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Review

Solution to optimal reactive power dispatch in transmission system using meta-heuristic techniques—Status and technological review

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ABSTRACT

Power system operation with proper planning is an utmost task for enhancing the economy of the country. The Optimal Reactive Power Dispatch (ORPD) plays an important task for secure, reliable and optimal operations of power system. ORPD is a complex, non-linear, non-convex, non-continuous and multi-model problem which involves discrete as well as continuous variables. Thus, its solution comprises of different objective functions like improving voltage profile, reducing power losses, voltage stability enhancement and transmission cost minimization. Due to the non-linear nature of problem, most of the techniques applied to ORPD are meta-heuristic. Despite the numerous articles published on these techniques, none has given sufficient emphasis on the comprehensively summarizing the existing meta-heuristic methods for solution of ORPD problem. This work presents a survey of different meta-heuristic techniques applied for solution of ORPD problems in power transmission system. Moreover, a new meta-heuristic Sine-Cosine algorithm is also proposed to solve the problem. A case study is performed where different meta-heuristic techniques are implemented to solve the same problem. Later, statistical analysis is performed to rank all implemented techniques. It is envisaged that the information gathered in this paper will be a valuable one-stop source of information for researchers working on this topic.

1. Introduction

Optimal Reactive Power Dispatch (ORPD) plays a major role in economical operation of power system. Complex power is drawn from the electric power system. Active power is utilized by the system while reactive power circulates in the power system. But, the reactive power plays important role in voltage stability and real power transfer within the system. Thus, it is mandatory to evaluate reactive power dispatch. The main objectives of ORPD are; active power losses minimization [1], improvement of voltage profile [2], minimization of transmission cost [3] and maximization of voltage stability in the power system [4].

The ORPD is a sub-problem of Optimal Power Flow (OPF) which manages the reactive power flow within the electric power system. ORPD is a complex nonlinear programming problem of mixed integers combining successive decision variables (tensions in the generation bars) and discrete variables (transformer taps and reactive power compensators). Because of this, most of the techniques used to solve this problem are based on meta-heuristics [5]. These meta-heuristics techniques are: Genetic Algorithm (GA), Differential Evolution (DE), Optimization by Mean Variance Mapping (MVMO), Evolutionary Programming (EP), Optimization by Swarming Particles (PSO), Moth Flame Optimization (MFO), etc.

Due to non-convex, non-linear and multimodal nature of ORPD problem, the above-mentioned techniques have been shown to be effective in finding high-quality solutions to this problem. DE have received great attention from researchers because of their ease of implementation and its effectiveness [6]. Although they are effective in solving complex problems, but meta-heuristic techniques do not guarantee overall optimality. These methods could possibly be stuck in local optima while solving complex multi-modal problems. In addition, their

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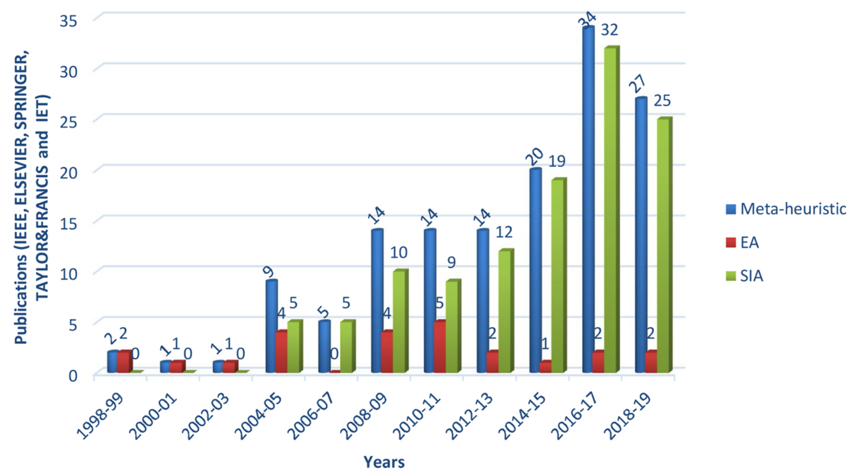

Fig. 1. Yearly Publications of ORPD.

speed of convergence depends on the appropriate adjustment of the parameters associated with each meta-heuristic [7].

To solve the issue of getting stuck in local optima, hybrid techniques have been developed [8]. This article presents a bibliographic survey of different techniques used to solve ORPD problem [9]. The data is taken from various databases like IEEE Explore, Elsevier, Springer, Taylor & Francis and IET. The increasing research interest in this field can be observed from Fig. 1. This figure shows the number of publications (journals) in the last 20 years, where ORPD is addressed by meta-heuristic techniques.

The rest of the manuscript is organized as follows; firstly, most common mathematical formulation of ORPD is presented along with changes in objective function and adaptive functions. In next section the techniques used to solve the ORPD are described and classified. Further several comparative studies are presented. Finally, some important conclusion is drawn to highlight potential avenues in this research area.

2. Mathematical modelling of ORPD

The general purpose of solving the ORPD problem is the minimization of complex and nonlinear function by satisfying both equality and in-equality constraints. Control variables are generator voltages, transformer taps and reactive power injection of switched capacitors and reactors. The dependent variables are swing bus power, load bus voltage, generator reactive powers and line flows.

ORPD problem can be of single objective as well as multi-objective nature. Both cases are discussed separately.

2.1. ORPD as a single objective optimization problem

Most of the researchers have solved the ORPD problem as a single objective optimization problem to minimize active power losses (f_1), improve voltage profile (f_2), improve voltage security (f_3) and minimize system costs (f_4). The mathematical models of these four objective functions are explained.

2.1.1. Active power losses minimization

In literature mostly ORPD problem are solved by the transmission loss minimization keeping control variables, (transformer taps, generator bus voltages and reactive power injection of capacitor bank) within specified limit. ORPD problem contains both equality as well as inequality constraints. Equality constrains of ORPD problem include power flow equations and inequality constrains include state variables such as load bus voltages, swing bus power, generator reactive power and line flows.

Objective function used for transmission loss minimization is [10]:

$$f_1^{'} = minP_{loss} = \sum_{k=1}^{Ni} g_k [(V_i)^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}] \tag{1}$$

where,

V_i: voltage at bus i
V_j: voltage at bus j
k: branch number
N_i: number of transmission lines
g_k: conductance
θ_{ij}: voltage angle difference
V: voltage magnitude

2.1.2. Voltage profile improvement

Voltage profile improvement have also been used as objective function in ORPD problem. The most common mathematical equations used for voltage profile improvement are as follows [2,9]:

$$f_2^{'} = min\left(\sum_{i=1}^{N_L} |V_{L_i} - V_{L_i}^{sp}|\right) \tag{2}$$

$$f_2^{''} = min\left(\sum_{i=1}^{N_L} \frac{|V_{L_i} - V_{L_i}^{sp}|}{N_L}\right) \tag{3}$$

$$f_2^{'''} = min\left(\sum_{i=1}^{N_L} \left|\frac{V_{L_i}^{sp} - V_{L_i}}{V_{L_i}^{max} - V_{L_i}^{min}}\right|\right) \tag{4}$$

$$f_2^{''''} = min\left(\sum_{i=1}^{N_L} (V_{L_i} - V_{L_i}^{sp})^2\right) \tag{5}$$

where,

i: bus number
V_{L_i}: actual voltage of bus
$V_{L_i}^{sp}$: specified voltage of buses (1 pu)
N_L: number of load buses

Eqs. (2) to (5) show the objective function that is used for voltage profile improvement in literature. However, most of the researchers have used Eq. (2) to deal with the objective of voltage profile improvement. That is because Eq. (2) is simpler than others and computational time is less than other equations being used in literature so it is best among all for its voltage profile improvement.

2.1.3. Voltage stability enhancement

Some researchers also include objective function of voltage stability index. Static as well as dynamic factors are included in the analysis of voltage stability. However, mostly the static factors are considered for

Table 1
Publications considering the ORPD as single & multi-objective problem.

