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Management of Var sources for the reactive power planning problem by oppositional Harris Hawk optimizer

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Abstract

Reactive power management has grown more crucial for increased synchronization in modern power systems, since transmission loss minimization is a basic condition for secure power system operation. This paper proposes the Oppositional-based Harris Hawk Optimizer technique as an advanced meta-heuristic nature inspired methodology, which is applied on the conventional Ward Hale 6 bus system and the IEEE 30 bus system. The solution space is further altered by combining HHO with the Oppositional Based Learning technique in order to enhance approximation for the current solution. The suggested OHHO outperforms HHO as well as other optimization methodologies recently published articles, according to simulation results obtained on typical test systems.

Keywords: Reactive power planning, Optimization techniques, Active power loss, Operating cost, Voltage profile

Introduction

Voltage stability, losses and cost are mostly determined by reactive power balancing. The production, transmission, and utilization of reactive electricity are all spread, by carefully balancing the hierarchy, spatial planning, and distribution of reactive power voltage at each node. Receiving power networks located far from the load center possess reactive power support, which might result in voltage collapse and devastation if the power system is disrupted. At the reactive power planning stage, challenges such as reactive reserve shortages and reactive power locations should be addressed. The two fundamental aspects of reactive power planning are capital planning and operational planning. At each node, capital planning seeks to determine the kind and capacity of reactive power compensation. Operational planning, which is based on capital planning, involves determining the power of a reactive power source and the position of transformer taps to guarantee that the power system is run safely, reliably, and inexpensively. The relationship between Total Operating Cost and Transmission Loss in reactive power planning is that minimizing transmission losses through effective management of reactive power flows contributes to lowering the overall operating cost of the power system. This is achieved by maintaining voltage profiles, reducing resistive losses, and optimizing the allocation of reactive power resources.

In the coming years, reactive power planning will look for an economic compensation method for new reactive power sources. This type of issue may be transformed into a constraint-based planning problem. Currently, many techniques simply evaluate one operating state of power systems and do not account for the influence of increasing uncertainty, which causes system running state variations. As a result, additional input in reactive power is required to keep the system running stable and securely when the future real-world operating environment changes significantly from expectations, resulting in adaptability and sustainability of the current plan. Therefore, a flexible method based on optimization technique is proposed and validated by testing on Ward Hale 6 bus systems and IEEE 14-bus system to obtain optimum solution for solving complex reactive power planning problems.

The work suggested in [1] is with a comprehensive standardized test network in reactive power prediction, where the parameters are optimized by metaheuristic optimization utilizing several standardized methodologies. Newton Raphson technique to analyze the nonlinear equations, which includes current and power mismatch functionality in [2]. Proposes [3] a new bio influenced Barnacles Mating Optimizer as a viable technique and demonstrates the best answer for the reactive power supply problem. The utmost expense, dependable, and optimal reactive power deliveries are accomplished in [4] using Moth swarm optimization technique and [5] using hybrid intelligent algorithm for economic dispatch, which might have a substantial impact on energy quality management. A conceptual approach for the placing of capacitor at multiple stages using a quasi- objective function is provided in research publication [6]. The best capacitor allocation in the distribution networks is suggested in [7] utilizing a General Solution Algorithm based Simulated Annealing. The authors use a unique strategy to solve the economic load dispatch problem by incorporating the Quasi-Oppositional method into the Sine Cosine Algorithm [8]. In [9] authors propose a bicriterion reactive power optimization model based on the SQP approach that balances economic and security objectives. For the issue of reactive volt-ampere sources, [10] describes and develops an Ordinal Optimization-based solution with superior and inferior levels. A multi-leader Harris Hawks optimizer with adaptive mutation is proposed in [11], wherein a multi-leader based position updating mechanism is proposed to increase the population diversity. The methodologies established in the research study [12] are KAGA and KAPSO to enhance the size of genetic driven computations for solving optimal power flow. An evaluation of the tactical allocation of reactive resource is presented by the author in [13]. An Enhanced Chimp-Harris Hawks Optimization Algorithm in [14] is used for copyright protection using Crypto-Watermarking Techniques. In [15] authors presented an improved Meta Heuristic Algorithm capable of solving continuous and discrete optimization problem. The author discusses ALC-PSO [16], GSA [17], HFA [18], BBO [19], and Opposition based Gravitational Search Algorithm OGSA [20] for RPP flow with more than one objective of reducing the real power losses for fixed generation schedule. To reduce active power losses, enhancement of voltage profile, and voltage stability, the work depicted in the two publications uses CLPSO [21] and

