i,j} \quad (29)$$

Above equation describes the procedure of generating jth element of child earthworm i1 from parent earthworm i. $u_{i1,j}$ and $u_{i,j}$ are jth element of earthworm i1 and i. $u_{max,j}$ and $u_{min,j}$ are maximum and minimum limits of the jth element of each earthworm. α is the similarity factor whose value lies between 0 and 1 and it determines the distance between parent and child earthworm.

3.2 Reproduction 2

Reproduction 2 uses an improved version of crossover operators. There are three types of improved crossovers namely single point crossover, multipoint crossover and uniform crossover.Number of child earthworms (M) may be 1, 2 or 3 in most of the cases and number of parent earthworms (N) may be any integer that is more than 1. In this paper uniform crossover is applied with N=2 and M=1. Two parent earthworms P1 and P2 are selected using roulette wheel selection. They can be expressed as follows.

$$P = \begin{bmatrix} P_1 \\ P_2 \end{bmatrix} \quad (30)$$

Firstly, two offsprings u_{12} and u_{22} are generated from two parents. A random number rand between 0 and 1 is generated and jth element of u_{12} and u_{22} can be generated as follows.

If rand > 0.5, $u_{12,j} = P_{1,j}$ and $u_{22,j} = P_{2,j}$ (31)

Otherwise, $u_{12,j} = P_{2,j}$ and $u_{22,j} = P_{1,j}$ (32)

Finally the generated earthworm ui2 from reproduction 2 are determined by (33) as follows. Let rand1 be another randomly generated number between 0 and 1.

$$u_{i2} = \begin{cases} u_{12} & for\ rand1 < 0.5 \\ u_{22} & else \end{cases} \quad (33)$$

3.3 Weighted Summation

After generating earthworms u_{i1} and u_{i2}, the earthworm u_i' for the next generation can be formed as follows.

$$u_i' = \beta u_{i1} + (1-\beta) u_{i2} \quad (34)$$

where, β is the proportional factor to adjust the proportion of the u_{i1} and u_{i2} and it can keep balance between global search and local search efficiently. It is given by (35).

$$\beta^{t+1} = \gamma \beta^t \quad (35)$$

where t is the current generation. Initially at t=0, β=1. γ is a constant which is similar to cooling factor of a cooling schedule in the simulated annealing (Pradhan et al., 2016).

3.4 Cauchy mutation

Cauchy mutation (CM) helps the solution to escape from local optima. Hence it improves the search ability of EWA. CM operator for EWA can be expressed in the following way.

$$W_j = \left(\sum_{i=1}^{N_{pop}} u_{i,j}\right) / N_{pop} \quad (36)$$

Where Wj is the weight vector for the jth element of population i and Npop is the population size.

The jth element of the final earthworm is as follows.

$$u_{i,j}'' = u_{i,j}' + W_j * C \quad (37)$$

Here C is a random number which can be drawn from a Cauchy distribution with τ = 1 where τ is a scale parameter.

3.5 Steps for EWA algorithm as applied to OPF in brief

Begin

Step 1: Initialize by setting crossover probability, initial mutation probability, elitism parameter (n), similarity factor, initial proportional factor, γ (similar to cooling factor) and maximum generation count.

Step 2: Read the input data including system parameters, security limits for state variables, generator fuel cost coefficients, emission coefficients of generators and population size.

Step 3: Assign values of control variables (elements of earthworm) randomly within the prescribed limits.

Step 4: Check the feasibility of the population (earthworm).

Step 5: Repeat step 3 and 4 until population size is reached.

Step 6: Check for duplicity among the populations. If duplicated change any randomly selected element of the duplicated population and check the feasibility of the population.

Step 7: Calculate the values of the objective functions for each population and arrange them in ascending order of these values.

Step 8: Display the result for the best population.

Step 9: Save n numbers of best populations or earthworms of previous generation in a temporary array.

Step 10: Produce an offspring using first way of reproducing.

Step 11: Produce another offspring using second way of reproducing.

Step 12: Take weighted summation of the two offsprings to get the new earthworm.

Step 13: Apply CM on the new earthworm to get final earthworm for the next generation.

Step 14: Check the feasibility of the new population.

Step 15: Repeat step 10 to 14 until population size is reached.

Step 16: Repeat step 7.

Step 17: Replace n numbers of worst populations with the n numbers of best population of the previous generation.

Step 18: Repeat step 6, 7&8.

Step 19: Repeat step 9 to 18 until the desired result is achieved or maximum generation count is reached.

End

4 Simulation results and discussion

In this paper IEEE 30-bus, IEEE 57-bus and IEEE 118-bus test systems are used to test the effectiveness of the proposed EWA algorithm to solve different single and multi objective OPF problems. All of the simulation was performed in MATLAB 9.0 with 8 GB RAM and Intel Core i5 processor of the laptop.

4.1 IEEE 30-bus test system

The IEEE 30-bus test system consists of 6 generator buses, 24 load buses and 41 branches of which 4 branches have tap setting transformers and 9 buses have shunt capacitors connected to it. The operating limits for active power generation and voltage magnitudes at PV buses are taken from [35]. The transformer tap settings are considered within the interval 0.9 – 1.1 p.u. and shunt capacitors are configurable from 0 to 5 MVAR [36]. The detailed data are taken from [35]. The cost and emission coefficients are same as that used in [24].

4.1.1 Cases with single objectives

Case 1: OPF with cost minimization as objective

This is a single objective case where the objective is to generate electricity with reduced cost. In this case the objective functionis expressed by (17). The optimal control variables obtained after running EWA technique are presented in Table 1 and the optimal generation fuel cost obtained is 798.9858 $/h whereas with BSA technique this is 799.0760 $/h. Therefore the optimal fuel cost obtained using EWA is better than that obtained using BSA. Fig. 1 shows the convergence characteristics of cost function using EWA for case 1 where the cost function has converged to the final value within 80 iterations.

