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Hybrid PSO-WOA for Solving ORPD Problem under Unbalanced Conditions

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Abstract: This paper presents the minimization of the voltage deviation and power loss, which is related to ORPD in unbalanced conditions. Moreover, a hybridization of two techniques (i.e.,) PSO and WOA termed Hybrid (PSO-WOA) algorithm is developed in this paper. Here, this proposed technique works on the control variables namely transformer tap settings, voltage, and load reactance that are diverse to attain optimum outcomes. The complete experimentation is performed on two IEEE bus systems, such as the IEEE 39 and 14 bus systems. The simulation outcomes of the proposed PSO-WOA technique are analyzed with conventional techniques to assure the proposed technique.

Keywords: Power System; ORPD; Active Power Loss; Voltage Deviation; IEEE bus system

Nomenclature

Abbreviations	Descriptions
PSO	Particle Swarm Optimization
WF	Wind Farm
WOA	Whale Optimization Algorithm
OPF	Optimal Power Flow
HSA	Harmony Search Algorithm
PDFs	Probability Density Functions
VD	Voltage Deviation
DE	Differential Algorithm
PMSG	Permanent Magnet Synchronous Generator
ORPD	Optimal Reactive Power Dispatch
SA	Simulated Annealing
SHADE	Success History Based Adaptive DE
GSA	Gravitational Search Algorithm
GAs	Genetic Algorithms
DERs	Distributed Energy Resources
RT-AR-OPF	Real-Time Active-Reactive OPF
2ArchMGWO	Two-Archive Multi-Objective GWO
ABC	Artificial Bee Colony Algorithm
SD	Standard Deviation
ALO	Ant Lion Optimizer
APL	Active power Loss
DS	Distribution System
VS	Voltage Stability
MFO	Moth-Flame Optimization
VP	Voltage Profile
GWO	Grey wolf optimizer
DN	Distribution Networks

1. Introduction

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During the past decades, the electrical power system has developed in a progressive manner, and the high significant issue occurs because of the recent economy, which runs by electricity. The electrical power system is a distributing system and producing, electricity for housing, transportation, and industrial, exploits. In addition, the electrical power system is considered as the main core of renewable energy systems [18]. The utilization of resources progressively enhances when the demands for electricity will improve. Incontrovertibly, the ORPD act as a significant role in the operation of power system because of its extraordinary power on the economic, consistency, and security operation problems [19]. As a sub-issue of OPF, ORPD is represented as a well-known nonlinear optimization issue in power system that concerns on both the continuous and discrete control variables when fulfilling both inequality and equality constraints. Therefore, the optimization method is exploited [25] [26] to attain the optimal probable control variables combinational as well as transformers tap setting, bus voltages generator, and reactive compensators sizing to reduce the objective models [22] [23].

To alleviate this ORPD disadvantage is used to reallocate reactive power system to the phase of least number of losses occurred in transmission line; enhancement VP; equipment capacities and network limits. Since the ORPD is an high non-convex, nonlinear, large-scale complicated static programming as well as multi-constrained issue, its solution consequently aims to recognize the best positioning of all control variables, whereas selected objective models are reduced [20] [21]. The design variables comprise continuous variables, such as generator bus voltages, as well as a discrete variable. So, reduction of APL (Ploss) and reduction of VD is considered as the objective models of the ORPD issue [5].

Over the past few years, various approaches have been effectively developed to pact the ORPD issue in an attempt to mitigate the aforesaid disadvantages namely, GAs [9], GSA [15] DE [10], SA [10], ABC [14], PSO [24], HSA [13], and GWO [16]. In the last decade, widespread competitions among researchers have been performed, in an attempt to search for a further appropriate/consistent method to handle the various optimization issues in power system [17]. In [16], seeker optimization method was exploited in order to solve ORPD in larger power system with comprehensive enlightenment of significant performance indices in that various objective models have examined namely reduction of APL, minimization of Voltage Stability Index and enhancement of VP.

The main aim of this paper is to develop the PSO-WOA method in order to solve the ORPD issue. At first, the disadvantages associated with the ORPD issue under unbalanced environments are focused. Subsequently, the capability of the proposed technique to handle an unbalanced Distributed System nature is described. Accordingly, the ORPD is estimated proficiently.

2. Literature Review

In 2019, Ni Wang et al [1] presented an ORPD model for PMSG in WF to reduce the loss of power. Here, the losses inside WTs and the transmission system losses were contemplated. Moreover, the PSO method was exploited to discover each WT for reactive power references that create the total loss of WF minimal. Here, two conventional RPD schemes were compared broadly with the proposed scheme at various cases; the outcomes exhibit that the proposed scheme attains minimum loss of power than the other two conventional schemes in all the experimental scenarios.

