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A hybridized approach for design and optimization of ORPD under unbalanced conditions

by

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Abstract: The issue of ORPD (Optimal Reactive Power Dispatch) for enhancing security and economy of a power system has been given substantial consideration in recent days. The major inspiration behind deploying an ORPD system for enhancing power system efficiency is to reallocate the RP (reactive power) in such a manner that power loss be minimized, and voltage profiles get enhanced. Hence, this paper concerns the major objectives, namely, reduction of power loss and voltage deviation that are related to solving ORPD problem under unbalanced condition. To attain these objectives, an amalgamation of two algorithms, called CS (Cuckoo Search) and GWSO (Glow Worm Swarm), is adopted for optimizing, and hence the proposed model is referred to as CP-GWSO. This algorithm functions with the control parameters, namely load reactance, voltage and transformer tap settings that are tuned to attain the optimum outcome. The entire empirical part of the investigations is performed on two IEEE standard test bus systems, the IEEE 14 and the IEEE 39 bus systems. Finally, the proposed scheme is compared to the conventional methods, and its efficiency is confirmed.

Keywords: ORPD, power loss, voltage profile, Cuckoo Search, Glow Worm Swarm

1. Introduction

The problem of ORPD refers to the effective service for setting up and functioning of power systems, and it was initially introduced in the 1960s. ORPD is regarded as one of the most significant fields within the OPF (optimal power flow). It is a critical problem for safe functioning, since voltage control is very much related to power networks (see, e.g., Ghasemi et al., 2014; Heidari, Abbaspour and Jordehi, 2017). Moreover, management of power in modern power networks has become a major issue, as any negligence can endanger the security of the system. The ORPD has become a point of raising awareness over the previous years (Nuaekaew et al., 2017; Mei et al., 2017; Rajan and Malakar, 2015). The cause is that ORPD brings about a significant effect regarding the economical function of electrical systems (Mouassa, Bouktir and Salhi, 2017). The intention behind the design of ORPD is to determine the tap ratio of transformers, the voltage of generators and shunt compensators so as to optimize transmission losses, taking into account the various parameters, considered through equality and inequality conditions (Jangir et al., 2017; Naderi et al., 2017; Aydin et al., 2017; Davoodi, Babaei and Mohammadi-ivatloo, 2018).

The abbreviations used throughout the paper:

Acronyms	**Descriptions**
ORPD	Optimal Reactive Power Dispatch
RP	Reactive Power
CS	Cuckoo Search
GWSO	Glow Worm Swarm Optimization
CP-GWSO CS	probability based GWSO algorithm
OPF	Optimal Power Flow
VP	Voltage profile
NLP	Nonlinear Programming
FF	FireFly
ABC	Artificial Bee Colony
ABC-FF	ABC based FF
IWO	Invasive Weed Optimization
NGBWCA	Gaussian bare-bones Water Cycle Algorithm
2ArchMGWO	Two-Archive Multi-Objective GWO
MFO	Moth-Flame Optimization
ALO	Ant Lion Optimizer
PSO	Particle Swarm Optimization
MVO	Multi Verse Optimizer
FAHCLPSO	Fuzzy Adaptive Heterogeneous Comprehensive-Learning PSO
APL	Active Power Loss

To mitigate the potential shortcomings, related to the ORPD systems (Grover-Silva, Girard and Kariniotakis, 2018; Attia, Sehiemy and Hasanien, 2018), it is necessary to reallocate power to the point of least power loss; to develop appropriate VPs; rated capabilities of network and equipment restrictions. In view of the fact that the problem of ORPD (see Engelmann et al., 2017; Pagnetti, Ezzaki and Anquoda, 2017) is a highly non-convex, nonlinear, large-scale static programming problem, with intricate multiple constrains, its (optimum) solution is by no means easily obtained. The modeled constraints involve, for instance, discrete variables, along with other hard-to-tackle aspects (Biswas, Suganthan and Amaratunga, 2017; Mohagheghi et al., 2018). The computational schemes, exploited for establishing the improved ORPDs in the past, have been the derivative based approaches, NLP and the like (El-Fergany and Hasanien, 2018; Xu et al., 2018).

Even though securing better execution, some of the approaches to date still involve certain shortcomings, which may negatively affect system reliability (see Shilaga and Ravi, 2017; Benedito et al., 2017; Roberge, Tarbouchi and Okou, 2016). Accordingly, appropriately modeled objective functions have to be established for purposes of tackling the design issues and the system consistency. Thus, the overall problem becomes largely the one of multi-objective optimization (see, in particular, Herrmann et al., 2016; Roald et al., 2015; Kshisundaram and Sreedharan, 2015; Kumar, Manjunath and Christopher, 2018; Kota and Gaikwad, 2017; Wagh and Todmal, 2015; Iyapparaja and Tiwari, 2017; Sarkar and Murugan, 2017).

