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Optimal Power Flow Using A New Evolutionary Approach: Animal Migration Optimization

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***Abstract*—A relatively new technique to solve the optimal power flow (OPF) problem inspired by the animal migration represented as Animal Migration Optimization(AMO) is presented in this paper. The generators active power, the generators voltage, tap settings of the transformers, and capacitive shunt VAR compensating devices, define the search space for the OPF problem. IEEE 57 bus test systems are assessed for various objectives to determine Animal Migration Optimization(AMO) efficiency in handling the OPF problem after satisfying constraints. The numerical simulated results are extensively verified through complete performance measurements with necessary subsequent discussions. The achieved results confirm the effectiveness, flexibility, and applicability of the proposed AMO based OPF methodology in comparisons to other recent competing heuristic-based algorithms in the literature.**

***Index Terms*—Large-scale power systems, Optimal power flow , Optimization, Fuel cost, IEEE-57 bus**

I. Introduction

Optimal power flow is an important aspect of power system studies [1]. Thus very topic has been a vital area of research and study since the last few decades. The complexity of the power flow is evident from the large number of variables and constraints involved with the problem . IEEE has standardized bus systems with specified data which can be used for the power system studies . Various solution techniques have been proposed for the optimal power flow. However on must also look into the fact that optimal power flow carries numerous cases of critical and non-critical optimal power flow along with it as defined by[2]. Apart from this, optimal power flow can be studied from the various objective functions point of view. The main objective of this formulation is to have an optimum flow of power in the system keeping the active and reactive power flows within the specified constraints and also fulfill the conditions of the objective functions like fuel cost, power loss, voltage deviation minimization and voltage stabilization. A number of optimization techniques have been proposed and tested for the optimal power flow formulation.

A complex optimal power flow can be solved using deterministic and non-deterministic approaches. However, the deterministic approach suffers from two shortcomings the algorithm may stuck in a local minimum prevent to reaching it's true minimum and another its depends on the initial condition of the problem [3] which is what makes the stochastic or non-deterministic techniques more popular. The non-deterministic techniques have superior global search properties and faster convergence characteristics with proper selection of parameters [3].Many swarm based or population based algorithm have been develop which have by inspired the biological instinct[4–8], or naturally occurring phenomenon [8, 9] .which each have their own drawback. Due to application of these algorithm to wide range of problem they are also known as general-purpose algorithm. Some popular global optimization algorithms include genetic algorithm (GA) [10], Teaching-learning based optimization [11],League championship algorithm(LCA)[8], Black-hole-based optimization(BHBO)[8], Particle swarm optimization (PSO) , Grey wolf optimization (GWO)[5] ,differential evolution (DE), Modified artificial bee colony (MABC) [6], Biogeography based optimization (BBO) [12], Gravitational search algorithm (GSA) [9], Seeker optimization algorithm[7], Tree-seed algorithm (TSA)[4], bacteria foraging algorithm [8], and Differential search algorithm [8] are used to solve the OPF problem in power systems. In this work a similar objective function as mentioned in the above references is chosen comprising of various cases for optimal power flow and a new stochastic method of optimization inspired from the animal behavior of migration is applied for the global solution search. The organization of the paper is initiated with a literature survey of various authors contribution towards the optimal load flow problem in the Introduction Section I, followed by the problem formulation in Section II. Exhaustive algorithm exploration in Section III. Section IV demonstrates numerical simulations results, comparative analysis and performance measures for the test cases under study. Finally, Section V sums up the conclusion.

II. OPTIMAL POWER FLOW PROBLEM FORMULATION

The main objective of optimal power flow is to optimize the power system parameters framed as control variables by the minimization of predefined objective functions with respect

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to limits of the system. The optimum power flow can be described as non-linear constrained optimization problem as given by [4, 6, 8, 10] which is:
Minimize j(x,u)
Subject to g(x,u)=0.
Where h(x,u)≤0.