In 2018, Partha P. Biswas et al. [2] presented a solution process and formulation for stochastic ORPD issues with uncertainties in the wind, solar power, and load demand. In order to form the stochastic power, as well as the load demand, which produces from the renewable energy sources, considers a suitable PDFs. Various cases were produced that runs on Monte-Carlo simulation and advanced minimization approach was implemented to pact with a minimized number of cases. Here, the objectives of optimizations were steady-state VD and real power loss of network load buses. Moreover, SHADE was adopted as the fundamental search technique. It was effectively incorporated with a constraint handling approach, termed Epsilon Constraint (EC), to handle constraints in ORPD issue.

In 2018, Khaled ben oualid Medani et al [3] presented a novel meta-heuristic method, which was enthused from the bubble-net hunting method of humpback whales, termed WOA. This WOA method was exploited to resolve the ORPD issue. ORPD was a meticulous case of the OPF. Generally, ORPD was represented as the minimization of an objective model instead of the total APL in the electrical networks. The restraint includes ratios of tap regulating transformers, generator voltages. The main aim of this paper was to analyze the optimal control variables vector so that the power loss lessening can be identified.

In 2016, Brett A. Robbins et al [4] worked on an approach of DERs contributions in order to set the optimal reactive power. Moreover, it present in DSs with the aim of regulating bus voltages. Here, the modeling of branch power flow method was exploited for radial power systems to make an OPF issue for the scenario while the network was balanced. A distributed technique was proposed that was based on the Alternating Direction Method of Multipliers (ADMM), which was used to competently solve

Quadratic Program (QP). Moreover, the unbalanced three-phase methodology was involved to expand the plans, which was developed for the balanced network scenario.

In 2017, Kasem Nuaekaew et al. [5] presented a novel 2ArchMGWO for solving Multi-Objective ORPD issues. The optimizer was enhanced from its novel Multi-Objective GWO by altering the reproduction operator and augmenting the 2-archive idea to the approach. Subsequently, resolving MORPD with objective models was implemented being the minimization of Active Power Loss and enhancement of VP (minimization of VD).

In 2017, Souhil Mouassa et al. [6] worked on the employ of a newly developed method, which was enthused in nature by the hunting method of antlions, termed ALO approach. This technique was exploited to solve the ORPD issue by contemplating a large-scale power system. The ALO method was enthused by the antlions hunting method. The major motivating facts in antlions were that they have a distinctive hunting behavior and show the maximum capacity of evasion the local optima stagnation.

In 2017, Rebecca Ng Shin Meia et al. [7] presented a novel surfaced nature-inspired optimization method termed MFO technique. This method was exploited to address the ORPD issue, which was enthused by the navigation natural method of moths while they explore at night, whereas they exploit visible light sources as assistance. Here, MFO was comprehended in ORPD issue in order to examine the optimal combination of control variables namely reactive compensators sizing, generators voltage, and transformers tap setting to attain least total power loss and VD.

In 2018, Erfan Mohagheghi et al. [8] developed a novel RT-AR-OPF model based on a lookup-table. In accordance with the forecasted wind power for a calculation horizon, circumstances were produced on the basis of its stochastic distribution. The consequent mixed-integer nonlinear programming problems were solved online that concurrently optimize the active and reactive reverse power flow, RPD of Wind Stations, as well as discrete slack bus voltage, resultant in a lookup table. An innovative understanding method was presented to assure both the possibility as well as the optimality of the realized operation scheme.

3. Objective Model

The ORPD main objectives are the reduction of the Active Power Loss and improvement of the stability and VP. As eq. (1), the dependent variables vector is indicated, where, P_G indicates the slack bus power, Q_G indicates the generator reactive power output ($i = 1,2....NG$), V_l denotes the voltage bus PQ ($i = 1,2....NPQ$). Moreover, NPQ denotes the number of the PQ bus and NG indicates the count of generator bus.

$$X = [P_{G1}, V_{l-1}.......V_{l-NPQ}, Q_{G-1}......Q_{G-NG}] \tag{1}$$

The control variables vector is indicated in eq. (2), where Q_{Ci} indicates the shunt VAR compensator output ($i = 1,2....NC$), V_{Gi} indicates the voltage-controlled bus for terminal voltage ($i = 1,2....NG$), T_i indicates the tap changing transformer for tap setting ($i = 1,2....NG$), NT indicates tap changing transformers and NC indicates the count for the shunt VAR compensators.