This paper contributes the methodology for solving the ORPD problem with reduction of power loss and of voltage deviation using a hybrid algorithm, referred to as CP-GWSO. The proposed CP-GWSO scheme is compared with the known algorithms such as GA (Vrionis, Koutiva and Vovos, 2014), FF (Wang et al., 2017), PSO (Zhang and Xia, 2017), ABC (Gao et al., 2016), ABC-FF (Shareef and Rao, 2018), GWSO (Zhou et al.,2013) and CS (Mareli and Twala, 2017), and the results are demonstrated. The paper is organized as follows: Section 2 reports on related research and reviews, related to the topic under consideration, while Section 3 describes the model of ORPD under unbalanced condition. Then, Section 4 describes parameter optimization with the use of a hybrid algorithm, Section 5 discusses the results, and Section 6 concludes the paper.

2. Literature review

2.1. Related works

In 2014, Ghasemi et al. (2014) introduced a consistent and effective approach depending on IWO for resolving the ORPD problem. Here, for realisation of the local search in the neighbourhood of the global best, several modifications were implemented, so as to improve the convergence rate in attaining a superior solution quality. Moreover, the hybrid MICA-IWO offered an enhanced outcome when compared to the conventional algorithms, and this was illustrated with appropriate results.

In 2017, Heidari, Abbaspour and Jordehi (2017) presented the NGBWCA approach, which was applied in dealing with the ORPD problem. Voltage variations and resistive losses were the objectives considered in this contribution. The effectiveness of the established NGBWCA scheme was analyzed and compared with the conventional approaches, and promising results were achieved. The experimental results and numerical tests clearly revealed the effectiveness of the NGBWCA algorithm in resolving the ORPD problem.

Also in 2017, Nuaekaew et al. (2017) presented the novel 2ArchMGWO technique for resolving the ORPD problem. Here, the optimizer was enhanced from its original form by updating the reproduction function and applying the 2-archive theory to the scheme. Moreover, the optimum outcomes, obtained from a variety of optimizers were assessed on the basis of the hypervolume indicator, and the results reported demonstrated that the adopted scheme was obviously better than the others in the comparison presented.

Then, Mei et al. (2017) suggested a novel method, termed MFO, to deal with the ORPD problem. MFO was applied to the ORPD problem to examine the optimal grouping of control constraints for attaining the reduced total power loss and reduced voltage variations. The experimentation results, reported with respect to this work demonstrated that MFO has the capability of generating better outcomes when compared to the conventional techniques.

Earlier, Rajan and Malakar (2015) introduced a new hybrid methodology that combines the FF scheme for resolving the problems, related to ORPD. The paper showed that the introduced methodology improved the convergence features and robustness in comparison with the original version of FF and other traditional schemes.

Mouassa, Boukir and Salhi (2017) presented the application of a newly developed approach, which was motivated by the hunting behavior of antlions, referred to as ALO, for resolving the ORPD problem, considering a large-scale power system. Evaluation of the obtained outcomes in comparison with those of the conventional studies demonstrated the advantage of the ALO scheme in terms of computational time and the magnitude of losses.

Jangir et al. (2017) adopted a novel scheme, based on hybrid PSO-MVO, which was checked on certain test functions and the ORPD was optimized by means of this novel proposed technique. The results obtained with this hybrid technique were compared with other methods, namely PSO and MVO. The effects of this comparison confirmed the efficiency of the new method relative to the benchmark PSO and MVO schemes.

Naderi et al. (2017) presented a novel FAHCLPSO technique for resolving the problems persisting in ORPD. After implementation, the results of the developed algorithm were compared with those of the conventional PSO, and the results obtained showed the superiority of the new technique in resolving the multifaceted optimization difficulties.

2.2. Review

Table 1 shows the methods, features, and challenges of the techniques referred to in terms of solving the ORPD problems. Thus, in the case of MICA, which was adopted by Ghasemi et al. (2014), which offers reduced power loss and minimized voltage deviation, more complicated engineering issues have to be solved. Concerning the NGBWCA, presented by Heidari, Abbaspour and Jordehi (2017), this approach provided for improved efficiency and also solved the convergence issues, but the recently developed heuristic schemes were not considered in that work. The GWO technique, adopted by Nuaekaew et al.

(2017), offers better exploration consistency along with the improved rate of convergence, but provides no capacity of solving the multi-objective ORPD problem. Then, the MFO, proposed by Mei et al. (2017), which secures the reduced transmission loss and is a simple approach, entailed more complex engineering issues that have to be solved. The FA and NM methodology, implemented by Rajan and Malakar (2015), offers better convergence and robustness, together with minimized real power loss, but this approach is more complex. Then, the ALO approach, which was proposed by Mouassa, Bouktir and Salhi (2017), and which offers reduced computational time and minimized loss of power, requires, though, an adequate empirical analysis. The PSO-MVO technique, presented in Jangir et al. (2017), which provides better convergence features along with minimization of fuel cost, requires more consideration of the RP loss. Finally, FAHCLPSO, which was introduced in Naderi et al. (2017), providing minimized voltage deviation along with reduced loss of power, offers no consideration as to solving the ORDP problem in very large systems. The limitations mentioned have, therefore, to be considered for solving the ORPD problems effectively.