A. VARIABLES

The main role of the control variables lie in the fulfillment of the power flow equations. The set of control variables for optimal power flow can be formulated as:
$b^T = [P_{G_2}...P_{G_{NG}} V_{G_1}...V_{G_{GN}} T_1....T_{NT} Q_{C_1}....Q_{C_{NC}}]$
where NG,NC and NT are the number of generator,Shunt VAR compensators and regulating transformers.
The state variables on the other hand are useful for the formulation of existing conditions of power system under consideration. The state variable vector is designated as: $a^T = [P_{G_1} V_{L_1}...V_{L_{LN}} Q_{G_1}....Q_{G_{GN}} S_{l_1}....S_{l_{nl}}]$ where NL and nl are the number of load buses and number of lines in the system. $P, Q, S, T\&V$,represent the active power,reactive power ,power ,transformer tap ratio and voltages. And their subscript$G, L, \&C$ represent the generator,line and Shunt VAR compensator receptively.

B. CONSTRAINTS

The optimal power flow is similar to other engineering optimization problems and comprises of both equality and non-equality constraints for better optimization. $EqualityConstraints$: The realizable state of the power system frames the equality constraints for the problem. In other words, the power flow equations are treated as the equality constraints.
Real Power Constraint

$$P_{G_i} - P_{D_i} = V_i \sum_{j=1}^{NB} V_j [G_{ij} [\cos(\Theta_{ij}) + B_{ij} \sin(\Theta_{ij})]$$

$ReactivePowerConstraint$:

$$Q_{G_i} - Q_{D_i} = V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\Theta_{ij}) - B_{ij} \cos(\Theta_{ij})]$$

Where, $\Theta_{ij} = \Theta_i - \Theta_j$,G and B are real and imaginary parts of the Y_{bus}.
$InequalityConstraints$: The limits of the power system which are defined for the efficient operation of the system leads to the formation of the inequality constraints.
$GeneratorConstraint$: The voltage, real power and reactive power generated by all the generators including the one present in the slack bus should lie within the stated limits. This is given as:

$$V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max} i = 1.....NG$$

$$P_{G_i}^{min} \le P_{G_i} \le P_{G_i}^{max} i = 1.....NG$$

$$Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max} i = 1.....NG$$

$TransformerConstraint$: The tap ratios of the transformers involved the system should be adjusted within the prescribed boundaries as follows:

$$T_i^{min} \le T_i \le T_i^{max} i = 1.....NT$$

Shunt VAR Constraint: The shunt VAR compensator's should have the compensatory outputs within their lower and upper bounds which is formulated as:

$$Q_{C_i}^{min} \le Q_{C_i} \le Q_{C_i}^{max} i = 1.....NC$$

$SecurityConstraint$:This is a qualitative parameter which is governed by the voltage magnitude on the load bus or the PQ bus and the line loadings which should fall within the minimum and maximum operational boundaries. The line loadings on the other hand should be less than or equal to the specified maximum loading of the line. The mathematical formulation of the security constraint is given as:

$$V_{L_i}^{min} \le V_{L_i} \le V_{L_i}^{max} i = 1.....NL$$

$$S_{l_i} \le S_{l_i}^{max} i = 1.....nl$$

The control variables are self-constrained [Trivedi, 2016]. They do-not require any external constraints. However the state variables involve the inequality constraints with them which consist of magnitudes of load bus voltage, active power generated at the reference bus, reactive power generated and the line loadings. These make up to a quadratic function. A penalty factor now enters the objective function which is dependent on the degree of violation of the limits by the state variables. Mathematically, the penalty function is framed as: $J_{avg} = J + \lambda_P (P_{G_1} - P_{G_1}^{lim})^2 + \lambda_V \sum_{i=1}^{NL} (V_{L_i} - V_{L_i}^{lim})^2 + \lambda_Q \sum_{i=1}^{NG} (Q_{G_i} - Q_{G_i}^{lim})^2 + \lambda_P \sum_{i=1}^{NL} (S_{l_i} - S_{l_1}^{lim})^2$
where $\lambda_P, \lambda_V \lambda_Q$and λ_S are penalty factor x^{lim} is defined as following

$$x^{lim} = \begin{cases} x^{max}; x \ > x^{max}, \\ x^{min};\ x < x^{min} \end{cases}$$