$$U = [V_{G-1},.....V_{G-NG}, Q_{C-1}.....Q_{C-NC}, T_1,.....T_{NT}] \tag{2}$$

As eq. (3), the chosen variables make equality and inequality constraints and formulate the objective function, where F_a indicate Active Power Loss and F_b indicate Voltage Deviation.

$$f_i = \alpha\ F_a + (1-\alpha\ )F_b \tag{3}$$

3.1 Minimization of ALP

Eq. (4) states the active power loss minimization, where P_l indicates the ALP system, N indicates the number of transmission lines and g_k represents the k^{th} branch conductance among the p^{th} and q^{th} buses. Moreover, δ_p and δ_q indicates the voltage phase angles of the p^{th} and q^{th} buses.

$$F_a = P_l = \sum_{k=1}^{N} g_k [V_p^2 + V_q^2 - 2V_p V_q \cos(\delta_p - \delta_q)] \tag{4}$$

3.2 Voltage Deviation

The (V_i) indicates the voltage magnitude reduction for the bus at the different loads system from a pre-specified (V^{ref}), which indicates the voltage magnitude reference value is exploited to increase the VP.

Eq. (5) represents VP enhancement and eq. (6) indicates the $\psi(x)$ is the step function. In eq. (5), LB represents the number of load buses and in eq. (7), V_i represents the voltage from the load flow analysis, in the balanced condition. Moreover, P denotes the real powers and Q denotes the reactive powers, x refers to the susceptance of the line and r refers to the resistance.

$$F_b = V_D = \sum_{i=1}^{LB} P_f \psi(V^{\min} - V_p) + P_f \psi(V_p - V^{\max}) \tag{5}$$

$$\psi(x) = \begin{cases} 1; & \text{if} \quad x \geq 0 \\ 0; & \text{otherwise} \end{cases} \tag{6}$$

$$\left|V_p\right|^2 = \left|V_i\right|^2 - 2(\tilde{r}_{ip} P_{ip} + \tilde{x}_{ip} Q_{ip}) + c_{ip}(P,Q) \tag{7}$$

$$\tilde{r}_{ip} = \mathrm{Re}\left\{aa^H\right\} \otimes r_{ip} + \mathrm{Im}\left\{aa^H\right\} \otimes x_{ip} \tag{8}$$

$$\tilde{x}_{ip} = \mathrm{Re}\left\{aa^H\right\} \otimes x_{ip} - \mathrm{Im}\left\{aa^H\right\} \otimes r_{ip} \tag{9}$$

$$a = \begin{bmatrix} 1 & e^{-j2\pi/3} & e^{j2\pi/3} \end{bmatrix} \tag{10}$$

$$c_{ip} = [z_{ip}[S_{ip}^* ./ V_i^*]] \otimes [z_{ip}^*[S_{ip_0} ./ V_i\ ]] \tag{11}$$

$$z_{ip} = r + jx \tag{12}$$

$$S_{ip} = \left[P_{ip} + jQ_{ip}\right] \otimes [\tilde{z}_{ip}(P_{ip} - jQ_{ip})] \tag{13}$$

$$\tilde{z}_{ip} = z_{ip} \otimes (a_i \bar{a}_i^H) \tag{14}$$

At all buses, the power system must endure the voltage that is under normal operating circumstances; it must also acclimatize to disturbances, namely the system configuration as well as the load change. In recent times, because of the voltage instability, several numbers of networks disintegrate. The VS indicator is reduced to enhance VS. (L_q) represents the value of L-index at each bus refers to the collapsed state of that particular bus voltage; hence, L_q of the p^{th} bus is indicated in eq. (15).

$$L_q = \left|1 - \sum_{p=1}^{NPV} F_{qp} \frac{V_p}{V_q}\right| \tag{15}$$

where $q = 1,2.......,NPQ$

$$F_{qp} = \left[Y_a\right]^{-1}\left[Y_b\right] \tag{16}$$

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} Y_a Y_b \\ Y_c Y_d \end{bmatrix} \begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix} \tag{17}$$

For all of the PQ buses, the L - Index value is determined, as well as the L_q value is set to 0 or 1, based on the voltage collapse state and a lack of load for q^{th} bus. Eq. (18) represents the objective model, where, $L_q = 1,2.....NPQ$

$$F_c = \max(L_q) \tag{18}$$

3.3 Equality and Inequality Constraints

To control the power system, the physical law uses the equality constraint, which refers to the load flow equations, and that is denoted in eq. (19) and (20).