Function type	Publications
F1	[15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,8,31,32,33,34,35,36,37,38,39,40,41,42,43]
F2	[2]
F3	[44,4,45],
F4	[46,12,47,48,49]
F1,F2	[50,51,52,53,54,55,56,57,14,58,59,60,61,62,63,64] [65,66,67,68,69,70,71]
F1,F3	[72,73,74,75]
F1,F4	[76,77]
F1,F2,F3	[78,79,80,81,82,83,84,85,86,87,88,89,90,91,92,93,94,95,96]
F1,F3,F4	[97,98]
F1,F2,F4	[99]
F1,F2,F3,F4	[100,101]

stability assessment and control due to time consuming in dynamic factors. Various objective function equations for voltage stability enhancement are available in the existing literature. Some commonly used objective function equations are as follows [4]:

$$f_3^{'} = min(L_{max}) = min[max(L_K)] \tag{6}$$

$K = 1,2,\ 3,\ \ldots, N_L$

$$L_K = \left| 1 - \sum_{i=1}^{N_G} F_{ji} \frac{V_i}{V_j} < \{\theta_{ij} + (\delta_i - \delta_j)\} \right| \tag{7}$$

$$F_{ji} = -\ [Y_{jj}]^{-1}[Y_{ji}] \tag{8}$$

where,

L_k: voltage stability indicator (L-index)
Y: admittance
θ : phase angle
N_G: number of generation buses

Another index of stress stability monitoring commonly found in the literature is as follows [11] :

$$f_3^{''} = max(VSM) = max(min\ |eig(\text{Jacobi})|) \tag{9}$$

where,

VSM: voltage stability margin
Jacobi: Jacobian matrix of the power system

eig(*J*) represents all the eigenvalues of the Jacobian matrix; min|*eig* (*Jacobi*)| is the minimum of the eigenvalues in the Jacobian matrix and max(min|*eig*(*Jacobi*)|) is maximizing the minimal eigenvalue in the Jacobian matrix.

$$f_3^{'''} = Lindex = \ max\{L_k\},\ k = 1,2,\ \ldots, N_L \tag{10}$$

$$L_K = \left| 1 + \frac{V_{ok}}{V_{L_i}} \right| \tag{11}$$

$$V_{0k} = \sum_{i=1}^{NG} H_{2k_i} L_{L_i} \tag{12}$$

where,

L_k: index value of bus k
H2k: sub matrix generated from partial inversion of Y_{bus}

2.1.4. Transmission cost minimization

This objective function includes the cost minimization of reactive power obtained from generator and compensators. Initial cost expressed as the reactive cost of the generator which is given by the equations as follows [12]:

$$C_{gpi} Q_{gi} = \ [C_{gpi} S_{gi\,max} - \ C_{gpi}\ (\sqrt{(S_{gi\,max}^2 - \ Q_{gi}^2)})] k_{gi} \ldots \tag{13}$$

A quadratic function:

$$C_{gpi}\ P_{gi} = aP_{gi}^2 + bP_{gi} + c \tag{14}$$

Reactive power cost of shunt compensators employed in the system is as follows;

$$C_{cj}\ Q_{cj} = \ r_j\ Q_{cj} \tag{15}$$

where,

r_j: reactive cost
Q_{cj}: reactive power purchased

The above costs can also be written in the form of objective function which are as follows

$$\text{Min}C_Q = \ \underset{i\in}{\Sigma} N_G\ C_{gpi}\ Q_{gi} + \ \underset{i\in}{\Sigma} N_c\ C_{ci}\ Q_{ci} \tag{16}$$

where,

C_Q: total cost of the generator and compensator
N_G: set of all generators
N_C: set of all compensation buses

2.2. ORPD as a multi-objective optimization problem

Most of the power system researchers have addressed ORPD as a multi-objective problem which include power loss minimization (F1), voltage profile improvement (F2), voltage stability enhancement (F3) and reactive power cost minimization (F4) by keeping all the control variables within defined limit.

Table 1 presents the articles that use the objective functions described above. It is evident from the table that the objective function implemented with the most recurrence is the minimization of active power losses.

2.3. ORPD considering the impact of Renewable Energy Sources

Renewable energy based Distributed Generation (DG) integration has a significant impact on reliability, security and economic operation of power system. However, improper allocation of such DG units (wind and solar) raises other issues such as voltage deviation, voltage instability, active and reactive power losses. The power system has become more complex and critical after the penetration of Renewable Energy Sources (RESs). RESs have made the reactive power control more critical. The uncertainties of RESs have made the system unstable and the voltage collapses are likely to occur due to volatile nature of such resources. In the recent studies, the impacts of various uncertainties on ORPD problem have been discussed in Ref. [13]. In Ref. [14] ORPD problem been solved considering load and wind power generation uncertainties using enhanced firefly algorithm. On the other hand, the integration of RESs has several advantages such as reduction of cost of energy, environmental benefits and so on. However, the operational and maintenance cost of such resources must be considered by system operators to obtain optimal dispatch of RESs.

2.4. Constraints

The ORPD must comply with the power balance (active and reactive) and with the operating limits of the system. These conditions are represented by equality and inequality constraints, respectively.

2.4.1. Equality constraints

Equality constraints usually represented by power balance equations which guarantee that the load demand is met by considering transmission losses of the system and shown as follows:

i By excluding swing bus, active power flow balance equation of all buses are;

$$P_{gi} - P_{Li} - V_i \sum_{j \in N_i} V_j \left(g_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right) = 0 \tag{17}$$

i Reactive power flow balance equation for all load buses are;

$$Q_{gi} - Q_{Li} - V_i \sum_{j \in N_i} V_j \left(g_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}\right) = 0 \tag{18}$$

where,

B_{ij} is the susceptance

2.4.2. Inequality constraints

In ORPD, there are two types of inequality constraints mainly named as control variables & state variable. The control variable includes setting of the transformer output, bus voltages of generator and the reactive power produced by the shunt capacitors. The state variables consist of load bus voltages, reactive power generation of PV buses, line flow limit and active power generation at the slack bus. The constraints are given below;

i The state variable for voltage magnitude of each bus is given by;

$$V_i^{min} \le V_i \le V_i^{max}, \; i \in N_B \tag{19}$$

where i is the bus number and N_B is the total number of buses.

i The state variable for reactive power generation limit is given by;

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max}, \; i \in N_g \tag{20}$$

where i is the bus number and N_g is total number of generators

i The control variable for reactive power output of the compensator is,

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max}, \; i \in N_c \tag{21}$$

where i is the bus number and N_c is total number of capacitors

i The control variable for transformer tap-setting constraint

$$T_k^{min} \le T_k \le T_k^{max}, \; i \in N_T \tag{22}$$

where k is the branch number and N_c is total number of capacitors

i The constraint for power flow limit of each transmission line

$$S_i \le S_i^{max} \tag{23}$$

2.4.3. Penalty function

The penalty function formed by transforming equality constraints and inequality constraints in terms of penalties.

$$P(t) = f(t) + \Omega(t) \tag{24}$$

$$\Omega(t) = \rho\{g^2(t) + [\max(0, h(t))]2\} \tag{25}$$

where,

P (t): Penalty function
Ω (t): Penalty term
ρ: Penalty factor
Mathematically, penalty function can be framed as follows:

$$P(t) = F_{loss} + \Omega_P + \Omega_Q + \Omega_C + \Omega_T + \Omega_V + \Omega_G \tag{26}$$

where,

$$\Omega_P = \rho \sum_{i=1}^{N_P} \left\{ P_{Gi} - P_{Di} - \sum_{j=1}^{N_s} |V_i|\,|V_j|\,|Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \right\}^2 \tag{27}$$

$$\Omega_Q = \rho \sum_{i=1}^{N_G} \left\{ Q_{Gi} - Q_{Di} - \sum_{j=1}^{N_s} |V_i|\,|V_j|\,|Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \right\}^2 \tag{28}$$

$$\Omega_C = \rho \sum_{i=1}^{N_C} \{\max(0, Q_{comp} - Q_{comp}^{max})\}^2 + \rho \sum_{i=1}^{N_C} \{\max(0, Q_{comp}^{min} - Q_{comp})\}^2 \tag{29}$$

$$\Omega_T = \rho \sum_{i=1}^{N_T} \{\max(0, T_i - T_i^{max})\}^2 + \rho \sum_{i=1}^{N_T} \{\max(0, T_i^{min} - T_i)\}^2 \tag{30}$$

$$\Omega_V = \rho \sum_{i=1}^{N_V} \{\max(0, V_i - V_i^{max})\}^2 + \rho \sum_{i=1}^{N_V} \{\max(0, V_i^{min} - V_i)\}^2 \tag{31}$$

$$\Omega_G = \rho \sum_{i=1}^{N_G} \{\max(0, P_G - P_{G,i}^{max})\}^2 + \rho \sum_{i=1}^{N_G} \{\max(0, P_{G,i}^{min} - P_{G,i})\}^2 \tag{32}$$

where,

i: starting bus; j: ending bus ; k: branch number ; Ω_P: penalty term for active power; Ω_Q: penalty term for reactive power; Ω_C: penalty term for shunt capacitors; Ω_T: penalty term for transformer taps; Ω_V: penalty term for bus voltage; Ω_G: penalty term for generated power; P_{Gi}: power generation of ith generator; $P_{G,i}^{max}$: max power generation of ith generator ; $P_{G,i}^{min}$: min power generation of ith generator; P_{Di}: power demand ; Q_{Gi}: reactive power generation of ith generator; Q_{Di}: reactive power demand

Q_{comp}: shunt compensator value ; Q_{comp}^{max}: max value of shunt compensators; Q_{comp}^{min}: min value of shunt compensator; T_i: transformer tap setting; T_i^{max}: max valve of transformer tap setting; T_i^{min}: min value of transformer tap setting; V_i: bus voltage ; V_i^{max}: max bus voltage; V_i^{min}: min bus voltage; N_G: total number of generator; N_C: total number of sources for reactive power generation; N_T: total number of transformers.

3. Methods of Solution

Meta-heuristics do not involve mathematical deterministic procedures. This is an intelligent approach used to search for the optimum solution. For this, different principles or mechanisms have been proposed. Below is a classification of different Meta-Heuristics for the ORPD solution.

