Chapter 7

Optimal Power Flow Using Recent Optimization Techniques

Mohamed Ebeed*, **Salah Kamel**[†] **and Francisco Jurado**[‡]
*Department of Electrical Engineering, Faculty of Engineering, Sohag University, Sohag, Egypt,
†Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan, Egypt,
‡Department of Electrical Engineering, University of Jaén, Linares, Spain

NOMENCLATURE

a_i, b_i, c_i	cost coefficient of the *i*th generator
d_i, e_i	coefficients reflecting the valve-point effect
F	the objective function
g_i	the equality constraints
G_{ij}, B_{ij}	conductance and susceptance of the admittance matrix
h_j	inequality constraints
K_G,K_Q, K_V, K_S	penalty factors
L_{max}	stability index
L_n	voltage stability local indicator of bus n
NC	number of shunt VAR compensators
NT	number of tap regulating transformers
NG	number of generation buses
NPV	number of PV buses
NPQ	number of load buses
NTL	number of transmission lines
P_{Di}	the active load demand at bus i
P_{G1}^{max}	maximum active power output of slack bus
P_{G1}^{min}	minimum active power output of slack bus
P_{Gi}	generator active power output of generating unit i
P_{Gi}	the generated active power of unit i
P_{G1}	active power generation of slack bus
P_{Gi}^{max}	maximum active power output of *i*th generating unit
P_{Gi}^{min}	minimum active power output of *i*th generating unit

Classical and Recent Aspects of Power System Optimization. https://doi.org/10.1016/B978-0-12-812441-3.00007-0

QG	the reactive power output of generators
Q_{G1}	active power generation of slack bus
Q_{Ci}	shunt VAR compensation of *i*th shunt compensator (MVAR)
Q_{Ci}^{max}	maximum VAR injection limit of *i*th shunt compensator (MVAR)
Q_{Ci}^{min}	minimum VAR injection limit of *i*th shunt compensator (MVAR)
Q_{Di}	the reactive load demand at bus *i*
Q_{Gi}	the generated reactive power of unit *i*
Q_{Gi}^{max}	maximum reactive power output of *i*th generating unit (MVAR)
Q_{Gi}^{min}	minimum reactive power output of *i*th generating unit (MVAR)
S_{Li}	transmission line loading of *i*th branch (MVA)
S_{Li}^{min}	maximum apparent power flow limit of *i*th branch (MVA)
STL	the apparent power flow in transmission line
T_i	transformer taps settings of *i*th transformer (p.u.)
T_i^{max}	maximum tap settings limit of *i*th transformer (p.u.)
T_i^{min}	minimum tap settings limit of *i*th transformer (p.u.)
u	vector of the control variables
V_{Gi}	voltage magnitude at PV bus *i*
V_{Li}^{max}	maximum load voltage of *i*th bus
V_{Li}^{min}	minimum load voltage of *i*th bus
VD	load bus voltage deviation
VL	the voltage of load bus
x	vector of the state variables
Yij	admittance matrix between bus *i* and bus *j*
$\gamma_i, \beta_i, \alpha_i, \zeta_i, \lambda_i$	coefficients of the *i*th generator emission
δ_{ij}	phase angle difference between buses *i* and *j*
$\omega_1, \omega_2, \omega_3$	weight factors for multiobjective functions

1 INTRODUCTION

Over the past half-century, the optimal power flow (OPF) has gained great attention due to its importance in power system operation. Optimal power flow is considered an important tool for efficient planning and enhancing the operation of electric power systems. The main task of optimal power flow is to determine the best or the most secure operating point (control variables) for certain objective functions while satisfying the system equality and inequality constraints. Various objective functions related to the electric power system can be optimized such as: transmission line losses, total generation cost, FACTS (Flexible Alternating Current Transmission System) cost, voltage deviations, total of power transfer capability, voltage stability, emission of generation units, system security, etc. The system control variables that can be adjusted include the generated active powers, the voltage of generation buses, transformer tap settings and sizing of FACTS devices. Several classical (deterministic) and recent (nondeterministic) heuristic optimization techniques have been proposed to find the solution of optimal power flow problem. Most of the classical optimization techniques use sensitivity analysis and gradient-based methods. It should be pointed out that the classical methods may be trapped in local optimum due to nonlinearity of optimal power flow problems thereby the metaheuristic optimization techniques are widely employed for solving the optimal power flow problems. This chapter presents a comprehensive survey of the recent optimization techniques used to solve optimal power flow problems. The presented optimization techniques are categorized based on their inspirations, such as nature-swarm-inspired methods (particle swarm optimization, cuckoo search algorithm, firefly algorithm, ant colony optimization algorithm, gray wolf optimizer, moth-flame optimizer, etc.), human-inspired algorithms (harmony search, teaching learning based optimization, tabu search, etc.), evolutionary-inspired algorithms (differential evolution, genetic algorithms, etc.), physics-inspired algorithms (simulated annealing , gravitational search algorithm, etc.), and artificial neural networks (ANN).