In eq. (20), Q_{Gp} indicates the and system reactive powers at the p^{th} bus, P_{Gp} refers generation of system active power, and *NB* represents the count of buses Q_{Dp} and P_{Dp} represents the demand linked with the reactive and active powers at the p^{th} bus and G_{pq} denotes the transfer conductance among the p^{th} and the q^{th} buses. Moreover, B_{mn} indicates the susceptance among the p^{th} bus and the q^{th} bus.

$$P_{Gp} - P_{Dp} - V_p \sum_{q=1}^{NB} V_q \left[G_{pq} \cos(\delta_p - \delta_q) + B_{pq} \sin(\delta_p - \delta_q)\right] = 0 \qquad p = 1,2........NB \tag{19}$$

$$Q_{Gp}-Q_{Dp}-V_p\sum_{q=1}^{NB}V_q[\ \left[G_{pq}\cos(\delta_p-\delta_q)+B_{pq}\sin(\delta_p-\delta_q)\right] \tag{20}$$

where, $p=1,2.........NB$

The design statement must have the capability to restrict the generator reactive power and magnitude of the output voltage. Therefore, the corresponding upper and lower limits are denoted in eq. (21) and (22). Eq. (23) represents the lower and upper limits in the shunt VAR compensators for the reactive power output. The physical considerations limit the lower and upper values of the transformer tap settings are indicated in eq. (24). In the security constraints, transmission lines loadings and the voltage magnitude at the PQ buses are incorporated. Eq. (25) represents the line flow of each line and there is a concerned limit for the buses voltage.

$$V_{Gp}^{min}\leq V_{Gp}\leq V_{Gp}^{max},\ p=1,2,.......NG \tag{21}$$

$$Q_{Gp}^{min}\leq Q_{Gp}\leq Q_{Gp}^{max},\ p=1,2,.......NG \tag{22}$$

$$Q_{Cp}^{min}\leq Q_{Cp}\leq Q_{Cp}^{max},\ p=1,2,.......NC \tag{23}$$

$$T_{p}^{min}\leq T_{p}\leq T_{p}^{max},\ p=1,2,.......NT \tag{24}$$

$$V_{Lp}^{min}\leq V_{Lp}\leq V_{Lp}^{max},\ p=1,2,.......NPQ \tag{25}$$

$$S_{lp}\leq S_{lp}^{max},\ p=1,2,.......N \tag{26}$$

4. Hybrid Optimization Algorithms Adopted for ORPD

4.1 Conventional PSO Algorithm

Generally, the PSO algorithm performs on the basis of the swarm of birds. Moreover, in a multidimensional search space, it moves in explore of food [24]. Here, every individual is represented as a particle. Moreover, this method consists of two significant kinds namely velocity and position that are exploited to discover the optimum value. In a d dimensional search space, a swarm of P particles moves. At first, every particle is initialized with arbitrary velocity and position within the search space. As per eq. (27), (28) and (29), the current velocity and location for each of the 'P' particles are updated. Moreover, the location of the global optimal particle represents as the optimal solution, which is attained using the PSO algorithm.

$$v_{id}^{k+1}=\omega\times v_{id}^{k}+r_1\times rand_1\times\left(p_{best}-x_{id}\right)+r_2\times rand_2\times\left(g_{best}-x_{id}\right) \tag{27}$$

$$x_{id}^{k+1}=x_{id}+v_{id}^{k+1} \tag{28}$$

In eq. (27), r_1 and r_2 indicates the cognitive and social components, where, P_{best} indicates the local optimal location of individual particles that are updated during every iteration. Eq. (29) indicates the global optimal location, which is defined by P_{best}. In eq. (30), w indicates the inertial weight and differs by iteration and $rand_1$ and $rand_2$ indicates two random numbers, which differs among 0 to 1. A maximum inertial weight value approves global search, hence a minimum value offers with local explorations.

$$g_{best}=\min\left\{p_{best1},p_{best2,........}p_{bestn}\right\} \tag{29}$$

$$w=\left(w_{max}-w_{min}\right)\times\frac{\left(iter_{max}-iter\right)}{iter_{max}}+w_{min} \tag{30}$$

Here, $iter_{max}$ represents the utmost number of iterations and $iter$ represents the current iteration and w_{max} and w_{min} represents the maximum value is 0.9 and the minimum value is 0.4 of the inertial weight. Here, acceleration constants r_1 and r_2 that drags the swarm to the global and local optimal of the search space are performed by time-varying. Eq. (31) and (32) is used to enable exploration in the first phase and faster convergence in the exploitation phases.

$$r_1=\left(r_{1f}-r_{1i}\right)\frac{iter}{iter_{max}}+r_{1i} \tag{31}$$

$$r_2=\left(r_{2f}-r_{2i}\right)\frac{iter}{iter_{max}}+r_{2i} \tag{32}$$

The main disadvantages of PSO are that every particle follows the G_{best}, hence if G_{best} obtains wedged in local optima, subsequently the remaining particles could not be capable to search the search-space well and therefore get wedged in local optima, thus foremost to stagnation result.