3.1. Evolutionary algorithms

The term Evolutionary Algorithms (EA) is used to describe systems for solving optimization or search problems based on biological evolution. Evolutionary computation uses an iterative process based on the development and growth of the population. The population is selected in a random search where the individuals mix and compete with each other such that the fittest prevail throughout the process, allowing to reach a desired objective. The paradigm of evolutionary computing techniques refers to the principles of the 50 s, when the idea of using Darwinian principles for automation problems was introduced [102]. Mostly used evolutionary algorithm is genetic algorithm.

Genetic algorithms (GA) are a class of adaptive search based on the principles derived from the dynamics of genetics. Proper representation or coding of individuals in the population is a key aspect to the success of this type of methodology. GA starts with the random or pseudo random creation of an initial population of individuals with certain characteristics. Each individual represents a candidate solution for the problem addressed. In the process of solution, the characteristics of the individuals are copied and transmitted to the new generations. The GA mechanisms consist of copying the characteristics and partially exchanging them. The GA requires three basic operators which are named according to the corresponding biological mechanisms: reproduction, crossing and mutation. In Refs. [24,50,55,103,104,105] the GA is used to address the ORPD problem.

Many conventional evolutionary algorithms are employed for the solution of ORPD [106]. In Refs. [3,6,11,33,107,108,109,110] the differential evolution (DE) technique is used. This technique was initially proposed by Storn and Price in 1997 [111]. In Ref. [3] an evolutionary algorithm inspired by Quantum is presented for the optimal dispatch of power. This type of algorithm combines principle of quantum and evolutionary computation; in this way, they seek to explore an additional level of randomness inspired by the concepts and principles of quantum mechanics. In Ref. [8], an imperialist competition algorithm applied to the ORPD is presented. This type of algorithm is based on the geopolitical interactions of the countries (which represent the solution candidates). During the iterative process, revolutions and annexations are presented; in this way the weakest empires are eliminated, giving way to stronger empires (better solution candidates). In Ref. [112], an algorithm based on the jump of the frogs is presented to give solution to the ORPD. In this case each "frog" is a vector that contains possible values of the control variables (solution candidate). A detailed description of this method can be found in Ref. [113]. Finally, in Refs. [114,115,116,117], hybrid evolutionary strategies are presented to address the ORPD problem. Table 2 presents some bibliographic references that have used EA's to solve ORPD problem. Objective function used in these articles are shown in column three of Table 2. The proposed techniques results are compared with different meta-heuristic techniques as shown in column 4.

The advantages, disadvantages and applications of EA discussed in Refs. [117,118] are summarized in Table 3.

EA's are intelligent algorithms that have been used as meta-heuristic techniques instead of linear programming (LP) and non-linear programming (NP) to solve complex engineering problems. The advantages and disadvantages of EA's have already been discussed in Table 3. EAs work with different structures in different environments. We cannot say that EAs always gives the global optimal results of complex engineering problems. So to enhance the capability of solving engineering optimization problem, swarm intelligence algorithms (SIA) was introduced which are discussed in next section.

3.2. Swarm intelligence algorithms

3.2.1. Algorithms based on natural phenomena

These algorithms are inspired by physical laws (forces between electric charges, gravity, river systems, birds flock, etc.) for its operation. Although there are many methods of Meta-Heuristic optimization that are based on physical phenomena have not been widely disseminated [118]. Algorithms involving physical phenomena include simulated annealing and GSA. Simulated annealing mimics emulation of the annealing of steel and ceramics. This technique involves heating and then slowly cooling the material to vary its physical properties. The SA was proposed by Kirkpatric, Gelatt and Vecci in Ref. [119]. On the other hand, the GSA is based on the gravitational and movement law. In this algorithm each agent is considered as an object and its mass represents its adaptation function. At the end of this algorithm, the position of the highest mass object represents the best solution. Other algorithms based on little-used physical phenomena are loaded system search, harmonic search and cultural algorithm. The Charged System Search (CSS) technique was introduced by Kaven and Talatahari in 2010 [120]. Laws of Gauss and Coulomb are used in CSS. In this algorithm, each individual represents a charged particle (CP). Each CP is considered as a solution candidate. The law of motion is also used to guide the path of CPs. CPs are affected by other charged particles with their adaptation values and separation distances. The force acting on each PC determines its new position, speed and acceleration. Harmonic Search (HS) is an algorithm of imitation of a phenomenon inspired by the process of improvisation of the musicians proposed by Zong Woo Geem in 2001[121]. In the HS, each musician modelled as decision variable plays (iteration) a note (value) to search for the best harmony (global optimum). This is done by following an established set of rules. On the other hand, the cultural algorithm was introduced by Robert G. Reynolds in 1994 [122]. It consists of generation of a space involving beliefs that are divided into various categories. These categories mimic various domains of knowledge in which population is a search space. At the end of each iteration, the belief space is updated to search the best individual (solution candidate) of the population. With respect to the ORPD problem, in Ref. [123] a simple gravitational search algorithm is used. In Ref. [124] a cultural algorithm is presented. In Ref. [125], a simulated annealing is discussed. A hybridization between a genetic algorithm with simulated annealing ideas is presented in Ref. [114]. Table 4 shows articles which used nature inspired swarm intelligence algorithms to solve ORPD.

Above table shows that the most of the researchers have used particle swarm optimization (PSO) and its modified forms to solve ORPD. A tendency have also been seen to solve ORPD using hybrid Nature inspired SIA which gives better results for engineering optimization problems. SIA derived from physical phenomena in the universe have been discussed in below section.

3.2.2. Algorithms based on physical phenomena

Some algorithms are based on statistical analysis and normalization of the search space. The most prominent algorithms of this type in ORPD applications include iterated local search [124] and teaching-learning-based optimization (TLBO). In [128], an algorithm known as optimization based on teaching-learning was proposed, which mimics

Table 2
Publications used Evolutionary algorithms to solve ORPD problem.

Reference	Proposed meta-heuristic technique	Objective function	Comparasion
[17]	Evolutionary Programming (EP)	F1	Conventional gradient based optimization
[24]	Self-Adaptive Real-Coded Genetic Algorithm (SARGA)	F1	PSO
[33]	Differential Evolution (DE)	F1	PSO, IP
[50]	Improved Genetic Algorithm (IGA)	F1, F2	Conventional Gradient based optimization
[72]	MNSGA-II	F1, F3	NSGA-II, MOPSO
[73]	Hybrid Fuzzy multi- objective Evolutionary algorithm (HFMOEA)	F1, F3	RCGA, NSGA-II, MNSGA-II
[87]	Opposition based Gravitational Search algorithm (OGSA)	F1, F2, F3	GSA, BBO, DE, CLPSO, PSO, SARGA
[92]	Multi-Objective Differential Algorithm (MODE)	F1, F2, F3	SPEA 2
[93]	Quasi-Oppositional Differential Evolution (QODE)	F1, F2, F3	DE
[95]	MNSGA-II	F1, F3	NSGA-II, MOPSO

Table 3
Advantages, disadvantages and further applications of Evolutionary algorithms.

Algorithm	Advantages	Disadvantages	Applications
Evolutionary Algorithms (EA)	1) No presumptions w.r.t problem space 2) Widely applicable 3) Low development and application cost 4) Easy to incorporate other methods 5) Solutions are interpretable unlike neural network 6) Can be run interactively 7) Accommodate user proposed solution 8) Provide many alternative solutions	1) No guarantee for optimal solution within finite time 2) Weak theoretical basis 3) May need parameter tuning 4) Often computationally expensive and slow	1) Numerical & computational optimization 2) System modeling and identifications 3) Planning and control 4) Data mining 5) Machine learning 6) Artificial life

teaching-learning phenomenon such as in classrooms. This algorithm comprises of two phases: the first known as Teacher phase and second is termed as Learner phase. TLBO is an algorithm where a group of students are known as the population and various subjects offered to the students are analogous to the design variables of the optimization problem. The best solution of the population is considered as the teacher. The reinforced learning algorithm [129] differs from TLBO because it focuses on online performance, which involves finding an equilibrium among exploration (of the non-tabulated territory) and exploitation (current knowledge). Mean-variance optimization algorithm was conceived and developed by István Erlich in 2010 [130]. The basic concept shares some similarities with other heuristic techniques, but the novel feature is the use of a mapping function applied to the mutation of the new generations based on the average and variance of the best population found so far. Other reinforced learning and teaching-learning-based algorithms applied to the ORPD problem are reported in Refs. [31,86,131]. Table 5 shows articles that used physical phenomena to solve ORPD.

Another form of SIA is artificial immune algorithm (AIA) which is discussed briefly in below section.