3. The model of ORPD under unbalanced condition

3.1. The objective model

The APL minimization and improvement of the stability and voltage profile are the major objectives of ORPD. The constraints considered as a vector are listed in Eq. (1). In (1), P_G indicates the slack bus power, V_{li} denotes the voltage bus PQ, indexed by i ($i = 1,\ 2,\ ,\dots NPQ$), Q_{Gi} symbolizes the RP output of generator, again indexed by i ($i = 1,\ 2,\ \dots,\ NG$), where NG denotes the generator bus count, and NPQ – the count of PQ bus. The control variable vector is given by Eq. (2).

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

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

In Eq. (2), V_{Gi} denotes the terminal voltage of the voltage controlled bus, indexed by i ($i = 1,\ 2,\ \dots,\ NG$), Q_{Ci} indicates the output of the shunt VAR compensator, also indexed by i ($i = 1,\ 2,\ \dots,\ NC$), T_i signifies the tap setting of the tap changing transformer, again indexed by i ($i = 1,\ 2,\ \dots,\ NG$), NC denotes the shunt VAR compensator count, and NT symbolizes the tap clanging transformer count.

The chosen parameters are bound by the equality and inequality conditions, and the overall objective function is given by Eq. (3), in which F_a indicates the APL part of the problem considered, while F_b signifies the one related to voltage deviation:

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

Table 1. Review of state-of-the-art ORPD problem-solving techniques

Reference	**Methodology**	**Features**	**Challenges**
Ghasemi et al. (2014)	MICA	- Reduced power loss - Minimized voltage deviation	- More complex engineering issues have to be solved
Heidari, Abbaspour & Jordehi (2017)	NGBWCA	- Improved efficiency - Solves the convergence issues	- No consideration of the recently developed heuristic schemes
Nuaekaew et al. (2017)	GWO	- Exploration consistency - Improved rate of convergence	- No consideration of solving multi-objective ORPD
Mei et al. (2017)	MFO	- Reduced transmission loss - Simpler approach	- More complex engineering issues have to be solved
Rajan and Malakar (2015)	FA and NM	- Better convergence and robustness - Minimized real power loss.	- Methodology is more complex
Mouassa, Bouktir & Salhi (2017)	ALO	- Reduced computational time - Minimized loss of power.	- Requires adequate empirical analysis
Jangir et al. (2017)	PSO-MVO	- Better convergence features - Minimization of fuel cost.	- Requires more consideration regarding RP loss
Naderi et al. (2017)	FAHCLPSO	- Minimized voltage deviation - Reduced loss of power.	- No consideration of solving ORDP in very large systems

3.2. Active power loss minimization

The APL minimization is performed with respect to the function, given by Eq. (4):

$$F_a = P_l = \sum_{k=1}^{N} g_k[V_m^2 + V_n^2 - 2V_m V_n \cos(\delta_m - \delta_n)]. \tag{4}$$

In Eq. (4), P_l indicates the APL of the system, N denotes the count of transmission lines and g_k signifies the k^{th} branch conductance between the m^{th} and n^{th} buses. In addition, δ_m and δ_n indicate voltage phase angles of the m^{th} and n^{th} buses, correspondingly.

3.3. Voltage deviation

The reduction of the voltage magnitude (V_i) of a bus at different loads from a predetermined reference value (V^{ref}) of V_i is used to measure the improvement of the voltage profile.

The voltage profile improvement is given by Eq. (5), in which $\psi(x)$ denotes the step function, given by Eq. (6).

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

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

In Eq. (5), LB denotes the count of load buses, in which, in addition,

$$|V_m|^2 = |V_i|^2 - 2(r_{im}^{\sim} P_{im} + x_{im}^{\sim} Q_{im}) + c_{im}(P, Q). \tag{7}$$

In Eq. (7), V_i signifies the voltage from load flow measurement at the balanced condition. Then, Q and P indicate the reactive and real power magnitudes, respectively. Furthermore, x and r denote the susceptance and the resistance of the line, correspondingly.

$$r_{im}^{\sim} = Re\left\{aa^H\right\} \otimes r_{im} + Im\left\{aa^H\right\} \otimes x_{im} \tag{8}$$

$$x_{im}^{\sim} = Re\left\{aa^H\right\} \otimes x_{im} - Im\left\{aa^H\right\} \otimes r_{im} \tag{9}$$

$$a = \left[\begin{array}{ccc} 1 & e^{-j2\pi/3} & e^{j2\pi/3} \end{array}\right] \tag{10}$$

$$c_{im} = [z_{im}[S_{im}^* ./V_i^*]] \otimes [z_{im}^*[S_{im_0} ./V_i]] \tag{11}$$

