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Optimal coordination of VAR sources for the solution of reactive power planning by Oppositional Harris Hawk Optimizer

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Abstract

Reactive power planning has attained a pivotal role for improved coordination in modern power system as minimization of transmission loss is an essential criterion for secured power system operation. This article proposes a meta-heuristic nature inspired Harris Hawk Optimizer (HHO) and Oppositional based Harris Hawk Optimizer (OHHO) algorithms which are implemented on standard Ward hale 6 bus system and IEEE 30 bus system. The HHO is a derivative free algorithm and does not exhibit any internal dependent parameters. Further, the search space is modified by hybridizing HHO with oppositional based learning technique in order to achieve enhanced approximation for the prevailing solution and the OHHO is proposed in the current work for minimization of transmission losses, operating cost and enhancement of voltage profile at the buses. The influence of updating mechanism of the optimizers is investigated with respect to the objective functions. The work majorly focuses on the constraints like reactive power generated by generator buses, shunt capacitors and transformer tap changing position. The simulation results obtained on standard test systems manifest the improved performance of proposed HHO and OHHO in comparison with the other optimization techniques that have emerged in the recent state-of-the-art literature.

Keywords: Harris Hawks Optimizer (HHO), Oppositional based Harris Hawk Optimizer (OHHO), transmission loss; operating cost; reactive power planning

Introduction

Power systems play a major role in generation, transmission and distribution. Power is transmitted over a long distance in a large interconnected power system which is to be operated and controlled. The modern power system control is broadly categorized into optimal power flow and reactive power planning. The reactive power planning (RPP) is the allocation of VAR sources based on location and size. The allocation of VAR sources is based on the optimization techniques or methods in RPP. The major objectives which are considered in RPP are as follows: minimization of active power loss, reactive power loss, operating cost and improvement of voltage profile in each bus by controlling transformer tap changing position, reactive power, voltage constrain and shunt capacitors.

The work proposed in [1] determines control variable settings using a differential evolution (DE) algorithm for reactive power dispatch in power system planning. The particle swarm optimization (PSO) technique in [2] determines a reactive power allocation strategy with continuous and discrete state variables. The passive power filters and hybrid active power filters are designed to satisfy the requirements of harmonic filtering in [3] and the particle swarm optimization algorithm was adopted for reactive power compensation. A flexible compensation method for economy, security and practicality is discussed in [4] using multi-scenario operations and reactive power division. A multi-level methodology is designed by incorporating fast voltage stability index device in [5] using differential search algorithm technique for reactive power planning. In this paper [6] a formulation method is described for the placement of capacitor at different levels using non differential objective function. By using general solution algorithm-based simulated annealing in [7] the optimal capacitor placements in distribution systems are proposed. Optimal reactive power dispatch problem using seeker optimization algorithm is discussed in [8] and compared with different methods of genetic algorithms and differential evolution optimization, also using conventional nonlinear programming method. A bicriterion reactive power optimization model based on successive quadratic programming (SQP) methods is proposed in [9] compromising between economical and security objective functions. An ordinal optimization-based approach containing upper and lower level is described and developed in [10] for reactive volt-ampere sources problem. The proposed method describes a full AC formulation of the optimization problem in [11], and is solved by implementation of the Newton method using interior point which is developed for the optimal power flow. In this paper [12], Kriging assisted genetic algorithm (KAGA) and a Kriging assisted particle swarm optimization (KAPSO) are the techniques developed to improve the performance of evolutionary based computation for solving optimal power flow. Authors have implemented black hole algorithm in [13] and glowworm swarm optimization [14] technique to solve the optimal power flow problem in the connected power systems network. The author describes particle swarm optimization (PSO) [15], aging leader and challengers (ALC-PSO) [16], gravitational search algorithm (GSA) [17], hybrid Nelder-Mead simplex- firefly algorithm (HFA) [18], biogeography based optimization (BBO) [19], opposition based gravitational search algorithm (OGSA) [20], for optimal reactive power flow with one or more objective of minimizing the active power losses for fixed generation schedule. The control variables are generator bus voltages, transformer tap settings and reactive power output of the compensating devices placed on different bus bars. The proposed method describes the comprehensive learning particle swarm optimization (CLPSO) [21], differential evolution (DE) [22] in which is implemented to minimize the real power losses, voltage profile improvement and voltage stability. Reactive power planning is performed in [23-26] by controlling VAR sources like reactive power generation, shunt capacitors, transformer tap positions by using evolutionary algorithms. Voltage controlled series compensator has been adopted by authors in [27-28] for improving the voltage profile and reduce the transmission loss. Plant growth simulation algorithm has been applied for controlling reactive power in [29]. The oppositional based learning is a learning based concept and first introduced by authors in [30]. The major existing algorithms like PSO, DE, GA, HFA, BBO and GSA etc. depend on some of the internal parameters like weight and acceleration factors, which are to be adopted very cautiously. Technique of HHO ensures adaptable establishment between exploitation and exploration to intensify global search ability of the proposed algorithm which does not depend on any of the internal dependent parameters. Also, the HHO algorithm is a derivative free algorithm which can be ratified easily. This unique feature of HHO algorithm has motivated the implementation in reactive power planning problem. The research work proposes the implementation of a metaheuristic algorithm of Harris Hawks Optimizer and Oppositional Harris Hawk Optimizer, which focuses on the reactive power planning. The core idea of optimization technique is to obtain the minimized transmission loss, operating cost and to maintain healthy voltage profile at each bus. The research paper initiates with the introduction, mathematical problem formulation, the proposed Harris Hawk algorithm works for better optimization of the objectives mentioned in the problem formulation, followed by simulation, result and conclusion.