DE [22]. The RPP is accomplished by applying chaotic krill herd algorithm in [23], Enhanced Transient Search Optimization in [24], bio-inspired optimization applications in renewable-powered smart grids [25] and RL-based algorithm is introduced to coordinate EV charging in [26] to manage reactive power generation, shunt capacitors, transformer tap locations and also distribution networks. The authors of [27] used FACTS devices under active and reactive steady state and in [28] authors used FACTS devices and proposed a unique planning strategy for reactive power in real world power transmission system. In [29], the Plant Growth Simulation Algorithm was used to manage reactive power. Authors presented the oppositional based learning idea in [30] and used it in conjunction with the Salp Swarm Algorithm to generate RPP solutions utilizing FACT devices in [31]. Authors in [32] proposed Hybridization of the CHOA and CSA to solve the complex engineering optimization problems to develop a better RPP solution. In [33] authors target to extend the application of the Fractional Reproducing Kernel Method to explore numerical solutions for model of fractional Lienard's equation in the Atangana-Baleanu-Caputo fractional derivative. The researcher in [34] discussed on damping Van der Pol model. According to researchers in [35], the homotopy analysis method is used to solve a series of fuzzy initial value issues under extensively generalized discretization. Authors in [36] proposed a HHO algorithm for complex reactive power planning to reduce the operating cost and transmission loss.

An in-depth literature review motivates authors to propose a systematic and stratospheric optimization technique relying on the recently evolved HHO, which features derivative-free eloquence, equal embedment between the exploitation and exploration phases, robust global optimization capacity, and massive adaptively. According to the literature review, modern algorithms such as PSO, DE, GA, BBO, and GSA, among others, have problems such as reliance on intrinsic parameters such as mass and accelerating factors, greater computing time contributing to sluggish convergence, and being stuck in local optima.

As a result, the study focuses primarily on the OHHO algorithm, which is a derivative-free approach. The HHO method alters the setup among exploitation and exploration to increase the global optimization capabilities of the proposed algorithm, which is independent of any internally dependent elements. The application of oppositional based learning improves system stability by speeding up the convergence process. The purpose of optimization is to obtain the lowest transmission loss and operating cost while keeping a healthy voltage profile at the buses, resulting in improved and more dependable grid operation.

In the proposed work for the different test system, the suggested solution applies the notion of employing multiple optimization techniques to discover the best magnitudes of reactive power provided by generators, transformer tap settings, and shunt capacitors placed at susceptible buses. It begins with an introduction in Sect. "Introduction", followed by a specification of the mathematical issue and a discussion of the suggested OHHO algorithm in Sect. "Minimize real power loss". Section 3 presents Harris Hawk Algorithm and Sect. 4 explains concept of oppositional based learning. Section 5 explains the result analysis for the various bus system methods. And Sect. 6 gives conclusion.

Mathematical objectives

The best distribution of reactive power sources recognizing the locations is the key to reactive power planning. These sites are developed using sophisticated optimization-based approaches leveraging Var sources in recent work mentioned in the literature. Optimization is a crucial aspect of reactive power allocation. Additionally, the improvement must take into account operating costs and the reduction of voltage variance in the system.

Minimize real power loss

The first major objective of the VCRPP is to reduce the real or active power loss, which is the useful power loss in the power flow analysis to be optimized. The active power loss is vital as it causes heating of conductors. Mitigation of active power loss in transmission lines may be formulated as below [24]:

$$\text{Minimize } \mathrm{P}_L = g_m\left[V_m^2 + V_n^2 - 2V_m\ V_n\ \mathrm{Cos}(\delta_m - \delta_n)\right] \tag{1}$$

Here the minimization function is related to sending end and receiving end voltages and their respective phase angles.

Reduction of operating cost

Combining the expenses of VAR sources installation at weak buses with the costs stemming from energy losses forms a comprehensive strategy. This strategy aims to reduce operational expenses in transmission lines, and its representation is as follows:

$$\text{Operating cost } = C_{\text{Energy}} + C_{\text{cap}}. \tag{2}$$

where C_{Energy} is the cost due to the dropping of energy, C_{Cap} = Cost of capacitors. $C_{\text{Energy}} = P_{\text{loss}} \times$ Energy rate. Energy Cost = 0.06 $/kwh, Cost of Capacitor/KVar = 3$, Cost of capacitor = 1000$, Cost data has been taken from [6, 7]. Energy rate = $24 \times 365 \times 0.06 \times 100{,}000$.

Improvement of voltage magnitude

The reactive power demand is directly related to a drop in voltage profile. If the recative power demand is not regulated than bus voltage drop occurs in a cascading manner which is detrimental to power system reliable operation. Limiting the variation of the load voltages is being used to improve the voltage stability. The objective for the same is formulated as below,

$$\text{Minimize, } VD = \sum_{i=1}^{n_b} \left|V_i - V_{\text{specified}}\right| \tag{3}$$

where n_{b} = No. of bus, $V_{\text{specified}} = 1.0$

The above-mentioned problem formulation should be minimized by satisfying most of the equal and unequal constraints listed as follows:

(i) Equality constraints

The equality constraints are provided as given as follows [24]:

$$P_{Gm} - P_{Dm} - V_m \sum_{N=1}^{N_b} V_n[G_{mn} \cos\,(\delta_{mn}) + B_{mn} \sin\,(\delta_{mn})] = 0 \tag{4}$$

$$Q_{Gm} - Q_{Dm} - V_m \sum_{N=1}^{N_b} V_n[G_{mn} \cos\,(\delta_{mn}) + B_{mn} \sin\,(\delta_{mn})] = 0 \tag{5}$$

(ii) Inequality constraints

The boundary zone of constraints which must be obeyed are provided as follows:

$$\left.\begin{array}{c} V_{gm}^{\min} \le V_g \le V_{gm}^{\max} \\ P_{Gm}^{\min} \le P_G \le P_{Gm}^{\max} \\ Q_{Gm}^{\min} \le Q_G \le Q_{Gm}^{\max} \\ Q_{Cm}^{\min} \le Q_C \le Q_{Cm}^{\max} \\ T_m^{\min} \le T_m \le T_m^{\max} \end{array}\right\} \tag{6}$$

Here min and max represents the minimum and maximum boundary limit for inequality constraints.

Harris Hawk algorithm technique

The Harris Hawks Optimizer is a chaotic optimization technique designed to address a wide range of optimization issues. The HHO optimization algorithm is proposed by Heidari.et.al [37] which mimics the nature and chasing style of prey by Harris Hawks. The hunting behavior of Harris Hawks is based on exploratory and exploitative.

Exploration phase

Harris Hawks use their strong vision to identify their target in this region, relying on the posture of the target, which are distinguished into 2 distinct accessible ways mentioned as below [33]:

$$Z(\text{iter} + 1) = (Z_c(\text{iter}) - Z_a(\text{iter})) - r_3(LB + r_4(UB - LB)) \tag{7}$$

$$Z(\text{iter} + 1) = Z_{\text{rand}}(\text{iter}) - r_1|Z_{\text{rand}}(\text{iter}) - 2r_2 Z(\text{iter})| \tag{8}$$

Z (iter) is the present point of hawks and Z (iter + 1) is the vector position for the next iteration. Z_c(iter) is the position of the prey. Z_{rand}(iter) is the random selected hawk from the current population. Random numbers r_1, r_2, r_3 and r_4, which are used to enhance and transform the exploration in the search space. The average point of hawks is gained as follows:

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

where Z_i (iter) is the position of every hawk and M is the total number of hawks.

The transformation is the phase where in the HHO algorithm transforms to the exploitation phase from exploration phase. In which the escaping energy of the prey is considered. This behavior of the prey is modeled which is based on the energy as follows:

$E = 2E_i(1 - \frac{t}{T})$ Where E_i is the primary stage of energy of the prey that falls in the limit of − 1 to 1, T is the extremity number of iterations, t is the current iteration.

Exploitation phase

The target of the transition from exploration to exploitation is to achieve Harris Hawks' sudden dive by intending prey which was blotched in the exploration phase. As the prey starts losing most of energy, the hawks promote the encircling process further to smoothly hook the frazzled prey. The HHO alternates between mild and severe besiege processes to depict this strategy. For each stage, the energy variable E is classified as described in the following:

Step 1: Soft besiege

When $r > 0.5$ and In this step the hawks encircle its prey softly to impoverish its remaining energy and then it performs its surprise pounce. The nature of hawk is given as follows:

$$Z(\text{iter} + 1) = \Delta Z(\text{iter}) - E[jZ_c(\text{iter}) - Z(\text{iter})] \tag{10}$$

$$\Delta Z(\text{iter}) = Z_c(\text{iter}) - Z(\text{iter}) \tag{11}$$

where ΔZ (iter) is the location vecto $|E| \geq 0.5 J = 2(1 - r_5)$ r of the prey and the present position in iteration t, r_5 is the random number within (0, 1), is the misleading pounce energy during the decampment process.

Step 2: Hard besiege

When $r \geq 0.5$ and $|E| < 0.5$, wherein the rabbit is weary and has almost little ability to escape.

$$Z(\text{iter} + 1) = Z_c(\text{iter}) - E[\Delta Z(\text{iter})] \tag{12}$$

Step 3: Soft besiege with progressive rapid dives

When $r < 0.5$ and $|E| \geq 0.5$, the rabbit admits that he still has enough stamina to make a spectacular escape. Based on the next movement it can be modeled as

$$Y = Z_c(\text{iter}) - E[JZ_c(\text{iter}) - Z(\text{iter})] \tag{13}$$

$$A = Y + S \times LF(D) \tag{14}$$

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

Step 4: Hard besiege with progressive rapid dives

When $r < 0.5$ and $|E| < 0.5$, the rabbit drops down its stamina completely to escape and a preplex attack is conducted by hawks and lastly assassinate the rabbit. We hypothesized that hawks can gradually choose the best dive toward the prey when they want to seize the prey in intense conditions, based on real-world hawk behavior. Then, in order to determine whether or not the plunge would be successful, they examine the potential outcome of such a maneuver to the prior plunge. When they get close to the rabbit, they also tend to make erratic, sudden, and quick dives if it was not feasible. This situation of the prey is like the soft besiege with the decreased distance for escaping rabbit.

$$Y = Z_c(\text{iter}) - E[JZ_c(\text{iter}) - Z_a(\text{iter})] \tag{16}$$

$Z_c(\text{iter})$ is the position of the prey, $Z_a(\text{iter})$ average point of the prey.

