Optimal reactive power dispatch problem: A comprehensive study on meta-heuristic algorithms

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The main mission of modern power systems is to supply the load in the most economical and reliable methods. One of the most challenging issues in this regard is the Optimal Reactive Power Dispatch (ORPD), since the crucial focus of planning and operation studies is mainly on only supplying the active power. The primary purpose of the ORPD issue, as a complex and nonlinear problem, is to identify the relevant control variables to minimize some objective functions, i.e. active power losses considering the system constraints. As the literature review shows, the application of meta-heuristic techniques to find the optimal solution to the ORPD problem is of great importance in this field. This paper, as a comparative case study, attempts to investigate the capability of some powerful meta-heuristic optimization algorithms to tackle the ORPD problem. The control variables are the generated power by the power plants, the voltage magnitude of PV buses, the installed capacity of parallel capacitors, and on-load transformer tap changers. All the simulations were implemented on the two case study systems, including the IEEE 30-, and 57-buses. The applied meta-heuristic algorithms to the problem are Orthogonal Crossover based Differential Evolution (OXDE), Hybrid Grey Wolf Optimization, and Particle Swarm Optimization Algorithm (HGWO-PSO), Sine Cosine Algorithm (SCA), and Hybrid PSO and Genetic Algorithm (HPSO-GA).

keywords: *Optimal reactive power dispatch, Optimization techniques, Reactive power, Meta-heuristic algorithms*

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1. INTRODUCTION

Reactive power compensation is a critical task in electrical power systems because of its main role in optimal reactive power flow management [1]. However, this issue itself has an undeniable impact on maintaining the power system stability and secure power flow. Generally, the ORPD problem is applied to optimal management of the reactive power sources in electrical transmission networks aiming at minimizing power losses and improving the voltage profile. Therefore, the ORPD problem plays a crucial impact on the economy and secure operation of the electric systems. This subject is realized by coordinating different reactive power sources in the electrical transmission networks [2].

A. Literature review

OPRD is a complex sophisticated optimization problem including nonlinear objective functions with multiple local minima and in the presence of some discontinuous and nonlinear constraints [3]. Generally, solving this problem is proposed in three main categories including analytical techniques, meta-heuristic methods, and mathematical programming approaches [4].
In the category of analytical methods, several nonlinear programming techniques have been reported in [5] to investigate the optimal solution to this problem. Moreover, several mathematical methods have been addressed to solve the OPRD problem in literature, including the Newton [6], and Interior Point (IP) [7] methods, Branch and Bound (B&B) [8], Mixed Integer Non-Linear Programming (MINLP) [9], [10], and Conic programming

[11]. Although the analytical methods are helpful to design the future framework of reactive power management, they are time-consuming and are not recommended for large-scale power networks [4]. Also, in the case of mathematical methods, in addition to not guaranteeing the finding of globally optimal solutions, they suffer from non-continuity and non-derivability of the objective functions [12], which requires significant simplifications in the formulation of the problem.

To overcome the shortcomings of the previous two category methods, the third class of optimization algorithms known as meta-heuristic methods is addressed in the literature. The stages of exploration and extraction are the main components of evolutionary search algorithms, in a way, their high balance increases the algorithm's ability to solve problems. Here, exploration refers to the universality of the search (i.e., the algorithm requires more search) and the purpose of extracting or efficiency is to find better answers around an optimal answer. Global exploration leads to new answers. But, extraction applies limited and significant changes to the current optimal response. At this stage, the algorithm, considering a solution, applies changes to it during execution. In exploration, the algorithm can respond more flexibly to the required changes by creating a different solution. This indicates the dependence of exploration on time. The reason this time is so long is that more search (ie the act of discovering) must be done. But in extraction, existing solutions are exploited to achieve more efficient operations. In short, exploration means ensuring that the search is universal. Also, the purpose of extracting or better response efficiency around an answer is a local search. Since several factors affect the determination of these two factors, each algorithm has different strengths and weaknesses according to its behavior compared to other algorithms. In the following some of the main meta-heuristic based references regarding OPRD problem are addressed.

In [13], [14], a class of Genetic Algorithms (GAs) have been employed to solve the different types of OPRD problems. Also, the Differential Evaluation (DE) algorithms are implemented in [15], [16] to explore the OPRD problem aiming at several objective functions, including minimizing VAR compensation, improving the voltage stability, and reducing the cost of power losses. Shahbazi, and Kalantar [17] have suggested the Seeker Optimization Algorithm (SOA) for solving the OPRD problem to minimize the voltage deviation and power loss in transmission networks. In [18] the OPRD problem has been solved by using evolutionary programming and evolutionary strategies. Also, the Ant Colony Optimization (ACO) algorithm has been used to solve the OPRD problem in transmission networks in [19]. In [20], the PSO algorithm has been applied to solve the OPRD problem. In [21], the Gaussian bare-bones TLBO (GBTLBO) algorithm has been used to solve this problem. Also, the Artificial Bee Colony (ABC) algorithm is applied in [22] to deal with this problem in a deregulated power system. Moreover, the Gravitational Search Algorithm (GSA) has been practiced in [23] to determine the optimal solution to this problem. Authors in [24] have tested the Teaching-Learning Algorithm (TLA) algorithm to handle the OPRD problem considering the power loss as the objective function of the problem. Furthermore, the Chemical Reaction Optimization (CRO) method is proposed to solve the OPRD aiming at minimizing the power loss, voltage deviation, and maximizing voltage stability in [25]. The OPRD problem has been solved by the Water Cycle Algorithm (WCA) in [26], Moth-Flame Optimization (MFO) algorithm [27], Improved Social Spider Optimization (ISSO) [28], Semi Definite Programming (SDP) [29], Tight Conic Relaxation [30], Modified Stochastic Fractal Search Algorithm (MSFS) [31], Improved Ant Lion Optimization algorithm (IALO) [32], Whale Optimization Algorithm (WOA) [33], Adaptive Chaotic Symbiotic Organisms Search algorithm (A-CSOS) [34], Hybrid PSO and Gravitational Search Algorithm (HPSO-GSA) [35], Gaussian bare-bones WCA (NGBWCA) [36], Fractional-Order Darwinian particle swarm optimization (FO-DPSO) [37], and the Differential Search Algorithm (DSA) [38].

As a result, a complete comparison of algorithms based on features, advantages, disadvantages, factors affecting performance, and their fields of application is presented in reference [40]. To summarize, more details in this field will be omitted in this paper and a summary of the algorithms used in the field of ORPD problem solving will be given and the reference study [40] is recommended to interested readers. Anyway, some details regarding the reviewed papers in this work, are addressed in Table 1.