Mathematical problem formulation

The key of reactive power planning is the optimal allocation of reactive power sources considering the locations. In recent works these locations are rigorous optimization-based methods by using the VAR sources. The important role of reactive power is optimization. i.e., to minimize the active power loss of all the VAR sources in the system. Also, the optimization must be done with respect to the operating cost and improve the voltage deviation in the system. Apart from this, the objective is to reduce the cost of the shunt capacitors.

Minimize active power loss

To minimize the active power loss in transmission lines it can be formulated as below:

$$P_L = g_{mn}\,[V_m^2 + V_n^2 - 2V_mV_n\cos(\delta_m - \delta_n)] \quad (1)$$

Where,

P_{loss} is active power loss, g_n is conductance of branch "n" which is connected between x^{th} and y^{th} bus,
V_m is the voltage magnitude of m^{th} bus,
V_n is the voltage magnitude of n^{th} bus,
δ_m is the voltage phase angle of m^{th} bus,
δ_n is the voltage phase angle of n^{th} bus respectively.

Minimize operating cost:

To minimize the operating cost in transmission lines it can be formulated as below (2).

Total operating cost = $S_{Energy} + S_{cap}$ (2)

Where,

S_{Energy} is the cost due to the loss of energy,
S_{Cap} is the cost of capacitors installed at the nodes which are weak.

$C_{Energy} = P_{loss} \times$ Energy rate
Energy Cost = 0.06$/kwh,
Cost of Capacitor /KVAR = 3$,
Cost of capacitor installed = 1000$, some of the cost data is collected from [4-5].
Energy rate = 0.06 × 100000 × 8760

Improvement of voltage profile:

The enhancement of voltage profile can be formulated by minimizing the deviation of the load voltages. The objective function for the same is formulated as below,

Minimize, $VD = \sum_{i=1}^{n_b} V_i - V_{specified}$ (3)

Where n_b is the total number of bus,
$V_{specified}$ is the specified bus voltage i.e. 1.0

The above-mentioned problem formulations needed to be optimized by satisfying all the equality constraints and inequality constraints as mentioned below:

(i) *Equality constraints*

The load flow equation for equality constraints are illustrated as follows:

$$P_{Gm} - P_{Dm} - V_m \sum_{N=1}^{N_b} V_n[G_{mn}\cos(\delta_{mn}) + B_{mn}\sin(\delta_{mn})] = 0,$$

N=1, 2, 3….., Nb (4)

$$Q_{Gm} - Q_{Dm} - V_m \sum_{N=1}^{N_b} V_n[G_{mn}\cos(\delta_{mn}) + B_{mn}\sin(\delta_{mn})] = 0,$$

N=1, 2, 3……, Nb (5)

Where,
n_b = number of buses,
P_{Gm} = Active power generation at the m^{th} bus,
Q_{Gm} = Reactive power generation at the m^{th} bus,
P_{Dm} = Active power demand at the m^{th} bus,
Q_{Dn} = Reactive power demand at the n^{th} bus,

G_{mn} = Transfer conductance between mth bus and nth bus,

Bmn = Transfer susceptance between mth bus and nth bus, respectively.

(ii) *Inequality constraints*

The inequality constraints include generator voltage magnitude, reactive power output by generator buses, shunt capacitors and transformer tap positions. The boundary limits of these constraints must be satisfied.

$$\left.\begin{aligned} V_{gm}^{\min} &\le V_g \le V_{gm}^{\max} \\ P_{Gm}^{\min} &\le P_G \le P_{Gm}^{\max} \\ Q_{Gm}^{\min} &\le Q_G \le Q_{Gm}^{\max} \\ Q_{Cm}^{\min} &\le Q_C \le Q_{Cm}^{\max} \\ T_m^{\min} &\le T_m \le T_m^{\max} \end{aligned}\right\} \quad (6)$$

Harris Hawk algorithm for proposed work

The Harris Hawks Optimizer is a stochastic optimization algorithm which has been developed to solve any kind of optimization problems. This unique nature-inspired, population-based, gradient-free optimization algorithm is proposed by Heidari.et.al [31] which mimics the behavior and chasing style of prey in nature by Harris hawks. Harris Hawks optimizer can be designed mathematically, where the angling (hunting) behaviors can be modeled in two phases namely exploratory and exploitative.