3.2.3. *Artificial immune algorithms*

The immune algorithms are adaptive systems, inspired by the theory of immunology, as well as functions, principles and models observed in the immune system. Among the most used immune algorithms are the artificial immune algorithms. The artificial immune algorithm (AIA) was proposed by Dasgupta in 1993 [132]. It is based on the principle of selecting the clonal and is a population-based algorithm in which antigens (candidate solution) and antibodies (target) interact to find an optimal solution following some biological rules. The main inspiration of AIA is by the immune system of human which is highly parallelized, evolved and Distributed Adaptive system which highlight the strengths: Immunological recognition, Reinforced learning, characteristic extraction, Immunological Memory, Diversity and Robustness. The AIA merge all these strengths and due to its adaptive capacity of learning and memory, it has gain attention. The vital power of search in AIA is based on the mutation operator and therefore, it is the unique factor of this technique. The algorithm of artificial immune recognition performs the identification of foreign bodies as molecules that are not native to the body to be eliminated. In Ref. [79] a multi-objective adaptive immune algorithm was implemented for the ORPD solution and in Ref. [133] an artificial immune system algorithm was implemented to address the same problem. Table 6 shows articles that used AIA to solve ORPD.

Table 4
Publications used natural phenomena to solve ORPD problem.

Reference	Perposed meta- heuristic technique	Objective function	Comparasion
[18]	Particle Swarm Optimization (PSO)	F1	Reactive TABU search (RTS), Enumeration Method
[19]	Multi-agent Particle Swarm optimization (MAPSO)	F1	SGA, PSO
[22]	Hybrid Multi-agent Particle Swarm optimization (HMAPSO)	F1	GA, HPSO, MAPSO, PSO
[25]	Comprehensive Learning Particle Swarm optimization (CLPSO)	F1	PSO
[26]	Ant Colony Optimization (ACO)	F1	LP, GA, PSO
[29]	Hybrid Artificial Bee colony assisted Differential Evolution algorithm (DE-ABC)	F1	DE, ABC
[37]	Whale Optimization Algorithm (WOA)	F1	MGBTLBO, PSO, PSO-TVAC
[38]	Moth Flame Optimization Algorithm (MFO)	F1	MICA-IWO, HAS, DE, GA, GWO
[48]	Cuckoo Search Algorithm (CSA)	F4	ABC, FA
[54]	Turbulent Crazy Particle Swarm Optimization (TRPSO)	F1, F2	PSO, GPAC, LPAC, CA
[57]	Combination of PSO and Biogeography-based optimization (BBO) algorithm (HPSOBBO)	F1, F2	CA, CPSO, LPAC, GPAC, IP-OPF
[14]	Enhanced Firefly Algorithm (EFA)	F1, F2	DE, EP, PSO, GA, FA
[58]	Grey Wolf Optimization Algorithm (GWO)	F1, F2	SGA, PSO, HAS
[60]	Hybrid Firefly Algorithm (HFA)	F1, F2	PSO, BFO, ABC, GSA, FA
[61]	Hybridization of Aging Leader and Challengers & PSO (ALC-PSO)	F1, F2	GSA. BBO, DE, CLPSO, PSO, SARGA
[66]	Two Archive Grey Wolf Optimization Algorithm (TAGWO)	F1, F2	MPSO, MBPIL, DEMO, NPGA-II, NSGA II, MPPA
[67]	Fuzzy Adaptive Heterogeneous Comprehensive-Learning PSO (FAHCLPSO)	F1, F2	PSO
[69]	Artificial Bee Colony and Firefly Algorithm (ABC-FF)	F1, F2	GA, FF, PSO, ABC
[75]	Ant Lion Optimization (ALO)	F1, F3	PSO, CLPSO, BA, GWO, ABC
[76]	Parallel Particle Swarm Optimization (PPSO)	F1, F4	SGA, PSO
[78]	Fuzzy adaptive Particle Swarm optimization (FAPSO)	F1, F2, F3	PSO
[89]	Strength Pareto Multi-Group search optimizer (SPMGSO)	F1, F2, F3	NPGA, NSGA, NSGA-II, MOPSO, SPEA, NSDE
[101]	Hybrid Particle Swarm Optimization-Multi Verse Optimization (PSO-MVO)	F1, F2, F3, F4	PSO, MVO
[126]	Hybrid Particle Swarm optimization and Imperialist competitive algorithms (PSO-ICA)	F1, F2	PSO, ICA
[127]	Improved GSA-Based Algorithm (IGSA-CSS)	F1, F2	GSA, PSO, GSA-CSS

Table 5
Research work based on physical phenomena to solve ORPD problem.

Reference	Perposed meta- heuristic technique	Objective function	Comparasion
[8]	Modified Imperialist competitive algorithm & Invasive Weed optimization (MICA-IWO)	F1	SGA, PSO, MAPSO, HAS, ICA, IWO
[23]	Seeker Optimization Algorithm (SOA)	F1	NLP, CGA, AGA, PSO, SPSO
[31]	Hybridization of Modified Teaching Learning algorithm (MTLA) and Double Differential Evolution (DDE) algorithm (MTLA-DDE)	F1	TLA, DE, MTLA, DDE, ABC, LCA, PSO, CSS, PBIL
[32]	The Gauss bare-bones TLBO (GBTLBO) Algorithm	F1	TLBO, BBPSO, BBDE
[36]	Chaotic Krill Herd Algorithm (CKHA)	F1	CKHA
[56]	Biogeography-Based optimization (BBO)	F1, F2	PSO, RGA, DE
[62]	Two-Point Estimation Method (TPEM)	F1, F2	DA, MCS
[63]	Chaotic Krill Heard Algorithm (CKHA)	F1, F2	PSOIWA, RCGA, DE, CRPSO, TRPSO, BBO
[64]	Oppositional Krill Herd Algorithm (OKHA)	F1, F2	BBO, DE, KHA
[68]	Backtracking Search Algorithm (BSA)	F1, F2	GA, PSO, DE
[83]	Gravitational Search Optimization (GCO)	F1, F2, F3	BBO, DE, CLPSO, PSO, SARGA
[85]	Opposition based self-Adaptive modified Gravitational search algorithm (OSAMGSA)	F1, F2, F3	EA, PSO, CA, GSA
[86]	Quasi-Oppositional TLBO (QOTLBO)	F1, F2, F3	TLBO
[90]	Chemical Reaction Optimization (CRO)	F1, F2, F3	DE, PSO
[91]	Exchange Market Algorithm (EMA)	F1, F2, F3	DE, GSA, OSGA, PSO
[97]	Multi-objective Harmony Search algorithm (MOHS)	F1, F3, F4	NSGA-II

Table 6
Publication used Artificial Immune Algorithm to solve ORPD problem.

Reference	Perposed meta-heuristic technique	Objective function	Comparasion
[79]	Multi-Objective Adaptive Immune Algorithm (MOAIA)	F1, F2, F3	IGA

The advantages, disadvantages and applications of SIA discussed in Refs. [134,135] are summarized in Table 7.

All the algorithms discussed above have their on way to solve complex engineering optimization problems. Each algorithm shows its performance in finding best solution, depending upon the problem. Due to the difference in their working they can be compared with each other. A case study analysis is being performed in the below section for the comparison of EA and SIA.

4. Case study: a comparative analysis of different meta-heuristic techniques for solving ORPD problem

To solve electrical energy crises, the world is looking forward to minimize transmission and distribution line losses by using full technical and engineering approach. The traditional model of optimal reactive power dispatch (ORPD) for power systems is based on the principle of income maximization, which aims at minimizing active power loss of the whole networks [12]. In ORPD problem most of the researchers have considered the objective of transmission power loss minimization as shown in Table 1. Previously, ORPD have been solved by numerous classical algorithms such as Linear programming [136], Nonlinear programming [137], Quadratic programming [16], Sequential quadratic programming [138] and interior point methods [139]. So in this case study, a deterministic algorithm and four different Meta-Heuristic techniques are used to minimize transmission line losses. This case study evaluates the behavior of both deterministic and Meta-Heuristic techniques to solve ORPD problem. ORPD solved by Newtons Method (NM), Differential Evolution (DE), Particle Swarm

Table 7
Advantages, disadvantages and further applications of Swarm Intelligence Algorithms.

Algorithm	Advantages	Disadvantages	Applications
Swarm Intelligence Algorithms (SIA)	1) These algorithms are scalable because same control architecture can be applied to couple of agents and thousands of agents.	1) Non-optimal, highly redundant and have no central control.	1) Movie effects- “lord of the ring”.
	2) These algorithms are flexible because agents can be easily added or removed without changing the structure.	2) Uncontrollable-it is very difficult to exercise control over a swarm.	2) Network routing-ACO routing.
	3) These algorithms are robust and simple in design.	3) Unpredictable-The complexity of swarm systems leads to unforeseeable results.	3) Swarm robotics- swarm bots.
	4) Reliance on individual agent is small so failure of single agent has little impact on systems performance.	4) Non-understandable-swarm based algorithms are a jumble of intersecting logics.	4) Human tremor analysis.
	5) These algorithms can adopt new situations easily.	5) Non-immediate- complex swarm systems with rich hierarchies take time. The more complex the swarm, the longer it takes to shift states	5) Human performance assessment.
			6) Ingredient mix optimization. 7) Evolving neural networks to solve problems. 8) U.S. Military is applying SI techniques to control of unmanned vehicles. 9) NASA is applying SI techniques for planetary mapping. 10) Medical Research is trying SI based controls for nanobots to fight cancer.