Oppositional based learning (OBL)

H.R. Tizhoosh [30] proposed a novel machine learning approach called OBL for speeding up the convergence of several heuristic optimization strategies. In comparison to both random and opposite-based solutions, an OBL solution has a higher chance of reaching global optima. The OBL idea is a novel machine learning method for increasing the speed of convergence of various heuristic optimization strategies. The use of OBL entails interpreting existing and opposing populations in order to obtain excels/enhanced potential solutions to a given issue in the same generations. In a nutshell, OHHO involves opposed factors for population and generation leaping, and integrates a better candidate solution from the beginning of the optimization. As a result, a unique hybrid approach called OHHO is examined in the proposed study. HHO is the parent algorithm in this case, and oppositional optimization is included into HHO to speed up convergence. The swarm intelligence-based optimization technique commences with a small population and attempts to converge to the best possible solution. An oppositional lattice is built to speed up the convergence rate of optimization techniques in the domain of process cognition. The OBL is explained as follows:

Let X_j^o be any control variable $\in \left[X^{\max}, X^{\min}\right]$, then any opposition variable can be obtained as

$$OX_j = X_j^{\max} + X_j^{\min} - X_j^0 \tag{17}$$

In this work, the maximum and minimum opposition variables are reactive power generation limits, transformer tap settings and shunt compensation limits as described in Eq. (18) and (19):

$$X_j^{\max} = \left[\; Q_{G1}^{\max} \;...\; Q_{Gj}^{\max} \;\; T_1^{\max} \;...\; T_j^{\max} \quad QC_1^{\max} \;...\; QC_j^{\max} \;\right] \tag{18}$$

$$X_j^{\min} = \left[\; Q_{G1}^{\min} \;...\; Q_{Gj}^{\min} \;\; T_1^{\min} \;...\; T_j^{\min} \quad QC_1^{\min} \;...\; QC_j^{\min} \;\right] \tag{19}$$

Therefore, the opposition matrix and quasi-opposition matrix are given by Eq. (20) and (21), respectively.

$$\text{OX} = \begin{bmatrix} X_{11}^{\max} + X_{11}^{\min} - X_{11}^0 & ... & X_{1j}^{\max} + X_{1j}^{\min} - X_{1j}^0 \\ ... & ... & ... \\ X_{i1}^{\max} + X_{i1}^{\min} - X_{i1}^0 & ... & X_{ij}^{\max} + X_{ij}^{\min} - X_{ij}^0 \end{bmatrix} \tag{20}$$

where $i =$ Number of population and $j =$ Number of variables.

$$\mathrm{QOX} = \begin{bmatrix} \mathrm{QOX}_{11} & \dots & \mathrm{QOX}_{1j} \\ \dots & \dots & \dots \\ \mathrm{QOX}_{i1} & \dots & \mathrm{QOX}_{ij} \end{bmatrix} \tag{21}$$

By using a quasi-opposite population matrix as the starting population, the convergence rate is improved. Jumping rate guides the production of another generation, and this is used into HHO optimization to improve computation efficacy and resilience.

The rules of optimization techniques which are required and majorly considered are given as follows:

1. The first step involves a candid definition of objective function and constraints by identifying key variables and parameters.
2. The identification of most apt optimization technique to start with a good initial condition which directly dictates the algorithm's efficacy.
3. Any optimization problem is guided by understanding the trade-offs which is more beneficial to the given system.
4. Testing on benchmark functions or practical data sets ascertains the strengths and limitations of the technique. They must be updated to be more robust and meet the changing requirements of the system.

A code optimizing process must follow the three rules given as follows:

- The output code must not, in any way, change the meaning of the program.
- Optimization should increase the speed of the program and if possible, the program should demand a smaller number of resources.
- Optimization should itself be fast and should not delay the overall compiling process.

Efforts for an optimized code can be made at various levels of compiling the process.

- At the beginning, users can change/rearrange the code or use better algorithms to write the code.
- After generating intermediate code, the compiler can modify the intermediate code by address calculations and improving loops.
- While producing the target machine code, the compiler can make use of memory hierarchy and CPU registers.

Results and discussion

Tests on Ward Hale 6 bus systems and IEEE 30 bus systems are carried out to test the efficiency and efficacy of the planned OHHO and HHO techniques. All the simulations are performed using MATLAB 2020b with 2.9 GHz and 8 GB RAM. Separate 30 trial runs with all test scenarios are done to prove the effectiveness of the suggested algorithms, with a comparison analysis presented in the next section.