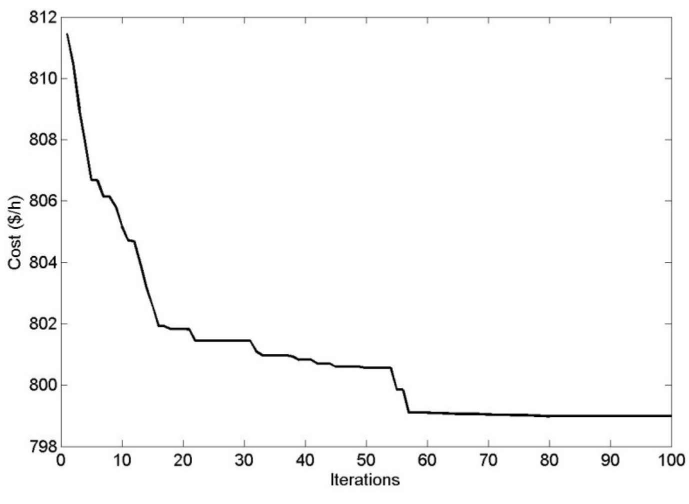

Fig. 1: Convergence characteristics for case 1 of single objective cases on IEEE 30-bus test system

Case 2: OPF with cost minimization using numerous fuel sources as objective

In reality there may be more than one fuel options for a generator. For IEEE 30-bus test system generator 1 and 2 have been considered to have multi-fuel options and the cost curve is represented by a piecewise quadratic function. Therefore, in this instance the objective function can be represented by (19). Table 1 representsthe optimal settings of control variables obtained after running EWA technique. The most advantageous fuel cost established in this instance is 645.9819 $/h which is less that that obtained using BSA. The convergence characteristics of the cost function using EWA is shown in Fig. 2.

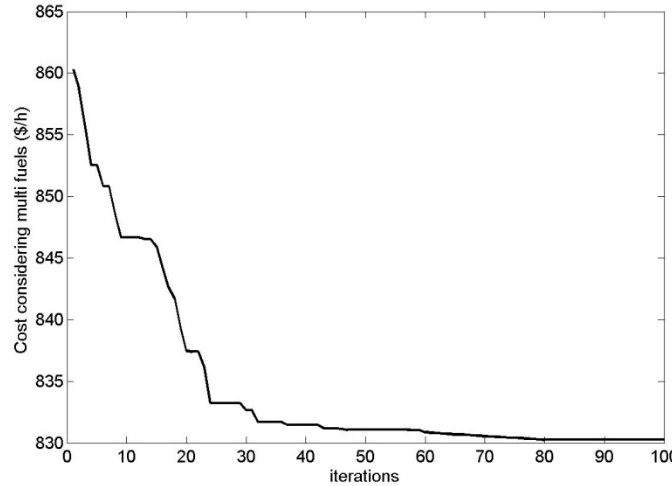

Fig. 2: Convergence characteristics for case 2 of single objective cases on IEEE 30-bus test system

Case 3: OPF with cost minimization giving consideration to valve-point effect as objective

The case minimizes the total generating cost considering the valve-point effect and the objective function is represented by (22). Table 1 represents the optimal settings of control variables obtained after running the optimization technique using EWA algorithm. The most advantageous fuel cost established in this instance is 830.2607 $/h which is greater than that obtained in case 1 of single objective cases on IEEE 30-bus test system due to the valve-point effect of the multi-valve steam turbines. The convergence characteristics of the cost function for this case is displayed in Fig. 3.

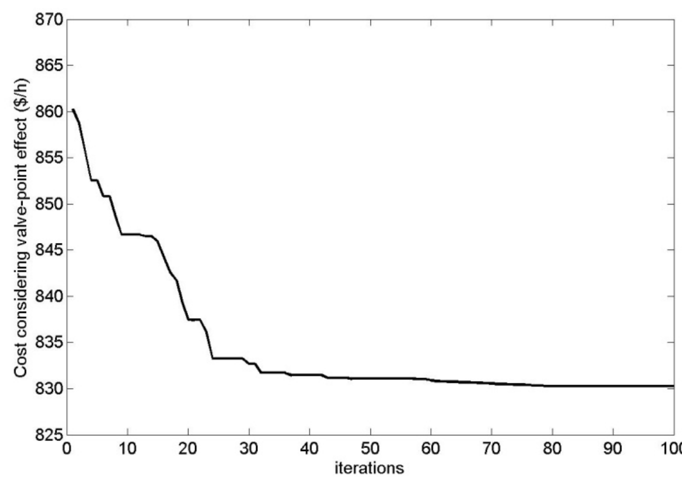

Fig. 3: Convergence characteristics for case 3 of single objective cases on IEEE 30-bus test system

Table 2 reflects statistical analysis of the performance of EWA and that of some other popular algorithms like BSA, GSO, DSA, MSA, BBO, IABC, ABC, PSO, DE and GA when applied to solve OPF problems on IEEE 30-bus test system with single objective. The performance evaluation shows that EWA is very efficient and consistent in giving better result in solving most of the OPF problems as compared to other algorithms.

4.1.2 Cases with multi objectives

Case 1: OPF with cost minimization and voltage profile enhancement as objectives

As case 1 of single objective cases is purely cost objective based OPF, it may produce an undesirable voltage profile. To overcome these shortcomings a two-fold objective function aiming to minimize cost and voltage deviation has been considered in this instance. Here (24) represents the objective function. After several testing the scaling factor λVD has been taken as 1000. The optimal control variables obtained after running EWA technique for this case are presented in Table 3 and the optimal generation fuel cost and voltage deviation obtained are 803.3416 \$/h and 0.1145 p.u. The conclusion that can be drawn from Table 3 is that voltage deviation has decreased from 1.8390 p.u. to 0.1145 p.u. whereas the cost of fuel has increased from 798.9858 \$/h to 803.3416 \$/h to keep balance between the two objectives. Table 3 also shows the comparison between EWA and BSA in which EWA reflects better result.