Table 8
Variable limits for the IEEE 30-bus test system.

Range	Generator bus voltage (V_g)	Load bus voltage (V_L)	Transformer tap settings (Tap)	Shunt compensator (Q_C)
Min (pu)	0.90	0.90	0.90	0
Max (pu)	1.1	1.1	1.05	0.05

Optimization (PSO), Whale Optimization Algorithm (WOA) and Sine Cosine Algorithm (SCA) and their behavior is compared graphically.

The primary objective of ORPD is to reduce transmission power loss to enhance the performance of system. Therefore, marginal improvement in losses reduction is its technical improvement. The other benefit that can be achieved is the cost of power losses reduction. It can be obtained in terms of fuel cost function of active power generation at slack bus given as follows [10,140]:

$$F_s = a_s \Delta Pg_s^2 + b_s \Delta Pg_s + c_s \tag{33}$$

where F_s is the operational cost in real power losses; ΔPg_s is increased incremental cost of slack generated power to match transmission power losses ($\Delta Pg_s = P_{loss}$); *and* a_s,b_s,c_s are the cost coefficient of slack power generation [140]. Cost of power loss reduction ($/h) for NM, DE, PSO, WOA and SCA are calculated using Eq. (24) and shown in Table 9.

4.1. Simulation setup

Above mentioned Meta-Heuristic techniques are implemented using MATLAB software. MATPOWER 3.2 is used for power flow analysis. The flow diagram for solution of ORPD using Meta-Heuristic techniques is shown in Fig. 2.

The number of control variables considered in case study analysis are 19, including six generator voltages (V_{g1}, V_{g2}, V_{g5}, V_{g8}, V_{g11}, V_{g13}), in the range [0.9, 1.1] p.u at buses 1 (i.e. slack bus), 2, 5, 8, 11 and 13, four number of transformer taps ($\boldsymbol{T}_{6-9}$, $\boldsymbol{T}_{6-10}$, $\boldsymbol{T}_{4-12}$, $\boldsymbol{T}_{28-27}$) in the range [0.9, 1.05] p.u. placed at the lines 6–9, 6–10, 4–12 and 28–27. There are 9 shunt compensation devices (QC_3, QC_{10}, QC_{12}, QC_{15}, QC_{17}, QC_{20}, QC_{23}, QC_{24}, QC_{29}) situated at buses 3, 10, 12, 15, 17, 20, 23, 24 and 29 within the range [0, 0.05] p.u. The maximum and minimum limits of control variables such as generator bus voltage (Vg), load bus voltage (VL), transformer tap setting (Tap) and shunt compensator (Qc) are shown in Table 8.

Four meta-heuristic techniques will be tested using IEEE 30-bus system. The Description of IEEE 30-bus system is given in Table 9.

The simulation setup is shown in Table 10. Population size, control variables limits, no of iterations and no of runs are kept constant to perform case study analysis. Later, superiority of one of the technique among DE, PSO, WOA and SCA will be shown using some statistical approach.

Step by step procedure for solving ORPD problem using Meta-Heuristic techniques is as follows:

Table 9
Description of IEEE 30-bus test system.

Description	IEEE 30-bus
Buses	30
Lines	41
Generators	6
Tap transformers	4
Shunt capacitors	9
Load buses	24
P load (MW)	283.40
Q load (Mvar)	126.20
P_{gen} (MW)	289.211
Q_{gen} (MW)	108.922
Initial P loss (MW)	5.812
Initial Q loss (Mvar)	32.417

(1) Define population size, no. of iteration (= 100) and input the data of IEEE 30-bus test system.
(2) Initialize (V_{g1}, V_{g2}, V_{g5}, V_{g8}, V_{g11}, V_{g13}, T_{6-9}, T_{6-10}, T_{4-12}, T_{28-27}, QC_3, QC_{10}, QC_{12}, QC_{15}, QC_{17}, QC_{20}, QC_{23}, QC_{24}, QC_{29}) within their permissible range.
(3) For each particle, run Newton Raphson (NR) load flow to find out losses.
(4) Calculate the fitness function of each particle using Eq. (4).
(5) Find out the best search agent among all the search agents.
(6) A Meta-Heuristic technique (DE, PSO, WOA, and SCA) is applied to update the search agents.
(7) If control variables are not in limits penalize otherwise move to step 8.
(8) Calculate the fitness function of each updated particle using Eq. (4).
(9) Go to step no. 6, until max. no. of iterations is completed.

Step by step procedure for solving ORPD problem using Newtons Method is shown in flow diagram in Fig. 3:

Based on above simulations, the obtained results are presented in the following sections.

4.2. Results

Newtons Method and All the four meta-techniques are implemented on MATLAB and best result for power losses minimization out of thirty runs is saved. The results are given in Table 11. Base case power losses (without capacitor placement) are 5.812 MW. In the table, control variables to find the power losses are generated bus voltage (V_{g1}, V_{g2}, V_{g5}, V_{g8}, V_{g11}, V_{g13}), transformer tap settings ($\boldsymbol{T}_{6-9}$, $\boldsymbol{T}_{6-10}$, $\boldsymbol{T}_{4-12}$, $\boldsymbol{T}_{28-27}$) and shunt VAR compensators (QC_3, QC_{10}, QC_{12}, QC_{15}, QC_{17}, QC_{20}, QC_{23}, QC_{24}, QC_{29}). All the control variables are in per unit (pu).

Table 11 shows the optimum values of control variables and minimized power losses for NM, DE, PSO, WOA and SCA. The results show that for given experimental setup (Table 10) SCA gives the best results. Working and convergence characteristics of these meta-heuristic techniques are shown in further section.

4.2.1. Differential evolution (DE) results

Differential evolution is a meta-heuristic technique proposed by Storn and Price. It is a population based algorithm that uses cross over, mutation and selection operators. DE works on simple cycle of stages as shown in Fig. 4.

Mathematical equation for the initialization of chromosome is as follows:

$$X_{a,b}(0) = X_b^L + rand(0,1).\ (X_b^U - X_b^L) \tag{34}$$

where,
X_b^U = Upper limit of population
X_b^L= Lower limit of population
rand(0,1)= Random number between 0 and 1
Mathematical equation for mutation operator is as follows:

$$V_{a,b}(t+1) = X_{r1,b}(t) + F.\ (X_{r2,b}(t) - X_{r3,b}(t) \tag{35}$$

where,
$V_{a,b}(t+1)$ = Donor vector generated from each initialized population
$X_{r1,b}(t)$ = First randomly chosen control variable not coinciding

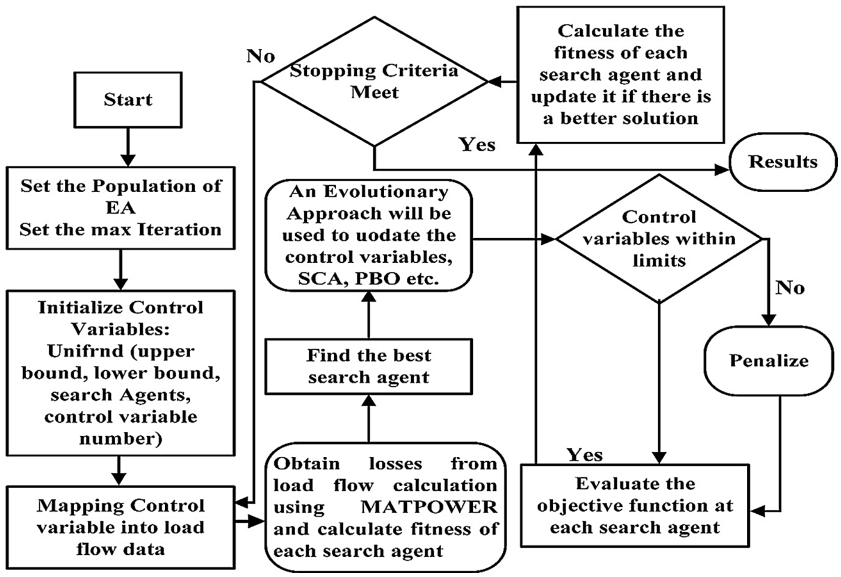

Fig. 2. Flow diagram to solve ORPD problem using Meta-Heuristic techniques.

Table 10
Experimental setup for case study.

Transmission system	IEEE 30 Bus System
No. of Generator variables	6
No. of Transformer variables	4
No. of Shunt compensators	9
Population size	50
No. of Iterations	100
No. of runs	30

with control variable which is already selected

$X_{r2,b}(t)$ = Second randomly chosen control variable not coinciding with control variable which is already selected

$X_{r3,b}(t)$ = Third randomly chosen control variable not coinciding with control variable which is already selected

F = Scaling factor between 0.4 and 1.