Table 1. A brief review of some relevant works.

Ref	Proposed algorithm	Objective function (s)	Case study (Bus numbers)
[13]	GA	Minimizing and maximizing the total cost of investing in reactive power support and the total social welfare of the system	6
[14]	GA	Minimizing active power losses, voltage deviations, and L-index	6 and 30
[15],[41]	DE	Total cost of active power losses and installation of VAR resources	30
[16]	DE	Minimization of active power losses	30
[17]	SOA	Minimizing of active power losses and voltage deviation	30
[18]	DE and EP	Minimizing of active power losses, voltage deviation and static voltage stability index	30
[19]	ACO	Minimization of active power losses	14 and 30
[21]	MGBTLBO	Minimization of active power losses	14 and 30
[22]	ABC	Minimizing of active power losses and L-index	30 and 508
[23]	GSA	Minimizing of active power losses	30, 57 and 118
[24]	MTLA	Minimizing of active power losses	14, 30 and 118
[25]	CRO	Minimizing of active power losses, voltage deviation and L-index	30 and 57
[26]	WCA	Minimizing of active power losses and voltage deviation	30
[27]	MFO	Minimizing of active power losses and voltage deviation	30, 57 and 118
[28]	ISSO	Minimizing of active power losses, voltage deviation and L-index	30 and 118
[29]	SDP	Minimizing of active power losses	30 and 118
[30]	convex relaxations	Minimizing of active power losses	3375
[31]	MSFS	Minimizing of active power losses, voltage deviation and L-index	30 and 118
[32]	IALO	Minimizing of active power losses, voltage deviation and L-index	30, 57 and 118
[33]	WOA	Minimizing of active power losses	14, 30 and 114
[34]	A-CSOS	Minimizing of active power losses and voltage deviation	30
[35]	PSOGSA	Minimizing of active power losses	30 and 118
[36]	NGBWCA	Minimizing of active power losses and voltage deviation	30, 57 and 118
[37]	FO-DPSO	Minimizing of active power losses and voltage deviation	30 and 57
[38]	DSA	Minimizing the investment cost of shunt compensation devices at the first level, Minimizing fuel cost at the second level, and Minimizing load voltage deviation at the third level	114
[42]	GSA	Minimizing of active power losses and voltage deviation	30

B. Innovation and novelty

The ORPD problem is a complex problem with a vast feasible space, including both continuous and discrete variables. Therefore, mathematical and analytical methods cannot be a suitable choice to solve this problem. As a practical alternative, meta-heuristic algorithms with a random search nature and the ability to find the optimal pan in a feasible solution space are excellent candidates for solving this problem.

In all reported cases, different algorithms have been proposed to solve the OPRD problem using various strategies. One of the most challenging issues in this regard is the setting of many control parameters that have an essential impact on optimal solutions. This issue is one of the main steps in applying different meta-heuristic algorithms. The more the number of setting parameters in the meta-heuristic algorithm is less, the more it is easy to be applied to different problems, and the accuracy of the solutions will be increased. Furthermore, the recognition and application of these algorithms are significant. In some cases, there is no need to change and innovation, and it may be possible to solve many problems in the simplest possible way by employing only an algorithm. This subject is essential in modern power systems to solve complex problems.

ORPD problem as the complex and non-convex problem in power system operation and control still needs to be tackle applying more powerful meta-heuristic algorithms. To this end, this paper, for the first time, reports applying the OXDE, HGWO-PSO, HPSO-GA, and SCA to the ORPD problem. Moreover, as a comparative case study, we tried to compare the ability of the proposed algorithms in solving the ORPD problem in terms of optimal solutions, convergence, and running time, using simulations on two standard networks of IEEE 30, and 57 buses.

This paper is organized as follows: The second section deals with the formulation of the ORPD problem. In the third section, the suggested algorithms are detailed. The fourth section presents the simulation and numerical results and the conclusions are described in the fifth section.

2. FORMULATION OF THE ORPD PROBLEM

The main objective function of the ORPD problem is to minimize the active power losses in the transmission network by Eq. (1) [43], [44], [3].

$$MinP_{\text{Loss}}\left(V,\delta\right)=\sum_{k=1}^{Nl}G_k\left(V_i^2+V_j^2-2V_iV_j\cos\delta_{ij}\right) \quad \textbf{(1)}$$

Where G_k is the conductance of line k between the buses i and j. Nl is the number of transmission lines, Vi is the voltage in the i-th bus and the voltage angle difference between the i-th and j-th buses. The main constraints are the equality of active and reactive powers expressed in Eq. (2) and Eq. (3).

$$P_{G_i}-P_{D_i}-V_i\sum_{j=1}^{NB}V_j\left(G_{ij}\cos\delta_{ij}+B_{ij}\sin\delta_{ij}\right)=0 \quad \textbf{(2)}$$

$$Q_{G_i}-Q_{D_i}-V_i\sum_{j=1}V_j\left(G_{ij}\sin\delta_{ij}-B_{ij}\cos\delta_{ij}\right)=0 \quad \textbf{(3)}$$

In which, NB is the number of system buses, P_{G_i} and Q_{G_i} are active and reactive power generated by the i-th bus, Q_{D_i} power consumption at bus i, respectively. G_{ij} and B_{ij}, are the real and imaginary parts of the admittance matrix between buses i and j. The inequality constraints also include the limitations expressed in relations Eq. (4) to Eq. (10):

$$P_{G_{\text{slack}}}^{\min}\leq P_{G_{\text{slack}}}\leq P_{G_{\text{slack}}}^{\max} \quad \textbf{(4)}$$

$$Q_{G_i}^{\min}\leq Q_{G_i}\leq Q_{G_i}^{\max},\forall i\in NG \quad \textbf{(5)}$$

$$V_{G_i}^{\min}\leq V_{G_i}\leq V_{G_i}^{\max},\forall i\in NG \quad \textbf{(6)}$$

$$T_i^{\min}\leq T_i\leq T_i^{\max},\forall i\in NT \quad \textbf{(7)}$$

$$Q_{C_i}^{\min}\leq Q_{C_i}\leq Q_{C_i}^{\max},\forall i\in NC \quad \textbf{(8)}$$

$$V_{L_i}^{\min}\leq V_{L_i}\leq V_{L_i}^{\max},\forall i\in NQ \quad \textbf{(9)}$$