Case 2: OPF with cost minimization using numerous fuel sources and voltage profile enhancement as objectives

This scenario has similarity with case 1 of cases with multi objectives where cost minimization and voltage profile enhancement both are taken as objectives. Here the only difference is that the multi-fuel options have been taken into account while calculating the fuel cost. The objective function for this instance can be depicted by (25) where λVD has been taken as 1000 to keep balance between the two objectives. The OPF problem has been solved by optimization technique using EWA algorithm and the optimal results obtained in this case are displayed in Table 3. The optimal fuel cost and voltage deviation obtained are 652.4092 \$/h and 0.1160 p.u. which is much better than that obtained using BSA.

Case 3: OPF with cost minimization giving consideration to valve-point effect and voltage profile enhancement as objectives

This scenario is identical to case 1 of cases with multi objectives where cost minimization and voltage profile enhancement both are taken as objectives. Furthermore, in this instance the valve-point effect, of the generating units with multi valve steam turbines, is considered also. The corresponding objective function is expressed by (26). The problem has been solved by EWA algorithm and the results obtained in this case are displayed in Table 3. The optimal fuel cost and voltage deviation obtained are 836.5098 \$/h and 0.1171 p.u. Table 3 also shows comparative data between EWA and BSA in which superiority of EWA has been observed.

Case 4: OPF with cost minimization and emission control as objectives

In recent years the global warming has become an issue of threat to the human civilization. Therefore the emission of the greenhouse gases from the power plants needs to be controlled and at the same time the economy of the power system is to be maintained also. Hence we take the two-fold objective of cost reduction and emission minimization simultaneously and the corresponding objective function is expressed by (28). The scaling factor λemission is taken as 1000 in this instance to correlate the two objectives. The outcome obtained after running EWA technique is tabulated in Table 3. The optimal fuel cost and emission obtained are 834.9863 \$/h and 0.2423 ton/h which show that the generation fuel cost has raised from 799.0760 \$/h to834.9863 \$/h whereas the emission has reduced from 0.3662 ton/h to 0.2423 ton/h in comparison to case with single objective of cost reduction. Furthermore, the comparison between EWA and BSA shows that EWA has performed better than BSA for this case.

4.2 IEEE 57-bus test system

The efficiency of the proposed algorithm is tested on IEEE-57 bus test system also. The IEEE 57-bus test system consists of 7 generator buses, 50 load buses and 80 branches of which 17 branches have tap setting transformers and 3 buses have shunt capacitors connected to it. The operating limits for active power generation and voltage magnitudes at PV buses are taken from [35]. The transformer tap settings are considered within the interval 0.9 – 1.1 p.u. and shunt capacitors are configurable from 0 to 20 MVAR [18]. The detailed data are taken from (Ghasemi et al., 2014). The cost and emission coefficients are same as that used in [24].

4.2.1 Cases with single objectives

Case 1: OPF with cost minimization as objective

In this instance, (17) represents the objective function and this aims to minimize the generating fuel cost. The optimal control variables obtained after running EWA technique for this case are presented in Table 4. The optimal generation fuel cost obtained using EWA is 5695.5984 \$/h whereas as obtained using BSA is 6411.0043 \$/h. This proves EWA has performed better for this case. The convergence characteristics of cost function using EWA is shown in Fig. 4.

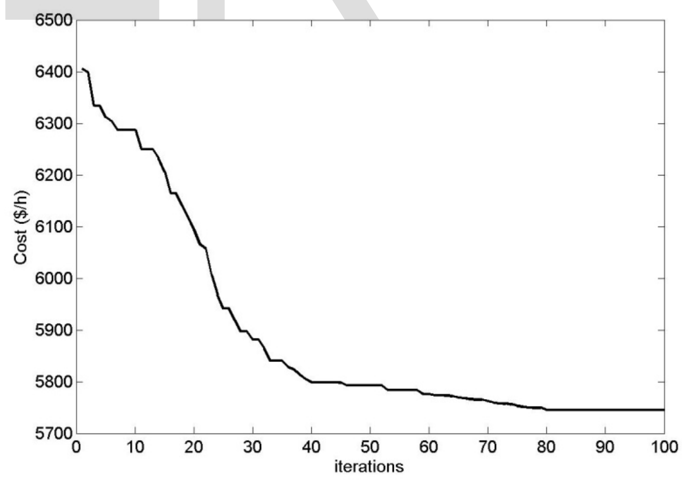

Fig. 4: Convergence characteristics for case 1 of single objective cases on IEEE 57-bus test system

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Table 1:Optimal settings of the control variables as obtained for single objective cases of IEEE 30-bus test system

