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# A bio-inspired novel optimization technique for reactive power flow

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ABSTRACT

In the arena of power system operation and planning, the optimal reactive power flow (ORPF) plays a pivotal role, wherein the application of classical techniques poses issues in obtaining the optimal solutions and hence is usually employed with the meta-heuristic and/or bio-inspired techniques, with a view to converge swiftly towards an optimal solution. Usually, ORPF can have uneven, intermittent objectives and multi-constraint functions; and such intricacies of ORPF can best be suppressed by employing a combination of nature-inspired algorithms as a process of hybridization. Thus, in this paper, an approach has been endeavoured to hybridize the Biogeography based optimization (BBO) with that of the predator-prey optimization (PPO), so as to be rightfully termed as "adaptive biogeography based predator-prey optimization" (ABPPO). In such a way, this paper elucidates a novel hybrid technique that includes adaptive mutation combined with predator-prey pattern for attaining the global optimal point. In adaptive mutation scheme, the diversity measure of distance-to-average point is the predominant feature that dodges the supremacy of extremely feasible solutions throughout enhancing the population diversity. The predators explore around the elite prey in a determined way, whereas the preys search the solution space so as to evade from the predators. This tool improves the utilization and searching abilities of the BBO exploration procedure, thereby offers a mean of evading from the suboptimal point and imposes the populace to attain at the global best point. The efficacy of this hybrid scheme is validated against the standard test cases of IEEE-30 and IEEE-57 bus systems. The results show the efficiency and vitality of the proposed method.



## 1. Introduction

Optimal reactive power flow (ORPF) is a very significant phenomenon in the field of power system operation, modeling and control, which is a sub-problem of optimal power flow and helps to effectively utilize the existing reactive power sources. The main objective of ORPF is minimization of real power loss with the aid of the optimal adjustment of the power system control variables. The power flow or load flow balance equations are taken as equality constraints. Independent variables with its limit and power system state variables with its operating limits are considered as inequality constraints. The problem control variables include the voltage magnitude of generator, tap settings of transformer, and the injected values of shunt capacitor. The problem dependent variables, on the other hand, include the specified magnitude of load bus, the generator reactive powers, and the line flows. Generally, the ORPF problem is a huge scale, heavily constrained, nonlinear, non-convex and multimodal optimization problem [1,2]. The further growth in energy demands, reduction of the prevailing generation and transmission resources originate a different type of problem, named as the phenomenon of voltage instability or voltage collapse in power systems. The phenomenon of voltage instability, described by a monotonic voltage drop, is lower at first and suddenly increases after some duration. It is mainly caused by variation in the operating conditions that create an increased demand for reactive power. Various indices that provide an indirect relative measure of proximity to voltage instability for assessing the voltage stability (VS) are suggested by the researchers [3,4]. The ORPF problem can be modified to enhance VS and improve voltage profile (VP) in addition to reducing the loss.

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**Nomenclature**

| | |
|---|---|
| ABPPO | Adaptive biogeography based predator-prey optimization |
| BBO | biogeography based optimization |
| DE | differential evolution |
| $D(t)$ | diversity measure at generation-$t$ |
| $d$ | euclide an distance between predator and prey |
| $E^{max}$ | maximum emigration rate |
| GA | genetic algorithm |
| $G_{ij}$ *and* $jBij$ | real and imaginary terms of bus admittance matrix corresponding to $k$-th row and $j$-th column |
| $g_{ij}$ | conductance of the transmission line connected between buses -$i$ and $j$ |
| $g(x_1,u_1)$ | equality constraint |
| *HSI* | Habitat Suitability Index |
| $h(x_1,u_1)$ | inequality constraint |
| $h_i$ | habitat-$i$ |
| $\bar{h}_j$ | population mean point of the $j$-th*SIV* |
| $h_{ij}$ | $j$th*SIV*of $i$-th habitat |
| $h_{predator}(t)$ | a possible solution that represents a predator at generation-$t$ |
| $h_{worst}(t)$ | the worst solution in the population at generation-$t$ |
| $I^{max}$ | maximum immigration rate |
| $J(x_1,u_1)$ | objective function |
| $L_j$ | Voltage stability index at load bus-$j$ |
| *ns* | number of shunt reactive power compensators |
| *nd* | number of decision variables |
| *nh* | number of habitats |
| *ng* | number of generators |
| *nt* | number of transformers |
| *n* | maximum number of species in the population |
| *neh* | number of elite habitats |
| NET | Net Execution Time |
| ORPF | Optimal Reactive Power Flow |
| PSO | Particle Swarm Optimization |
| $P^{mod}$ | modification probability of the habitat |
| $P_m$ | rate of mutation |
| $P_m^0$ | initial mutation rate |
| $Q_{Gi}$ | reactive power generation at bus-$i$ |
| $Q_{Ci}$ | reactive power injection by $i$-th shunt compensator |
| $Q_{Gi}^{limit}$ | limit violated reactive power generation at $i$-th PV bus |
| *SIV* | Suitability Index Variable |
| TTS | tap settings of the transformer |
| $t_{max}$ | maximum number of generations |
| VDS | deviations of the voltage |
| VPE | voltage profile |
| VSY | voltage stability |
| VSI | voltage stability index |
| $V_i$ | voltage at $i$-th bus |
| $V_{Li}^{limit}$ | limit violated voltage magnitude at $i$-th load bus |
| $V_{Gi}$ | voltage magnitude at $i$-th generator bus |
| $V_{Li}$ | voltage magnitude at $i$-th load bus |
| $w$ | weight values |
| $\rho$ | rate of hunting |
| $\lambda$ and $\mu$ | rate of immigration and emigration |
| $\lambda_V$ and $\lambda_Q$ | limit violation factors (penalty) |
| $\delta_{ij}$ | voltage angle between buses-$i$ and $j$ |
| $\mathscr{R}$ | a set of load buses, whose voltages violate either the lower or upper limits. |
| $Z$ | a set of generator buses, whose $Q_G$ violate either the lower or upper limits |
| $\mathfrak{I}$ | a set of transmission lines |
| $\Phi$ | a set of load buses |
| $\Omega$ | a set of generator buses |
| $\Psi$ | augmented objective function to be minimized |
| $\chi$ | length of the longest diagonal in the search space |
| superscript min and max | lower and upper limits respectively |