Mathematical equation for cross over operation is as follows:

$$U_{a,b}(t) = \begin{cases} V_{a,b}(t) \; if \; rand(0,1) < CR \\ X_{a,b}(t) \; else \end{cases} \tag{36}$$

where,

CR = Cross over ratio [0.9,1]

$U_{a,b}(t)$ = Child that will compete with parent $X_{a,b}(t)$

$V_{a,b}(t)$ = Donor vector obtained from mutation

Mathematical equation for selection operator is as follows:

$$\begin{cases} U_a(t) \; if \; f(U_a(t)) \le f(X_a(t) \\ X_a(t) \; if \; f(X_a(t) \; < f(U_a(t)) \end{cases} \tag{37}$$

where $f(U_a(t))$ = Power Losses (PL) is the function to be minimized.

The convergence characteristics of algorithm are shown in Fig. 4. For first 40 iterations control variables have not shown any decrease in power losses because cross over, mutation and selection operators updated the control variables to the values which are unable to reduce the

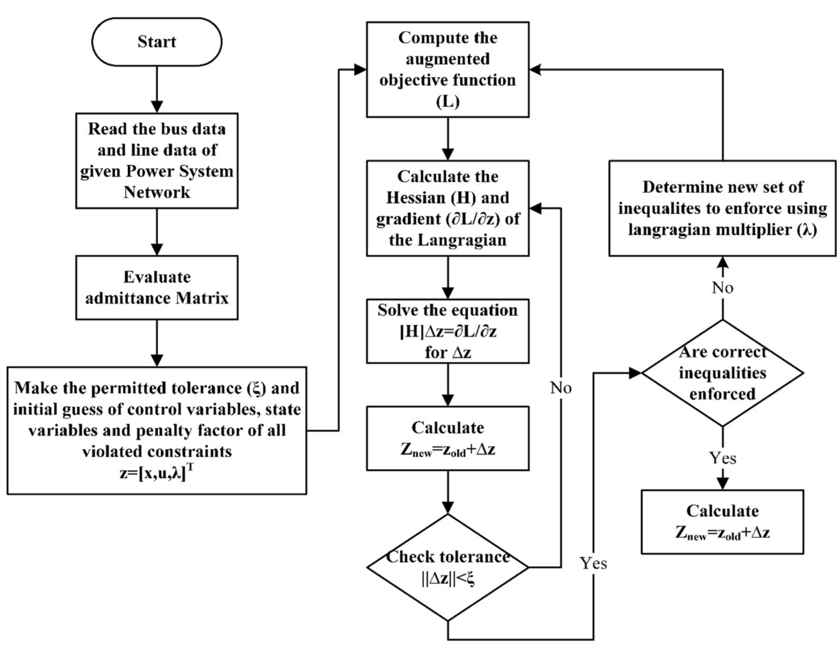

Fig. 3. Flow diagram to solve ORPD problem using Newtons Method.

Table 11
Comparison of the results of case study.

Control variables	Base case variables (without capacitor placement)	Optimal variable for NM	Optimal variable for DE	Optimal variables for PSO	Optimal variables for WOA	Optimal variables for SCA
V_{g1} (pu)	1.05	1.09713	1.099425	1.1	1.098734	1.1
V_{g2}(pu)	1.04	1.09446	1.096135	1.0930	1.098659	1.1
V_{g5} (pu)	1.01	1.08282	1.071103	1.0731	1.098547	1.0869
V_{g8} (pu)	1.01	1.08157	1.077679	1.0743	1.098547	1.0870
V_{g11} (pu)	1.05	1.06924	1.065779	1.0275	1.098547	1.1
V_{g13} (pu)	1.05	1.05356	1.003751	1.0335	1.05	1.0800
T_{6-9} (pu)	1.078	0.9609	0.99476	1.0161	1.05	1.05
T_{6-10} (pu)	1.069	0.9157	0.996979	1.0008	1.05	1.05
T_{4-12} (pu)	1.032	1.0317	1.0369	1.0089	1.05	1.05
T_{28-27} (pu)	1.068	0.9957	1.020303	1.0245	1.05	1.05
QC_3 (pu)	0	0.02949	0.01911	0.0364	0.029414	0.04631
QC_{10} (pu)	0	0.02154	0.039475	0.03541	0.018422	0.03089
QC_{12} (pu)	0	0.04027	0.034769	0.01664	0.036252	0.05
QC_{15} (pu)	0	0.02980	0.029612	0.04009	0.010411	0.04697
QC_{17} (pu)	0	0.03205	0.03146	0.0406	0.022164	0.02129
QC_{20} (pu)	0	0.00736	0.003442	0.0408	0.049714	0.03191
QC_{23} (pu)	0	0.02778	0.017326	0.0414	0.031847	0.05
QC_{24} (pu)	0	0.01944	0.028057	0.03948	0.03902	0.04388
QC_{29}(pu)	0	0.01267	0.042639	0.02246	0.030282	0.03575
Power Losses (PL) (MW)	**5.812**	**5.0318**	**5.0989**	**4.7797**	**5.0625**	**4.7086**
% reduction	–	13.422	12.422	17.792	12.89	18.98
Cost of power losses reduction $/h	–	1.656	1.4281	2.0722	1.5011	2.2113

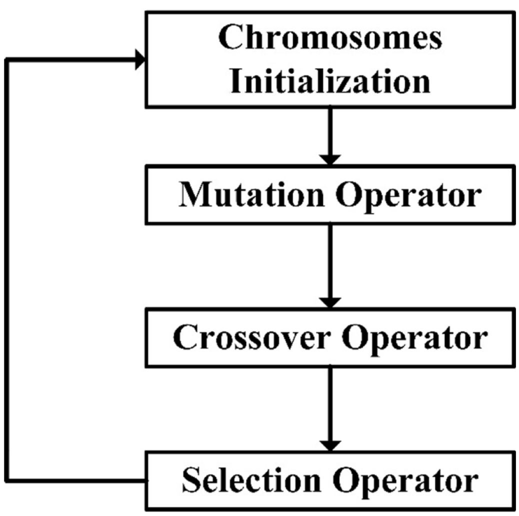

Fig. 4. DE is cycle of stages.

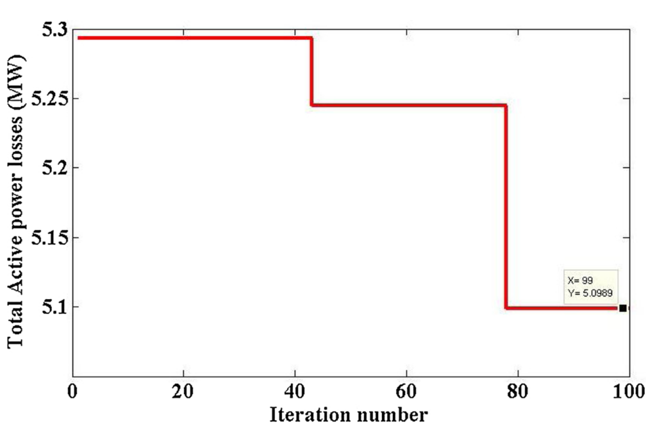

Fig. 5. Power losses minimization by using Deferential Evolution.

power losses. From approximately 42th iteration DE show reduction in power losses from 5.3 MW TO 5.24 MW. Approximately after 43th iteration DE got stuck in local optima and did not show any decrease in power losses till 77th iteration. DE Converges at approximately 78th iteration. At 78th iteration cross over and mutation operator provide such updated values of control variable which reduce the power losses to minimum value. For given experimental setup the algorithm reaches a minimum value of **5.0989 MW.** Optimal values of control variables are given in third column of Table 9. Comparison of the power losses obtained from DE with base case power losses (5.812 MW) show 12.4220% power losses reduction. The cost of power loss reduction for DE is 1.4281 $/hr as calculated by means of Eq. (24) (Fig. 5).

4.2.2. Particle swarm optimization (PSO) results

PSO is an efficient population-based optimization algorithm which utilizes the mechanism of birds flocking and fish schooling. It was proposed by Eberhart and Kennedy. Each particle updates its position based upon its own best position, global best position among particles and its previous velocity vector according to the following equations:

$$V_i^{k+1} = w.\ V_i^k + c_1.\ r_1.\ (P_{best} - X_i^k) + c_2.\ r_2.\ (g_{best} - X_i^k) \quad (38)$$

$$X_i^{k+1} = X_i^k + \alpha.\ V_i^{k+1} \quad (39)$$

where,
V_i^{k+1} = Velocity of i^{th} particle at $(k+1)^{th}$ iteration
w = Inertia weight of the particle
V_i^k = Velocity of i^{th} particle at k^{th} iteration
c_1, c_2 = Constants having values between 0 and 2.5
r_1, r_2 = Randomly numbers between 0 and 1
P_{best} = The best position of the i^{th} particle obtained based upon its own experience
g_{best} = Global best position of the particle in the population
X_i^{k+1} = The position of i^{th} particle at $(k+1)^{th}$ iteration
X_i^k = The position of i^{th} particle at k^{th} iteration
α = Constriction factor which will help to insure convergence

Optimally selected inertia weight w provides good balance between global and local explorations. So the equation for inertia weight is as follows:

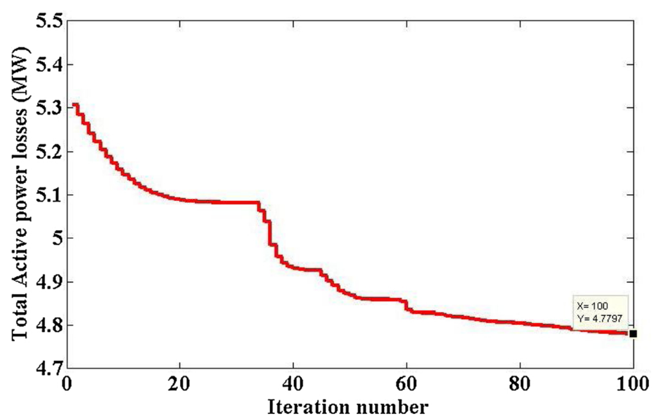

Fig. 6. Power losses minimization by using Particle swarm optimization.