Control variables	Case 1		Case 2		Case 3	
	EWA	BSA	EWA	BSA	EWA	BSA
$P_{g1(1)}$	177.1477	177.3838	139.9931	139.9204	199.9900	198.7223
$P_{g2(2)}$	48.5579	48.8335	54.9919	54.9886	41.5215	44.3031
$P_{g3(5)}$	21.3951	21.2907	23.8685	23.2095	18.0632	18.5637
$P_{g4(8)}$	20.7415	21.0186	30.3795	35.0000	10.4918	10.0000
$P_{g5(11)}$	11.9433	11.4675	19.5189	18.5930	11.2586	10.1017
$P_{g6(13)}$	12.2143	12.0602	21.0608	18.3118	12.2534	12.0000
$V_{g1(1)}$	1.0999	1.1000	1.0979	1.0863	1.0997	1.1000
$V_{g2(2)}$	1.0860	1.0806	1.0849	1.0699	1.0857	1.0778
$V_{g3(5)}$	1.0581	1.0545	1.0584	1.0403	1.0582	1.0520
$V_{g4(8)}$	1.0644	1.0633	1.0705	1.0532	1.0648	1.0574
$V_{g5(11)}$	1.0928	1.0946	1.0985	1.0679	1.0999	1.0802
$V_{g6(13)}$	1.0981	1.1000	1.0981	1.0541	1.0997	1.0803
$TAP_{1(6-9)}$	1.0072	1.0250	1.0183	1.0625	1.0363	1.0000
$TAP_{2(6-10)}$	0.9365	0.9000	0.9094	0.9125	0.9063	1.0125
$TAP_{3(4-12)}$	0.9857	0.9625	0.9681	1.0000	0.9814	1.0250
$TAP_{4(28-27)}$	0.9630	0.9625	0.9541	0.9875	0.9615	1.0000
$Q_{C1(10)}$	4.9517	4.2998	4.8586	5.0000	4.9836	4.3411
$Q_{C2(12)}$	4.9238	4.6378	4.8191	5.0000	4.9924	4.9527
$Q_{C3(15)}$	4.6677	4.9106	4.8568	5.0000	4.9967	4.2358
$Q_{C4(17)}$	4.9229	5.0000	4.9280	5.0000	4.9801	4.7605
$Q_{C5(20)}$	4.5498	4.0889	4.2927	3.1123	4.3017	4.0597
$Q_{C6(21)}$	4.9734	5.0000	4.7688	5.0000	4.9834	4.5901
$Q_{C7(23)}$	2.9148	3.1843	2.7550	3.9314	2.7776	4.1971
$Q_{C8(24)}$	4.8466	4.8423	4.8945	5.0000	4.9838	5.0000
$Q_{C9(29)}$	2.4049	2.5810	2.1941	1.4393	2.3481	4.1450
Cost ($/h)	798.9858	799.0760	645.9819	646.1504	830.2607	830.7779
Power Loss (MW)	8.6000	8.6543	6.4124	6.6233	10.1793	10.2908
Voltage Deviation (pu)	1.8390	1.9129	2.0336	1.0273	1.8857	1.2050
Emission (ton/h)	0.3662	0.3671	0.2822	0.2833	0.4420	0.4377

Table 2: Performance evaluation of EWA with BSA, DE, PSO, GA, ABC and BBO for solving different single objective OPF problems on IEEE 30-bus test system

Algorithm	Case 1			Case 2			Case 3		
	Best	Mean	Worst	Best	Mean	Worst	Best	Mean	Worst
EWA	798.9858	799.1211	799.4321	645.9819	646.2222	647.8751	830.2607	831.9243	834.2176
BSA	799.0760	799.2721	799.6240	646.1504	647.5781	649.0638	830.7779	832.0811	834.3303
GSO	799.0500	799.0600	799.9100	-	-	-	-	-	-
DSA	800.3887	-	-	-	-	-	-	-	-
MSA	800.5099	-	-	646.8364	646.8603	648.0322	-	-	-

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BBO	799.1267	801.1927	803.1429	647.1179	651.0801	656.9323	831.4581	835.8153	842.5715
IABC	799.3210	799.3210	799.3220	-	-	-	-	-	-
ABC	799.0541	799.6945	802.6327	648.5069	652.1451	657.9807	831.5783	834.4691	839.0831
PSO	800.9310	-	-	647.2879	681.7314	839.6854	837.5082	-	-
DE	799.0376	799.3047	801.5552	645.3627	646.7220	650.7419	830.4425	831.4997	842.7195
GA	800.1636	802.6876	806.2791	649.9246	650.6596	671.9717	834.2404	840.9013	854.9337

Table 3: Optimal settings of the control variables as obtained for multi objective cases of IEEE 30-bus test system