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

$$S_{im} = [P_{im} + jQ_{im}] \otimes [z_{im}^{\sim}(P_{im} - jQ_{im})] \tag{13}$$

$$z_{im}^{\sim} = \mathrm{z}_{\mathrm{im}} \otimes (a_i a_i^{H^-}). \tag{14}$$

The power system has to maintain the voltage at all of the buses that are under the normal functioning conditions, and it must be able to adapt to the interferences like the variation of load and the configuration of the system. Recently, numerous main networks have been collapsing owing to voltage instability. The voltage stability indicator is introduced in order to assess and maintain the stability of voltage. L index value, calculated for each bus (L_n), denotes the (potentially distorted) voltage condition of that specific bus. The value of L_n for the n^{th} bus is given through Eq. (15), in which $n = 1, 2, ..., NPQ$.

$$L_n = \left| 1 - \sum_{m=1}^{NPV} F_{nm} \frac{V_m}{V_n} \right| \tag{15}$$

$$F_{nm} = [Y_a]^{-1} [Y_b]. \tag{16}$$

In Eq. (15), NPV denotes the PV bus count, while Y_b and Y_a in Eq. (16) denote appropriate sub-matrices. The values of I_{PQ} and I_{PV} are given by (17), following the separation of constraints regarding the PQ and PV buses.

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

The L index value is calculated for the all of the PQ buses and the value of L_n is fixed as zero or one, based on the voltage collapse and no load condition of the n^{th} bus. Hence, the objective function could be as given by Eq. (18), where $n = 1, 2, \ldots, NPQ$.

$$F_c = \max(L_n). \tag{18}$$

3.4. Inequality and equality constraints

The equality conditions control the power system, including the load flow condition formulations that are given below.

$$\begin{gathered} P_{Gm} - P_{Dm} - V_m \sum_{n=1}^{NB} V_n \left[B_{mn} \sin(\delta_m - \delta_n) + G_{mn} \cos(\delta_m - \delta_n) \right] = 0 \\ m = 1, 2........., NB \end{gathered} \tag{19}$$

$$\begin{gathered} Q_{Gm} - Q_{Dm} - V_m \sum_{n=1}^{NB} V_n \left[B_{mn} \sin(\delta_m - \delta_n) + G_{mn} \cos(\delta_m - \delta_n) \right] = 0 \\ m = 1, 2.........., NB. \end{gathered} \tag{20}$$

Accordingly, in Eq. (20), NB denotes the bus count, Q_{Gm} and P_{Gm} denote, respectively, production of reactive and active power of the system at the m^{th} bus, Q_{Dm} and P_{Dm} represent the demand related to the reactive and active power at the m^{th} bus, respectively, and G_{mn} signifies the transfer conductance between the m^{th} and n^{th} buses. In addition, B_{mn} represents the susceptance between the m^{th} and n^{th} buses.

The design prescription must include the capacity to restrict the magnitude of RP and output voltage of generator and therefore, the respective upper and lower limits are formulated as given by Eq. (21) and Eq. (22):

$$Q_{Gm}^{\min} \leq Q_{Gm} \leq Q_{Gm}^{\max},\ m = 1, 2, ..., NG \tag{21}$$

$$V_{Gm}^{\min} \leq V_{Gm} \leq V_{Gm}^{\max},\ m = 1, 2, ..., NG. \tag{22}$$

The lower and upper limits on the RP at output in shunt VAR compensators are determined as in Eq. (23).

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

The physical aspects restrain the lower and upper values of the transformer tap setting in the way given by Eq. (24).

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

The transmission line loadings and voltage magnitude at the PQ buses are incorporated in the security parameters. There exists a certain bound for the voltage in the buses, and hence each line flow is appropriately constrained as in Eq. (25) and Eq. (26).

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

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

4. Parameter optimization using a hybrid algorithm

4.1. Solution encoding

The constraints, such as those on RP (Q), voltage magnitude (V) and transformer tap setting (T), are given as input to the proposed CP-GWSO model for solving the ORPD problem. The RP of five generator buses (bus numbers: one, two, three, six and eight), voltage magnitudes of buses thirteen and three, transformer tap settings of three buses: numbers eight, nine and ten, are optimally fixed by means of the adopted CP-GWSO model that can minimize the power loss and voltage deviation.

$$\boxed{Q_1}\boxed{Q_2}\boxed{Q_3}\boxed{Q_6}\boxed{Q_8}\boxed{V_{13}}\boxed{V_3}\boxed{T_8}\boxed{T_9}\boxed{T_{10}} \longrightarrow X_i$$