Traditional mathematical programming techniques such as Gradient method [1,2], Newton method [5], Linear Programming [6–9], interior point method [10] and non-linear programming [11] have been used in order to solve the ORPF problem. A modified objective function, derived from a local voltage stability index for ORPF problem, has been built and solved using an iterative algorithm with a view of improving VS margin in [12]. The multi-period ORPF with security constraints has been formulated as a mixed-integer nonlinear programming problem and solved using generalized benders decomposition in [13]. The ORPF with discrete control variables has been solved using interior-point filter line search algorithm, which assumes all variables as continuous and rounds off the original discrete variables to the nearest discrete value in [14]. An elegant LP based solution method for ORPF has been suggested for hybrid AC-DC power systems with FACTS devices in [15], where in the formulation of the problem involves additional control variables representing the DC links and FACTS devices. Unfortunately, classical methods so mentioned have severe limitations in handling non-linear and discontinuous objectives and constraints. The gradient and Newton methods, for instance, suffer from difficulty in handling inequality constraints. The linear programming, on the other hand, requires the objective and constraint functions to be linearized during optimization, which may lead to the loss of accuracy. Thus it is a need for evolving simple and effective methods for obtaining the global optimal solution for the ORPF problem. Heuristic methods such as Genetic Algorithm (GA) [16–18], Evolutionary Programming (EP) [19], Particle Swarm Optimization (PSO) [20], Differential Evolution (DE) [21–23] and Seeker Optimization Algorithm (SOA) [24] were suggested for validating ORPF-oriented hybrid approaches involving variable scaling, mutation and probabilistic state transition rule used in the ant system, with an aspect of achieving towards the optimum operating point, which was presented in [25]. A modified teaching learning based optimization algorithm involving quasi-opposition based learning concept with a view to accelerate the convergence, speed and improve solution quality for solving multi-objective ORPF problem has been suggested in [26]. A method involving Gravitational search algorithm and opposition-based learning with a view of obtaining better quality solution for ORPF problem has been notified in [27]. A hybrid multi-agent based PSO method, which allows searching in different zones of the solution space, for ORPF problem has been suggested with a view of avoiding local optima traps in [28]. The novelties of AGA for validating ORPF problem has been outlined [29]. The approach handles different objectives and treats specified voltage of the generators, transformer tap settings values, and shunt compensators as variables. It adjusts the population size during the solution process. A DE based solution algorithm with random localization technique for ORPF problem has been outlined with a view of improving the convergence in [30]. A gravitational search technique has been suggested for validating optimal reactive power flow problem with multiple objectives of minimizing the loss and maximizing the VS margin in [31,44]. These heuristic approaches have been found to be extensive applications in solving complex optimization problems, when the traditional optimization techniques cannot be applied. The above suggested techniques mostly converge towards the best optimal point because they examine number of points in the bounded area and do not need assuming that the bounded area is differentiable or continuous. Dan Simon developed Biogeography-Based Optimization (BBO), which is mainly focused on population. In this technique fitness values are majorly taken into consideration while making a solution and this information is shared between the candidates. [32–34]. One of its applications is on power system optimization problems and it has performed efficiently. The predator-prey concept [36,37] has been incorporated in the BBO algorithm for obtaining better solutions and for enhancing the exploring capability and also applied to optimize the construction parameters of a brushless dc wheel motor [38]. However, selecting proper parameters for BBO are very important [42–43], in other words the improper choice of BBO parameters affects the convergence and accordingly leads to a local optimal solution, but not a global optimal one.

The attempt in this paper is to form a hybrid strategy, named as ABPPO, comprising the biogeography, the concept of predator-prey optimization and an adaptive mutation scheme with an aspect to effectively examine the solution space and inhibit the convergence to local minima by enhancing the population diversity; and employ the improved strategy in solving the ORPF problem with an aspect of getting the global best solution.

## 2. Adaptive biogeography based predator-prey optimization

### 2.1. Adaptive BBO

Biogeography based optimization is a stochastic optimization technique which is mainly based on biological distribution of species for evaluating multimodal optimization problems [32]. In BBO, a solution is denoted by a habitat-$i$ consisting of solution features named Suitability Index Variables (*SIV*), which are denoted by real numbers. It is denoted for a problem with $nd$ decision variables as

$$h_i = [SIV_{i,1}, SIV_{i,2}, SIV_{i,3}, \cdots, SIV_{i,nd}] \tag{1}$$

The suitability of withstanding more number of species of a habitat-$i$ can be described as a fitness measure stated to Habitat Suitability Index (*HSI*) as

$$HSI_i = f(h_i) = f(SIV_{i,1}, SIV_{i,2}, SIV_{i,3}, \cdots, SIV_{i,nd}) \tag{2}$$

High *HSI* denotes a better quality solution and low *HIS* represent an inferior solution. The objective is to locate optimal solution in terms of *SIV* that maximizes the *HSI*. Every habitat is categorized by its own immigration rate $\lambda$ and emigration rate $\mu$. A good solution relishes a higher $\mu$ and lower $\lambda$ and vice versa. The immigration and emigration rates are the functions of the number of species in the habitat and can be defined for a habitat holding $k$-species as

$$\mu_k = E^{\max}\left(\frac{k}{n}\right) \tag{3}$$

$$\lambda_k = I^{\max}\left(1 - \frac{k}{n}\right) \tag{4}$$

when $E^{\max} = I^{\max}$ , the immigration and emigration rates can be interrelated as

$$\lambda_k + \mu_k = E^{\max} \tag{5}$$

A population of candidate solutions is denoted as a vector of habitats. The salient qualities (features) amid the habitats are shared via migration operation, which is probabilistically restricted through habitat modification probability, $P^{mod}$. If a habitat $h_i$ in the population is chosen for changes, then its $\lambda$ is used to probabilistically decide whether or not to change each *SIV* in that habitat. The $\mu$ of other results are taken into consideration for choosing the habitats in the population will move randomly chosen *SIV*s to the chosen solution $h_{i.}$

The catastrophic events that extremely modify the *HSI* of a habitat are denoted by mutation of *SIV*. The process or operation can be enhanced, if the mutation rate is fine-tuned during the iterative process. A new adaptive mutation scheme has been implemented for the BBO algorithm with an aspect to effectively enhance the global exploring capability and inhibit the convergence to local minima by enhancing the population diversity. This mutation scheme uses a distance-to-average-point diversity measure [39], controls heuristically the mutation rate evaluated from the current search state and improves the exploration and the utilization capabilities of the search process and support to land at the global best solution. The suggested mutation rate can be estimated from the diversity measure $D(t)$ of the population at generation-t as

$$P_m(t+1) = P_m^0 \cdot \left(1 + \frac{D(1) - D(t)}{D(1)}\right) \tag{6}$$

where

$$D(t) = \frac{1}{nh \cdot \chi} \cdot \sum_{i=1}^{nh} \sqrt{\sum_{j=1}^{nd} (h_{ij} - \bar{h}_j)^2} \tag{7}$$

$$\bar{h}_j = \frac{1}{nh} \cdot \sum_{i=1}^{nh} h_{ij} \tag{8}$$

The proposed methodology enhances the mutation rate when the diversity of the population reduces and vice versa and guarantees higher diversity regardless of *HSI* values of the population.