1) *Exploration phase*

In this section, the exploration phase of HHO is proposed. Harris hawks detect their prey with their powerful eyes depending upon the position of the prey, they are divided into two different approach methods. Which is modelled as follows

$$Z(iter+1) = (Z_c(iter) - Z_a(iter) - r_3(LB + r_4(UB - LB)) \quad (7)$$

$$Z(iter+1) = Z_{rand}(iter) - r_1\big(Z_{rand}(iter) - 2r_2 Z(iter)\big) \quad (8)$$

Z(iter) is the current location of hawks and Z (iter+1) is the vector location for the next iteration. Zc(iter) is the position of the prey. Zrand(iter) is the random selected hawk from the current population. r_1, r_2, r_3 and r_4 are the random numbers which are used to enhance and transform the exploration in the search area, LB and UB are the lower and upper bounds of search area. The average position of hawks is obtained using the expression

$$Z_a(iter) = \frac{1}{M}\sum_{i=1}^{M} Z_i(iter) \quad (9)$$

Where Z_i(iter) is the position of each hawk and M is the total number of hawks.

The HHO algorithm can be transformed from exploration phase to exploitation phase. In this phase the behavior of the prey is based on its escaping energy. The escaping energy of the prey is modelled as

$$E - 2E_i\left(1 - \frac{t}{T}\right)$$

Where E_i is the initial energy stage of the prey which lies in the interval between -1 to 1, T is the maximum number of iterations, t is the current iteration.

2) *Exploitation phase*

The transformation from exploration to exploitation phase is to achieve the surprise pounce of Harris hawks by attacking its prey which was identified in the exploration phase. The hawks encircle the prey either hardly or softly depending upon the energy of the prey retained. As the prey starts losing more energy, the hawks enhance to encircling process to smoothly catch frazzled prey. For portraying this approach, the HHO switches between soft and hard besiege process. The energy parameter E is categorized for different steps as follows:

Step 1: *Soft besiege*

When r>0.5 and E 0.5 , where the rabbit still has sufficient energy to escape by its misleading jumps, but it cannot escape finally. In this step the hawks encircle its prey softly to exhaust its left-out energy and then it performs its surprise pounce. This nature of hawk is modelled by below mentioned rules.

$$Z(iter+1) = \Delta Z\,(iter) - E[jZ_c(iter) - Z(iter)] \quad (10)$$

$$\Delta Z\,(iter) = Z\,(iter) - Z\,(iter) \quad (11)$$

Where △ Z (iter) is the position vector of the prey and the current location in iteration t, r_5 is the random number inside (0, 1), J = 2(1 – r_5) is the misleading jump strength during the escaping process. The value of J changes in each iteration randomly to mimic the nature of rabbit motions.

Step 2: *Hard besiege*

When r ≥ 0.5 and |E|<0.5, where the rabbit is exhausted and has much less escaping energy.

$$Z(iter+1) = Z_c(iter) - E\Delta Z\,(iter) \quad (12)$$

Step 3: *Soft besiege with progressive rapid dives*

When r<0.5 and |E| ≥ 0.5, the rabbit acknowledges to still have energy to escape strongly. So, the hawks make the move to quagmire it effectively and dive towards the rabbit. Based on the next move it can be modelled as

$$Y = Z_c(iter) - E[jZ_c(iter) - Z(iter)] \quad (13)$$

$$A = Y + S \times LF(D) \quad (14)$$

Where, D is the dimension of search space, S is the randomly selected vector of dimension 1D. LF (D) is the levy flight function

$$X(t+1) = \begin{cases} Y \text{ if } F(Y)\langle F(X(t)) \\ A \text{ if } F(A)\langle F(X(t)) \end{cases} \quad (15)$$

Step 4: *Hard besiege with progressive rapid dives*

When r<0.5 and |E|<0.5, the rabbit loses its complete energy to escape and the hawks construct a surprise pounce and reduce the distance between them and finally kill the rabbit. This situation of the prey is similar to the soft besiege with the decreased distance for the escaping rabbit.

$$Y = Z_c(iter) - E[jZ_c(iter) - Z_a(iter)] \quad (16)$$

3.1 Oppositional based learning

Oppositional based learning (OBL) is a new machine learning strategy introduced by H.R.Tizhoosh [30] for intensifying the convergence speed of diversified heuristic optimization techniques. The implementation of OBL implicates interpretation of current population and opposite population to obtain an enhanced candidate solution of the given problem in the same generation. The concept of OBL is used in several metaheuristic optimization technique to intensify the convergence speed.

The OBL concept of opposite number is explained as follows:

Let A ($A \in |m, n|$) be a real number

The opposite number A^0 is defined as

$$A^{\circ} = m + n - A$$

For d- dimensional search area, this equation can be further extended as

$$A_i^{\circ} = m_i + n_i + A_i$$

Where A_1, A_2 ----- A_d be the point in d-dimensional search area.

$(A_i \in |m_i, n_i|)$

Where; i= (1,2,3 ------d)

The approach of OBL is used in the initialization process and in every iteration using the generation jump rate Jr, for any oppositional based optimization.