Figure 1. Solution encoding

4.2. The Cuckoo Search algorithm

The Cuckoo Search (CS) algorithm is a method that has been developed by mimicking the reproduction of cuckoos (Mareli and Twala, 2017). Usually, cuckoos lay their eggs in the nests of former cuckoos with the expectation of their babies being grown up by the alternative parents. During a certain period the alternative parents can find out that the eggs in their nests do not actually belong to them. In such circumstances, the unfamiliar eggs are pushed out from the nests or the nests are deserted. The resulting approach is sketched through the subsequent three conditions:

1. Every cuckoo chooses a nest arbitrarily and lays one egg in it.
2. The best nests with increased quality of eggs would be taken over for the subsequent generation.
3. For a predetermined quantity of nests, a host cuckoo can find out an alien egg with the probability $P \in [0,\ 1]$. Under such conditions, the host cuckoo can either throw the egg or leave the nest and construct a new nest in another place.

The final condition can be estimated by substituting a fraction of the v host nests with the new ones. The fitness or quality q_i of a solution can be measured with the value of the objective function. From the execution point of view, every egg in a nest indicates a solution, and every cuckoo can lay only one egg, i.e. produce one solution. Moreover, no importance shift can be performed among an egg, a cuckoo or a nest. The objective is to use the novel and capable cuckoo egg (i.e. solution) to substitute for the worst solution in the nest. The balance among global and local random walks is adjusted by a switching constraint $G \in [0,1]$. The global and local random walks are performed as shown in Eqs. (27) and (28), respectively. Accordingly, in Eq. (27), $X_i(U)$ and $X_k(U)$ denote the present positions, chosen by arbitrary permutation, β indicates the positive step size scaling factor, $X_i(U{+}1)$ designates the subsequent position, s denotes the step size, $\otimes$ indicates the entry-wise product of two vectors, O signifies the Heaviside step function, G symbolizes a variable that is exploited to switch among the global and random walks, ε denotes an arbitrary variable from the uniform distribution. Further, in Eq. (28), $M(s,\tau)$ indicates the Levy distribution exploited to describe the step size of arbitrary walk.

$$X_i(U+1) = X_i(U) + \beta\, s \otimes\, O\,(G-\varepsilon) \otimes\, (X_j(U) - X_k(U)) \tag{27}$$

$$X_i(U+1) = X_i(U) + \beta\, M\,(s,\tau)\,. \tag{28}$$

4.3. Glow Worm Swarm optimization

The glow worms (see Zhou et al., 2013) hold a quantity of a luminescent substance named luciferin inside them. These insects have the habit of making their own decisions based on their decision domain Z_{di} $(0 < Z_{di} \leq Z_u)$. Assume i glow worm that considers the k as the neighbor glow worm only if k lies within its neighborhood limit.

Particularly, the neighborhood is described as a local decision domain with Z_{di}, which includes a variable neighborhood range that is limited by a radial sensor range of Z_u $(0 < Z_{di} \leq Z_u)$.

- **Initialization:** During this phase, the glow worms are dispersed arbitrarily in the search space, endowed with the objective of moving towards high luminescence intensity. In addition, these glow worms hold the identical luciferin intensity within the identical decision domain Z_0, where Z_0 is the initial radiant sensor range.
- **Luciferin-update:** The position or location of glow worm i at time U is $X_i(U)$ and the relevant value of the objective function at i^{th} glow worm location at U is $C(X_i(U))$. Subsequent to this, we place $C(X_i(U))$ in place of $I_i(U)$, where $I_i(U)$ denotes the level of luciferin, which is associated to glow worm j at U. In Eq. (29), υ denotes the luciferin decay constant $(0 < \upsilon < 1)$, while γ indicates the improvement constant of luciferin.

$$I_i(U) = (1 - \upsilon) I_i(U - 1) + \gamma (C(X_i(U))) \tag{29}$$

- **Movement:** Here, every glow worm chooses its neighbor and further shifts towards it with a specific probability; the j's neighbor glow worm is required to satisfy two conditions: (i) the glow worm is within the decision domain of the j^{th} glow worm; (2) luciferin value is superior to the luciferin value of the j^{th} glow worm; j^{th} glow worm shifts toward neighbour k, which originates from $W_i(U)$ with a specific probability, given by $K_{ik}(U)$, as shown in Eq. (30).

$$K_{ik}(U) = \frac{I_k(U) - I_i(U)}{\sum_{l \in W_i(U)} I_l(U) - I_i(U)}. \tag{30}$$

After the movement of the j^{th} glow worm, the position is updated, which is portrayed by Eq. (31), in which $size$ denotes the step size.

$$X_i(U + 1) = X_i(U) + size * \left(\frac{X_k(U) - X_i(U)}{||X_k(U) - X_i(U)||} \right). \tag{31}$$

- **Neighborhood range update:** The update model is given by Eq. (32), in which α signifies a constant and n_U represents a variable for controlling the neighbor count.