### 2.2. Predator-prey model

The efficiency of the exploration can be enhanced with the theory of predator-prey model [37,38] with an aspect to avoid local optimum traps. The predator-prey optimization procedure is encouraged by hunting habit of predators to a cluster of animals/birds (prey). The victims (prey) find challenging to halt at their chosen places when raced by predators and have to explore for new places where predators are not found. This theory of predator said the preys to explore the available area more efficiently. The predators are modeled based on the worst solutions as

$$h_{predator}(t) = h_{worst}(t) + \rho \cdot \left(1 - \frac{t}{t_{\max}}\right) \tag{9}$$

To obtain globally best solution, the fugue of prey can be modeled through maintaining distance between predator and prey as

$$\begin{aligned} h(t+1) &= h(t) + \rho \cdot e^{-|d|}, \quad \textit{if } d > 0 \\ h(t+1) &= h(t) - \rho \cdot e^{-|d|}, \quad \textit{if } d < 0 \end{aligned} \tag{10}$$

### 2.3. ABPPO algorithm

As seen in Fig. 1, proposed approach combines adaptive BBO and predator prey model to force the population to arrive globally optimal position.

## 3. Problem formulation

The objective function of ORPF problem is:

$$\text{Minimize} J(x_1, u_1) \tag{11}$$

Start
Generate initial population of habitats
While $t < t_{max}$
1 Calculate the *HSI* of each individual habitat.
2 Evaluate the immigration and emigration rates for each habitat using Equations (3) and (4).
3 Probabilistically choose the immigrating habitats based on the immigration rates.
4 Use roulette wheel selection based on the emigration rates to select the emigrating habitats.
5 Migrate randomly the chosen SIVs based on the selected habitats in the previous step.
6 Probabilistically perform mutation for each habitat based on the mutation rate.
7, Evaluate the population diversity using Eq. (7).
8, Compute mutation rate using Eq. (6)
9, Hunt the solutions using Equations (9) and (10)
10, $t = t + 1$
End

**Fig. 1.** ABPPO algorithm.

Subject to

$$g(x_1, u_1) = 0 \tag{12}$$

$$h(x_1, u_1) \leq 0 \tag{13}$$

where $x_1$is the vector of dependent variables consisting of load bus voltage magnitudes, reactive power generation at generator buses and real power generation at slack bus $u_1$ is the vector of control or independent variables comprising of generator bus voltage magnitudes, transformer tap settings and output of reactive shunt compensators. The equality constraints $g(x_1,u_1)$ are the sets of non-linear power flow equations that govern the power system

$$P_{Gi} = P_{Di} + V_i \sum_{j=1'}^{nb} V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \tag{14}$$

$$Q_{Gi} = Q_{Di} + V_i \sum_{j=1'}^{nb} V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \tag{15}$$

The inequality constraints $h(x1,u1)$ represent the operating limits on reactive power generations, transformer tap settings and voltage magnitudes.

$$Q_{Gi}^{\min} \leqslant Q_{Gi} \leqslant Q_{Gi}^{\max} \tag{16}$$

$$Q_{Ci}^{\min} \leqslant Q_{Ci} \leqslant Q_{Ci}^{\max} \tag{17}$$

$$T_i^{\min} \leqslant T_i \leqslant T_i^{\max} \tag{18}$$

$$V_{Gi}^{\min} \leqslant V_{Gi} \leqslant V_{Gi}^{\max} \tag{19}$$

$$V_{Li}^{\min} \leqslant V_{Li} \leqslant V_{Li}^{\max} \tag{20}$$

The objective function $J(x_1, u_1)$ can take different forms. Six different cases involving real power loss, VP and VS, which are evaluated from the load flow solution, are taken in altering the objectives of this paper.

Scenario-1: Real power loss

$$\text{Minimize} \quad J_1(x_1, u_1) = P_L \tag{21}$$

$$\text{where} \quad P_L = \sum_{k \in \Im} g_{ij} \left( |V_i|^2 + |V_j|^2 - 2|V_i||V_j| \cos(\delta_i - \delta_j) \right) \tag{22}$$

Scenario-2: Voltage profile

One of the most important security and service quality indices is bus voltage because voltage constraints set all the bus voltages towards their maximum limits with a view of achieving the chosen goals and consequently reduce the reserve generation capacity for reactive power, which is essential for ensuring stability during contingencies. Moreover, the utilities are designed to perform well only when the bus voltages are almost 1.0 per unit. The objective function can therefore be built for improving the VP through minimizing the net voltage deviations of all buses with respect to nominal bus voltage of 1.0 per unit as [1]:

$$\text{Minimize} \quad J_2(x_1, u_1) = \sum_{j \in \Phi} |V_j - 1| \tag{23}$$

Scenario-3: Voltage stability

The VS index (VSI), also called $L$-index that varies in the range between 0 (no load of the system) and 1 (voltage collapse) for each load bus, is popular among the researchers in assessing the VS [3]. The control against voltage collapse is based on minimizing the sum of L-indices for a given operating condition.

$$\text{Minimize} \quad J_3(x_1, u_1) = \sum_{j \in \Phi} L_j \tag{24}$$

$$\text{where} \quad L_j = \left| 1 - \sum_{i = \Omega} F_{ij} \frac{Vi}{V_j} \right| \tag{25}$$

The values of $F_{ij}$ are obtained from the bus admittance matrix.

The multi-objective ORPF problem is tailored by blending several objectives through suitable weight factors with a view of optimizing the chosen objectives simultaneously [1]. The different cases with multiple objectives considered in this article are

Scenario-4: Real power loss and VP.
Scenario-5: Real power loss and VS.
Scenario-6: Real power loss, VP and VS.

## 4. Proposed method

The proposed ABPPO based solution process involves representation of problem variables and formation of a fitness function.

### 4.1. Representation of control variables

The control variables in the proposed formulation are voltage magnitude at generator buses, transformer tap positions and reactive power of shunt compensators. Each habitat in the proposed method is defined to denote these control variables in vector form as [1]:

$$h = [V_{G1}, V_{G2}, \cdots, V_{Gng}, T_1, T_2, \cdots, T_{nt}, Q_{C1}, Q_{C2}, \cdots, Q_{Cnc}] \tag{26}$$

### 4.2. HSI function

The algorithm searches for optimal solution by maximizing a *HSI* function, which is formulated from the objective function and the penalty terms representing the limit violation of the dependent variables such as reactive power generation at PV buses and voltage magnitude at load buses. The *HIS* function is written as [1]:

$$\text{Maximize} \quad HSI = \frac{1}{1+\Psi} \tag{27}$$

where

$$\Psi = J(x_1, u_1) + \lambda_V \sum_{i \in \Re} (V_{Li} - V_{Li}^{\text{limit}})^2 + \lambda_Q \sum_{i \in Z} (Q_{Gi} - Q_{Gi}^{\text{limit}})^2 \tag{28}$$

$$V_{Li}^{\text{limit}} = \begin{cases} V_{Li}^{\min} & \text{if } V_{Li} < V_{Li}^{\min} \\ V_{Li}^{\max} & \text{if } V_{Li} > V_{Li}^{\max} \\ 0 & \text{else} \end{cases} \tag{29}$$

**Table 1**
ABPPO variables.

| Variable | Value |
|---|---|
| $nh$ | 30 |
| $P^{\text{mod}}$ | 0.96 |
| $P_m^0$ | 0.03 |
| $E^{\max}$ | 1 |
| $I^{\max}$ | 1 |
| $neh$ | 3 |
| $t_{\max}$ | 300 |
| $\rho$ | 0.038 |

$$Q_{Gi}^{\text{limit}} = \begin{cases} Q_{Gi}^{\min} & \text{if } Q_{Gi} < Q_{Gi}^{\min} \\ Q_{Gi}^{\max} & \text{if } Q_{Gi} > Q_{Gi}^{\max} \\ 0 & \text{else} \end{cases} \tag{30}$$

### 4.3. Stopping criterion

The process of generating new population can be terminated either after a fixed number of iterations or if there is no further significant improvement in the global best solution [1].