Case study of ward hale 6 bus system

The Ward hale 6 bus system comprises of the three power generators attached to seven transmission lines on buses 1, 2 and 3, two of which have tap changing

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	0.9901	0.9831	1.1
Tap (4–6)	0.9	1.01	0.9901	0.9830	1.1
VG (1)	0.95	1.05	1.0832	1.0835	1.1
VG (2)	0.95	1.125	1.0832	1.0836	1.1
VG (3)	0.95	1.07	1.0832	1.0833	1.1
QC(10)	0.0	0.939	0.0259	0.0477	0.05
Transmission Loss (MW)	10.250	05.25	05.19		
Total operating cost ($)	5.3874	2.7588	2.7273		

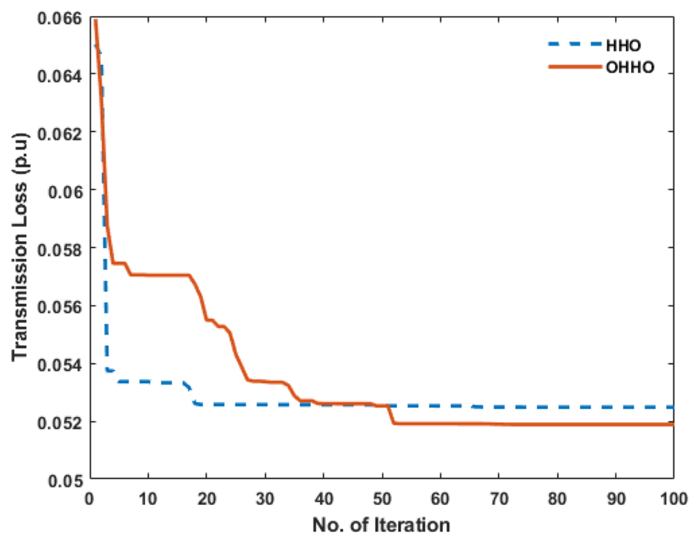

Fig. 1 Convergent Contour for Transmission Loss

transformers (3–5 and 4–6). The total demands are $P_{\text{load}} = 2.1$p.u. and $Q_{\text{load}} = 2.1$ p.u. at 100 MVA base [29]. For the test system considered shunt var sources is placed at the 10$^{\text{th}}$ bus and thereafter, HHO and OHHO techniques are furnished to reduce real loss and operating cost. Table 1 presents the optimal Sizing of Var sources.

It can also be noticed that all the control parameters 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 48.78% using HHO and 49.36% by OHHO. It is also observed that the system operating cost which is a crucial parameter for optimal planning is 2.7588×10^6\$ and 2.7273×10^6\$ by HHO and OHHO techniques, respectively. With regard to the starting cost of operation, hybridizing oppositional based results in a large decrease in running costs of 49.376%. The variation of transmission loss at all the buses is represented by the convergence curve as given in Fig. 1. The total active power loss by implementing HHO is 0.0525 p.u. and has been further diminished to 0.0519 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.