$$\left|S_{l_i}\right|\leq S_{l_i}^{\max},\forall i\in Nl \quad \textbf{(10)}$$

That, NG, NT, NC, and NQ respectively represent the number of generators, transformers, reactive power compensation sources and load buses, $P_{G_{\text{slack}}}$, $P_{G_{\text{slack}}}^{\max}$, and $P_{G_{\text{slack}}}^{\min}$ represent respectively the active power, the maximum and minimum active power of the slack generator, Q_{G_i}, $Q_{G_i}^{\max}$ and $Q_{G_i}^{\max}$ respectively represent the amount of reactive power, the maximum and minimum reactive power of the generator, V_{G_i}, $V_{G_i}^{\max}$ and $V_{G_i}^{\min}$ represent respectively the amount of generator voltage, maximum and minimum generator voltage, T_i, $T_i^{\max}$ and $T_i^{\max}$ respectively represents the amount of transformer tap, the maximum and minimum transformer tap, Q_{C_i}, $Q_{C_i}^{\max}$ and $Q_{C_i}^{\min}$ respectively represent the capacitance, the maximum and minimum size of the capacitor, V_{L_i}, $V_{L_i}^{\max}$ and $V_{L_i}^{\min}$ respectively represent the load voltage, maximum and minimum load voltage, S_{l_i} and $S_{l_i}^{\max}$ are also indicates the capacity of the transmission line and its maximum transmission capacity.

A. Proposed flowchart for solving the ORPD problem

The proposed flowchart for solving the ORPD problem is presented in Fig. 1.

The main steps of the proposed flowchart for solving ORPD problem are detailed here. The process starts by determining the setting parameters for the algorithm (these parameters are different based on the type of the algorithm) and the needed data of case studies are provided in the suitable format. Then the initial population is formed according to the used parameters in each study. The test network parameters (i.e. voltage of generators, transformer tap setting, and capacitor capacity) are updated as the simulation program progresses. Here, we calculate the test network losses using AC power flow, and the relevant cost is calculated accordingly. At this stage, the stopping criteria, including the number of iteration and the desired conditions, are checked. If these conditions are met, the algorithm will be terminated and the result will be printed. Otherwise, the process returns to update the parameters of the test network.

3. SUGGESTED META-HEURISTIC ALGORITHMS

In this paper, OXDE, HGWO-PSO, HPSO-GA, and SCA optimization algorithms are used to solve the ORPD problem. In this section, some details regarding these meta-heuristic algorithms are presented.

A. OXDE algorithm

This algorithm is a method for improving the ability of the DE algorithm by using a gradual crossover spatial combination [39]. This algorithm, as in other population-based optimization algorithms, it consists of two initialization and evaluation steps. The intersection operator in this algorithm is based on Eq. (11), a discrete combination of the test vector $U_i(t)$ and the vector of the parent $X_i(t)$ for producing the child $X_i'(t)$.

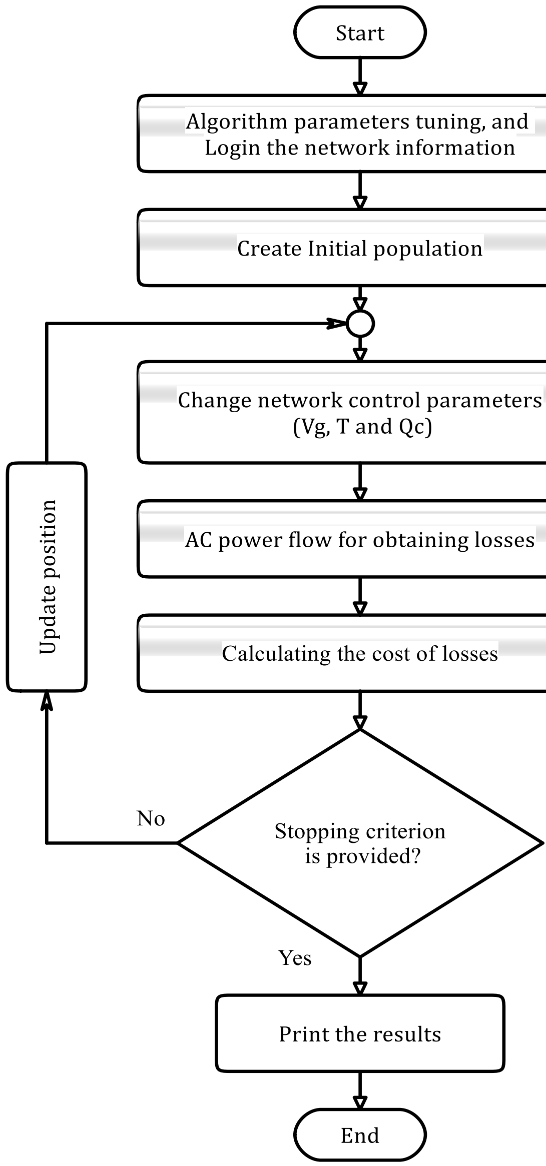

Fig. 1. Proposed flowchart for solving the ORPD problem.

$$X_i'(t) = \begin{cases} U_{ij}(t) & \text{if } j \in J \\ X_{ij}(t) & \text{otherwise} \end{cases} \quad \textbf{(11)}$$

In which, X_{ij} returns the j-th element of the vector $X_{ij}(t)$ and x is the set of intersection points that are subject to change and in this method, by determining the minimum and maximum limits of the answers, a search range is created as Eq. (12).

$$l_{i,j} = \min(e_i, g_i) + \frac{j-1}{Q-1} \cdot (\max(e_i, g_i) - \min(e_i, g_i)), \quad j = 1, \ldots, Q \quad \textbf{(12)}$$

The difference between the OXDE and DE methods is in the random selection of $\vec{X_{ij}}$ for this purpose, QOX is applied to $\vec{X_{ij}}$ in each generation to produce $\vec{v_{ij}}$ vector. By doing so, the ability to search for the optimal answer is strengthened.

B. Hybrid PSO-GA algorithm

The advantages of the PSO algorithm over GA are its simplicity, comprehensibility, and speed control capability as well as convergence. In the GA algorithm, the mutation rate and the probability of intersection affect the convergence of the algorithm, but cannot like the inertia factor in the PSO, easily control the convergence rate. Also, the main problem of both algorithms is the initial population dependence. On the other hand, by decreasing the inertia factor in the PSO algorithm, it can be observed that the convergence speed increases. But the main limitation of the PSO is precocious convergence and trapping in the local minimum.