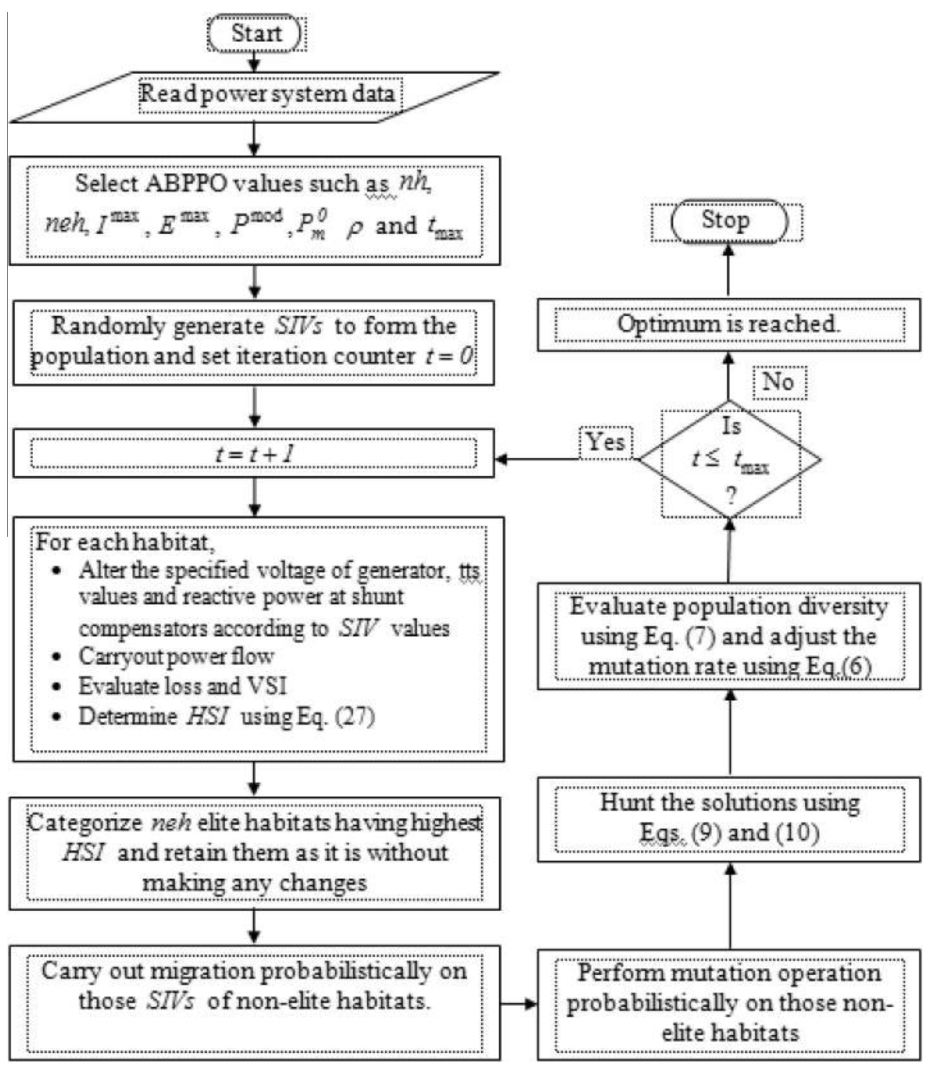


**Fig. 2.** Flow chart of the ABPPO based ORPF.

### 4.4. Solution process

An initial population of habitats is obtained by generating random values within their respective limits to every individual in the population. The *HSI* is calculated by considering of each habitat; and the migration and mutation operations are performed for non-elite habitats with a view of maximizing the *HSI*. The preys (habitats) are moved in the solution space with a view to avoid the hunting of predators, thereby escaping from the suboptimal solutions. The migration rate is then adjusted through evaluating the population diversity; and the iterative process is continued till convergence [1]. The flow of the proposed ABPPO strategy is shown in Fig. 2.

## 5. Simulation condition

The suggested ABPPO technique is implemented on IEEE-30 and 57 bus test systems, whose data have been taken from Ref. [2] and [40] respectively. Programs are designed in Matlab13 and implemented on an Intel core i5 processor. NR method [41] was implemented to carryout load flow analysis during the process of optimization. The results of the ABPPO methodology are reviewed with those of the method proposed in [17,20,21,23,35] with a aspect to validate the efficacy. The ABPPO variables selected for the suggested algorithm are given in Table 1.

### 5.1. IEEE 30 bus test system

The system consists of 6 generators at buses 1, 2, 5, 8, 11 and 13 and four tap changing transformers at lines 6–9, 6–10, 4–12 and 28–27. To acquire reactive power control the adjustable shunt compensators (reactive power sources) are connected at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29. The net power demand of the system is 2.834 per unit on 100 MVA base. The lower and upper voltage limits for both generator and load buses are 0.95 and 1.1 per unit respectively. The optimal solution of scenario-1 for IEEE