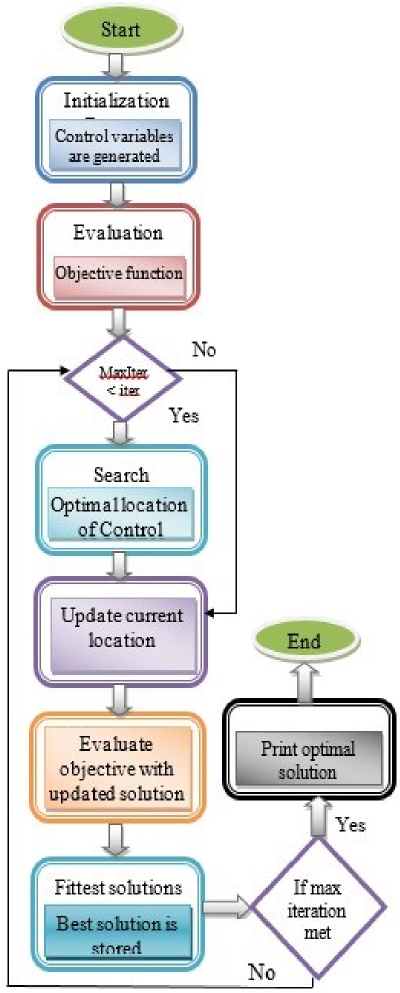

Figure 1: Flow chart for the proposed work

4. Result and discussions

For the purpose of verifying the performance and efficiency of proposed OHHO and HHO techniques, tests are carried out on Ward Hale 6 bus system and IEEE 30 bus system. All the simulations are carried out by using MATLAB 2013b, computed on core (Tm) i5-3520M CPU with 2.9GHz and 8GB RAM. For establishing the superiority of the proposed algorithms 30 independent trial runs are performed for all the test cases with a comparative study reported in the following section. Figure 1 above provides the flowchart of the proposed work.

4.1 *Case study of Ward Hale 6 bus system*

The Ward Hale 6 bus system consists of three generating units at buses 1, 2 and 3 interconnected with 7 transmission lines of which two branches (3-5 and 4-6) are equipped with tap changing transformer. This is considered as test system 1. Bus 1 is selected as the slack bus. The total demands of this test system are P_{load}=2.1p.u. and Q_{load}=2.1 p.u. at 100 MVA base [29]. Figure 2 depicts the Ward Hale 6 bus line diagram. For the test system considered shunt VAR sources are placed at the 10th bus and thereafter, HHO and OHHO techniques are implemented in order to minimize transmission loss as well as operating cost. Table 1 presents the optimal setting for system constraints.

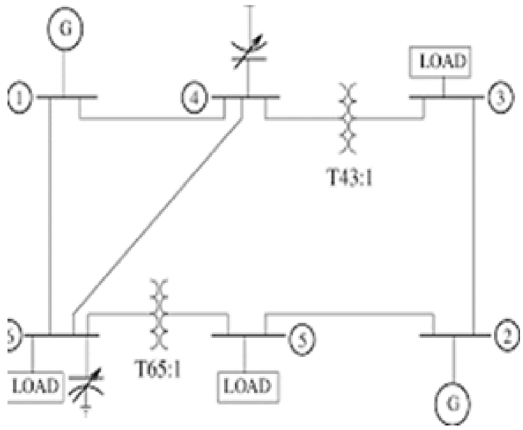

Figure 2: Ward Hale 6 bus test system used for study [29]

Table 1: Optimal sizing of VAR sources for Ward Hale 6 bus system

Control variables (p.u.)	Minimum	Initial [29]	HHO	Proposed OHHO	Maximum
Tap (3-5)	0.9	1.010	0.9861	1.0	1.1
Tap (4-6)	0.9	1.01	0.9862	1.0	1.1
VG (1)	0.95	1.05	1.0822	1.10	1.1
VG (2)	0.95	1.125	1.0822	1.10	1.1
VG (3)	0.95	1.07	1.0822	1.0869	1.1
QC(10)	0.0	0.939	0.0258	0.0405	0.05
Transmission Loss (MW)		10.250	05.34	05.18	
Total Operating Cost $\times 10^6$ ($)		5.3874	2.8086	2.7223	

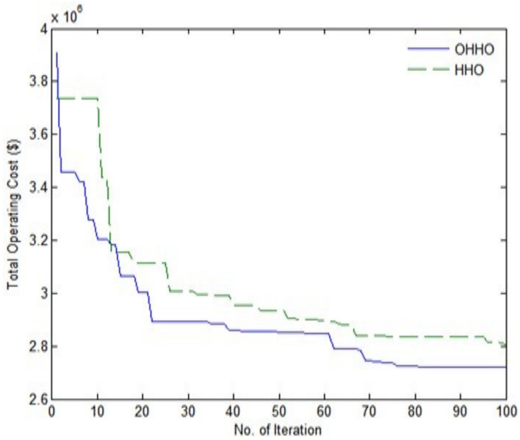

Figure 4: Convergence curve for operating cost of Ward Hale 6 bus system

It can also be observed that all the control variables are within the permissible limits and are satisfying inequality constraints. It is also verified that with implementation of the proposed methods the total transmission line loss is reduced by 47.9% using HHO and 49.46% by OHHO. It is also observed that the system operating cost which is a crucial parameter for optimal planning is 2.8086×106 and 2.7223×106 by HHO and OHHO techniques respectively. There is a significant reduction in operating cost by 49.551% by hybridizing oppositional based with respect to the initial cost of operation.