4.2 Conventional WOA Algorithm

The WOA approach [3] is enthused from the food searching method for a humpback whale. Initially, it explores for prey i.e., exploration, subsequently, it encircles the prey and eventually attacks it i.e. exploitation. The best solution of the explore space is unidentified; hence WOA chooses an arbitrary objective prey as the current optimal candidate solution at the exploration stage. Next to the optimal search agent is described; later the other search agent's aim is to update their location to the optimal solution exploiting eq. (33) and (34).

$$\vec{S} = \left|\vec{C} \cdot \vec{Y} * (t) - \vec{Y}(t)\right| \tag{33}$$

$$\vec{Y}(t+1) = \vec{Y}^* - \vec{B}\vec{S} \tag{34}$$

In eq. (33), $\vec{B}$ and $\vec{C}$ indicates the coefficient vectors, $\vec{Y}^*$ denotes the location vector of the optimal solution attained hitherto. $\vec{Y}$ represents the current location vector. As a result, each iteration $\vec{Y}^*$ will be updated if there subsists an optimal solution.

$$\vec{B} = 2\vec{a}\vec{r} - \vec{a} \tag{35}$$

$$\vec{C} = 2\vec{r} \tag{36}$$

The vector $\vec{a}$ minimizes from 2 to 0 against the iteration course and $\vec{r}$ represents the arbitrary vector which ranges from [0, 1]. Generally, whales exploit two kinds of Bubble Net Attacking approaches on the basis of the probability factor pf. Subsequently, the shrinking encircling approach is attained by the minimizing value of $\vec{a}$. The whale moves spirally in the direction of its prey to update the location in the spiral updating position. In addition, the distance $\vec{S}$ among the location of the whale (Y, X) and its prey $\left(Y^*, X^*\right)$ is computed using eq. (37).

$$\vec{Y}(t+1) = \vec{S}e^{b.l}\cos(2\pi l) + \vec{Y}^* \tag{37}$$

Here, b represents a constant and l is a random number among [-1, 1] and $\vec{S} = \left|\vec{Y}^* - \vec{Y}\right|$.

Spiral and shrinking methods contain an equal likelihood. Each search agent fitness value is computed subsequent to the initialization of the population. Consequently, the optimal search agent $\vec{Y}^*$ is determined by comparison. All the parameters included are updated on the basis of the probability factor pf. At present, if $pf < 0.5$ and $|B| < 1$, the updating process for the location of the current search agent is done using eq. (33) and (34). Conversely, if $pf < 0.5$ and $|B| > 1$; subsequently, an arbitrary search agent is chosen Y_{random} from the current population, as well as using eq. (38) and (39), the updating process for the location of the current search agent is done.

$$\vec{S} = \left|\vec{C}\vec{Y}_{random} - \vec{Y}\right| \tag{38}$$

$$\vec{Y}(t+1) = \vec{Y}_{random} - B\vec{S} \tag{39}$$

In addition, if $pf \geq 0.5$ after that the current location of the particle is updated using eq. (37), where, l represents an arbitrary number among [−1, 1] and differs as stated by eq. (40)

$$l = (a_2 - 1) \times random + 1 \tag{40}$$

4.3 Proposed Algorithm

In the proposed approach, the idea of iterative hybridization is exploited that comprises of two iterations (i.e.,) first and second. Initially, to discover a tentative solution the PSO approach is applied by exploring the search space subsequently, the whale Optimization method is applied to improve the solution by functioning on the solution, which is decided using PSO method in the first iteration. Next, in the second iteration, a new idea of 'Forced Whale' is adopted that aims to direct PSO particles by the explorations ability of 'Forced' WOA. In proposed Hybrid PSO-WOA, using both the PSO and Whale approach, the exploration is performed by means of the 'Forced Whale' idea. Conversely, exploitation is done only exploiting the PSO approach with another new concept termed 'Capping' that is applied for second iterations to minimize monotonically with an augment in the number of first iterations. Hence, Whale movement is limited to the exploration stage solely. In the exploitation phase, hybridization of WOA will bring redundant randomization as well as complexity to the approach.