III. Basic Explanation of Animal Migration Optimization(AMO) [13]

Li [13] has presented a very powerful optimization algorithm based on the principle of animal migration where they move from a given location termed as their current territory to another location or migrate to a new territory in search of better options for food, climate change, environment conditions etc. The entire concept of movement revolves round the collective behavior of the animals living in a herd. During their journey in quest of finding a new habitat they go through a search process and finally settles at a place which satisfy their needs. This phenomenon exactly mimics that of a numerical optimization problem where the primary concern is to find the global optimum. And hence it is obviously expected that animal migration behavior if can suitably be modeled in a mathematical frame work, can emerge as a highly efficient optimization tool to effectively solve complex problems and Li was extremely successful in presenting such a nature inspired algorithm to achieve the said goals.

A. Mathematical Model involving the process

The fundamental principle that governs this algorithm solely depends upon certain assumptions. The leader is chosen among the possible candidates whose fitness is the highest and is retained till the next generation when it undergoes a fitness test again to validate its claim else will be replaced by a new one. While the search space is being explored and exploited with a given number of individuals (animals) at the disposal, the fitness of each individual is evaluated and in case the fitness is found less than a given threshold, a new individual will replace the current individual (which will be completely eliminated) keeping the number of animals employed in the search process constant. There are two distinct phenomena embedded into this optimization technique. While the first one is denoted as migration phase, the second phase is involved in population updating. During the migration phase however it is mandatory for each individual to follow certain rules as outlined here under

- Movement should be in the direction of its neighbors representing a collective approach rather than a personal endeavor.
- While on move it must maintain a close proximity with the neighbors there by increasing chance of success, else leaving the herd will altogether diminish the possibility of clinging to the group, thereby losing its identity completely.
- Caution must be taken to ensure that while moving closer it will not collide with any other individual in the neighborhood because the exploitation will then be affected, as no new information regarding optimum condition can be extracted simply because there will be a repetition of the observation.

In the migration phase the movement of the individual take place under the constraints mentioned above and mathematical expression is accordingly formulated. However before the same is applied, initialization process is carried out followed by migration phase and then reinforced by population update phase and finally culminates with validating the so called movements (from the two phases) according to their fitness values. The entire process is explained as given below.

1) Initialization:

- A randomly distributed population of size NP is generated with animal positions $X_1, X_2, X_3 ...., X_{NP}$ and each animal position X_i is denoted by a D-dimensional parameter vector which represents the variables of a given system to be optimized within a bounded domain with a lower limit of a_j and an upper limit of b_j as mentioned in AMO [13].

So, the j^{th} component (variable to be optimized) of i^{th} vector (individual) can be expressed as

$$x_{i,j} = a_j + rand(b_j - a_j) \tag{1}$$

where $rand$ is a uniformly distributed number between $[0, 1]$ and $i = 1, 2, ...NP$ and $j = 1, 2, ...D$.