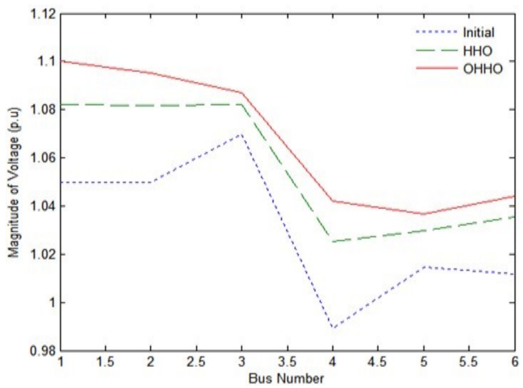

Figure 5: Magnitude of voltage in each bus of Ward Hale 6 bus system

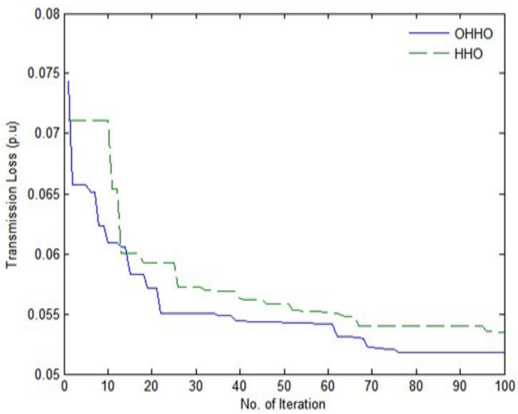

Figure 3: Convergence curve for transmission loss of Ward Hale 6 bus system.

The variation of transmission loss at all the buses is represented by the convergence curve as given by figure 3. The total active power loss by implementing HHO is 0.0534 p.u. and is further diminished to 0.0518 p.u. by oppositional HHO technique. There is a considerable reduction from base case loss value of 0.1025 p.u. using both the optimization algorithms. Similarly, figure 4 provides the convergence curve for total system operating cost wherein OHHO algorithm depicts considerable reduction thus leading to optimal and secured reactive power dispatch. Figure 5 depicts the voltage profile at all the buses for base case, with HHO and OHHO optimization. It is candidly observed that the voltage profile improvement has occurred by both the techniques but OHHO generates the best results. The voltage profile also depicts that the voltage at all buses are within the prescribed limits with average value using HHO and OHHO - 1.056 p.u. and 1.0675 p.u. respectively.

4.2 Case study of IEEE 30 bus system

The modified 30 bus system consists of six generating units at buses 1, 2, 5, 8, 11, 13 and 24 buses interconnected with 41 transmission lines of which four branches (6-9, 6-10, 4-12 and 28-27) are equipped with tap changing transformer and nine branches having shunt VAR compensators at buses (10, 12, 15, 17, 20, 21, 23, 24 and 29). Bus 1 is selected as the slack bus. The total real and reactive power demand of this test system are 2.834pu and 1.262 p.u. at 100MVA base respectively. All the load data, line data and initial values of control variables may be found in [16].

For the test system considered shunt VAR sources are placed at the 10, 12, 15, 17, 20, 21, 23, 24 and 29th buses and thereafter, HHO and OHHO techniques are implemented in order to minimize transmission loss as well as operating cost. The tap setting, voltage and var setting have been closely set within the limits satisfying all the required inequality constraints. Table 2 shows the optimal setting for system constraints. It is also verified that with implementation of the proposed methods the total line loss is reduced by 46.82% using HHO and OHHO. It is also observed that the system operating cost which is a vital aspect for optimal planning is 1.6260×106 by HHO and 1.6222×106 by OHHO. There is a significant reduction in operating cost by 46.886% by hybridizing oppositional based learning with Harris Hawk algorithm from initial system cost.

The convergence curve for transmission loss at all the buses is represented by Figure 6. The total active power loss obtained is receded by 0.0309 p.u. using HHO and oppositional HHO technique. There is an appreciable reduction from base case loss value of 0.05811 p.u. using both the optimization algorithms. Similarly, Figure 7 gives the convergence curve for total system operating cost wherein OHHO algorithm depicts considerable reduction thus leading to optimal and secured reactive power dispatch. Figure 8 illustrates the voltage profile at all the buses for base case, with HHO and OHHO optimization. It is honestly observed that the voltage profile improvement has occurred by both the techniques but OHHO generates the best results. Figure 9 provides the comparative analysis of the transmission real power loss minimization with other optimization techniques as published in literature. The proposed work is compared with 12 algorithms implemented in a similar problem of optimal reactive power dispatch. The proposed algorithms of HHO and OHHO have generated superlative results considering transmission loss along with appreciable reduction in operating cost as an additional parameter. The proposed work is further extended in maintaining voltage consistency with average value using HHO and OHHO are 1.0918 p.u. and 1.0889 p.u. respectively. Hence, this justifies the robustness of the algorithm in handling large interconnected power system problem.