As stated by eq. (41) and (42) the ‘Forced’ Whale occurrence all the whale parameters are done dependent not merely on second iterations but as well on a number of first iterations.

$$a = 2 - \left[\mathrm{it} \times \left(\frac{2}{\mathrm{im}_2} \right) \right] \tag{41}$$

$$a = -1 + \left[\mathrm{it} \times \left(\frac{-1}{\mathrm{im}_2} \right) \right] \tag{42}$$

Here, i_t indicates the first iteration ‘variable’ and im_2 indicates the highest number of second iterations. From eq. (41), the parameter a plays an important part in the updating of the location for WOA during exploration phase that is done on the basis of the first iteration that minimizes with maximizing in a number of first iterations. As shown in eq. (41) and (42), with further increase in a number of first iterations a few parameters turn out to be constants as it doesn’t modify in the second iterations. In eq. (43), B and C indicates constants.

$$\mathrm{im}_2 = [B \times (\mathrm{it}) + C] \tag{43}$$

$$\mathrm{im}_2 = \left[\frac{-50}{\mathrm{im}-2} \times (\mathrm{it}) + 25 \times \frac{\mathrm{im}}{\mathrm{im}-2} \right] \tag{44}$$

The proposed approach starts with a population of P Particles that have arbitrary location and velocity within the dimensional search space d boundary. Accordingly, P_{best} and G_{best} are assigned accordingly from the initial arbitrary position. The first iteration starts with updating the location, velocity, P_{best} and G_{best} that follows the method of PSO as stated in eq. (27) and (32). The WOA is executed for every number of the first iteration at a certain amount of second iterations until the exploitation stage is attained. At first, WOA aim leader or prey whale is chosen as G_{best} of PSO in second iterations.

The optimal solution found by a whale and the fitness comparison is performed among the G_{best}, which is found by PSO during every number of the second iteration. Next final allotment of the optimal location of the particles is determined. If the global optimal fitness of PSO is minimum than the fitness of the optimal Whale after that global optimal location is allocated to the leader whale (Whale’s optimal) and inversely until the end of second iterations. At the first stage, the main aim is to search the search space, the objective models namely multi minima models require maximum explorations. In primary iterations, the PSO starts the explorations, with the methods stated in eq. (27) to (32). In dynamic second iterations, by the exploit of ‘Forced’ WOA the exploration ability is enhanced. As whale searches the search space capably by arbitrarily choosing its search agents and by an arbitrary probability factor the search method is also chosen. This probability factor differs among 0 and 1 and also determines the functioning method of the whale. This exploit of ‘Forced’ WOA in dynamic second iterations is formulated by eq. (41) and (42). In the second iterations, the search strategies in WOA are characterized by ideology and equations as stated in eq. (38) to (44). At last, in the exploitation stage, the PSO strategy is exploited to converge the solution to the optimum value attained at the exploration stage.

This is formulated by the exploited ‘Capping’ Phenomenon in eq. (43) and (44), that enthusiastically minimizes the secondary iterations to 0, as well as merely first iterations of PSO are performed. Fig. 1 demonstrates the flow diagram of proposed hybrid PSO-WOA.