**Table 2**
Results of scenario-1 for IEEE 30 bus test systems.

| Control variables | Base case | Scanario-1 | | | | | |
|---|---|---|---|---|---|---|---|
| | | ABPPO | BBO [35] | DE [23] | CLPSO [20] | PSO [20] | GA [17] |
| $V_{G1}$ | 1.05 | 1.10000 | 1.10000 | 1.1000 | 1.10000 | 1.10000 | 1.0373 |
| $V_{G2}$ | 1.04 | 1.09409 | 1.09440 | 1.0931 | 1.10000 | 1.10000 | 1.0310 |
| $V_{G5}$ | 1.01 | 1.07463 | 1.07490 | 1.0736 | 1.07950 | 1.08670 | 1.0119 |
| $V_{G8}$ | 1.01 | 1.07605 | 1.07680 | 1.0756 | 1.10000 | 1.10000 | 1.0143 |
| $V_{G11}$ | 1.05 | 1.10000 | 1.09990 | 1.1000 | 1.10000 | 1.10000 | 1.0071 |
| $V_{G13}$ | 1.05 | 1.10000 | 1.09990 | 1.1000 | 1.10000 | 1.10000 | 1.0262 |
| $T_{6-9}$ | 1.078 | 1.02599 | 1.04350 | 1.0465 | 0.91540 | 0.95870 | 1.0500 |
| $T_{6-10}$ | 1.069 | 0.90117 | 0.90117 | 0.9097 | 0.90000 | 1.05430 | 1.0750 |
| $T_{4-12}$ | 1.032 | 0.96604 | 0.98244 | 0.9867 | 0.90000 | 1.00240 | 1.1000 |
| $T_{28-27}$ | 1.068 | 0.96236 | 0.96918 | 0.9689 | 0.93970 | 0.97550 | 0.9250 |
| $Q_{C10}$ | 0.0 | 0.05000 | 0.05000 | 0.05000 | 0.04927 | 0.04280 | 0 |
| $Q_{C12}$ | 0.0 | 0.04997 | 0.04987 | 0.05000 | 0.05000 | 0.05000 | 0 |
| $Q_{C15}$ | 0.0 | 0.04999 | 0.04991 | 0.05000 | 0.05000 | 0.03029 | 0.02857 |
| $Q_{C17}$ | 0.0 | 0.05000 | 0.04997 | 0.05000 | 0.05000 | 0.04037 | 0.02857 |
| $Q_{C20}$ | 0.0 | 0.04616 | 0.04990 | 0.04406 | 0.05000 | 0.02670 | 0.02857 |
| $Q_{C21}$ | 0.0 | 0.05000 | 0.04995 | 0.05000 | 0.05000 | 0.03889 | 0.08571 |
| $Q_{C23}$ | 0.0 | 0.03588 | 0.03875 | 0.02800 | 0.05000 | 0.00000 | 0.02857 |
| $Q_{C24}$ | 0.0 | 0.05000 | 0.04987 | 0.05000 | 0.05000 | 0.03588 | 0 |
| $Q_{C29}$ | 0.0 | 0.01975 | 0.02910 | 0.02598 | 0.05000 | 0.02842 | 0.05714 |
| Power LOSS | 0.05812 | **0.04535** | 0.04551 | 0.04555 | 0.04562 | 0.04628 | 0.04650 |
| Net VD | 1.1283 | 2.07179 | – | – | – | – | – |
| Max VSI | 0.1712 | 0.11525 | – | – | – | – | 0.2237 |
| Net VSI | 2.0877 | 1.46572 | – | – | – | – | – |

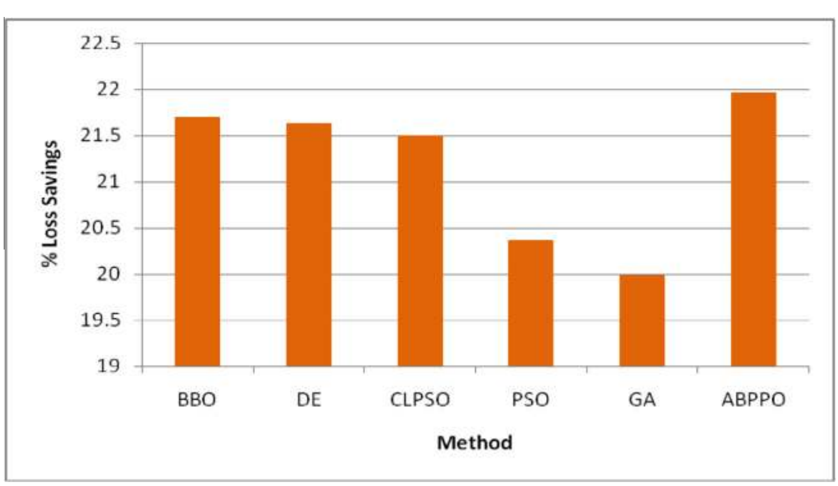


**Fig. 3.** Percentage loss savings for scenario-1 of IEEE 30 bus Test system.

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30 bus system is analyzed with other techniques such as BBO [35], DE [23], PSO [20], comprehensive learning PSO (CLPSO) [20] and GA [17] in Table 2. It is very obvious that the ABPPO algorithm is very efficient in reduction of the loss to the lowest value of 0.04535 per unit, which leads to 21.97% loss savings with regard to base case; and is much higher than that of BBO (21.70%), DE (21.63%), CLPSO (21.50%), PSO (20.37%) and GA (19.99%) as mentioned in Figure 3. The solutions for scenarios 2–6 are organized in Table 3. Scenario-2, ABPPO tenders a flat load VP via decreasing the sum of voltage deviations to a minimum value of 0.09025, while matched to that of DE [23]. However, this flat VP enhances the loss; still it is lower than that of DE [23]. It is to be observed that the results of DE [23] worsen the VS by enhancing the base-case maximum VSI of 0.1712 to 0.5734 but the ABPPO reluctantly improves the VS via decreasing the maximum VSI to 0.13651.

In Scenario-3, the ABPPO improves the VS via decreasing the net VSI of all the load buses. The net VSI of Scenario-3 is decreased by 31.11% from the base case, and also it will affect the maximum VSI in the system given in the same table. The maximum VSI of the ABPPO is 0.05899, which is less than that of DE [23]. It is to be observed that this VS improvement somewhat reduces the loss savings to 21.90%.

When various objective function comprising loss, VP and/or VS are presented in scenarios 4–6, this method brings a compromised