Control variables	Case 1		Case 2		Case 3		Case 4	
	EWA	BSA	EWA	BSA	EWA	BSA	EWA	BSA
$P_{g1(1)}$	176.1883	173.1714	139.5997	139.5830	194.8822	197.0323	114.2958	112.9189
$P_{g2(2)}$	48.8723	48.3093	54.9991	54.2062	39.4247	41.8254	58.9363	59.3719
$P_{g3(5)}$	21.5367	23.4476	28.1466	24.4755	18.0763	22.0463	27.6262	27.6576
$P_{g4(8)}$	21.9044	22.1097	26.8330	28.6711	14.9332	10.7320	34.9424	34.9989
$P_{g5(11)}$	12.3612	13.3916	18.0067	22.2083	10.5477	10.8690	27.2093	27.0652
$P_{g6(13)}$	12.2804	12.3455	22.8656	21.5854	12.0681	12.0000	26.7135	26.4502
$V_{g1(1)}$	1.0397	1.0441	1.0238	1.0356	1.0447	1.0514	1.0994	1.1000
$V_{g2(2)}$	1.0239	1.0245	1.0142	1.0177	1.0233	1.0278	1.0887	1.0855
$V_{g3(5)}$	1.0104	1.0037	1.0090	1.0037	1.0095	1.0086	1.0629	1.0606
$V_{g4(8)}$	1.0043	1.0005	1.0010	1.0012	1.0109	1.0018	1.0742	1.0757
$V_{g5(11)}$	1.0122	1.0316	1.0342	1.0240	0.9898	1.0263	1.0996	1.1000
$V_{g6(13)}$	1.0106	1.0049	1.0273	1.0111	1.0047	1.0061	1.0996	1.1000
$TAP_{1(6-9)}$	1.0142	1.0500	1.0196	1.0375	0.9594	1.0250	1.0176	1.0000
$TAP_{2(6-10)}$	0.9267	0.9000	0.9440	0.9000	0.9413	0.9125	0.9127	0.9500
$TAP_{3(4-12)}$	0.9897	0.9625	1.0142	0.9875	0.9671	0.9625	0.9716	1.0000
$TAP_{4(28-27)}$	0.9562	0.9625	0.9701	0.9625	0.9745	0.9750	0.9594	0.9625
$Q_{C1(10)}$	4.9614	5.0000	4.9566	4.3687	3.2731	3.8622	4.8202	3.4844
$Q_{C2(12)}$	3.8815	0.7241	0.2688	5.0000	2.4214	1.9742	4.8868	4.5129
$Q_{C3(15)}$	4.9456	3.7630	4.8772	3.3418	3.3301	2.4068	4.8539	4.7990
$Q_{C4(17)}$	1.9286	2.3539	2.7373	0.0000	0.1279	0.0000	4.9430	4.9965
$Q_{C5(20)}$	4.9857	4.9912	4.9941	5.0000	4.8878	5.0000	4.2310	3.9809
$Q_{C6(21)}$	4.9098	3.6589	4.9691	3.9460	4.7900	5.0000	4.9008	4.7684
$Q_{C7(23)}$	4.7775	4.9775	4.9993	4.9261	4.9587	4.5359	2.7445	3.8535
$Q_{C8(24)}$	4.8502	4.8500	4.9938	5.0000	4.9378	4.9781	4.9157	4.2332
$Q_{C9(29)}$	1.0815	2.2713	3.4201	3.7995	3.8384	4.2463	2.2400	1.6339
Cost ($/h)	803.3416	803.4294	652.4092	653.1019	836.5098	836.8811	834.9863	835.0199
Power Loss (MW)	9.7430	9.3751	7.4479	7.3386	11.5320	11.1050	5.0236	5.0626
Voltage Deviation (pu)	0.1145	0.1147	0.1160	0.1161	0.1171	0.1194	2.0805	1.9214
Emission (ton/h)	0.3633	0.3546	0.2813	0.2805	0.4412	0.4300	0.2423	0.2425

Table 4:Optimal settings of the control variables as obtained for single objective cases of IEEE 57-bus test system

Control variables	Case 1		Case 2	
	EWA	BSA	EWA	BSA
$P_{g1(1)}$	571.5628	537.1555	570.9600	509.4963
$P_{g2(2)}$	97.5331	100.0000	98.0187	99.9995
$P_{g3(3)}$	76.5168	68.4433	77.9964	64.7584
$P_{g4(6)}$	98.8940	100.0000	93.6517	99.9946
$P_{g5(8)}$	89.9058	165.0000	61.8135	165.0006
$P_{g6(9)}$	99.8574	100.0000	79.5223	100.0000
$P_{g7(12)}$	260.8936	218.4831	315.0648	246.1003
$V_{g1(1)}$	1.0546	1.0600	1.0491	1.0600
$V_{g2(2)}$	1.0498	1.0531	1.0548	1.0548
$V_{g3(3)}$	1.0451	1.0315	1.0343	1.0382
$V_{g4(6)}$	1.0236	1.0152	1.0142	1.0257
$V_{g5(8)}$	1.0151	1.0147	1.0025	1.0278
$V_{g6(9)}$	1.0159	0.9962	1.0058	1.0082
$V_{g7(12)}$	1.0254	1.0092	1.0206	1.0204
$TAP_{1(4-18)}$	0.9478	0.9250	0.9136	0.9500
$TAP_{2(4-18)}$	0.9981	0.9750	0.9834	0.9625
$TAP_{3(7-29)}$	0.9636	0.9500	0.9713	0.9500
$TAP_{4(9-55)}$	0.9830	0.9375	0.9739	0.9500
$TAP_{5(10-51)}$	1.0068	0.9500	0.9405	0.9500
$TAP_{6(11-41)}$	0.9588	0.9125	0.9176	0.9000
$TAP_{7(11-43)}$	0.9174	0.9375	0.9649	0.9375
$TAP_{8(13-49)}$	0.9129	0.9125	0.9069	0.9125
$TAP_{9(14-46)}$	0.9685	0.9375	0.9335	0.9375
$TAP_{10(15-45)}$	0.9387	0.9500	0.9299	0.9625
$TAP_{11(21-20)}$	0.9876	1.0125	1.0273	1.0250
$TAP_{12(24-25)}$	0.9580	0.9250	0.9578	0.9500
$TAP_{13(24-25)}$	1.0569	0.9375	0.9621	0.9125
$TAP_{14(24-26)}$	0.9764	0.9875	1.0345	0.9875
$TAP_{15(34-32)}$	1.0347	0.9125	0.9496	0.9250
$TAP_{16(39-57)}$	0.9333	0.9625	0.9941	0.9625
$TAP_{17(40-56)}$	0.9731	1.0000	1.0441	1.0125
$Q_{C1(18)}$	15.7974	5.0000	19.2373	4.9582
$Q_{C2(25)}$	5.3072	4.9944	4.9716	4.7275
$Q_{C3(53)}$	7.0924	4.9773	7.6302	5.0000
Cost ($/h)	5695.5984	6411.0043	5775.5420	6462.4093
Power Loss (MW)	44.3646	38.2819	46.2262	34.5497
Voltage Deviation (pu)	1.3230	1.1009	1.2410	1.2425
Emission (ton/h)	2.2050	1.9726	2.2721	1.8333

Table 5: Performance evaluation of for solving different single objective OPF problems on IEEE 57-bus test system