To prevention of this problem, the best mass position of the particles in each iteration must be changed. For this purpose, by incorporating mutation operators and the intersection of the GA algorithm in PSO, it can increase diversity among its population members and reduce the probability of being caught in local minimums.

The convergence process will also increase in finding the optimal solution. For this purpose, the HPSO-GA algorithm uses standard PSO and GA algorithms so that in the early stages, the PSO algorithm generates an initial population, then the population is sent to the GA algorithm and by applying mutation operators and new population intersection probability (new solutions) as the best population moves to PSO algorithm to update global solutions. This process will continue until the stop criterion is completed. Therefore, we can catch advantage of PSO's global search (Social thinking) capability along with the GA's local search capability. Further explanation of this method is provided in the reference [45].

C. Hybrid GWO-PSO algorithm

The GWO algorithm is similar to other nature-based algorithms based on the initial population. In this algorithm, a variety of gray wolves such as α, β, δ, and ω are used to simulate the wolf leadership hierarchy, in which three basic steps of hunting, prey searching, prey siege, and prey attack are performed [46].

Optimization is performed by using the motion of the wolves α, β, δ. In this algorithm, a wolf is assumed to be the primary director of the algorithm. It is also assumed that the wolves β and δ also participate in the main guidance and the rest of the wolves are considered as followers. Therefore, modeling the process of hunting surrounds is done in two ways Eq. (13) and Eq. (14) [46]:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad \textbf{(13)}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad \textbf{(14)}$$

Where $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}_p$ Hunting location vector, and $\vec{X}$ is a Location vector of each wolf and it is also an iteration number. In these equations, the coefficients $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \quad \textbf{(15)}$$

$$\vec{C} = 2\vec{r}_2 \quad \textbf{(16)}$$

Where the components of a decrease linearly over consecutive iterations from 2 to 0.

After the prey surround processing, given that α, β and δ have better information about prey position, the hunting process is mathematically simulated. α, β and δ are the three best solutions so far to achieve the optimal solution of performance target. Wolf ω, β, δ solutions update their locations according to the locations of α, β and δ. The method of hunting is described in [46]. Here the wolves α, β and δ have better prey information to estimate the hunting position (objective function). The rest of the wolves also randomly update their position around the hunt, according to information from the wolves α, β and δ. Therefore, the method of hunting is described as follows [46].

$$\begin{cases} \vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \\ \vec{D}\beta = \left|\vec{C}_2 \cdot \vec{X}\beta - \vec{X}\right| \\ \vec{D}\delta = \left|\vec{C}_3 \cdot \vec{X}\delta - \vec{X}\right| \end{cases} \tag{17}$$

$$\begin{cases} \vec{X}_1 = \vec{X}\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha) \\ \vec{X}_2 = \vec{X}\beta - \vec{A}_2 \cdot (\vec{D}\beta) \\ \vec{X}_3 = \vec{X}\delta - \vec{A}_3 \cdot (\vec{D}\delta) \end{cases} \tag{18}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{19}$$

In these relations $\vec{X}(1)$, $\vec{X}(2)$, and $\vec{X}(3)$ are the positions of the wolves α, β and δ. There is an important point in the GWO algorithm, that exploration and operation in local optimization are a powerful algorithm, but dependent or limited in the balance between exploration and operation. The PSO algorithm can be used to fix this problem. Because the PSO algorithm is suitable for global optimization but suffers from local optimization. Therefore, to achieve the global optimum without trapping the local optimum, the HGWO-PSO algorithms are combined. Therefore, the hunting method in the hybrid algorithm is modified as follows [47].

$$\begin{cases} \vec{D}\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| - w * \vec{X} \\ \vec{D}\beta = \left|\vec{C}_2 \cdot \vec{X}\beta - \vec{X}\right| - w * \vec{X} \\ \vec{D}\delta = \left|\vec{C}_3 \cdot \vec{X}\delta - \vec{X}\right| - w * \vec{X} \end{cases} \tag{20}$$

$$\begin{cases} \vec{X}_1 = \vec{X}\alpha - \vec{A}_1 \cdot \left(\vec{D}_\alpha\right) \\ \vec{X}_2 = \vec{X}\beta - \vec{A}_2 \cdot (\vec{D}\beta) \\ \vec{X}_3 = \vec{X}\delta - \vec{A}_3 \cdot (\vec{D}\delta) \end{cases} \tag{21}$$

$$\begin{aligned} \vec{v}_i^{t+1} = {} & w * (\vec{v}_i^t + C_1 * r_1 * (\vec{X}_1 - \vec{X}_i^t)) \\ & + C_2 * r_2 * (\vec{X}_2 - \vec{X}_i^t) \\ & + C_3 * r_3 * (\vec{X}_3 - \vec{X}_i^t) \end{aligned} \tag{22}$$

$$\vec{X}_i^{t+1} = \vec{v}_i^{t+1} + \vec{X}_i^t \tag{23}$$

$$w = 0.5 + \left(\frac{r}{2}\right) \tag{24}$$

$$\vec{v}_i^t = 0.3 * r \tag{25}$$

In these relationships, the coefficient w is the weight coefficient, coefficient r_i is the random numbers in the interval between zero and one, as well as the coefficients C_i of the particle are related to the social learning coefficient that is considered to be 0.5 [47].

D. SCA algorithm

The SCA algorithm is also a new optimization technique introduced in 2015 [48]. In this algorithm, a mathematical model based on sinus and cosine functions is used to minimize the solution. In this algorithm, the particle position is expressed by Eq. (26) and Eq. (27).

$$X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times \left|r_3 P_i^t - X_i^t\right| \tag{26}$$

$$X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times \left|r_3 P_i^t - X_i^t\right| \tag{27}$$

In these equations, X_i is the position of the particles in the i-th dimension and j-th repeats. r_1, r_2 and r_3 are random numbers that represent the position of the particles in the i-th dimension. These two equations are combined and used in the form of Eq. (28).

$$X_i^{t+1} = \begin{cases} X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times \left|r_3 P_i^t - X_i^t\right|, & r_4 < 0.5 \\ X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times \left|r_3 P_i^t - X_i^t\right|, & r_4 \geq 0.5 \end{cases} \tag{28}$$

In this equation, r_4 is a random number between the interval [0,1].

According to Eq. (23), there are four main parameters r_1 to r_4 in the SCA algorithm:

-r_1 determines the dimension of the search space (confine of answers).

-r_2 determines the range of behavior to the optimal response.

-r_3 determines the particle weight coefficients in moving towards the optimum point.