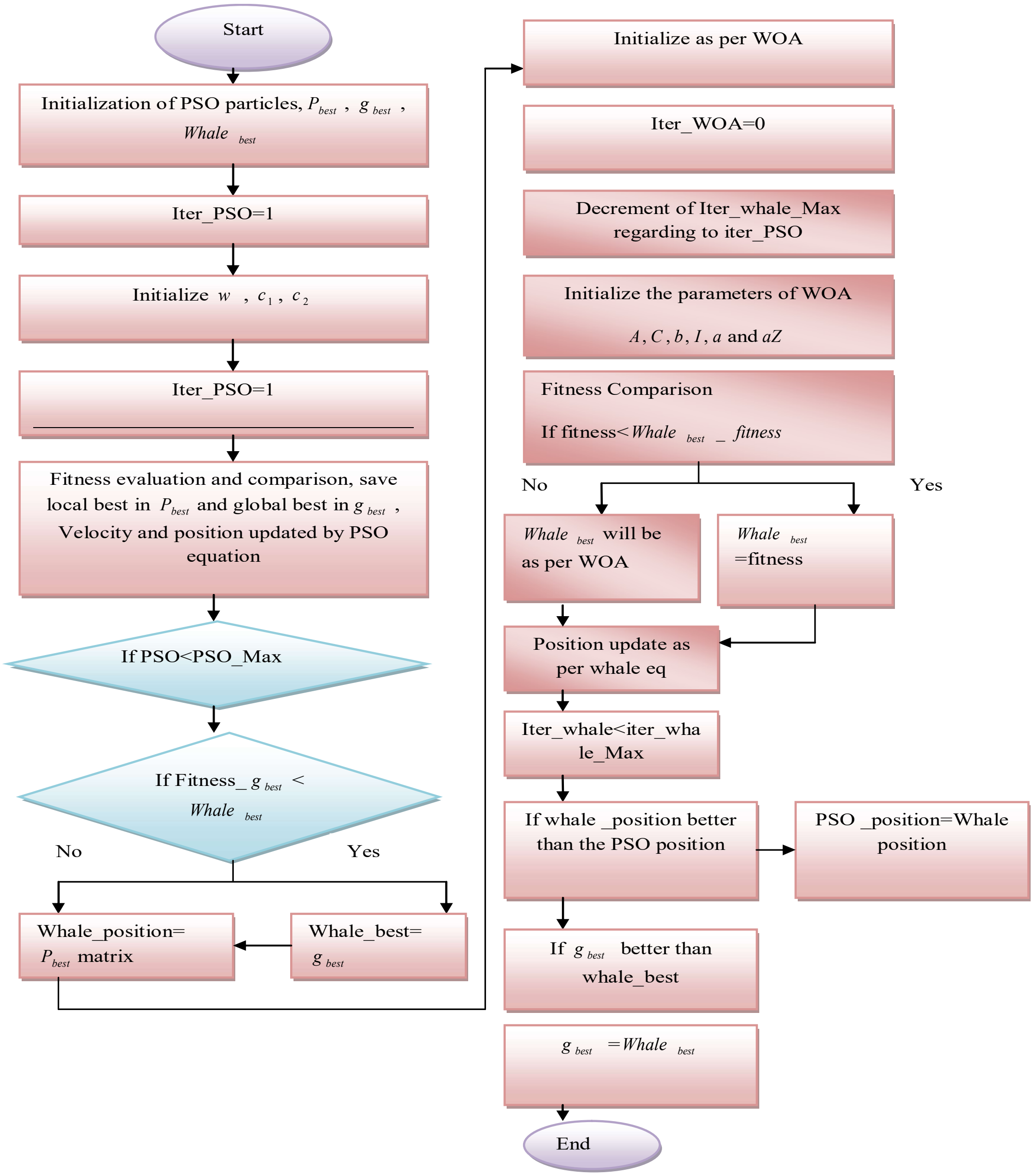

Fig. 1. *Flowchart of Hybrid PSO-WOA*

5. Results and Discussions

5.1 Experimental Setup

The proposed method is simulated in MATLAB, and the experimentation was performed in the IEEE 14 and 39 bus systems. To determine the ORPD, the experiments were performed in base case loading circumstances, as well as the converging of individual objectives, namely the Voltage penalty (F_b), ACP (F_a) and the fitness function, were analyzed. The performance analysis of the proposed technique was compared with conventional optimization methods, such as WOA and PSO. Since all these methods were stochastic in nature and greatly based depend upon the initial arbitrary solutions, the statistical analysis was performed by demeanor the experimentation for just about five iterations. Consequently, the best mean, worst, and median performances were analyzed. Further, the standard deviation was computed to comprehend the method consistency, and the statistical analyses were performed for more inference.

5.2 Performance analysis of the IEEE 14 Bus system

To attain the ORPD, the reactive power of all the five generator buses namely bus 1, bus 2, bus 3, bus 6 and bus 8, the voltage magnitudes of bus 3 and bus 13 as well as the transformer tap settings of bus 8, bus 9 and bus 10 are optimally fixed by the proposed technique and the conventional techniques, the outcomes are summarized in Table 1. Here, the values of all objectives for all 14 bus systems are diverse, and the transformer taps settings, consequent loss, voltage penalty are analyzed. From Table 1, the final fitness of the proposed method is found to be 2% superior to the system without ORPD and 1.5% superior to PSO and 2.3% superior to WOA methods. The F_a in the proposed method is 1.2% superior to the PSO method, hence enhanced power dispatch is provided. As stated in eq. (3), the main aim of this paper is to minimize the function. The variable 'V' is the control variable, which is to be optimized to obtain this objective. The fitness is minimized by the proposed method while comparing with the conventional approaches. The statistical report of the proposed and conventional techniques is shown in Table 2.