$$Z_{id}(U + 1) = \min\{Z_{ud}, \max\{0, Z_{id}(U) + \alpha(n_U - |W_i(U)|)\}\}. \tag{32}$$

4.4. The proposed CP-GWSO algorithm

The conventional GWSO includes more iterations and also exploits large swarms. The here proposed GWSO algorithm constitutes an improvement by hybridizing through addition of the CS algorithm. Initially, the switching constraint G of the CS algorithm is set at 0.25. In addition, an auxiliary random variable

($rand$) has been introduced into the proposed model. The new CP-GWSO algorithm for optimal power flow is updated using the GWSO algorithm if the value, relative to the switching constraint G, is greater than this random number. Or else, the proposed model will be updated using the Levy flight of the CS algorithm, see formula (28). The pseudocode of the proposed CP-GWSO is given by Algorithm 1.

Algorithm 1: Pseudocode of CP-GWSO algorithm		
Set d- the number of dimensions		
Set n- the number of glow worms		
Consider $size$ as the step size		
Let $Z_{id}(U)$ be the position or location of i glow worm at U time		
Arbitrarily arrange the agents		
for i =1 to n do $I_i(0) = I_0$		
$Z_{id}(0) = Z_0$		
Set $\max^{it}$ as the maximum iteration number		
Set U =1		
while $\left(U \leq \max^{it}\right)$ do		
{		
	For each i glow worm, evaluate $I_i(U)$ as defined in Eq. (29)	
	For each i glow worm do	
	{	
	Set G as 0.25 as CS algorithm	
	If $rand > G$	
	Update position using GWSO algorithm	
		$W_i(U) = \{k : d_{ik}(U) < Z_{id}(U) : I_i(U) < I_k(U)\};$
		For each $j \in W_i(U)$ do
		Evaluate $K_{ik}(U)$ as per Eq. (30)
		k = choose glow worm $(\vec{K})$
		Evaluate $X_i(U+1)$ as per Eq. (31)
		Evaluate $Z_{id}(U+1)$ as per Eq. (32)
	Or else	
	Update position using Eq. (28) of CS algorithm	
	}end for	
	$U = U + 1$	
}		

5. Results and discussion

5.1. Simulation procedure

The proposed CP-GWSO algorithm for enhanced solution to the ORPD problem was implemented in MATLAB, and the experiments were performed on the IEEE 14 and IEEE 39 standard bus systems. The investigations were carried out for solving ORPD problems under certain loading conditions like APL (F_b) and voltage penalty (F_a). Moreover, the performance of the CP-GWSO model was compared with seven well known optimization models, namely, GA (Vrionis, Koutiva and Vovos, 2014), FF (Wang et al., 2017), PSO (Zhang and Xia, 2017), ABC (Gao et al., 2016), GWSO (Zhou et al., 2013), ABC-FF (Shareef and Rao, 2018), and CS (Mareli and Twala, 2017). As all of these schemes are stochastic in nature and significantly depend upon the initial (arbitrary) solutions, the final examination was made by carrying out tests more than five times. Consequently, the best, worst, median and mean performances were noticed. In addition, the standard deviation was also evaluated, in order to assess the consistency of the model.

5.2. Comparative analysis

In order to achieve a better ORPD, the RP of five generator buses were fixed optimally by means of the adopted CP-GWSO model. In this context, the proposed scheme was compared with other schemes, as mentioned before, and the results obtained are demonstrated in Table 2.

From this table, it can be seen that the overall cost function, obtained using CP–GWSO for the IEEE 14 test bus system is by 1.39% better than for GA, by 0.57% better than for FF, PSO, and ABC, by 1.76% better than for GWSO, by 0.57% better than for ABC-FF, and by 1.31% better than for CS algorithms (the values are obtained by expressing in per cent the ratio of the difference of performance of the new and compared technique, divided by that for the compared technique; a similar measure is also used further on in the subsequent comparisons).

The performance of the techniques considered for IEEE 39 standard bus system was examined in an analogous manner as this was done for the IEEE 14 bus. The results of the performance examination for the IEEE 39 standard bus system are shown in Table 3. The analysis performed with respect to the other algorithms considered shows that the cost function for the adopted scheme is by 0.29% better than for the GA, by 0.3% better than for the FF, by 0.7% better than for the PSO, by 0.3% better than for the ABC, by 0.3% better than for the GWSO, by 0.29% better than for the ABC-FF, and by 0.29% better than for the CS.