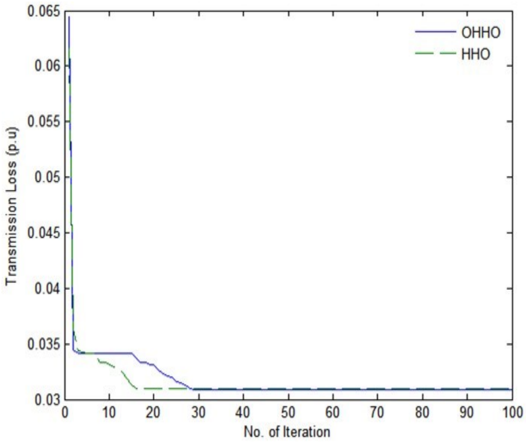

Figure 6: Convergence curve for transmission loss of IEEE 30 bus system

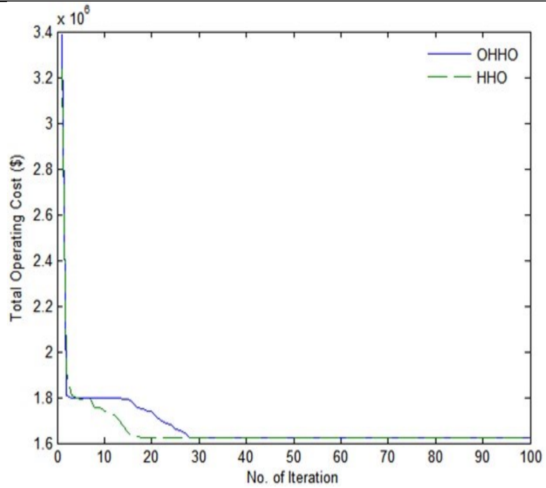

Figure 7: Convergence curve for operating cost of IEEE 30 bus system

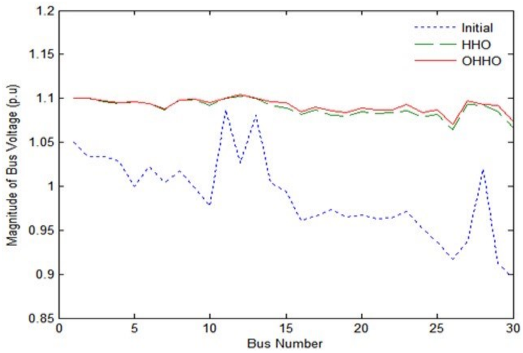

Figure 8: Convergence curve for voltage profile of IEEE

30 bus system

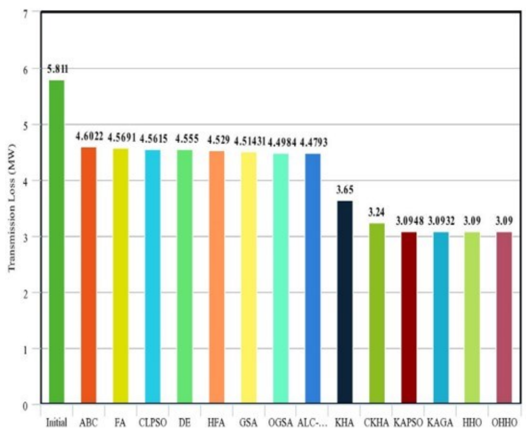

Figure 9: Comparative analysis for active power loss with various algorithms for IEEE 30 bus system

Table 3: Statistical analysis of HHO and OHHO after 30 trials

	Ward hale 6 Bus System		IEEE 30 Bus System	
	HHO	**OHHO**	**HHO**	**OHHO**
Minimum	0.0534	0.0518	0.0309	0.0309
Average	0.0539	0.0521	0.0314	0.0312
Maximum	0.0580	0.0554	0.0345	0.0342
No. of times solution was obtained	24	26	22	24
Standard Deviation	0.0012	8.7549e-04	9.0736e-04	7.5492e-04
Iteration per second	0.1481	0.1475	8.1577	8.1423