Algorithm	Case 1			Case 2		
	Best	Mean	Worst	Best	Mean	Worst
EWA	5695.5984	5696.3319	5701.4682	5775.5420	5776.8849	5781.7863
BSA	6411.0043	6411.7690	6414.9844	6462.4093	6464.3423	6468.4281
BBO	6418.5723	6450.9358	6639.2789	6468.6389	6688.4624	11512.1470
ABC	6411.4506	6423.8702	6449.4900	6467.8272	6477.5392	6493.1610
PSO	6748.6052	-	-	7149.1144	-	-
DE	6410.1888	-	-	6462.7525	-	-
GA	6673.7958	-	-	6737.3653	-	-

Table 6:Optimal settings of the control variables as obtained for multi objective cases of IEEE 57-bus test system

Control variables	Case 1		Case 2	
	EWA	BSA	EWA	BSA
$P_{g1(1)}$	557.6841	532.0307	336.8482	380.4090
$P_{g2(2)}$	98.4379	100.0000	94.8619	100.0000
$P_{g3(3)}$	60.0385	57.4381	132.0164	118.8113
$P_{g4(6)}$	98.8886	100.0000	97.9513	99.9954
$P_{g5(8)}$	88.7568	165.0000	135.5346	165.0018
$P_{g6(9)}$	98.2994	99.7228	84.9675	100.0000
$P_{g7(12)}$	292.9076	236.3389	394.2192	310.8383
$V_{g1(1)}$	1.0348	1.0307	1.0291	1.0600
$V_{g2(2)}$	1.0334	1.0235	1.0311	1.0560
$V_{g3(3)}$	1.0184	1.0111	1.0155	1.0433
$V_{g4(6)}$	1.0021	1.0039	1.0077	1.0237
$V_{g5(8)}$	1.02	1.0229	0.9738	1.0223
$V_{g6(9)}$	1.0247	1.0026	1.0148	1.0058
$V_{g7(12)}$	1.0029	1.0200	1.0016	1.0197
$TAP_{1(4-18)}$	0.9747	1.0000	1.0173	0.9750
$TAP_{2(4-18)}$	1.0366	0.9625	0.9994	0.9500
$TAP_{3(7-29)}$	0.9594	0.9500	0.9765	0.9500
$TAP_{4(9-55)}$	0.9933	0.9750	0.9437	0.9500
$TAP_{5(10-51)}$	0.9787	1.0000	0.9480	0.9500
$TAP_{6(11-41)}$	0.9007	0.9000	1.0651	0.9250
$TAP_{7(11-43)}$	0.9507	0.9375	0.9345	0.9375
$TAP_{8(13-49)}$	0.9422	0.9000	0.9528	0.9125
$TAP_{9(14-46)}$	0.9134	0.9625	0.9085	0.9375
$TAP_{10(15-45)}$	0.9689	0.9375	0.9152	0.9625
$TAP_{11(21-20)}$	0.9828	0.9750	0.9545	1.0250
$TAP_{12(24-25)}$	0.9967	0.9625	1.0343	0.9625
$TAP_{13(24-25)}$	0.9301	0.9625	1.0381	0.9125
$TAP_{14(24-26)}$	1.0272	1.0375	1.0699	1.0000
$TAP_{15(34-32)}$	0.9559	0.9250	0.9081	0.9250
$TAP_{16(39-57)}$	0.909	0.9125	0.9023	0.9750
$TAP_{17(40-56)}$	1.0411	1.0250	0.9697	1.0125
$Q_{C1(18)}$	16.7493	3.7851	16.6291	4.9368
$Q_{C2(25)}$	5.979	5.0000	1.8421	4.9580
$Q_{C3(53)}$	7.7724	5.0000	7.0691	5.0000
Cost ($/h)	5737.2122	6436.7551	6636.7535	6652.9484
Power Loss (MW)	44.2105	39.7304	25.5991	24.2558
Voltage Deviation (pu)	0.6772	0.6888	1.2697	1.2286
Emission (ton/h)	2.1567	1.9600	1.2450	1.2796

Table 7:Optimal settings of the control variables as obtained for the single objective case of IEEE 118-bus test system Case 1 using EWA