**Table 3**
solutions of scenarios 2–6 for IEEE 30 bus test systems.

| Control variables | Scenario-2 | | Scenario-3 | | Scenario-4 | Scenario-5 | | Scenario-6 |
|---|---|---|---|---|---|---|---|---|
| | ABPPO | DE [23] | ABPPO | DE [23] | ABPPO | ABPPO | DE [21] | ABPPO |
| $V_{G1}$ | 1.01805 | 1.0100 | 1.10000 | 1.0993 | 1.03489 | 1.10000 | 1.0700 | 1.03489 |
| $V_{G2}$ | 1.01566 | 0.9918 | 1.08781 | 1.0967 | 1.02579 | 1.09409 | 1.0629 | 1.02480 |
| $V_{G5}$ | 1.01830 | 1.0179 | 1.05005 | 1.0990 | 1.00509 | 1.07463 | 1.0446 | 1.00509 |
| $V_{G8}$ | 1.00318 | 1.0183 | 1.07067 | 1.0346 | 1.00133 | 1.07603 | 1.0430 | 1.00133 |
| $V_{G11}$ | 0.98370 | 1.0114 | 1.09845 | 1.0993 | 0.97899 | 1.10000 | 1.0974 | 0.97820 |
| $V_{G13}$ | 1.01432 | 1.0282 | 1.09973 | 0.9517 | 1.01399 | 1.10000 | 1.0613 | 1.01287 |
| $T_{6-9}$ | 0.99619 | 1.0265 | 0.98923 | 0.9038 | 0.99265 | 1.02799 | 0.9000 | 0.99265 |
| $T_{6-10}$ | 0.90042 | 0.9038 | 0.91311 | 0.9029 | 0.90694 | 0.90001 | 0.9000 | 0.91184 |
| $T_{4-12}$ | 0.98391 | 1.0114 | 0.96416 | 0.9002 | 0.98852 | 0.96643 | 1.0093 | 0.98852 |
| $T_{28-27}$ | 0.97129 | 0.9635 | 0.96551 | 0.9360 | 0.97083 | 0.96422 | 1.0119 | 0.97215 |
| $Q_{C10}$ | 0.01853 | 0.049420 | 0.02691 | 0.00685 | 0.05000 | 0.05000 | 0.0426 | 0.05000 |
| $Q_{C12}$ | 0.04997 | 0.010885 | 0.04970 | 0.04716 | 0.04892 | 0.04997 | 0.0260 | 0.04998 |
| $Q_{C15}$ | 0.04998 | 0.049985 | 0.04983 | 0.04493 | 0.04982 | 0.05000 | 0.0275 | 0.04999 |
| $Q_{C17}$ | 0.00002 | 0.002393 | 0.04924 | 0.04510 | 0.01978 | 0.05000 | 0.0282 | 0.03803 |
| $Q_{C20}$ | 0.04999 | 0.049958 | 0.04284 | 0.04477 | 0.04997 | 0.04970 | 0.0458 | 0.04997 |
| $Q_{C21}$ | 0.04994 | 0.049075 | 0.04953 | 0.04608 | 0.04994 | 0.05000 | 0.0380 | 0.04994 |
| $Q_{C23}$ | 0.05000 | 0.049863 | 0.04914 | 0.03881 | 0.04982 | 0.03800 | 0.0531 | 0.04982 |
| $Q_{C24}$ | 0.04999 | 0.049663 | 0.04999 | 0.04285 | 0.04999 | 0.05000 | 0.0258 | 0.05000 |
| $Q_{C29}$ | 0.03356 | 0.022325 | 0.04595 | 0.03254 | 0.02858 | 0.02392 | 0.0309 | 0.03304 |
| Power loss | 0.05568 | 0.06476 | 0.04685 | 0.07073 | 0.05271 | 0.04536 | 0.04850 | 0.05268 |
| Net VD | **0.09025** | 0.0911 | 2.07169 | 1.4191 | 0.10636 | 2.07788 | – | 0.10792 |
| Max VSI | 0.13651 | 0.5734 | **0.05899** | 0.1246 | 0.13664 | 0.11491 | 0.1310 | 0.13593 |
| Net VSI | 1.74604 | – | 1.42813 | – | 1.74123 | 1.46293 | – | 1.73361 |

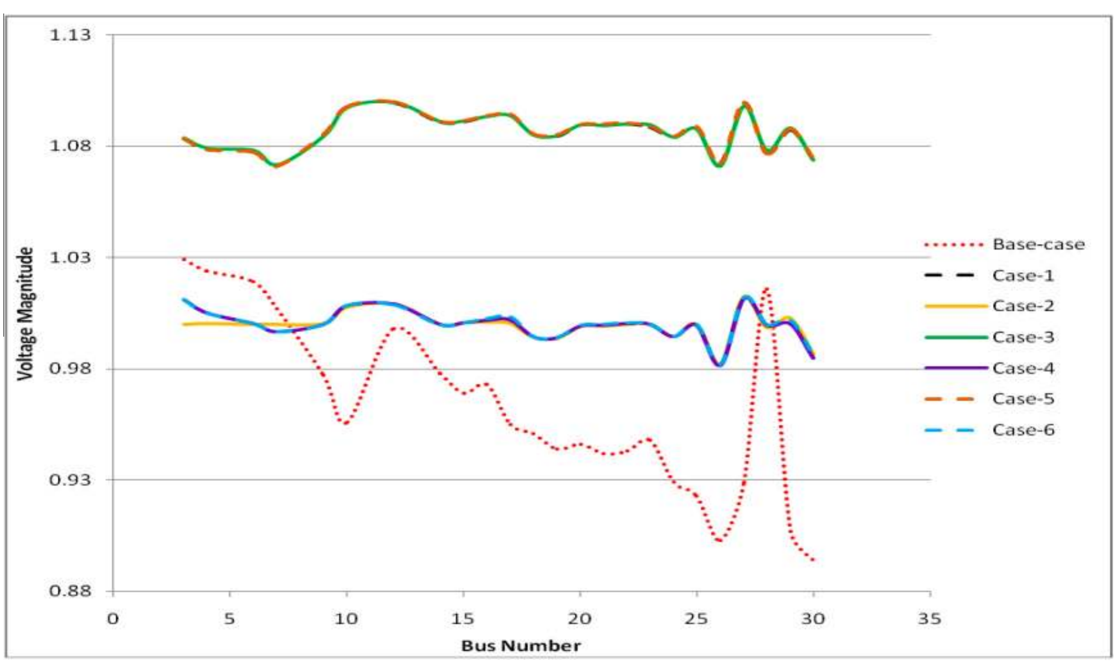


**Fig. 4.** VP of IEEE 30 bus test system.

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**Table 4**
Solution of different methods of IEEE 57 bus test systems.

| | Method | Real power loss (p.u) | Net VD | Max VSI | Net VSI |
|---|---|---|---|---|---|
| Base Case | – | 0.2722 | 1.2195 | 0.2914 | 5.8388 |
| Scanario-1 | ABPPO | **0.23434** | 2.63118 | 0.25641 | 5.17923 |
| | BBO | 0.23458 | 2.61312 | 0.25694 | 5.18472 |
| | DE | 0.23484 | 2.77960 | 0.25403 | 5.14127 |
| | GSA [44] | 0.23461 | – | – | – |
| Scanario-2 | ABPPO | 0.25526 | **0.73016** | 0.27952 | 5.71843 |
| | BBO | 0.25779 | 0.73339 | 0.27897 | 5.71444 |
| | DE | 0.25974 | 0.88069 | 0.27739 | 5.69639 |
| Scanario-3 | ABPPO | 0.24770 | 2.98061 | **0.24103** | 5.12554 |
| | BBO | 0.26587 | 2.85162 | 0.24273 | 5.18916 |
| | DE | 0.25001 | 3.02806 | 0.24291 | 5.13114 |
| Scanario-4 | ABPPO | **0.25039** | **1.65001** | 0.26582 | 5.39205 |
| | BBO | 0.25543 | 1.83635 | 0.26941 | 5.43344 |
| | DE | 0.25601 | 1.75562 | 0.26914 | 5.45222 |
| Scanario-5 | ABPPO | **0.23501** | 2.58449 | **0.25568** | 5.18513 |
| | BBO | 0.24344 | 2.62818 | 0.24669 | 5.19656 |
| | DE | 0.25951 | 2.59401 | 0.24530 | 5.21670 |
| Scanario-6 | ABPPO | **0.23588** | **2.29448** | **0.25744** | 5.23571 |
| | BBO | 0.24622 | 2.28267 | 0.25075 | 5.26645 |
| | DE | 0.24658 | 2.50003 | 0.24871 | 5.22148 |