Table 1: Optimal sizing of VAR sources for IEEE 30 bus system

Control variables	Initial [19]	ABC [17]	FA [17]	CLPSO [21]	DE [22]	HFA [18]	GSA [17]	OGSA [20]	ALC-PSO [16]	KHA [23]	CKHA [23]	KAPSO [12]	KAGA [12]	HHO	Proposed OHHO
Tap_{11}, p.u.	1.078	0.97	1	0.9154	1.0465	0.980051	1.098450	1.0585	0.9521	0.9541	0.9916	1.0314	1.0442	0.9881	0.9879
Tap_{12}, p.u.	1.069	1.05	0.94	0.9	0.9097	0.950021	0.982481	0.9089	1.0299	1.0412	0.9538	0.9581	0.9119	0.9881	0.9879
Tap_{15}, p.u.	1.032	0.99	1	0.9	0.9867	0.970171	1.095909	1.0141	0.9721	0.9514	0.9603	0.9698	0.9883	0.9881	0.9879
Tap_{36}, p.u.	1.068	0.99	0.97	0.9397	0.9689	0.970039	1.059339	1.0182	0.9657	0.9541	0.9670	0.9777	0.9821	0.9881	0.9879
V_{G1}, p.u.	1.05	1.1	1.1	1.1	1.1	1.1	1.071652	1.0500	1.0500	1.0500	1.0500	1.0825	1.0797	1.10	1.10
V_{G2}, p.u.	1.04	1.0615	1.0644	1.1	1.0931	1.054332	1.022199	1.0410	1.0384	1.0381	1.0473	1.0641	1.0621	1.10	1.10
V_{G5}, p.u.	1.01	1.0711	1.07455	1.0795	1.0736	1.075146	1.040094	1.0154	1.0108	1.0110	1.0293	1.0332	1.0333	1.10	1.10
V_{G8}, p.u.	1.01	1.0849	1.0869	1.1	1.0756	1.086885	1.050721	1.0267	1.0210	1.0250	1.0350	1.0374	1.0362	1.10	1.10
V_{G11}, p.u.	1.05	1.1	1.09164	1.1	1.1	1.1	0.977122	1.0082	1.0500	1.0500	1.0500	1.0819	1.0621	1.10	1.10
V_{G13}, p.u.	1.05	1.0665	1.099	1.1	1.1	1.1	0.967650	1.0500	1.0500	1.0500	1.0500	1.0398	1.0544	1.10	1.10
QC_{10}, p.u.	0	5	3	4.9265	5	4.700304	1.653790	0.0330	0.0090	0.0089	0.0092	4.9797	4.5972	0.05	0.05
QC_{12}, p.u.	0	5	4	5	5	4.706143	4.372261	0.0249	0.0126	0.0000	0.0000	2.2098	2.5990	0.05	0.495
QC_{15}, p.u.	0	5	3.3	5	5	4.700662	0.119957	0.0177	0.0209	0.0141	0.0153	4.9254	5.0	0.05	0.0241
QC_{17}, p.u.	0	5	3.5	5	5	2.30591	2.087617	0.0500	0.0500	0.04989	0.0497	4.6838	3.8280	0.05	0.05
QC_{20}, p.u.	0	4.1	3.9	5	4.406	4.80352	0.357729	0.0334	0.0031	0.0314	0.0302	2.9661	4.3910	0.05	0.05
QC_{21}, p.u.	0	3.3	3.2	5	5	4.902598	0.260254	0.0403	0.0293	0.0345	0.0500	4.9994	5.0	0.05	0.05
QC_{23}, p.u.	0	0.9	1.3	5	2.8004	4.804034	0.000000	0.0269	0.0226	0.0241	0.0134	3.6618	2.1225	0.05	0.044
QC_{24}, p.u.	0	5	3.5	5	5	4.805296	1.383953	0.0500	0.0500	0.0500	0.0500	4.8890	5.0	0.05	0.0407
QC_{29}, p.u.	0	2.4	1.42	5	2.5979	3.398351	0.000317	0.0194	0.0107	0.0107	0.0121	2.8936	3.3295	0.05	0.0421
P_{loss}, MW	5.811	4.6022	4.5691	4.5615	4.555	4.529	4.514310	4.4984	4.4793	3.6500	3.2400	3.0948	3.0932	3.09	3.09
Total Operating Cost $\times 10^6$ ($)	3.0542	Not Reported												1.6260	1.6222

Table 3 depicts the statistical analysis which provides a significant relevance for assessing the performance of the proposed algorithms. The algorithms are run for a maximum of 30 trials and the number of times the solution was generated is sufficiently high which proves the computational efficiency. Also, the iterations per second justifies the computational speed of the proposed algorithms.

Conclusion

In the proposed work, one of the recently improved meta-heuristic algorithms has been applied in solving voltage constrained reactive power planning problem while satisfying all the constraints in the test power system. In this study, different objective functions were considered like minimization of operating cost, minimization of transmission loss and improvement of voltage profile in each bus. The proposed OHHO and HHO has been investigated successfully in Ward Hale 6 bus and IEEE 30 bus system. The simulation results have proved robustness and superiority of the proposed approach to solve RPP problem. The results are compared with other evolutionary optimization techniques as published in literature and justify the potential of the algorithms to generate accurate solution for large interconnected power networks.

References

[1] Varadarajan, M., and K. S. Swarup. "Volt-var optimization using differential evolution." Electric Power Components and Systems 36, no. 4 (2008): 387-408.

[2] Fukuyama, Yoshikazu. "Comparative studies of particle swarm optimization techniques for reactive power allocation planning in power systems." IEEJ Transactions on Power and Energy 124 (2004): 690-696.

[3] He, Na, Dianguo Xu, and Lina Huang. "The application of particle swarm optimization to passive and hybrid active power filter design." IEEE transactions on industrial electronics 56, no. 8 (2009): 2841-2851.

[4] ShiHong, Wang, Zhan Ghong, He Rui, Xiao QingMing, Chen Jian, and Xu Ming Chang. "A new reactive power planning based on system multiscenario operations." Energy Procedia 14 (2012): 782-787.

[5] Amrane, Youcef, Mohamed Boudour, and Messaoud Belazzoug. "A new optimal reactive power planning based on differential search algorithm." International Journal of Electrical Power & Energy Systems 64 (2015): 551-561.

[6] Chiang, H-D., J-C. Wang, Orville Cockings, and H-D. Shin. "Optimal capacitor placements in distribution systems. I. A new formulation and the overall problem." IEEE Transactions on Power Delivery 5, no. 2 (1990): 634-642.