2) Movement during migration: During this process a ring topology is formed in the neighborhood of the individual (purely arbitrary) with a dimension of 5. Thus for i^{th} individual, the $X_{neighborhood}$ comprises of $(i-2)^{th}$, $(i-1)^{th}$, $(i)^{th}$, $(i{+}1)^{th}$, $(i{+}2)^{th}$ individuals. Once the neighborhood topology has been constructed, the neighbor is chosen randomly and the new position is updated using following equation.

$$X_i(k+1) = X_i(k) + \delta(X_{neighbourhood}(k) - X_i(k)) \tag{2}$$

Where $X_{neighborhood}(k)$ is the current position (k^{th}) of the neighborhood and δ is a random number between $[0, 1]$ controlled by a Gaussian distribution and $X_i(k)$ is given by $X_i(k) = [x_{i,1}(k), x_{i,2}(k), ...x_{i,D}(k)]$

3) Population updating phase: This is a critical phase where an important decision is made either accepting or rejecting a new movement strategy (mimicking the concept of discarding unfit individual and creating a new one) of an individual depending upon the probability of the fitness value P_a compared with a random (dynamic) threshold value. In case the individual is a winner (indicating a much better fitness value) it is retained to take part again in the competition in the next iteration with others but if the individual loses the game (indicating a poor fitness value), another new individual is generated and replaces it keeping the population size fixed. Mathematically the explanation can be described as [13].

For $i = 1$ to NP

For $j = 1$ to D

if *rand* $> P_a$

$$X_i(k+1) = X_{r_1}(k) + \beta(X_{best}(k) - X_i(k)) + \alpha(X_{r_2}(k) - X_i(k)) \tag{3}$$

end if

end

end

where α , β and *rand* are random numbers generated from uniform distribution and X_{r_1} and X_{r_2} denote the positions of the individuals randomly picked from shuffled sequence vector of the population list among the entire population with the indices value r_1 and r_2 which are integers with the constraint $r_1 \neq r_2 \neq i$. This is a second movement is the search space pertaining to the same iteration where the individual is subjected to a new exploration. Here a new position is randomly picked X_{r_1} and then an weighted difference between the best position X_{best} and current position X_i is added to it along with further addition of an weighted difference between another randomly picked new position X_{r_2} and current position X_i and the process repeats till all the variables in the entire population is exhausted. If the probability of the fitness function is more than a dynamically set threshold value(controlled by the random numbers) the population update sequence will be bypassed and the positions already updated in the migration phase is retained.

4) Validating the positions: Once the positions are updated using the Eq. 3 , the fitness value for the updated positions

TABLE I **Pseudo Code of Animal Migration Optimization Algorithm**

1) Initialize NP (no. of population), D (no.of variables to be optimized), $Itmax$ (maximum number of iteration) and the prescribed fitness function $F_i^{desired}$
2) The maximum and the minimum boundary limits for the variables are set. Initial positions $X_i^S = X_i(k)$ is randomly generated where $[X_i] = x_{i,j}$ for $j = 1, 2, ...D$.
3) Fitness F_i^s for each individual(animal) with position X_i^s is computed.
4) New positions $X_i^{new-m} = X_i(k)$ are determined using Eq.2 and the corresponding fitness value F_i^{new-m} is evaluated in the migration phase.
5) F_i^{new-m} is compared with previously stored F_i^s and if $F_i^{new-m} > F_i^s$ then the corresponding positions X_i^{new-m} replace the X_i^s positions previously held else X_i^s is retained. Thus X_i^{mig} position is created along with fitness F_i^{mig}. Further, a probability indices vector P_a of dimension NP is generated .
6) In the population update phase a second movement is done using Eq.3 ,and creating a new position X_i^{new-p}, if a dynamically assigned threshold value (randomly generated number) is more than the probability P_a, else the movement is prohibited. Then the positions are updated to formulate X_i^{pop} by taking into account the successful X_i^{new-p} and X_i^{mig} values.
7) The fitness F_i^{pop} corresponding to X_i^{pop} is computed again and compared with F_i^{mig} and if $F_i^{pop} > F_i^{mig}$, the positions corresponding to F_i^{pop} is accepted else positions X_i^{mig} are retained.
8) Iteration counter is incremented $k = k + 1$ and accordingly a new set of positions $X_i(k + 1))$ (either X_i^{pop} or X_i^{mig} as the case may be) and the corresponding fitness $F_i(k + 1)$ are evaluated to take part in the process for the next iteration.
9) Once iteration counter k reaches maximum number of iterations i.e, $k > Itmax$ as prescribed or the termination criteria based on fitness function is achieved i.e, $F_i(k+1) > F_i^{desired}$, the optimization process stops yielding the optimal result else replace X_i^s with $X_i(k+1))$ and goto Step 3.