Table 1. *Performance analysis of different methods with respect to the cost minimization function in the IEEE 14 Bus system*

Optimal Control Variables	Without ORPD	With ORPD		
		PSO	WOA	Proposed
Q,1	1	1.070	1.703	1.862
Q,2	11.6	12.327	13.08	14.65
Q,3	18	16.80	14.98	18.04
Q,6	6.6	7.17	6.66	8.16
Q,8	0	1.84	1.615	1.842
V,13	1.26	0.926	0.962	0.965
V,3	1.23	1.90	1.79	1.98
T,8	1.062	1.952	1.956	1.940
T,9	1.968	1.953	1.952	1.031
T,10	1.233	1.92	1.923	1.932
F_a	12.4	12.3	13.3	13.4
F_b	3.4618	2.4684	2.4695	2.4863
Final fitness	1.343	1.294	1.294	1.283

Table 2. *Statistical Report of different methods for the IEEE 14 Bus system*

Metrics	Best	Worst	Mean	Median	Standard deviation
PSO	5.21	7.82	4.32	3.21	1.21
GWO	5.34	7.43	4.21	3.11	1.13
Proposed	5.16	7.34	4.11	3.05	1.05

The statistical analysis in Table 2 summarizes the rival performance of the proposed approach against the existing methods while testing in the IEEE 14 bus system. Here, in all five experimental rounds, the fitness for the performance of best-case exhibits the optimal convergence level that is attained by each method. Likewise, the performance of worst-case indicates the minimum fitness function attained by each technique. As the name refers to mean and the median indicates average as well as the median values of fitness, which are attained by each method in all the experimental iterations. In the best-case, the proposed method is set up to attained the optimal convergence, when the worst convergence is shown by conventional methods that are set up to converge to the similar fitness point, while they had several fitness values at early iterations. While considering the worst-case, the proposed approach not succeeds to attain good outcomes while comparing with the conventional methods. Cooperatively, the proposed method performs better with respect to the best-case and shows poor performance with respect to the worst-case. A fairer outcome is attained by calculating the mean and the median, for that the proposed method attains the optimal convergence. On the other hand, the fact of SD is that a lesser deviation offers more consistent performance. The proposed method is extremely degraded compared to the conventional method. On the other hand, the higher median and mean performances reached the effect of debasing performance because of the SD.

5.3 Performance Analysis of IEEE 39 Bus system

The performance of the IEEE 39 benchmark bus system is analyzed in this section by a similar process, which was exploited for the IEEE 14 bus. Here, the reactive power of the six-generation such as bus no 31, bus no 32, bus no 33, bus no 34, bus no 35, and bus no 38 and the transformer tap settings of bus 36, bus 38 and bus 35 are fixed to attain the ORPD. In Table 3, the performance analysis of the IEEE 39 benchmark bus system is demonstrated.

The performance analysis of Table 3 exhibits that the proposed technique attains an enhanced performance, with a 5. 03% enhancement attains against the no ORPD circumstances. Moreover, the proposed method creates superior outcomes than the existing methods, when F_a is 1.2% better than the GWO method. The statistical analysis of the IEEE 39 bus system is summarised in Table 4.

In Table 4, the best-case of the proposed method is 5.2% superior to the conventional PSO method. Similarly, the worst-case of the proposed technique is superior to all the traditional techniques. In addition, the proposed method is found to give a superior performance than the existing method, subsequent to the analysis of the median, mean, and SD.

Table 3. *Performance analysis of Proposed and existing techniques with respect to the cost minimization function in IEEE 39 Bus system*

Optimal Control Variables	**no-ORPD**	**With ORPD**		
		PSO	WOA	Proposed
Q,31	1.5	1.953	1.8234	1.331
Q,32	0.1	-0.62	-0.842	-0.63
Q,35	0.6	0.486	0.657	-0.563
Q,38	1.0265	1.0753	1.0259	1.0484
Q,33	2.97	2.12	2.18	2.891
Q,34	2.04	2.08	2.032	2.31
T,44	2.06	1.96	2.11	1.97
T,38	2.67	2.05	2.05	2.0528
T,35	2.16	1.0299	1.037	1.0135
T,36	2.016	2.048	2.05	2.87
F_a	3.51	3.17	3.67	2.75
F_b	0.352	0.90	1.34	1.35
Final fitness	8.99	6.298	6.304	5.469

Table 4. *Statistical Report of different methods in IEEE 39 Bus system*

Metrics	**Best**	**Worst**	**Mean**	**Median**	**Standard deviation**
PSO	16.28	27.122	14.121	36.18	12.28
GWO	16.29	26.313	16.431	26.42	12.26
Proposed	16.18	26.233	13.113	16.39	12.18

6. Conclusion

In this paper, the proposed PSO-WOA technique was shown and effectively applied. Moreover, the ORPD issue was stated as a non-linear optimization issue with inequality and equality constraints. Here, the objective models were the Voltage Deviation and the Active Power Loss. Besides, the proposed PSO-WOA technique was efficiently reduced the Voltage Deviation and Active Power Loss. For both the IEEE 14 and 39 benchmark bus systems, the performance of the proposed technique was compared with conventional approaches. The proposed method has ensued in a reduced cost function. Finally, the performance analysis was revealed that the proposed method provides high-quality solutions to sustain high-grade power systems.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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