-r_4 also determines the amount of displacement between Sin and Cos in Eq. (28).

As we know, each algorithm must balance the results obtained to find the optimal point, in this algorithm, Eq. (26) and Eq. (27) are used to balance Eq. (29).

$$r_1 = a - ta/T \tag{29}$$

4. SIMULATION AND NUMERICAL RESULTS

A. The standardized network studied

The first system examined is the IEEE 30-bus standard network [43]. This system consists of 6 power plants, 4 transformers, 41 transmission lines, and 3 capacitor banks. The magnitude of active and reactive powers produced in this system are 298.23 MW and 139.1 MVAr respectively, and consumed active and reactive powers are 283.4 MW and 126.2 MVAr respectively. The amount of active losses in this system is 5.832 MW.

The range of control parameters for this system is presented in three operation statuses in Table 2 [44].

Table 2. The IEEE 30-bus standard network control parameters (p.u.)

Case	V_G^{max}	V_G^{min}	V_{PQ}^{max}	V_{PQ}^{min}	T_K^{max}	T_K^{min}	Q_C^{max}	Q_C^{min}
1	1.1	0.9	1.05	0.95	1.05	0.95	0.36	-0.12
2	1.1	0.95	1.1	0.95	1.1	0.9	0.3	0
3	1.1	0.95	1.1	0.95	1.1	0.9	0.36	0

The second system examined is the IEEE 57-bus standard network. This system consists of 7 power plants, 15 transformers, 80 transmission lines, and 3 capacitor banks. The amount of

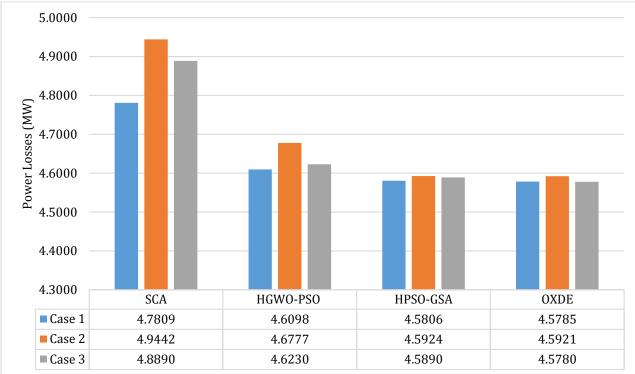

Fig. 2. Solution quality across case studies in the IEEE standard 30-bus network.

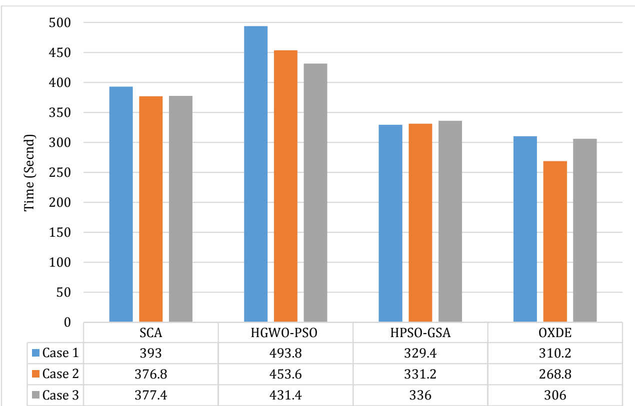

Fig. 3. Run-time of applied algorithms in different case studies for the IEEE standard 30-bus network.

active and reactive power produced in this system is 1278.66 MW and 321.08 MVar, respectively, the amount of active and reactive power consumption is 1250.8 MW and 336.4 MVar. Also, the amount of active losses in this system is 27.864 MW. The range of control parameters for this system is presented in three operation modes in Table 3 [44].

Table 3. The IEEE standard 57-bus network control parameters (p.u.)

V_G^{max}	V_G^{min}	V_{PQ}^{max}	V_{PQ}^{min}	T_K^{max}	T_K^{min}	Q_C^{max}	Q_C^{min}
1.06	0.94	1.06	0.94	1.1	0.9	$Bus_{18} = 0.10$	0
-	0.95	-	-	-	-	$Bus_{25} = 0.059$	0
-	0.95	-	-	-	-	$Bus_{53} = 0.063$	0

B. Simulation results on the IEEE standard networks

B.1. IEEE 30-bus standard network

The best results of the proposed algorithms after 20 independent runs of the algorithms, including the electrical losses, are summarized in Tables 4-6 and Figs. 2 and 3 for IEEE 30-bus standard network.

The results for the IEEE 30-bus test system in three different cases in terms of the time of the objective function value and the execution time of the algorithm are shown in Figs. 2 and 3.

Fig. 2 shows that the HPSO-GSA and OXDE algorithms in different network conditions present almost better results compared to the other two algorithms, including the SCA, and HGWO-PSO. This verifies the better performance of HPSO-GSA and OXDE algorithms in solving the ORPD. As an important note, the effect of reactive power generation sources on voltage stability should be detailed in a time domain. The ORPD plays a significant role in optimizing the performance of the power system. Since voltage stability is basically dynamic, the long run-time of the algorithm may lead to longer reactive power programming in terms of time, which is not desirable. The longer the time required to make the necessary calculations to decide on the optimal performance of reactive power sources, or ORPD, the lower the possibility of voltage stability, and the system enters the voltage instability conditions. This raises more serious concerns, especially in larger power systems with more complex structures that increase the run-time. Accordingly, solving the ORPD problem in the shortest possible time will be very desirable. This subject requires less run-time of the optimization problems. Fig. 3 shows the run-time of different algorithms for solving the ORPD.

Since the heuristic algorithms make possible solving the ORPD problem in shorter run-time, the solution found should not be too far from the optimal point. It is therefore suggested that in cases where the two goals are at odds, a balance will be struck between the timing and accuracy of the proposed solution.

The longer the reactive power calculations, the greater probability of voltage instability. This may be due to the large size of the network. Therefore, due to the importance of voltage stability, this time cannot be considered more than a certain range for the understudy system to achieve a stable operation.

Fig. 3 depicts a brief comparison between the run-time of SCA, HGWO-PSO, HPSO-GSA, and OXDE algorithms. In all case studies, the run-time of OXDE algorithm is shorter than the other algorithms, regardless of the studied network conditions. This indicates the optimal performance of the OXDE algorithm in solving the ORPD in terms of run-time. The run-time for other algorithms is longer, from HPSO-GSA, SCA, to HGWO-PSO respectively. Also, the performance of the HPSO-GSA algorithm can be considered desirable. Fig. 4 shows the convergence curve of the proposed algorithms in the IEEE 30-bus network.