Table 2. Optimal control parameters and cost function reduction for IEEE 14 bus system

Optimal control parameters	Without ORPD	With ORPD							
		CP-GWSO	GA[a]	FF[a]	PSO[a]	ABC[a]	ABC-FF[a]	GWSO[a]	CS[a]
Q_1	0	1.0702	3.7031	8.862	8.5772	3.7402	8.4847	9.2259	6.221
Q_2	12.7	12.327	13.08	4.6506	2.9578	9.9836	19.854	10.873	13.193
Q_3	19	2.8097	7.9879	8.0045	3.7	10.393	16.746	20	6.1003
Q_6	7.5	17.172	6.6635	8.165	2.0333	1	7.3906	19.978	1.9331
Q_8	0	2.8407	15.615	14.842	8.845	19.027	3.7973	1	11.013
V_{13}	1.05	0.99065	0.98627	0.9605	0.92844	1.1	1.022	0.98625	1.1
V_3	1.01	0.90079	1.0997	0.98461	0.94751	0.9	0.92425	0.98713	1.1
T_8	0.978	0.95	0.95	0.94021	1.0415	0.89552	0.95	0.95	0.95
T_9	0.969	0.95	0.95	1.01	0.97696	0.98732	0.95	0.95	0.95
T_{10}	0.932	0.95	0.95	0.93552	0.98368	0.95	0.95	0.95	0.95
F_a	13.393	13.364	13.364	13.418	13.368	13.388	13.348	13.364	13.386
F_b	1.4817	1.4694	1.4694	1.4868	1.5929	1.4613	1.4804	1.4694	1.461
Final fitness	0.29742	0.29496	0.29496	0.29844	0.29496	0.29333	0.29715	0.29496	0.29327

[a]these algorithms are implemented according to the previously mentioned references, here and in the following tables

Table 3. Optimal control parameters and cost function reduction for IEEE 39 bus system

Optimal control parameters	Without ORPD	With ORPD							
		Metrics	GA	FF	PSO	ABC	ABC-FF	GWSO	CS
Q_{31}	4.6	0.93619	0.82819	0.33262	0.13958	-0.98668	-0.60778	-0.99	-0.60778
Q_{32}	0	-0.69109	-0.08438	-0.50416	0.52142	-0.39638	-0.8088	0.94075	-0.8088
Q_{35}	0	0.38439	0.85027	-0.63735	-0.63288	-0.78022	0.28178	-0.45557	-0.93019
Q_{38}	1.0265	1.0753	1.0259	1.0484	1.1	1.0715	1.0241	0.9	0.99502
Q_{33}	0.9972	1.088	1.0828	0.97989	0.92709	1.0828	1.0152	0.90952	1.0152
Q_{34}	1.0123	1.0868	1.0522	1.013	1.045	0.90138	1.0059	1.0859	1.0059
T_{44}	1.025	0.96451	1.0099	0.98367	0.96439	0.96534	1.0025	0.96534	0.96619
T_{38}	1.07	1.05	1.05	1.0528	1.05	1.05	1.0338	1.05	1.05
T_{35}	1.006	1.0299	1.037	1.0135	1.0093	1.036	1.0327	1.0393	1.05
T_{36}	1.006	1.0418	1.05	1.0187	1.0138	1.0465	1.0408	1.0498	1.05
F_a	43.591	43.147	43.637	42.755	43.28	43.142	43.088	43.142	43.078
F_b	50.352	8.9004	12.334	11.325	8.5168	8.9218	14.49	8.922	8.651
Final fitness	38.995	36.298	36.304	36.469	36.327	36.298	37.368	36.298	36.192

5.3. Statistical analysis

The statistical analysis of the results, obtained by the proposed CP-GWSO algorithm in the attempts of attaining better ORPD is provided in Table 4 for the IEEE 14 bus system. From the table, it is clear that the best performance of the adopted scheme is by 0.57% better than that of GA, by 0.5% better than that of FF, by 0.92% better than that of ABC, by 2.04% better than that of ABC-FF, by 0.57% better than that of GWSO, and by 0.57% better than that of the CS algorithm. Further, the worst performance of the CP-GWSO scheme is by 1.16% superior to that of PSO and by 1.05% superior to that of the ABC-F technique. Then, the mean performance of the presented method is by 0.12% better than that of GA, by 0.12% better than that of FF, by 0.78% better than that of ABC, by 0.12% better than that of ABC-FF, by 0.11% better than that of GWSO, and by 0.22% better than that of the CS algorithm.

Analogously, Table 5 shows the comparative statistical analysis of the results, obtained with the adopted scheme for the IEEE 39 bus system. So, its mean best performance is by 0.29% superior to that of GA, by 0.29% superior to that of FF, by 0.24% superior to that of PSO, by 0.29% superior to that of ABC-FF and FF, by 0.29% superior to that of GWSO and by 3.09% superior to that of the CS method. Then, the mean performance of the proposed CP-GWSO approach is by 4.13% better than that of GA, by 4.68% better than that of FF, by 0.35% better than that of PSO, by 0.2 % better than that of ABC, by 3.3% better than that of ABC-FF, by 2.89% better than that of GWSO, and by 3.3% better than that of CS.