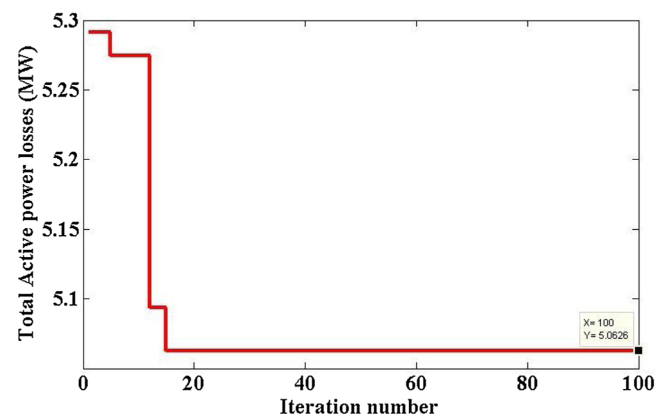

Fig. 7. Power losses minimization by using Whale Optimization Algorithm.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}}.\,(iter) \tag{40}$$

where,

w_{max}= Inertia weight at the beginning of iterations
w_{min}= Inertia weight at the end of iterations
$iter$ = Current iteration number
$iter_{mzx}$ = Maximum number of iterations

Minimum losses found by PSO are **4.7797 MW**. Optimal values of control variables for PSO are shown in fourth column of Table 9. The convergence characteristics of PSO are shown in Fig. 6. The drawback of PSO is that it is more a local search algorithm rather than global search. That is why PSO have taken maximum number of iterations to reach an optimum value. PSO Converges at 99th iteration. PSO got stuck in local optima and converges slowly. Comparison of power losses obtained from PSO with base case losses (5.812 MW) show 17.792% power losses reduction. The cost of power losses reduction for PSO is 2.0722$/hr as calculated via Eq. (24). Thus, PSO also gives better results as compared to DE.

4.2.3. Whale optimization algorithm (WOA) results

WOA is a noval nature inspired meta-heuristic optimization algorithm which utilizes the social behavior of humpback whales. WOA was introduced by Mirjalili and Lewis. It uses encircling and spiral updating mechanism of whales. Mathematical model of different behavior shown by humpback whales are given below.

Mathematical equations of encircling behavior of whales is as follows:

$$D = |C.\ X^{*}(t) - X(t)| \tag{41}$$

$$X(t+1) = X^{*}(t) - A.\ D \ if \ p < 0.5 \tag{42}$$

where,

p = Random number between 0 and 1
t = Current iteration
A&C = Coefficient vectors
X* = Position vector of the best solution

$$A = 2.\ a.\ r - a \tag{43}$$

$$C = 2r \tag{44}$$

where,

a = linearly decreased from 2 to 0 in both exploration and exploitation
r = Random number between 0 and 1

Mathematical model of spiral updating phenomena is as follows:

$$D^{/} = X^{*}(t) - X(t) \tag{45}$$

$$X(t+1) = D^{/}.\ e^{bl}.\ (\cos 2.\ pi.\ l) + X^{*}(t) \ if \ p \geq 0.5 \tag{46}$$

where,

p = random number between 0 and 1
b = Constant to define the shape of spiral
l = Random number uniformly distributed in the range [1, −1]

For global search we do not relay on best solution rather we choose random control variable. The global search will be done when value of A is greater than 1. The equations for global search are as follows:

$$D = |C.\ X_{rand} - \mathrm{X(t)}| \tag{47}$$

$$X(t+1) = X_{rand} - A.\ D \tag{48}$$

where,

X_{rand} = Randomly chosen from current population

Minimum losses found by WOA are **5.0625 MW.** Optimal values of control variables for WOA are shown in fifth column of Table 9. The convergence characteristics of WOA are shown in Fig. 7. It can be seen that WOA is a global search algorithm and did not stuck in local optimum. WOA converges before 20th iteration, in comparison to the 78th and 99th iteration attained by DE and PSO respectively.

Comparison of power losses obtained from WOA with base case losses (5.812 MW) show 12.89% power loss reduction which is slightly better than DE. The cost of power losses reduction for WOA is 1.5011 $/hr as calculated from Eq. (24). Hence, the WOA gives better results as compared to DE.

4.2.4. Sine cosine algorithm (SCA) results

SCA is a population based algorithm proposed by Seyed ali Mirjalili. SCA uses the adaptive nature of sine and cosine functions to get the optimum result of desired problem. SCA uses the following position updating equations for both phases (exploration and exploitation):

$$X_i^{t+1} = X_i^t + r_1 \times sin(r_2) \times \left| r_3 P_i^t - X_i^t \right| \tag{49}$$

$$X_i^{t+1} = X_i^t + r_1 \times cos(r_2) \times \left| r_3 P_i^t - X_{ii}^t \right| \tag{50}$$

where X_i^t is the position of the current solution in *i*-th dimension at *t-th* iteration, *r1/r2/r3* are random numbers, P_i^t is position of the destination point in *i*-th dimension, and || indicates the absolute value. These two equations are combined to be used as follows:

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times sin(r_2) \times \left| r_3 P_i^t - X_i^t \right| & r_4 < 0.5 \\ X_i^t + r_1 \times cos(r_2) \times \left| r_3 P_i^t - X_{ii}^t \right| & r_4 \geq 0.5 \end{cases} \tag{51}$$

where,

$$r_1 = a - a\frac{t}{T}\, a = 0.09, \tag{52}$$

where *t* is the current iteration, *T* is the maximum number of iterations, and "*a*" is a constant.

r2 = 2*pi*rand()
r3 = 2*rand()
r4 = rand()

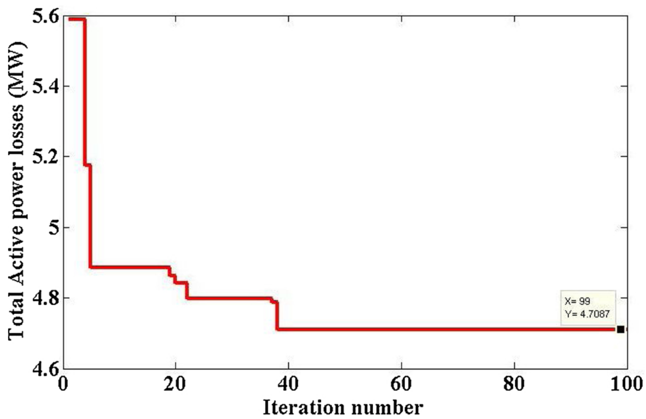

Fig. 8. Power losses minimization by using Sine Cosine Algorithm.

Above mentioned parameters $r1$, r2, r3, r4 are responsible for the behavior of graph. r_1 dictates the position region or the movement of direction of search agents (exploration). r_2 dictates how far the movement should be towards or outwards the best solution (exploitation). The parameter r3 gives the random weight for destination to emphasize ($r3 > 1$) and to deemphasize ($r3 < 1$). Finally r4 is used to equally switch between sine and cosine functions as shown in Eq. (53). r4 is responsible for the usage of adaptive nature of sine and cosine function.

Minimum losses found by SCA are 4.7067 MW. Optimal values of control variables for SCA are shown in sixth column of Table 9. The convergence characteristics of SCA are shown in Fig. 8. It can be seen that initially search agents show large fluctuations approximately till 5th iteration which shows the exploration phase of SCA but control variable got stuck in local optima before 10th iteration and found a way out at approximately 20th iteration. After that there is small decrease in power losses which shows the exploitation phase of SCA. During this whole process SCA switches between sine and cosine function depending upon the value of r4. At approximately 39th iteration due to stochastic nature of SCA again there is exploration phase and large fluctuation which then converge around best solution. It can be seen that SCA converges before 40th iteration so its convergence is better than both PSO and DE. Comparison of power losses obtained from SCA with base case losses (5.812 MW) shows 18.98 % power loss reduction. The cost of power losses reduction for DE is 2.2113 $/hr as calculated from Eq. (24). SCA gives the best result out of all the techniques used for case study analysis.

4.2.5. Newton method (NM) results

Newtons Method is well known tool for the solution of Optimal power flow problems [141]. The Newton approach is a flexible formulation that can be adopted to develop different OPF algorithms suited to the requirements of different applications. This method is a very powerful algorithm because of its rapid convergence near the solution. This property is especially useful for power system applications because an initial guess near the solution is easily attained.