Since the real power network is larger and more complicated than the standard test power network, therefore, the run-time for the real power network will be more than this amount of time. To this end, the algorithm with less run-time should be considered.

As shown in Fig. 3, the results box of the OXDE and HPSO-GA algorithms with the HGWO-PSO and SCA algorithms are in a lower position. The results also show that the OXDE algorithm has less execution time regardless of the case study, which illustrates the power of this algorithm to solve this problem. Fig. 4 also shows the convergence diagram of the proposed algorithms in the second case of the IEEE 30-bus standard network.

B.2. IEEE standard 57-bus network

The best results of the proposed algorithms after 20 independent runs of the algorithms, including the electrical losses, are summarized in Table 7 and Fig. 5 for the standard network of the IEEE 57-bus. The performance time of the various algorithms applied to the ORPD problem is shown in Fig. 6.

Table 4. Best control variables settings and active power losses for the IEEE 30-bus standard network for case 1 (p.u.)

Variable	SGA [3]	PSO [3]	MAPSO [3]	SGA [49]	PSO [49]	HAS [49]	ICA [44]	IWO [44]	MICA-IWO [44]	GWO [50]	OXDE	HPSO-GA	HGWO-PSO	SCA
ǀVG1ǀ	1.0751	1.0725	1.078	1.0512	1.0313	1.0726	1.0785	1.06965	1.07972	1.10	1.10	1.10	1.10	1.10
VG2	1.0646	1.0633	1.0689	1.0421	1.0114	1.0625	1.06943	1.06038	1.07055	1.096149	1.0942	1.094082	1.094062	1.10
VG5	1.0422	1.041	1.0468	1.0322	1.0221	1.0339	1.04698	1.03692	1.04836	1.080036	1.0749	1.074784	1.077258	1.10
VG8	1.0454	1.041	1.0468	0.9815	1.0031	1.0422	1.04714	1.03862	1.04865	1.080444	1.0769	1.076735	1.074705	1.10
VG11	1.0337	1.0648	1.0728	0.9766	0.9744	1.0318	0.03485	1.02973	1.07518	1.093452	1.10	1.078176	1.10	1.10
VG13	1.0548	1.0597	1.0642	1.10	0.9987	1.0681	1.07106	1.05574	1.07072	1.10	1.10	1.10	1.10	1.10
T6-9	0.94	1.03	1.04	0.95	0.97	1.01	1.08	1.05	1.03	1.04	1.03	1.04	1	1.05
T6-10	1.04	0.95	0.95	0.98	1.02	1	0.95	0.96	0.99	0.95	0.95	0.95	0.97	1
T4-12	1.04	0.99	0.99	1.04	1.01	0.99	1	0.97	1	0.95	0.95	0.95	1	0.95
T28-27	1.02	0.97	0.97	1.02	0.99	0.97	0.97	0.97	0.98	0.95	0.96	0.95	0.97	0.95
QC3	0	0	0	0.12	0.17	0.34	-0.06	0.08	-0.07	0.12	0.09364	0.067	0.01	0.06
QC10	0.37	0.16	0.16	-0.1	0.13	0.12	0.36	0.35	0.23	0.3	0.24689	0.34	0.14	0.36
QC24	0.06	0.12	0.12	0.3	0.23	0.1	0.11	0.11	0.12	0.08	0.08807	0.087	0.09	0.06
Ploss	**0.0498**	**0.049262**	**0.048747**	**0.049408**	**0.049239**	**0.049059**	**0.048637**	**0.049344**	**0.048599**	**0.045984**	**0./04578533**	**0.04580623**	**0.04609763**	**0.047809**

Table 5. Best control variables settings and active power losses for the IEEE 30-bus standard network for case 2 (p.u.)

Variable	RGA [51]	CMAES [51]	MOPSO [51]	NSGA-II [51]	MNSGA-II [51]	DE [52]	PSO [52]	ICA [44]	IWO [44]	MICA-IWO [44]	OXDE	HPSO-GA	HGWO-PSO	SCA
VG1	1.0695	1.07167	1.05006	1.07052	1.07319	1.05	1.05	1.06955	1.06435	1.07	1.10	1.10	1.10	1.10
VG2	0.06138	1.06253	1.0439	1.06135	1.0641	1.0446	0.9679	1.05976	1.05455	1.06136	1.09396	1.09396	1.094708	1.10
VG5	1.04038	1.04026	1.02311	1.04023	1.04163	1.0247	1.0262	1.04053	1.03736	1.04406	1.07457	1.0745	1.073695	1.10
VG8	1.04056	1.04041	1.02161	1.0404	1.04225	1.0265	1.0267	1.04536	1.03745	1.04595	1.07647	1.07653	1.080387	1.10
VG11	1.03695	1.03685	1.012	1.03239	1.02028	1.10	1.10	1.09843	1.08534	1.10	1.10	1.088	1.027678	1.10
VG13	1.06025	1.06026	1.04226	1.05991	1.05318	1.10	1.10	1.09839	1.09997	1.10	1.10	1.10	1.081537	1.10
T6-9	0.99	1	1.02	1.02	1.03	1	0.97	1	1	1	1.09	1.072	1/015	1.10
T6-10	0.98	0.92	1.03	0.92	0.92	1.10	1.10	0.92	0.92	0.91	0.9	0.922	1.069	0.90
T4-12	0.98	0.98	0.95	0.98	0.97	1.08	1.06	0.98	1.04	1	0.97	0.969	1.068	1.10
T28-27	0.99	0.99	0.99	0.99	0.99	0.92	0.92	0.96	0.96	0.95	0.96	0.962	1.009	0.982
QC10	0.18	0.19	0.20	0.17	0.18	0.26	0.30	0.05	0.06	0.06	0.2472	0.29031	0.29042	0.1062
QC24	0.06	1	0.09	0.09	0.10	0.10	0.10	0.05	0.05	0.05	0.0895	0.08922	0.09688	0
Ploss	**0.04951**	**0.04945**	**0.04951**	**0.04952**	**0.049454**	**0.05011**	**0.05116**	**0.049444**	**0.049995**	**0.049178**	**0.04592089**	**0.04592408**	**0.04603473**	**0.04944244**

Table 6. Best control variables settings and active power losses for the IEEE 30-bus standard network for case 3 (p.u.)