are compared with the previous one i.e, Eq. 2. Because while the entire search space is probed, the primary concern is to determine the optimum location. The decision to accept or discard the updated one or the previous one exclusively depends upon the fitness value. This infact validates that the algorithm is capable of delivering the objective or not. Thus the search continues till the termination condition is encountered, i.e, whether the iteration counts are all exhausted or the desired value is reached, whichever is earlier. The pseudo code if given in the Table.I

IV. SIMULATION RESULTS AND DISCUSSION

The algorithm described above as Animal Migration Optimization has been applied to obtain the optimal power flow of an IEEE 57 bus system. The algorithm aims to optimize the parameters of the system framed into various objective functions. The Computational resources used for the fulfillment of the task are codes written in MATLAB 2016b with additional package MatPower 6.0 version is used for IEEEbus standards. The simulation is done on a 2.60GHz i5 PC with 8GB RAM. The authenticity of the proposed algorithm is tested and the practical feasibility is verified by applying it to an IEEE 57 bus system which is shown in FIG 1 The system includes 7 generating units, 17 regulating transformers and 3 shunt VAR compensator's . The algorithm, Animal Migration Optimization has been exhaustively applied and tested with 3 different cases for the minimization of fuel cost, voltage deviation and active power loss which relate to the performance of the power system. Table II gives the optimization parameters which have been considered for the work. The population size is fixed as 10 animals with maximum number of iterations as 1000 and the dimension of the search space is 34. The random value is chosen between 0 and 1[13].

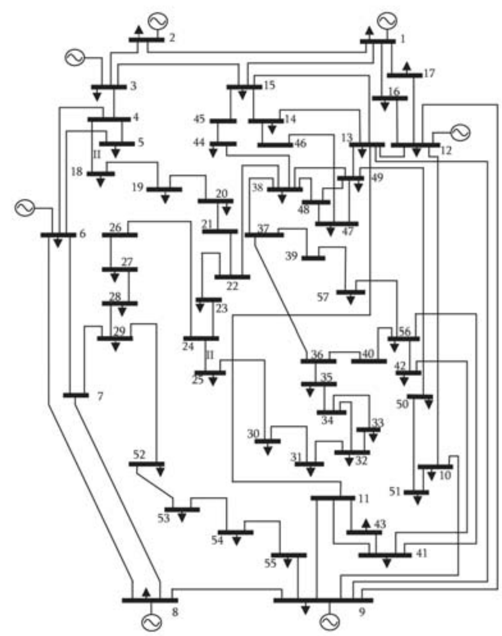

Fig. 1 Single line diagram of Transmission network 57-bus system

A. CASE I: Fuel Cost Minimization

The most common objective function optimized for a standard power system is, the cost of the fuel used for the generation of power. It is minimized because of its direct relation with the economics of the system. So our first and foremost fitness function is the equation giving the fuel cost which should be as minimum as possible. Therefore the fitness function is:

$$F_{obj1} = \sum_{i=1}^{NG} f_i(\$/h)$$

where f_i is the fuel cost of the i^{th} generator and can be simplified as

$$f_i = a_i + b_i P_{G_i} + c_i P_{G_i}^2$$

where, a_i, b_iandc_i are basic, linear cost coefficient of the i^{th} generator [4, 6, 8, 10].
Animal Migration Optimization when applied to the above objective function gives the minimal cost as low as 41679.83$/hr the fuel cost for the case study when the fitness function is evaluated without any optimization technique. The convergence curve as obtained for this case is shown in Fig 2 where it is clear that the discussed technique reaches the aforesaid global optima at around 500 iterations.