[7] Chiang HD, Wang JC, Cockings O, Shin HD. Optimal capacitor placements in Distribution systems: part 2: solution algorithms and numerical results. IEEE Trans Power Deliv 1990;5 (2).

[8] Dai, Chaohua, Weirong Chen, Yunfang Zhu, and Xuexia Zhang. "Seeker optimization algorithm for optimal reactive power dispatch." IEEE Transactions on power systems 24, no. 3 (2009): 1218-1231

[9] Grudinin, N. "Reactive power optimization using successive quadratic programming method." IEEE Transactions on Power Systems 13, no. 4 (1998): 1219-1225.

[10] Lee, Wen-Tung, Shih-Cheng Horng, and Chi-Fang Lin. "Application of Ordinal Optimization to Reactive Volt-Ampere Sources Planning Problems." Energies 12, no. 14 (2019): 2746.

[11] Parker, C. J., I. F. Morrison, and D. Sutanto. "Application of an optimisation method for determining the reactive margin from voltage collapse in reactive power planning." IEEE Transactions on Power Systems 11, no. 3 (1996): 1473-1481.

[12] Deng, Zhida, Mihai D. Rotaru, and Jan K. Sykulski. "Kriging Assisted Surrogate Evolutionary Computation to Solve Optimal Power Flow Problems." IEEE Transactions on Power Systems (2019).

[13] Bouchekara, H. R. E. H. "Optimal power flow using black-hole-based optimization approach." Applied Soft Computing 24 (2014): 879-888.

[14] Reddy, Salkuti Surender, and Ch Srinivasa Rathnam. "Optimal power flow using glowworm swarm optimization." International Journal of Electrical Power & Energy Systems 80 (2016): 128-139.

[15] Singh, Rudra Pratap, V. Mukherjee, and S. P. Ghoshal. "Optimal reactive power dispatch by particle swarm optimization with an aging leader and challengers." Applied Soft Computing 29 (2015): 298-309.

[16] Duman, Serhat, Y. Sönmez, U. Güvenç, and N. Yörükeren. "Optimal reactive power dispatch using a gravitational search algorithm." IET generation, transmission & distribution 6, no. 6 (2012): 563576.

[17] Rajan, Abhishek, and T. Malakar. "Optimal reactive power dispatch using hybrid Nelder–Mead simplex based firefly algorithm." International Journal of Electrical Power & Energy Systems 66 (2015): 9-24.

[18] Bhattacharya, Aniruddha, and Pranab Kumar Chattopadhyay. "Solution of optimal reactive power flow using biogeography-based optimization." International Journal of Electrical and Electronics Engineering 4, no. 8 (2010): 568576.

[19] Lee, K.Y., Park, Y.M., Ortiz, J.L.: 'Optimal real and reactive power dispatch', Electr. Power Syst. Res., 1984, 7, (3), pp. 201–212.

[20] Shaw, Binod, V. Mukherjee, and S. P. Ghoshal. "Solution of reactive power dispatch of power systems by an opposition-based gravitational search algorithm." International Journal of Electrical Power & Energy Systems 55 (2014): 29-40

[21] Mahadevan, K., and P. S. Kannan. "Comprehensive learning particle swarm optimization for reactive power dispatch." Applied soft computing 10, no. 2 (2010): 641-652.

[22] El Ela, AA Abou, M. A. Abido, and S. R. Spea. "Differential evolution algorithm for optimal reactive power dispatch." Electric Power Systems Research 81, no. 2 (2011): 458-464.

[23] Mukherjee, A. and Mukherjee, V., 2015. Solution of optimal reactive power dispatch by chaotic krill herd algorithm. IET Generation, Transmission & Distribution, 9(15), pp.2351-2362.

[24] Bhattacharyya, Biplab, and Saurav Raj. "PSO based bio inspired algorithms for reactive power planning." International Journal of Electrical Power & Energy Systems 74 (2016): 396-402.

[25] Raj, Saurav, and Biplab Bhattacharyya. "Reactive power planning by opposition-based grey wolf optimization method." International Transactions on Electrical Energy Systems 28, no. 6 (2018):

[26] Bhattacharyya, Biplab, and Saurav Raj. "Differential evolution technique for the optimization of reactive power reserves." Journal of Circuits, Systems and Computers 26, no. 10 (2017): 1750155.

[27] Mahapatra, Sheila, A. N. Jha, and B. K. Panigrahi. "Hybrid technique for optimal location and cost sizing of thyristor controlled series compensator to upgrade voltage stability." IET Generation, Transmission & Distribution 10, no. 8 (2016): 1921-1927.

[28] Mahapatra, Sheila, Nitin Malik, A. N. Jha, and B. K. Panigrahi. "Voltage Stability Enhancement by IGSA-FA hybrid technique implementation for optimal location of TCSC." Journal of Engineering Science and Technology 12, no. 9 (2017): 23602373.

[29] Wang, Chun, Hao Zhong Cheng, and L. Z. Yao. "Reactive power optimization by plant growth simulation algorithm." In 2008 Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, pp. 771774. IEEE, 2008.

[30] Tizhoosh, Hamid R. "Opposition-based learning: a new scheme for machine intelligence." In International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'06), vol. 1, pp. 695701. IEEE, 2005.