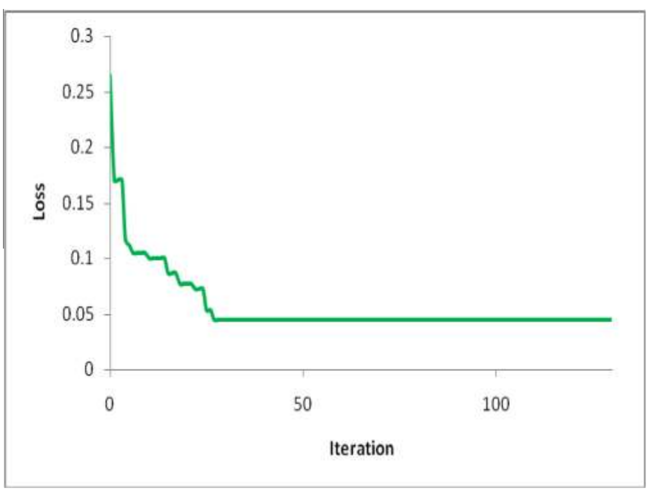


**Fig. 5.** Convergence characteristic of scenario-1 of IEEE30 bus test system.

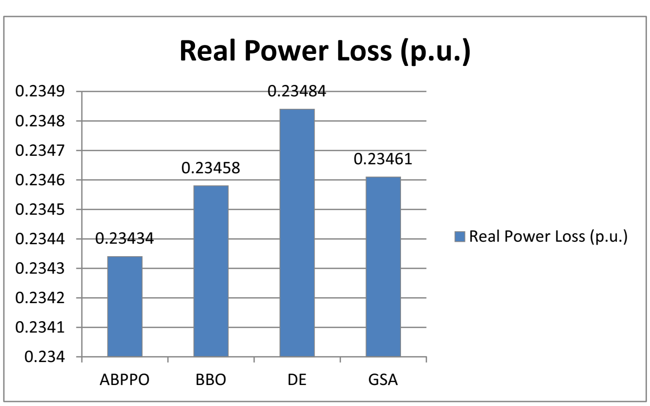


**Fig. 6.** Convergence characteristic of scenario-1 of IEEE 57 bus test system.

solution. This lies amid of the appropriate results of scenario-1, 2 and 3. The load bus voltages for all the three scenarios are presented in Fig 4. It is noted from the graph that the ABPPO is very

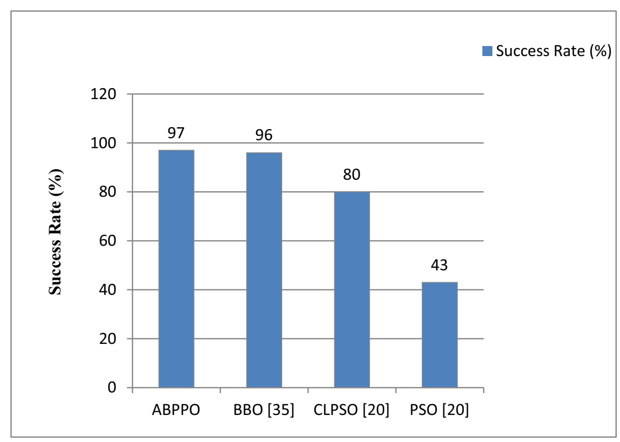


**Fig. 7.** Success rate Vs different methods of IEEE 30 bus test system.

efficient in controlling all the bus voltages within the lower and upper limits of 0.95 and 1.1 per unit for all the cases and almost a flat VP is obtained for scenarios-2, 4 and 6.

### *5.2. IEEE 57 bus system*

This system comprises seven generators at buses 1, 2, 3, 6, 8, 9 and 12 and fifteen tap changing transformers. The controllable shunt reactive power sources with a capacity of 0.1, 0.06 and 0.063 per units are connected at buses 18, 25 and 53 respectively. The total system active and reactive power demand are 12.508 per unit and 3.364. The system base value is 100 MVA. The lesser bound and higher bound bus voltages are 0.95 and 1.1. The ORPF problem is solved for all the test cases of the IEEE 57 bus system using BBO and DE in addition to solving by the proposed ABPPO and the performances are compared in Table 4. This table results clearly indicate that the proposed ABPPO method offers better performances in respect of the loss, VP and VS than those of BBO and DE based approaches.

The convergence characteristic that represents the variation of loss against the number of iterations of the proposed ABPPO algorithm for case-1 of IEEE 30 is shown in Fig. 5. The figure indicates

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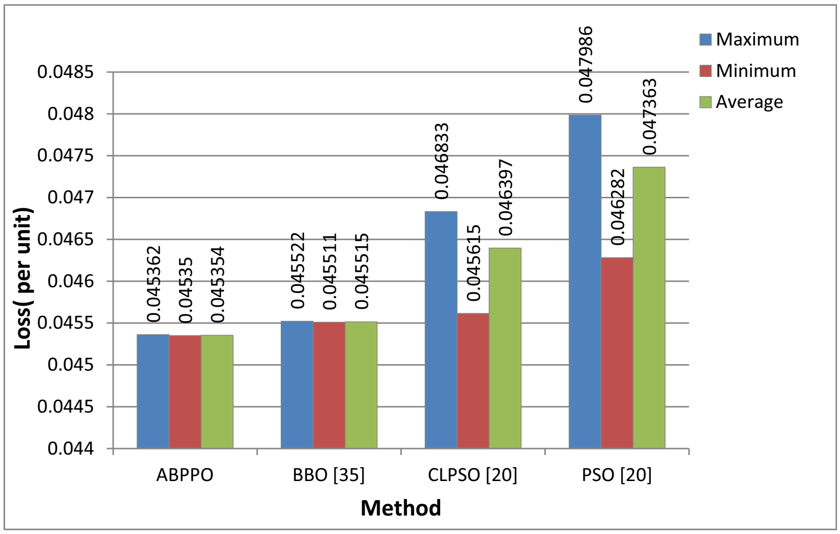


**Fig. 8.** Loss Vs different methods of IEEE 30 bus test system.

that this ABPPO algorithm is much efficient in converging to the optimal point in less than 30 iterations. The convergence characteristics of the ABPPO, BBO and DE based approaches for scenario-1 of IEEE 57 test system are presented in Fig. 6. The convergence characteristics clearly show that the ABPPO, BBO and DE requires around 45, 70 and 150 iterations to reach best optimal point. It is very clear that the ABPPO is capable of converging to the best optimal point in less number of iterations than those of the existing BBO and DE based approaches (Figs. 7–11).