2 OPF OVERVIEW

OPF was first proposed by Carpentier [1]. Then, several conventional methods have been applied to solve the OPF problem, such as Newton method network flow programming, linear programming, nonlinear programming, quadratic programming, and the interior point [2–18]. The main shortages of classical methods are they are nonsuitable for large and difficult OPF problems which are high nonlinear and multimodal optimization problems, hence these methods may be trapped in local minima.

Recently, many intelligence optimization methods have been developed to solve the optimal power flow (OPF), particularly the nonlinear complex optimization problems. Intelligence optimization methods are based on different concepts such as evolutionary inspired algorithms, human inspired algorithms, natural inspired algorithms and artificial neural networks [19–109]. The conventional and more recent optimization methods that have been applied for solving the OPF problem are depicted in Fig. 1.

In this chapter, a comprehensive survey is presented to illustrate the application of recent optimization algorithms for solving the optimal power flow problem. Organization of the remaining chapter is as follows: Section 3 describes an overview of the optimal power flow problem, the common objective functions and the system constraints. Section 4 presents a brief survey of conventional methods based OPF. Section 5 shows the new applied optimization techniques for optimal power flow. Section 6 is a conclusion of the chapter.

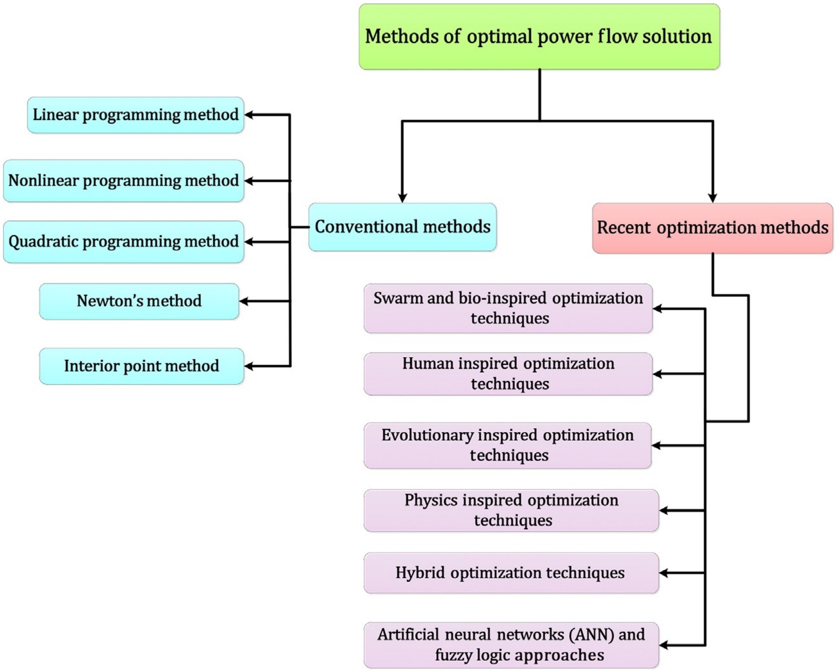

FIG. 1 Solution methods of optimal power flow problem.

3 OPTIMAL POWER FLOW PROBLEM FORMULATION

Solution of the optimal power flow problem aims to optimize an objective function by optimal adjustments of power system control variables with satisfying various equality and inequality constraints. Generally, the optimization problem can be mathematically represented as follows:

$$Min\ F(x,u) \tag{1}$$

Subjected to

$$g_j(x,u)=0 \quad j=1,2,\ldots,m \tag{2}$$

$$h_j(x,u)\leq 0 \quad j=1,2,\ldots,p \tag{3}$$

where F acts the objective function, x is a vector represents the dependent variables (state variables), u is a vector represents the independent (the control) variables, g_j and h_j represent equality and inequality constraints, respectively. m and p are number of equality and inequality constraints, respectively.