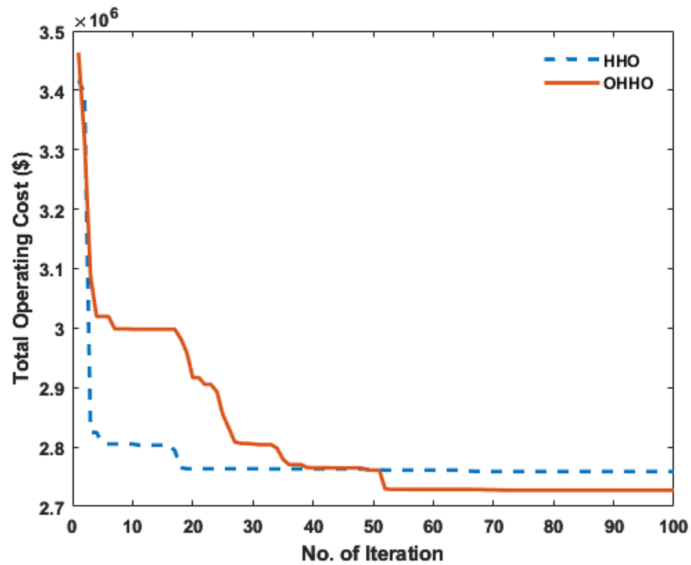

Fig. 2 Convergent Contour for Operating Cost

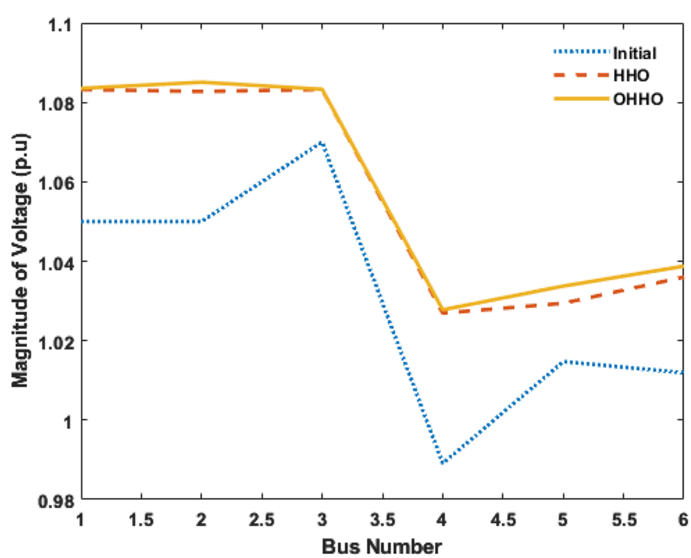

Fig. 3 Magnitude of Voltage in each Bus

However, the reduction in loss value is more for proposed OHHO algorithm. Similarly, Fig. 2 provides the convergence curve for total system operating cost wherein OHHO algorithm depicts considerable reduction thus leading to optimal and secured reactive power dispatch. The inclusion of oppositional based learning to HHO has improved the performance by a considerable margin.

Figure 3 depicts the voltage profile at all the buses for base case, with HHO and OHHO optimization. It is imperative to generate RPP solution coupled with consistent voltage profile for secured power system operation. 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 is within the prescribed limits with average value using HHO and OHHO are 1.056 p.u. and 1.0675 p.u., respectively.

Case study of IEEE 30 bus system

In order to further validate the efficacy of the proposed OHHO algorithm, it is now tested on a larger system. The upgraded 30 bus model consists of six power sources at buses 1, 2, 5, 8, 11, 13 and 24, which are coupled with 41 overhead lines, four of which (6–9, 6–10, 4–12, and 28–27) are provided with distribution feeders transformers and nine limbs at buses have shunt—connected capacitors (10, 12, 15, 17, 20, 21, 23, 24 and 29). 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].

The tapping, volt, and var settings have all been kept well inside the limitations, ensuring that all of the relevant inequality restrictions are met. The ideal setup of var sources for system restrictions is shown in Table 2. It is also verified that with implementation of the proposed methods the total line loss is reduced by 46.82% and 46.99% using HHO and OHHO. It is also observed that the system operating cost which is a vital aspect for optimal planning is $1.6231 \times 10^6$$ by HHO and $1.6205 \times 10^6$$ by OHHO. There is a significant reduction in operating cost by 46.856% by hybridizing oppositional based learning with Harris Hawk algorithm from initial system cost. Hence, it is evident that a reduction in total operating cost by such a larger extent will boost the RPP solution positively.

The convergence curve for transmission loss at all the buses is represented in Fig. 4. 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, Fig. 5 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 6 epitomizes the voltage profile for HHO and OHHO optimization in all the buses for the base case. It is fairly observed that the voltage profile improvement has occurred by both the techniques but OHHO spawns the best results. Table 3 provides a comparative analysis with other optimizing techniques published in literature of the real power loss minimization transmission. The proposed approach is contrasted with 12 algorithms in a related reactive power dispatch problem. The proposed HHO and OHHO algorithms produced prodigious results that consider transmission losses as an additional parameter, together with a considerable reduction in operating costs. The proposed work is further extended in maintaining voltage consistency with average value using HHO and OHHO are 1.0918p.u. and 1.0889 p.u., respectively. Hence, this justifies the robustness of the algorithm in handling large, interconnected power system problem.

Table 4 shows the statistical analysis, which includes the lowest value, highest amount, mean, and standard deviation, and is useful for evaluating the efficacy of the proposed HHO and OHHO techniques for the Ward Hale 6 bus system and the IEEE 30 bus system. To demonstrate the program's outstanding outcome, the

Table 2 Optimal sizing of Var sources

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}	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	0.9888	0.9887
Tap_{12}	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	0.9888	0.9887
Tap_{15}	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	0.9888	0.9887
Tap_{36}	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	0.9888	0.9887
V_{G1}	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}	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}	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}	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}	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}	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}	0	5	3	4.9265	5	4.700304	1.653790	0.0330	0.0090	0.0089	0.0092	4.9797	4.5972	0.05	0.0398
QC_{12}	0	5	4	5	5	4.706143	4.372261	0.0249	0.0126	0.0000	0.0000	2.2098	2.5990	0.05	0.0381
QC_{15}	0	5	3.3	5	5	4.700662	0.119957	0.0177	0.0209	0.0141	0.0153	4.9254	5.0	0.0398	0.0374
QC_{17}	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}	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	0.0383
QC_{21}	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}	0	0.9	1.3	5	2.8004	4.804034	0.000000	0.0269	0.0226	0.0241	0.0134	3.6618	2.1225	0.0344	0.0362
QC_{24}	0	5	3.5	5	5	4.805296	1.383953	0.0500	0.0500	0.0500	0.0500	4.8890	5.0	0.05	0.05
QC_{29}	0	2.4	1.42	5	2.5979	3.398351	0.000317	0.0194	0.0107	0.0107	0.0121	2.8936	3.3295	0.5	0.0411
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	3.08
Total operating cost $\times 10^6$ ($)	3.0542	Not Reported												1.6231	1.6205