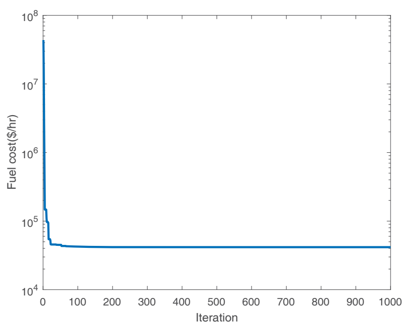

Fig. 2 Evolution of Fuel cost (case 1)

B. CASE II: ACTIVE POWER LOSS MINIMIZATION

The flow of power in the transmission lines come with some losses as well which is the price paid for transmitting power. The power loss is seen as a liability to the generators since they dont aid for revenue generation. Therefore it is desirable that this loss should be minimized and that can be done by optimizing the following objective function[4]:

$$F_{obj3} = P_{loss} = \sum_{i=1}^{NB} P_{G_i} - \sum_{i=1}^{NB} P_{D_i}$$

.where P_{loss} is the power loss calculated as the difference between the total active power generated and the total active power consumed in the system. Table II shows that AMO when applied to the objective function of active power loss, the global minima achieved is $10.51MW$. The figure 4 shows the convergence curve for the case of active power loss minimization of the considered IEEE 57 bus system.

C. CASE III: Voltage Profile Improvement

The next vital power system parameter is the voltage profile of the system. It is a measure of the degree of divergence of the system voltage from the ideally desired voltage level that is 1 p.u. Although in some cases the fuel cost can be drastically minimized but at the cost of huge voltage deviations which affects the system operations greatly. Hence the voltage deviation minimization is also equally important. The objective

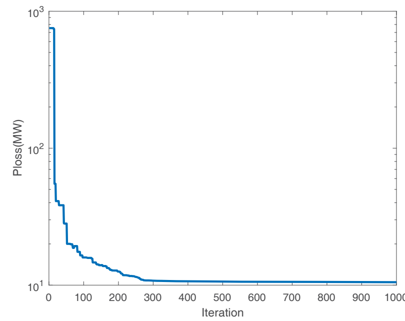

Fig. 3 Minimization of active power transmission loss(case 2)

function can be framed as the following expression[4–9, 11, 12, 14]:

$$F_{obj3} = \sum_{i=1}^{NL} \mid V_i - 1.0 \mid$$

where $V_i$is the output voltage of each PQ or load buses. The objective function here needs to be minimized and thereby improve the voltage profile. The same algorithm as applied to previous case is applied here also. The convergence pattern of total voltage deviation(TVD) is shown in Fig. 4.

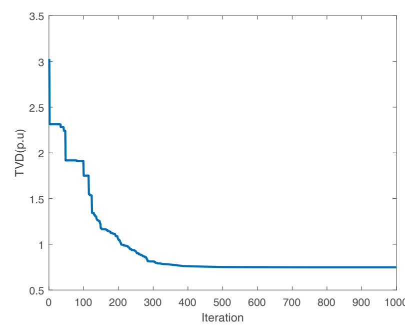

Fig. 4 Evolution of Total Voltage Deviation(p.u) (case 3)

Using the same parametric set up (control variables limits, initial conditions, and system data) for a fair comparison OPF results with other evolutionary algorithms based OPF results.Table III specifies detailed comparisons among the AMO results and many optimization algorithms for fuel cost, system P_{loss} and Total Voltage Deviations (TVD) in the IEEE 57-bus system. A comparative study of all the above three cases shown in the Table III lead us to the conclusion that each parameter is equally important and plays a vital role in the power system operations. It is also seen that minimizing any one parameter only will not suffice since they are interrelated. Therefore a balance needs to be maintained among the three parameters and a optima needs to be achieved for maximum utilization of the resources with minimum wastage.