Table 4. Statistical analysis of the results for the IEEE 14 bus system obtained by various techniques

TECHNIQUES	METRICS				
	BEST	WORST	MEAN	MEDIAN	STANDARD DEVIATION
GA	0.29496	0.29496	0.29496	0.29496	6.67×10^{-9}
FF	0.29496	0.29496	0.29496	0.29496	1.66×10^{-10}
PSO	0.296	0.29844	0.29694	0.29693	0.000933
ABC	0.29496	0.29496	0.29496	0.29496	3.26×10^{-9}
ABC-FF	0.29333	0.29806	0.2948	0.29424	0.001938
GWSO	0.29432	0.29715	0.29527	0.29496	0.001086
CS	0.29496	0.29496	0.29496	0.29496	1.41×10^{-15}
CP-GWSO	0.29327	0.29496	0.29462	0.29496	0.000752

5.4. Analysis by altering the value of α

The proposed CP-GWSO model achieves the reduced loss also by altering the variable α of the fitness function as given by Eq. (3). The graphical demon-

Table 5. Statistical analysis of the results for the IEEE 39 bus system obtained by various techniques

Techniques	Metrics				
	Best	Worst	Mean	Median	Standard deviation
GA	36.298	36.305	36.301	36.299	0.003591
FF	36.298	36.313	36.303	36.302	0.006306
PSO	36.28	36.491	36.413	36.469	0.09631
ABC	36.298	36.482	36.359	36.327	0.077518
ABC-FF	36.298	36.298	36.298	36.298	5.11×10^{-9}
GWSO	37.347	37.368	37.364	37.368	0.00955
CS	36.298	36.298	36.298	36.298	2.38×10^{-14}
CP-GWSO	36.192	36.322	36.286	36.304	0.05332

stration of the results from the proposed scheme by altering α is shown in Fig. 2.

Thus, in Fig.2 (a), for the IEEE 14 bus system, the α value in fitness function is altered, and the voltage penalty, loss, as well as the final fitness are evaluated. The loss is similar for the entire range of values of α. The voltage penalty is minimum for the value of $\alpha = 0.4$, and the most reduced final fitness is attained for $\alpha = 0.8$. In Fig.2 (b), for the IEEE 39 standard bus system, it is shown that loss is the lowest when choosing $\alpha = 0.6$, voltage penalty is most reduced for $\alpha = 0.6$, and best possible final fitness is attained in choosing $\alpha = 0.2$.

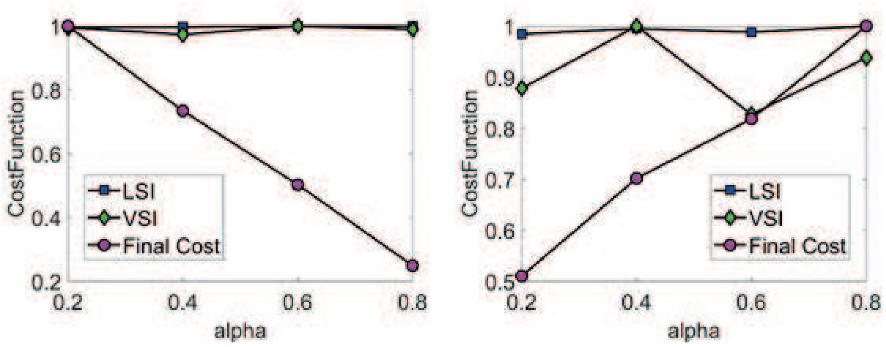

Figure 2. Graphical representation of the results for the ORPD problem with altering of the value of α for (a) IEEE 14 bus system (b) IEEE 39 bus system

6. Conclusions

The adopted CP-GWSO algorithm is described in this paper as used for the aim of solving the ORPD problem. Here, the ORPD problem was represented as a non-linear optimization problem. It is being resolved by considering the twin objectives of reduction of power loss and reduction of voltage deviation. For achieving such objectives, CS and GWSO schemes were hybridized, and the resulting procedure was termed CP-GWSO. The performance of the CP-GWSO scheme was compared with that of a number of other techniques, here also referred to, and satisfactory results have been obtained. In terms of statistical analysis, the best performance of the adopted scheme was by 0.57% better than that of GA, by 0.5% better than that of FF, by 0.92% better than that of ABC, by 2.04% better than that of ABC-FF, by 0.57% better than that of GWSO, and by 0.57% better than that of the CS algorithm for IEEE 14 bus system. For the IEEE 39 bus system the mean best performance of the adopted new scheme was by 0.29% superior to that of GA, by 0.29% superior to that of FF, by 0.24% superior to that of PSO, by 0.29% superior to that of ABC-FF and FF, by 0.29% superior to that of GWSO, and by 3.09% superior to that of the CS method. Hence, the superiority of the adopted method in the terms of the results for the ORPD problem has been substantiated successfully.

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