Variable	C-PSO [53]	CL-PSO [53]	LDI-PSO [53]	B-DE [53]	R-DE [53]	SFLA [53]	NMSFLA [53]	ICA [53]	IWO [44]	MICA-IWO [44]	OXDE	HPSO-GA	HGWO-PSO	SCA
VG1	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10	1.10
VG2	1.10	1.0947	1.0946	1.0946	1.0949	1.0945	1.0945	1.09284	1.09314	1.09272	1.09415	1.09416	1.09439	1.10
VG5	1.0747	1.0755	1.0753	1.0754	1.0707	1.0751	1.0753	1.07541	1.07411	1.07559	1.0749	1.07487	1.07518	1.10
VG8	1.0867	1.0774	1.0773	1.0774	1.073	1.077	1.0773	1.078	1.07789	1.07717	1.0769	1.07692	1.07743	1.10
VG11	1.10	1.10	1.10	1.0999	1.065	1.0949	1.10	1.09145	1.09132	1.09999	1.10	1.07987	1.10	1.10
VG13	1.10	1.10	1.10	1.1.000	1.0961	1.10	1.10	1.09941	1.0998	1.10	1.10	1.10	1.10	1.10
T6-9	0.99	1.08	1.08	1.08	1.05	0.98	1.06	1.03	1.03	1.10	1.07	1.048	1.0168	1.10
T6-10	1.05	0.90	0.90	0.90	0.90	1.03	0.92	1.01	1.01	0.90	0.90	0.934	0.9	0.90
T4-12	0.99	0.96	0.96	0.96	1	0.96	0.95	0.99	1.01	0.96	0.95	0.943	0.9755	1.10
T28-27	0.96	0.96	0.96	0.96	0.97	0.96	0.96	0.98	0.97	0.96	0.95	0.953	0.9685	1.0255
QC3	0.09	0.07	0.07	0.07	0.01	0.08	0.08	0.08	0.08	0.10	0.1035	0.1174	0.1973	0
QC10	0.3	0.25	0.25	0.25	0.26	0.31	0.26	0.34	0.26	0.35	0.2656	0.3411	0	0
QC24	0.08	0.10	0.10	0.10	0.12	0.10	0.10	0.12	0.11	0.12	0.0878	0.0871	0.0946	0.03371
Ploss	**0.046801**	**0.046124**	**0.046124**	**0.046124**	**0.049975**	**0.046148**	**0.046118**	**0.046155**	**0.046287**	**0.045984**	**0.04578174**	**0.04578982**	**0.04639018**	**0.048891**

5. RESULTS AND DISCUSSION

As the obtained results indicate, regardless of the dimensions of the problem (size of the studied network), the OXDE and HPSO-GA algorithms have been more effective in solving the ORPD problem. The results show that these two algorithms are two exploration and extraction factors well utilize these two algorithms. This means that the evolutionary search algorithms of two exploration and extraction factors and the balance between these two factors are very crucial in solving the problem. In terms of exploration, a global search and the purpose of extraction is also very important to obtain more optimal answers. Exploration is following the global search, so it offers new solutions but the extraction is looking for modest changes that apply changes to the current solution. In this way, the algorithm considers a solution and applies changes to it during the running process. In the exploration step, the alternative solution is generated to be able to respond more flexibly to the changes required by the process. The level of exploration optimality is time-dependent. It can be stated that the OXDE and HPSO-GA algorithms in three cases of the IEEE 30-bus standard network have less runtime for solving the problem. But in terms of time, the IEEE 57-bus standard network is in second place compared to other algorithms. The reason is that in some algorithms the search operation (the discovery operation) is more than extraction. Applying different meta-heuristic algorithms to ORPD problem leads to different values of objective functions. This subject is exactly in the line with the findings of all engineering optimization algorithms in general and in the field of power systems planning and operation studies in particular. In other words, due to the different capabilities and performance of the optimization algorithms, which are derived from the evolutionary nature defined by them in various phases and steps, we

Table 7. Best control variables settings and active power losses for the IEEE 57-bus standard network (p.u.)

Variable	SOA [52]	PSO-W [52]	PSO-cf [52]	L-SaDE [52]	ICA [44]	IWO [44]	MICA-IWO [44]	OXDE	HPSO-GA	HGWO-PSO	SCA
VG1	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06
VG2	1.058	1.0578	1.0586	1.0574	1.05747	1.05912	1.05841	1.05948	1.06	1.0595	1.06
VG3	1.0437	1.04378	1.0464	1.0438	1.04232	1.04716	1.04568	1.04921	1.04958	1.0483	1.06
VG6	1.0352	1.0356	1.0415	0.0364	1.03504	1.03817	1.03969	1.04348	1.04343	1.0452	1.06
VG8	1.0548	1.0546	1.06	0.0537	1.05088	1.05926	1.06	1.05999	1.06	1.06	1.06
VG9	1.0369	1.0396	1.0523	0.0366	1.01917	1.02729	1.02737	1.04503	1.04511	1.0454	1.06
VG12	1.0339	1.0334	1.0371	1.0323	1.02869	1.0374	1.03499	1.0415	1.0412	1.0424	1.06
T4-18	1	0.90	0.98	0.94	0.90	1.05	1.01	0.90	0.90	0.90	1.10
T4-18	0.96	1.02	0.98	1	1.01	1	0.95	0.90	0.90	1.05	0.90
T21-20	1.01	1.01	1.01	1.01	1	1.07	1.02	0.98	0.99	1.09	0.90
T24-26	1.01	1.01	1.01	1.01	1.01	1.02	1.01	0.99	0.99	0.98	0.90
T7-29	0.97	0.97	0.98	0.97	0.97	0.97	0.96	0.90	0.90	0.90	0.90
T34-32	0.97	0.97	0.97	0.97	0.98	0.99	0.98	0.97	0.97	1	1.10
T11-41	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
T15-45	0.97	0.97	0.97	0.97	0.96	0.96	0.95	0.90	0.90	0.90	0.90
T14-46	0.95	0.95	0.96	0.96	0.94	0.95	0.94	0.90	0.90	0.90	0.90
T10-51	0.96	0.96	0.97	0.96	0.95	0.98	0.95	0.91	0.91	0.92	0.90
T13-49	0.92	0.92	0.93	0.92	0.92	0.93	0.91	0.90	0.90	0.90	0.90
T11-43	0.96	0.96	0.97	0.96	0.95	0.99	0.95	0.90	0.90	0.96	1.07
T40-56	1	1	0.99	1	1	1.01	1	1.01	1.01	1.06	1.10
T39-57	0.96	0.96	0.96	0.96	0.96	1.04	0.97	0.98	0.98	1	1.09
T9-55	0.97	0.97	0.98	0.97	0.96	0.96	0.96	0.90	0.90	0.90	0.90
QC18	0.09984	0.05136	0.09984	0.08112	0.041	0.0442	0.1	0.0999	0.050514	0.016263	0
QC25	0.05904	0.05904	0.05904	0.05808	0.053	0.0433	0.059	0.059	0.059	0.053389	0.059
QC53	0.06288	0.06288	0.06288	0.06192	0.063	0.0615	0.063	0.063	0.063	0.047172	0.063
Ploss	**0.2426548**	**0.2427052**	**0.2428022**	**0.2426739**	**0.244799**	**0.245939**	**0.2425684**	**0.2347065**	**0.2347658**	**0.2391005**	**0.2540635**