V. Conclusion

This paper has presented the application of AMO to solve the OPF problem in electric power systems with the standard

TABLE II Optimal results for CASE 1 through CASE 3

Control Variable	Case 1	Case 2	Case 3
P_{G_1} (MW)	142.9591	201.9982	549.1549
P_{G_2} (MW)	87.34414	0.178164	13.74047
P_{G_3} (MW)	44.91829	139.9226	27.86313
P_{G_6} (MW)	72.36826	99.98645	2.09679
P_{G_8} (MW)	461.165	309.2318	407.448
P_{G_9} (MW)	96.47669	99.99681	52.28
$P_{G_{12}}$ (MW)	360.7639	409.9963	231.8669
V_{G_1} (p.u)	1.043192	1.023852	1.021706
V_{G_2} (p.u)	1.040698	1.0188	1.012088
V_{G_3} (p.u)	1.033568	1.026888	1.004953
V_{G_6} (p.u)	1.046623	1.030174	1.003695
V_{G_8} (p.u)	1.0649	1.037337	1.011436
V_{G_9} (p.u)	1.033456	1.013597	0.985326
$V_{G_{12}}$ (p.u)	1.02761	1.016208	1.007158
T_{4-18} (p.u)	1.017333	1.030147	0.900036
T_{4-18} (p.u)	0.990691	0.956972	0.900061
T_{21-20} (p.u)	0.910129	0.903418	1.006189
T_{24-25} (p.u)	0.90481	0.901531	0.900007
T_{24-25} (p.u)	1.084807	1.09928	0.900004
T_{24-26} (p.u)	0.909221	0.901592	0.952824
T_{7-29} (p.u)	0.906805	0.926185	0.900007
T_{34-32} (p.u)	1.058765	1.051339	1.099985
T_{11-41} (p.u)	0.957012	1.08408	1.099995
T_{15-45} (p.u)	1.059081	1.046528	1.09932
T_{14-46} (p.u)	0.918647	0.918988	0.900003
T_{10-51} (p.u)	1.047126	1.097351	1.099162
T_{13-49} (p.u)	1.091921	1.094715	0.900127
T_{11-43} (p.u)	0.928345	0.920286	0.900499
T_{40-56} (p.u)	0.904553	0.902909	0.900038
T_{39-57} (p.u)	1.099324	1.091785	1.099878
T_{9-55} (p.u)	1.056397	1.072664	1.099989
Q_{C18} (MVar)	11.65213	10.47622	2.394016
Q_{C25} (MVar)	14.38414	14.76687	13.62671
Q_{C53} (MVar)	12.58973	13.29287	10.22354
Fuel Cost($/hr)	**41679.83**	45036.95	56093.91
P_{loss}	15.19535	**10.51031**	33.65017
Q_{loss}	174.3293	262.2002	45.04514
TVD(p.u)	2.487451	1.651117	**0.74825**

TABLE III Comparison of the simulation result for all cases[4]

Method	Fuel Cost $/hr	Method	P_{loss}	Method	TVD(p.u)
ABC	41,781.00	ABC	12.63	ABC	0.85
IABC	41,684.00	IABC	11.16	IABC	0.66
PSO	41,688.68	PSO	25.02	PSO	0.74
TSA	41,685.07	TSA	12.47	TSA	0.72
AMO	41,679.83	AMO	10.51	AMO	0.75

IEEE57-bus systems. The optimization procedure is based on sequential optimization for different objective functions of the OPF problem. The AMO is capable of dealing with the continuous and discrete control variables in the bus system. Detailed comparisons among the results of the AMO based OPF and other evolutionary algorithms have confirmed the validity, robustness, and effectiveness of the proposed methodology. The fuel cost shows a decrement of 1.17$/hr when compared Artificial Bee Colony(ABC). In case of Power loss $0.65MW$ decrement when compared to Improved ABC. The simulation is performed on

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