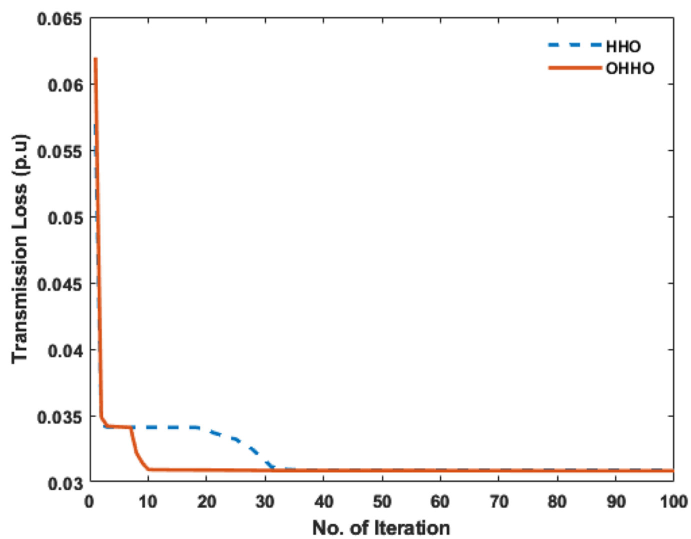

Fig. 4 Convergent Contour for Transmission Loss

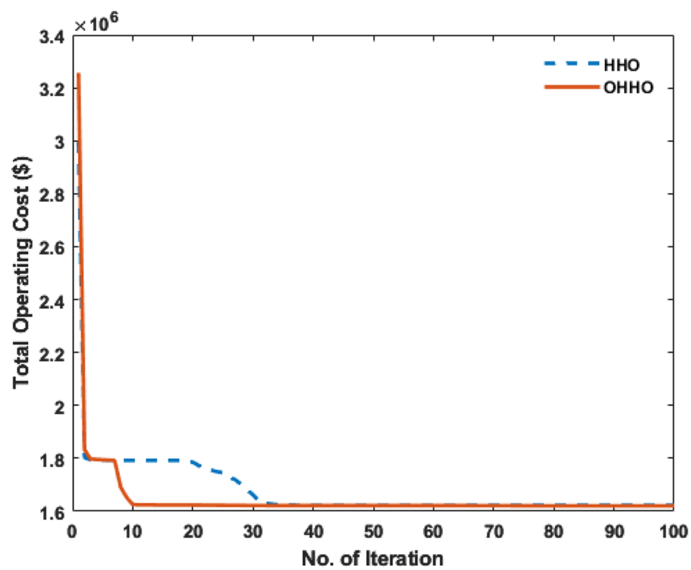

Fig. 5 Convergent Contour for Operating Cost

techniques are utilized for up to 30 tests and a respectable couple of times a response has been created. The envisaged algorithms' computational speed is also justified by the iteration per second. The statistical analysis can be used to understand the algorithm's competitiveness and implications because it yields vertebral virtues for every iteration.

Conclusion and recommendations

The work is carried out step by step on standard bus test system. The following conclusions may be drawn from the current research.

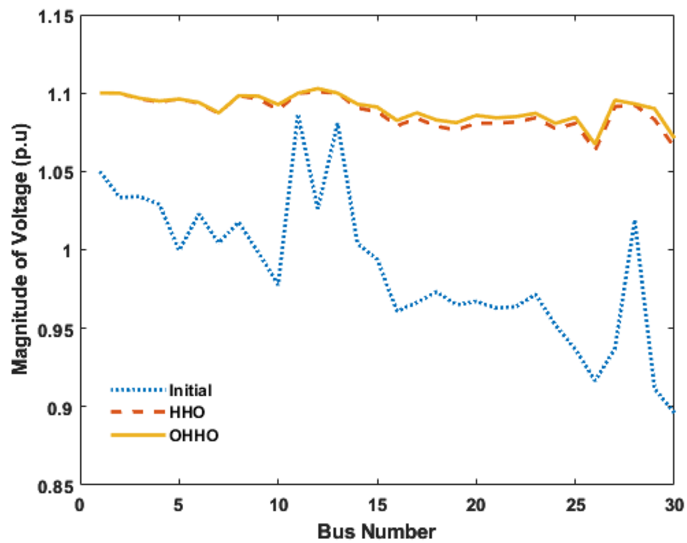

Fig. 6 Magnitude of Voltage in each Bus

Table 3 Comparative analysis for real power loss

Algorithm	Transmission loss
(MW)	
Initial	5.8110
ABC [17]	4.6022
FA [17]	4.5691
CLPSO [17]	4.5615
DE [22]	4.5550
HFA [18]	4.5290
GSA [17]	4.5143
OGSA [17]	4.4984
ALC-PSO [16]	4.4793
KHA [23]	3.6500
CKHA [23]	3.2400
KAPSO [12]	3.0948
KAGA [12]	3.0932
HHO	3.0881
OHHO	3.0831