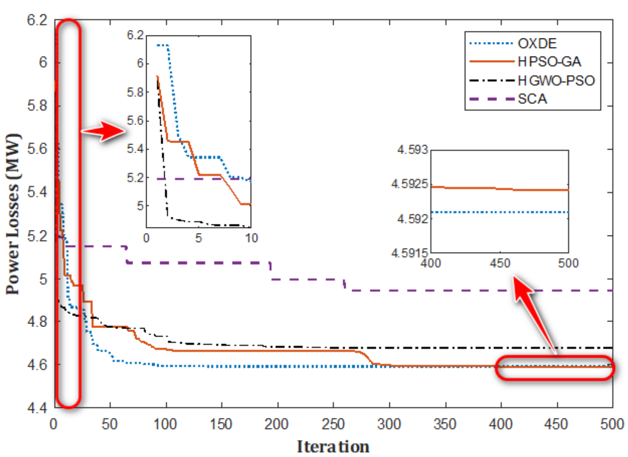

Fig. 4. Example of convergence curves in the IEEE standard 30-bus network.

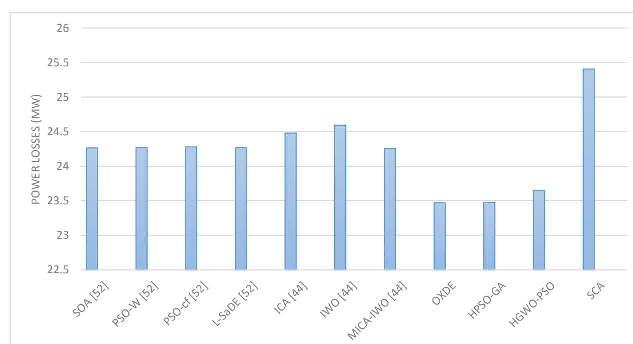

Fig. 5. Power losses obtained by different algorithms in three cases regarding the IEEE 57-bus system.

cannot expect all algorithms lead to exactly similar solutions, even by increasing the number of iterations to many times or greatly increasing the time of the simulation. This procedure was examined by the authors for the studied problem. The results of multiple simulations showed that even with a very high number of iterations, the values of the objective function in different algorithms remain different from each other. In general, and according to the simulation results and studies for determining the number of iterations, and optimizing parameters, it can be concluded that the objective function and network are too paramount for selecting the algorithm. From somewhere, for more iteration, more improvement cannot be seen in the results. Therefore, in the ORPD problem which the power loss minimization is the goal, more iteration does not guarantee the optimal solution. The fact is that there are some issues regarding applying different meta-heuristic algorithms that should be discussed or even compared between various algorithms. The long list of these subjects includes fitness function, parameter setting/tuning, run-time, convergence criterion, obtained objective function value (here the power losses), and computational complexity. Presenting a comprehensive guide for mentioned items, such as it was addressed in [54] is really behind the scope of this work. But as a general guide, it can be remarked that an algorithm would be more desirable to establish an accept-

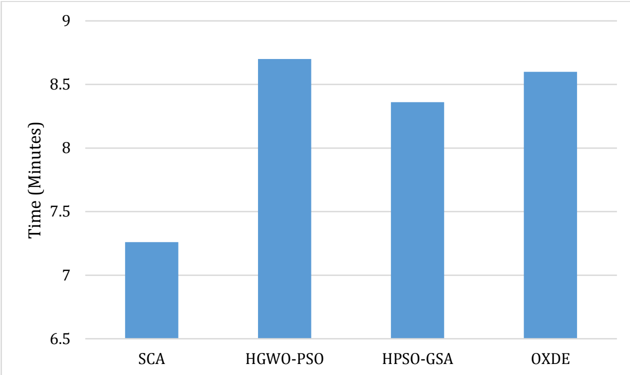

Fig. 6. Run-time of different algorithms for IEEE-57 bus system.

able compromise between all the mentioned cases. If there is no time limitation in performing the calculations (similar to various long-term studies in the field of power system planning), the optimal algorithm will be determined based on the minimum power losses. If presenting an optimal or quasi-optimal solution in the online operation mode of the system is considered, then an algorithm will be desirable that will solve in a faster time. In general, it can be said that the closer the study horizon is from the planning mode to operation, the short run-time of the algorithm is necessary due to the system operation requirements to quickly make appropriate decisions regarding changes to the system to maintain a stable operating condition. This point in operation studies changes to the importance of finding optimal solutions regardless of the run-time of the algorithm.

6. CONCLUSION

The ORPD problem is one of the most essential challenging issues in power grids. The purpose of this complex problem is to provide reactive power resources to manage sufficient reactive power in the power system. This item can affect the reliable and economical supply of energy. Today, the design of electrical power companies is based on the economical principles of the market and, therefore, in such a competitive market, optimal distribution can play an important role in restoring reactive power. The purpose of the ORPD problem is to identify control variables to minimize the objective function for system constraints. In this paper, due to the nonlinearity of the problem, meta-heuristic algorithms such as OXDE, HPSO-GA, HGWO-PSO, and SCA are considered and are applied on the IEEE 30 and 57 bus standard networks. Also, 4 implemented algorithms have been compared with the other 7 evolutionary algorithms in the IEEE 57-bus system. Also, these 4 algorithms have been studied and compared with the other 10 evolutionary algorithms in the IEEE 30-bus system. Due to the simulation results and evaluations, it has been illustrated for larger networks the SCA is not able to find an optimized solution. Therefore, the SCA is not a proper choice for large and complex networks. To sum up, the results show that the implemented algorithms are better than the other evolutionary algorithms in terms of accuracy and performance. The other advantage of using the proposed optimization method is the quick search of the response, spatial points that increase the incentive to use it in solving nonlinear optimization problems.

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