Control variables	Values	Control variables	Values	Control variables	Values
$P_{g1(1)}$	477.7648	$P_{g46(103)}$	37.9421	$V_{g37(80)}$	1.0057
$P_{g2(4)}$	33.6002	$P_{g47(104)}$	1.6899	$V_{g38(85)}$	1.0119
$P_{g3(6)}$	61.1196	$P_{g48(105)}$	23.8418	$V_{g39(87)}$	0.9882
$P_{g4(8)}$	42.2377	$P_{g49(107)}$	11.7119	$V_{g40(89)}$	1.0147
$P_{g5(10)}$	20.1128	$P_{g50(110)}$	17.6310	$V_{g41(90)}$	1.0038
$P_{g6(12)}$	173.7230	$P_{g51(111)}$	37.0377	$V_{g42(91)}$	1.0173
$P_{g7(15)}$	72.5895	$P_{g52(112)}$	48.9904	$V_{g43(92)}$	1.0053
$P_{g8(18)}$	46.8755	$P_{g53(113)}$	16.0863	$V_{g44(99)}$	1.0069
$P_{g9(19)}$	74.9478	$P_{g54(116)}$	31.1419	$V_{g45(100)}$	1.0223
$P_{g10(24)}$	31.2043	$V_{g1(1)}$	1.0145	$V_{g46(103)}$	1.0283
$P_{g11(25)}$	20.7422	$V_{g2(4)}$	1.0198	$V_{g47(104)}$	1.0136
$P_{g12(26)}$	117.0107	$V_{g3(6)}$	1.0115	$V_{g48(105)}$	1.0117
$P_{g13(27)}$	142.6273	$V_{g4(8)}$	1.0100	$V_{g49(107)}$	1.0112
$P_{g14(31)}$	43.3374	$V_{g5(10)}$	1.0164	$V_{g50(110)}$	0.9795
$P_{g15(32)}$	5.4571	$V_{g6(12)}$	1.0308	$V_{g51(111)}$	0.9894
$P_{g16(34)}$	19.3807	$V_{g7(15)}$	1.0072	$V_{g52(112)}$	0.9863
$P_{g17(36)}$	37.2842	$V_{g8(18)}$	1.0039	$V_{g53(113)}$	1.0267
$P_{g18(40)}$	59.7262	$V_{g9(19)}$	1.0326	$V_{g54(116)}$	1.0300
$P_{g19(42)}$	60.8611	$V_{g10(24)}$	1.0099	$TAP_{1(8-5)}$	1.0251
$P_{g20(46)}$	57.7327	$V_{g11(25)}$	1.0119	$TAP_{2(26-25)}$	1.0319
$P_{g21(49)}$	33.7434	$V_{g12(26)}$	1.0150	$TAP_{3(30-17)}$	0.9708
$P_{g22(54)}$	146.8288	$V_{g13(27)}$	1.0345	$TAP_{4(38-37)}$	0.9964
$P_{g23(55)}$	52.0292	$V_{g14(31)}$	0.9915	$TAP_{5(63-59)}$	1.0424
$P_{g24(56)}$	40.9250	$V_{g15(32)}$	1.0072	$TAP_{6(64-61)}$	0.9971
$P_{g25(59)}$	60.3546	$V_{g16(34)}$	0.9876	$TAP_{7(65-66)}$	1.0979
$P_{g26(61)}$	147.6603	$V_{g17(36)}$	0.9864	$TAP_{8(68-69)}$	0.9635
$P_{g27(62)}$	136.2140	$V_{g18(40)}$	0.9818	$TAP_{9(81-80)}$	0.9840
$P_{g28(65)}$	46.1484	$V_{g19(42)}$	0.9941	$Q_{C1(5)}$	0.5247
$P_{g29(66)}$	193.3027	$V_{g20(46)}$	0.9860	$Q_{C2(34)}$	0.9290
$P_{g30(69)}$	247.4550	$V_{g21(49)}$	0.9959	$Q_{C3(37)}$	0.0891
$P_{g31(70)}$	63.1080	$V_{g22(54)}$	0.9911	$Q_{C4(44)}$	0.5721
$P_{g32(72)}$	18.8301	$V_{g23(55)}$	0.9836	$Q_{C5(45)}$	4.3039
$P_{g33(73)}$	27.8665	$V_{g24(56)}$	0.9964	$Q_{C6(46)}$	0.9818
$P_{g34(74)}$	39.3780	$V_{g25(59)}$	0.9841	$Q_{C7(48)}$	10.9093
$P_{g35(76)}$	33.5423	$V_{g26(61)}$	0.9824	$Q_{C8(74)}$	8.6821
$P_{g36(77)}$	8.7299	$V_{g27(62)}$	0.9990	$Q_{C9(79)}$	19.3855
$P_{g37(80)}$	407.3962	$V_{g28(65)}$	0.9916	$Q_{C10(82)}$	0.7848
$P_{g38(85)}$	29.4720	$V_{g29(66)}$	1.0120	$Q_{C11(83)}$	9.3014
$P_{g39(87)}$	9.3085	$V_{g30(69)}$	1.0150	$Q_{C12(105)}$	0.9448

$P_{g40(89)}$	418.9805	$V_{g31(70)}$	1.0093	$Q_{C13(107)}$	0.3103
$P_{g41(90)}$	31.7485	$V_{g32(72)}$	1.0153	$Q_{C14(110)}$	0.0299
$P_{g42(91)}$	58.8636	$V_{g33(73)}$	1.0128	Cost ($/h)	135195.2170
$P_{g43(92)}$	24.2787	$V_{g34(74)}$	1.0000	Power Loss (MW)	60.4917
$P_{g44(99)}$	60.2427	$V_{g35(76)}$	0.9966	Voltage Deviation (pu)	0.8129
$P_{g45(100)}$	141.6858	$V_{g36(77)}$	1.0008		

Table 8: Performance evaluation of EWA with BSA, DE, PSO, GA, ABC and BBO for solving different single objective OPF problems on IEEE 118-bus test system

Algorithm	Case 1		
	Best	Mean	Worst
EWA	135195.2170	135240.0006	135337.8332
BSA	135333.4743	135511.5451	135689.1275
BBO	135263.7289	135684.1137	136611.2731
ABC	135304.3584	135567.2697	135973.6155
PSO	-	-	-
DE	-	-	-
GA	-	-	-

Case 2: OPF with cost minimization giving consideration to valve-point effect as objective

This case aims to minimize cost where the ripple-like valve-point effect has been taken into consideration in the cost function. Hence the objective function for this scenario can be depicted by (22). EWA is run in order to have the optimal settings of control variables and the results obtained are provided in Table 4. In this case the optimal fuel cost has raised from 5695.5984 $/h to 5775.5420$/h in comparison to the previous case due to the valve-point effect of the multi-valve steam turbines. The comparison between EWA and BSA in Table 4 confirms the superiority of EWA again. The convergence characteristic of the cost function is displayed in Fig. 5.