To solve ORPD using Newtons Method we must convert objective into lagrangian function as shown below;

$$\mathrm{L(x)} = \mathrm{f(x)} + \mu_{(x)}^T + \tau_{(x)}^T \tag{53}$$

where μ and τ are vectors of lagrangian multiplier.

A gradient and Hessian of the Lagrangian is then defined as Gradient

$$\nabla L(z) = \begin{pmatrix} \partial L(Z) \\ \partial (Z_i) \end{pmatrix} \tag{54}$$

where $\nabla L(z)$ is a vector of the first partial derivatives of the Lagrangian.

The flow diagram for the solution of ORPD using Newtons Method is shown in Fig. 3. The convergence characteristics of Newtons Method are shown in Fig. 9. Power losses reduced to value of 5.031 MW showing a percentage decrease of 13.422% and cost reduce to value of 1.656 $/h.

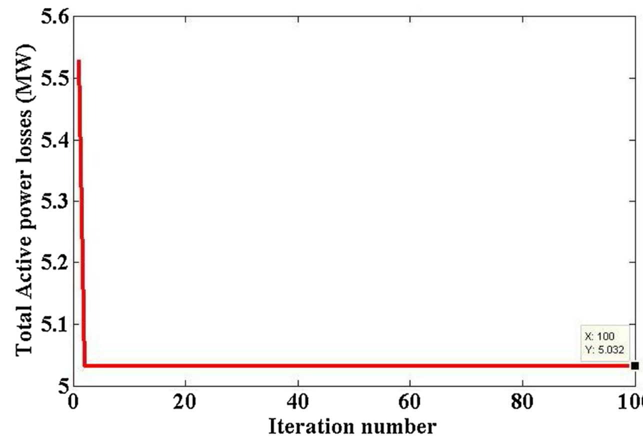

Fig. 9. Power losses minimization by using Newtons Method.

Newton based techniques have some drawbacks due to which it is not suitable for the solution of large test systems. Its convergence characteristics are sensitive to the initial conditions and they may even fail to converge due to inappropriate initial conditions [142]. It is not possible to develop practical ORPD programs without employing sparsity techniques.

The comparative study of four techniques is performed which shows that SCA gives best results after thirty runs. However, in the technical literature, several comparisons between methods are reported to address the ORPD problem. Tables 2–5 present articles that carry out such comparisons. Despite the multiple comparisons that have been reported between methodologies to address the ORPD, it is not possible to affirm that there is one superior to the others. This is because a particular characteristic of meta-heuristics is that their operators can be modified to improve their performance. Thus, one can report the superiority of one method over another and later reverse this condition. For example, in Refs. [98,110] the superiority of evolutionary techniques versus techniques based on swarm intelligence is shown; however, in Refs. [143] and [19] the reverse situation is shown. However, from the literature, it is evident that in recent years there has been a tendency to explore new Meta-Heuristic techniques to solve the ORPD. Due to its effectiveness, the evolutionary algorithms have remained valid over the time. Additionally, it is observed that publications on studies carried out in swarm intelligence have increased in recent years.

As mentioned earlier, in this manuscript, the ORPD problem have been solved using four different meta-heuristic techniques including DE, PSO, WOA and SCA. IEEE 30-bus system have been used to implement these algorithm and results of 30 independent trail runs have been saved for each technique. Then, to prove the superiority of one of the meta-heuristic techniques, a statistical analysis is performed showing best, worst, mean, standard deviation and rank of each technique as performed in Ref. [144]. This statistical analysis is performed on IEEE 14-bus, 30-bus and 57-bus system by taking the data of 30 runs independently for all techniques as discussed previously and results are shown in Table 12.

For small system such as 14 bus system as shown in table, WOA ranked better than PSO but as we move to larger system WOA ranked less than PSO. It can be seen from Table 12 that SCA outperforms all algorithms in all test system which shows its strength in solving complex engineering problems.

On the basis of data obtained from 30 independent trial runs of each technique, a statistical graph is plotted on the basis of probability density function (PDF) which shows the superiority of SCA as shown in Fig. 9.

It can be seen from Fig. 9 that for 14-bus system results of power losses for all Meta-Heuristic techniques lies between 12.274 MW to 15.22 MW as shown in Table 12. For 30-bus system, the results of 30 independent trial runs for all four Meta-Heuristic techniques lies between 4.708 MW to 6.201 MW. Similarly, for 57-bus system, results of all Meta-Heuristic techniques lies between 24.054 MW to 28.729 MW.

Table 12
Statistical analysis performed to prove superiority of one technique

Test systems	14-bus system				30-bus system				57-bus system			
Algorithms	DE	PSO	WOA	SCA	DE	PSO	WOA	SCA	DE	PSO	WOA	SCA
Best result (MW)	12.663	12.469	12.432	12.274	5.098	4.779	5.062	4.708	27.062	25.386	25.657	24.054
Worst result (MW)	15.272	14.569	13.723	12.832	6.201	5.876	5.996	5.286	30.644	26.951	28.729	25.527
Mean	13.356	13.332	12.901	12.526	5.501	5.273	5.243	5.030	29.047	26.250	27.223	24.694
Variance	0.303	0.212	0.110	0.022	0.154	0.045	0.050	0.017	0.744	0.174	0.506	0.119
Std	0.550	0.461	0.332	0.149	0.393	0.212	0.225	0.133	0.863	0.418	0.711	0.345
Rank	4	3	2	1	4	2	3	1	4	2	3	1

Table 13
Execution time of different algorithms.

Algorithm	SCA	PSO	WOA	DE	NM
Execution Time (s)	90	103	140	145	158

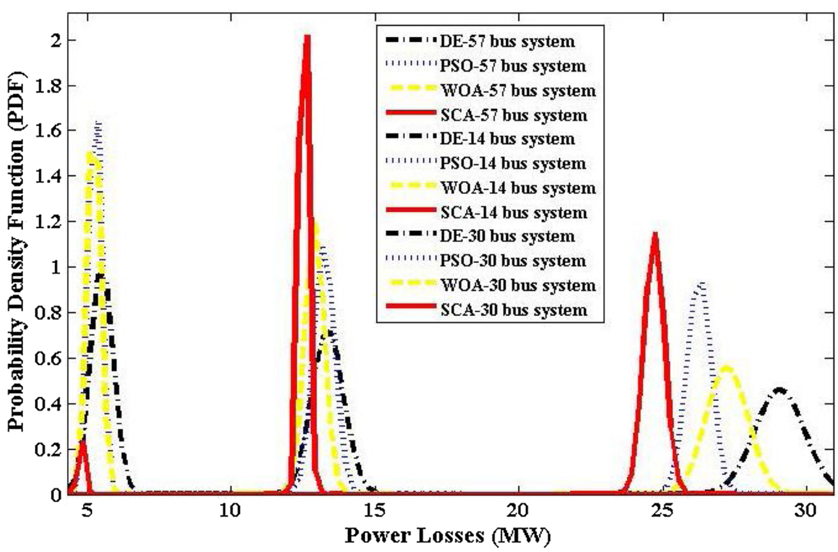

Fig. 10. Power losses in (MW) plot on the basis of PDF.

These results are evident that for all test systems, SCA power losses have less distribution. The closest distribution of results of SCA in graph shows that the losses obtained in all 30 trail runs are close to optimal result obtained in SCA. The data distribution is widest in case of DE which shows that deviation from optimal power losses is highest in case of DE.

Complexity of any algorithm depends on its time of execution. Execution time of our own implemented algorithms is given below in Table 13.

The above table shows that complexity level of SCA is minimum. SCA involve less mathematical calculations to find the optimum result of specified problem (Fig. 10). < – >

5. Conclusion

This review presents the meta-heuristic techniques which are used to solve the ORPD problem. The mathematical formulation of the objective and aptitude functions commonly used in the ORPD were also presented. These techniques are classified on the basis of their objective functions. Furthermore, these are categorized into evolutionary algorithms and swarm intelligence algorithms. From the last 20 years survey, it can be seen that for the first decade, evolutionary algorithms were frequently used to solve the ORPD problem. On the other hand, a tendency was found in the last decade to approach the ORPD through swarm intelligence algorithms. The main advantage of each meta-heuristic technique lies in its versatility to handle multi-objective problems, restrictions and the fact of finding a set of high-quality optimal solutions. From this survey we can conclude that most of the researchers have considered the objective of active power losses minimization in transmission system for the solution of ORPD problem. Based on this conclusion a case study is performed in the last part of this survey, considering the objective function of power losses minimization where DE, PSO, WOA and SCA are employed to solve ORPD problem for a single test system by keeping the same initialized parameters for all techniques. The results show that DE gives the worst results and SCA gives the best results in terms of power losses minimization among the four compared techniques. Finally, a statistical analysis is also performed to evaluate the performance of techniques under discussion. The analysis shows that SCA outperforms which would attracts the researchers to use this technique for solving various engineering optimization problems.

Conflict of interests

On behalf of all authors, I hereby declare that we have no conflict of interests.

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