Table 4 Statistical analysis of HHO and OHHO after 30 trials

	Ward hale 6 bus system		IEEE 30 Bus system	
	HHO	OHHO	HHO	OHHO
Minimum	0.0525	0.0519	0.0308	0.0308
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

- In the prospective work, a mutated algorithm of OHHO is applied by culmination of OBL technique with HHO algorithm in alleviative VCRPP problem while satisfying all the constraints in the test power system.
- Numerous objective factors were explored in this analysis, including operational cost minimization, transmission loss reductions, and voltage profile enhancement in every bus.
- The simulation result comparison has proved vigorous and supremacy of the approach to solve RPP problem.
- The work is justified to prove the OHHO algorithm its supremacy functionality on the test systems.
- The outcomes are compared with various different literature-based evolutionary optimization techniques and justify the potential of algorithms to produce accurate solutions for large interconnected power networks.

A review of current state-of-the-art literature reveals that the proposed technique is advantageous in terms of competency, flexibility, and ignoring local optima. The proposed hybrid technique also has the advantage of being a derivative-free algorithm with minimal system parameters. Long calculation times are a common drawback of any heuristic computing technique if the solution obtained is difficult to explore. Like other nature-inspired algorithms, the performance of HHA can depend on parameter settings. The algorithm's performance might vary based on the complexity and characteristics of the optimization problem.

Improving the work in major test systems using FACTS controllers like SVC, TCSC, SSSC, and UPFC to investigate their efficacy in providing optimal reactive power solutions is one of the probable potential results. The future scope may include other extended applications such as inclusion of FACTS controller, integrating renewables to the existing system. Also, considering the adaptable nature of the proposed approach it can also be successfully implemented to other complex power system issues like economic demand dispatch issues, power system stability issues, load forecasting, etc. even in larger test system or in a practical system.

Abbreviations

ABC	Artificial bee colony
ALC-PSO	Aging leader and challengers particle swarm optimization
BBO	Biogeography-based optimization
CHOA	Chimp optimization algorithm
CKHA	Chaotic krill herd algorithm
CLPSO	Comprehensive learning particle swarm optimization
CS	Cuckoo search
DE	Differential evolution
FA	Firefly algorithm
FACTS	Flexible AC transmission system
GA	Genetic algorithm
GSA	Gravitational search algorithm
HFA	Hybrid nelder-mead simplex-firefly algorithm
HHO	Harris Hawks optimizer
KAGA	Kriging-assisted genetic algorithm
KAPSO	Kriging-assisted particle swarm optimization
KHA	Krill herd algorithm
OBL	Oppositional-based learning
OGSA	Opposition-based gravitational search algorithm
OHHO	Oppositional-based Harris Hawk optimizer
PSO	Particle swarm optimization
RPP	Reactive power planning

SCA	Sine cosine algorithm
SQP	Successive quadratic programming
SSSC	Static synchronous series compensator
SVC	Static Var compensator
TCSC	Thyristor controlled series compensator
UPFC	Unified power flow controller
VCRPP	Voltage constrain reactive power planning
VD	Voltage deviation

List of symbols

N_{b}	Number of buses
P_{L}	Active power loss
g_{mn}	Conductance of branch "*n*" which is connected between *x*th and *y*th bus
V_m	Voltage magnitude of *m*th bus
V_n	Voltage magnitude of *n*th bus
δ_m	Voltage phase angle of *m*th bus
δ_n	Voltage phase angle of *n*th bus
C_{Cap}	Capacitor cost at weak nodes
C_{Energy}	Cost due to the loss of energy
P_{Gm}	Active power generation at the *m*th bus
Q_{Gm}	Reactive power generation at the mth 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 *m*th bus and nth bus
B_{mn}	Transfer susceptance between *m*th bus and nth bus
Z(iter)	Current location of Hawks
Z(iter + 1)	Vector location for the next iteration
Z_{c}(iter)	Position of the prey
Z_{rand}(iter)	Randomly selected hawk from the current population
Z_{i}(iter)	Position of each Hawk
E_{i}	Initial energy stage of the prey which lies in the interval between − 1 to 1
T	Maximum number of iterations
t	Current iteration
ΔZ(iter)	Position vector of the prey and the current location in iteration t
J	Jump strength of prey
D	Dimension of search space
S	Randomly selected vector of dimension 1D
LF (D)	Levy flight function
LB	Lower bound of search area
UB	Upper bound of search area
A_{d}	D-dimensional search area
J_{r}	Generation jump rate
V_{Gm}	Generator voltage
Q_c	Shunt capacitors
T_m	Transformer tap changers

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Data availability

Data will be made available on reasonable request to its authors.

Declarations

Competing interests

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