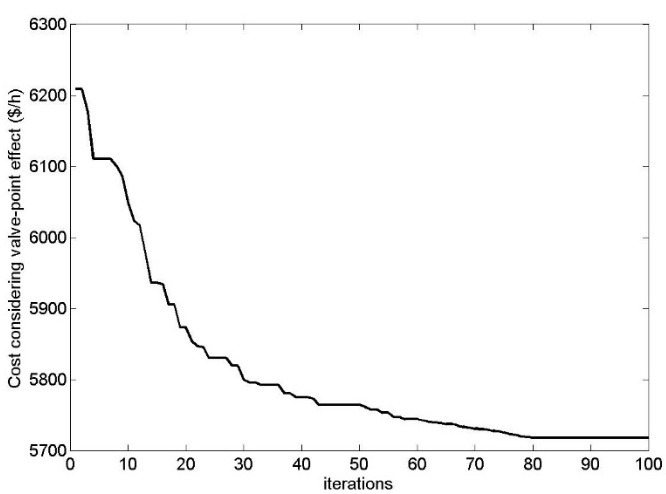

Fig. 5: Convergence characteristics for case 2 of single objective cases on IEEE 57-bus test system

Table 5 shows statistical analysis of the performance of EWA and that of some other popular algorithms like BSA, BBO, ABC, PSO, DE and GA for solving single objective OPF problems on IEEE 57-bus test system. The performance evaluation shows that EWA performs better consistently for different objectives and gives better result in solving most of the OPF problems as compared to other algorithms.

4.2.2 Cases with multi objectives

Case 1: OPF with cost minimization and voltage profile enhancement as objectives

This scenario has two-fold objective function aiming to reduce cost and voltage deviation and can be expressed by (24). The scaling factor λVD has been taken as 10000 to keep balance between the two objectives. The optimal control variables obtained after running EWA technique for this case are presented in Table 6 and the optimal fuel cost for power generation and voltage deviation obtained are 5737.2122 $/h and 0.6772 p.u. which shows further improvement of voltage profile with a little compromise to the fuel cost as compared to the single objective case on IEEE 57-bus test system with cost reduction as objective. Table 6 shows EWA performs better than BSA in this case.

Case 2: OPF with cost minimization and emission control as objectives

This case aims to minimize cost and emission simultaneously and the corresponding objective function is expressed by (28). The scaling factor λemission is selected as 1000 for this case. The results obtained after running EWA technique are presented in Table 6 where the optimal fuel cost and emission obtained are 6636.7535 $/h and 1.2450 ton/h. This shows that the generation fuel cost has increased from5745.3827 $/h to 6636.7535 $/h whereas the emission has reduced from 2.1723 ton/h to 1.2450 ton/h in comparison

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to the case 1 of single objective cases on IEEE 57-bus test system. Simulation results show that EWA has performed better than BSA for this case.

4.3 IEEE 118-bus test system

An even more larger-scale test system namely IEEE 118-bus test system is used to test the efficiency of the proposed algorithm. The IEEE 118-bus test system consists of 54 generator buses, 64 load buses and 186 branches of which 9 branches have tap setting transformers and 14 buses have shunt capacitors connected to it. The operating limits for active power generation and voltage magnitudes at PV buses are taken from [35]. The transformer tap settings are considered within the interval 0.9 – 1.1 p.u. and shunt capacitors are configurable from 0 to 30 MVAR [36]. The detailed data and the cost coefficients are derived from [35].

4.3.1 Case with single objective

Case 1: OPF with cost minimization as objective

In this scenario, the objective function can be depicted by and this aims to minimize the fuel cost for power generation. The optimal control variables obtained after running EWA technique for this case are given in Table 7 and the optimal generation fuel cost obtained is 135195.2170 $/h. The optimal fuel cost obtained using BSA is 135333.4743 $/h. Therefore it can be concluded that EWA performs better than BSA even for the larger-scale power systems. The convergence characteristic for the cost function is displayed in Fig. 6 which shows EWA converges to the final result within 60 iterations.

The performance of EWA has been evaluated in comparison to that of some other popular algorithms like BSA, BBO, ABC, PSO, DE and GA for solving OPF problem on IEEE 118-bus test system. The simulation result for EWA and other algorithms are recorded in Table 8 for OPF problem with cost reduction as objective on IEEE 118-bus test systems. The comparative performance evaluation shows that EWA is very efficient and gives better result for large scale test systems also.

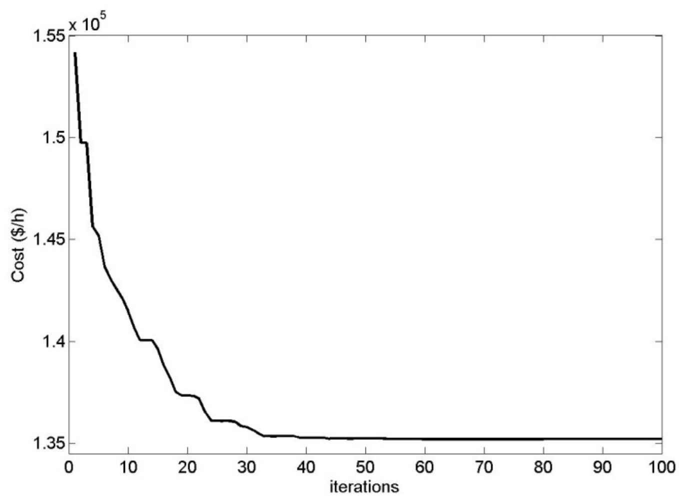

Fig. 6: Convergence characteristics for case 1 of single objective cases on IEEE 118-bus test system

5 CONCLUSION

In this article, an attempt has been made to use a newly developed evolutionary algorithm namely earthworm optimization algorithm (EWA) for solution of different OPF problems. IEEE 30-bus, 57-bus and 118-bus test systems are used to test the superiority of the proposed algorithm. Simulation results followed by performance evaluation show the superiority of EWA over other existing control algorithms like BSA, DE, PSO, ABC, GA and BBO. Moreover EWA has good convergence characteristics. This confirms that the proposed EWA method can effectively handle several single and multi-objective OPF problems and is a very efficient and promising one to solve OPF problems even in large-scale power systems.

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