The comparisons of real power loss gained by the proposed ABPPO algorithm are compared with the prevailing techniques over 100 iterations are presented in Tables 5 and 6 of scenario-1 of IEEE 30 and 57 test bus systems respectively. In addition, the minimum, maximum average values over 100 iterations are presented in that table. It is observed that average loss gained by the proposed algorithm is nearly close to the minimum loss. Moreover, the rate of success over 100 trials is higher than that of the existing approaches for both the test systems. The higher success rate and lower average real power loss significantly confirm the effectiveness of the ABPPO algorithm with a aspect of reaching at the optimum point or best solution.

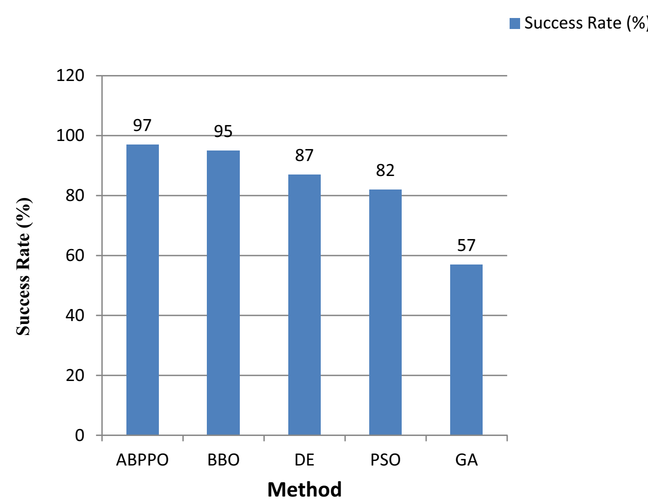


**Fig. 10.** Success rate Vs different methods of IEEE 57-bus system.

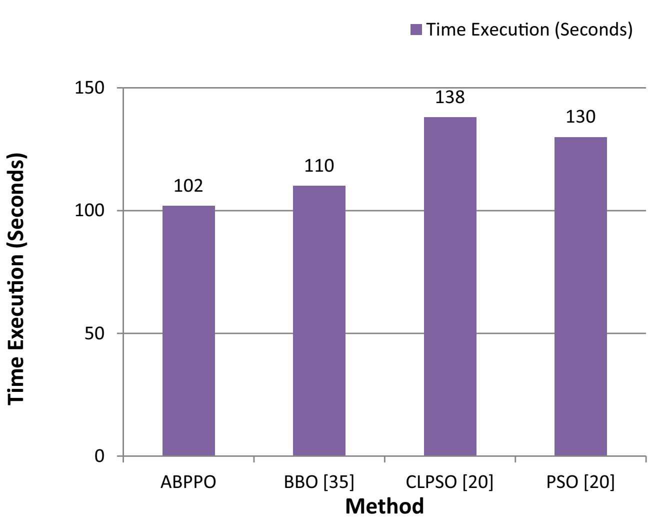


**Fig. 9.** Execution time Vs different methods of IEEE 30 bus test system.

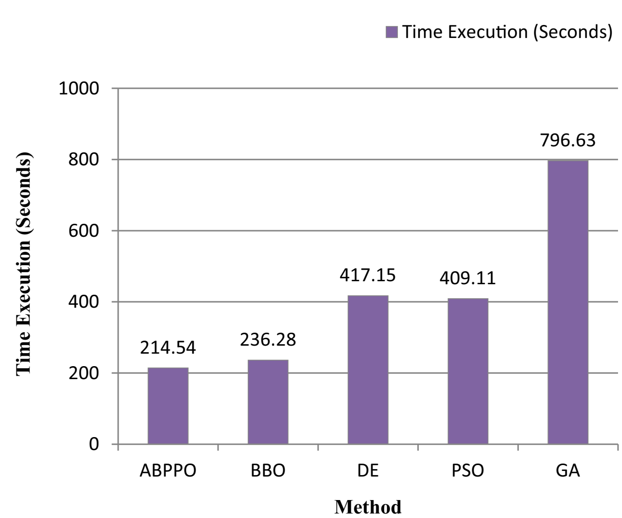


**Fig. 11.** Execution time Vs different methods of IEEE 57 bus system.

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**Table 5**
Success rate and execution time comparison of scenario-1, IEEE 30 test bus system.

| Different techniques | Loss (per unit) | | | Success rate (%) | Execution time (S) |
|---|---|---|---|---|---|
| | Maximum | Minimum | Average | | |
| ABPPO | 0.045362 | 0.045350 | 0.045354 | 97 | 102 |
| BBO [35] | 0.045522 | 0.045511 | 0.045515 | 96 | 110 |
| CLPSO [20] | 0.046833 | 0.045615 | 0.046397 | 80 | 138 |
| PSO [20] | 0.047986 | 0.046282 | 0.047363 | 43 | 130 |

**Table 6**
Success rate and execution time comparison of scenario-1, IEEE 57 bus system.

| Different techniques | Loss (per unit) | | | Success rate (%) | Execution time (S) |
|---|---|---|---|---|---|
| | Maximum | Minimum | Average | | |
| ABPPO | 0.23625 | 0.23434 | 0.23440 | 97 | 214.54 |
| BBO | 0.23911 | 0.23458 | 0.23472 | 95 | 236.28 |
| DE | 0.24104 | 0.23484 | 0.23793 | 87 | 417.15 |
| PSO | 0.24206 | 0.23753 | 0.23984 | 82 | 409.11 |
| GA | 0.26547 | 0.24269 | 0.24826 | 57 | 796.63 |

The NET of the proposed ABPPO is compared with the prevailing algorithm for scenario-1 of IEEE 30 and 57 bus systems in Tables 5 and 6 respectively. Since all these methods use time consuming NR load flow technique for evaluating the *HSI*, the overall execution time of all the methods appear to be higher. However, it can be observed from these tables that the proposed ABPPO is relatively faster than the other approaches. The relatively lower execution time of the ABPPO confirms its robustness.

## 6. Conclusion

The ORPF is an important study in power system operational planning. A hybrid solution strategy for multi-objective ORPF problem comprising Bio geography and Predator-Prey Optimization is suggested with a view to increase the population diversity, avoid the supremacy of greatly feasible results and provide a mean of escaping from the sub-optimal points. BBO is a nature inspired and population-based stochastic optimization technique and a best opponent to its better known siblings. This algorithm is mainly based on two operators namely migration and mutation. This is similar to other nature inspired techniques. Each solution are considered as habitats and the models of BBO are implemented for finding the optimum solution. The predator-prey model permits the solutions to evade from the local minima and the adaptive mutation rate is adjusted and the population diversity is enhanced. It is very clear from the results of ORPF that the ABPPO strategy is much efficient and robust in landing to the global optimum point with less computational time. It has been employed that the novel strategy for resolving ORPF will go a long way in serving as a valuable tool in load dispatch centre. This algorithm involving NR technique may not work on ill-conditioned systems. The algorithm may be suitably modified for such ill-conditioned systems besides considering the fuel costs with non-convexities created by valve point loading effects, prohibited operating zones, discrete representation of transformer tap positions and environmental issues as future work.

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