The dependent variables (x) in power system can be described as follows:

$$x=\left[P_{G1},V_{L1}\ldots V_{L,NPQ},Q_{G,1}\ldots Q_{G,NG},S_{TL,1}\ldots S_{TL,NTL}\right] \tag{4}$$

where P_{G1} is slack bus power, V_L is voltage of load bus, Q_G is the generator reactive power output, S_{TL} is the apparent power flow in transmission line, NPQ is number of load buses, NG is number of generation buses, and NTL is number of transmission lines.

The independent variables u of power system can be described as follows:

$$u = [P_{G,2} \ldots P_{G,NG}, V_{G,1} \ldots V_{G,NG}, Q_{C,1} \ldots Q_{C,NC}, T_1 \ldots T_{NT}] \tag{5}$$

where P_G is output active power of generator, V_G is voltage of generation bus, Q_C is the injected reactive power of shunt compensator, T is tap setting of transformer, NC is number of shunt compensator units, and NT is the number of transformers.

3.1 Objective Functions

3.1.1 Single Objective Functions

The optimization techniques can be applied for optimal power flow solution where the most common objective functions can be presented as follows:

(1) Quadratic fuel cost

The objective function is the quadratic equation of total generation fuel cost which formulated as follows:

$$F_1 = \sum_{i=1}^{NG} F_i(P_{Gi}) = \sum_{i=1}^{NPV} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \tag{6}$$

where, F_i is the fuel cost of the ith generator. a_i, b_i, and c_i are the cost coefficients of ith generator.

(2) Quadratic cost with valve-point effect

Practically, the quadratic fuel costs of some generation units are nonsmooth functions due to influences of the steam admission from their control valves which call valve-point loading effect. Steam admission will lead to occurrence of ripples in fuel cost. The valve-point loading effect is considered by adding a sine term to the fuel cost as follows:

$$F(x,u) = \sum_{i=1}^{NG} F_i(P_{Gi}) = \sum_{i=1}^{NG} \left(a_i + b_i P_{Gi} + c_i P^2{}_{Gi}\right) + \left|d_i sin\left(e_i\left(P_{Gi}^{min} - P_{Gi}\right)\right)\right| \tag{7}$$

where, d_i and e_i are the fuel cost coefficients of the ith unit with valve-point effects.

(3) Piecewise quadratic cost functions

Practically, the thermal generation unit may have several fuel sources such as coal, natural gas, and oil. Hence, the fuel cost functions of these units will be nonconvex problem and it is split as piecewise quadratic cost functions for different fuel types as follows:

$$F(P_{Gi}) = \begin{cases} a_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 & P_{Gi}^{min} \le P_{Gi} \le P_{G1} \\ a_{i2} + b_i P_{Gi2} + c_i P_{Gi}^2 & P_{G1} \le P_{Gi} \le P_{G2} \\ \dots & \\ a_{ik} + b_i P_{Gik} + c_i P_{Gi}^2 & P_{Gi(k-1)} \le P_{Gi} \le P_{Gi}^{max} \end{cases} \quad (8)$$

(4) Voltage profile improvement

The third objective function is minimizing the voltage deviations of load buses from a specified voltage. The required objective function can formulate as follows:

$$F_3 = VD = \sum_{i=1}^{NPQ} |(V_i - 1)| \quad (9)$$

(5) Voltage stability enhancement

Voltage stability index (L) is an important value proposed by Kessel and Glavitsch to indicate system stability [110]. This value is calculated for all load buses, which vary between 0 (no load case) to 1 maximum loading point (voltage collapse case) hence, the minimizing of this value keeps the system far away from voltage collapse of power system. However, this objective function can be formulated as follows:

$$F_4 = min(L_{max}) = min(max(L_n)) \quad n = 1, 2, \dots, NPQ \quad (10)$$

where, L_n is the voltage stability index of bus nth that can be calculated as follows:

$$L_n = \left| 1 - \sum_{i=1}^{NPV} F_{ij} \frac{V_i}{V_j} \right| \quad (11)$$

where, V_i is the voltage of ith generator bus and V_j is the voltage of load bus. F_{ij} can be obtained from system Y_{bus} matrix as follows:

$$\begin{bmatrix} I_G \\ I_L \end{bmatrix} = \begin{bmatrix} Y_{GG} & Y_{GL} \\ Y_{LG} & Y_{LL} \end{bmatrix} \begin{bmatrix} V_G \\ V_L \end{bmatrix} \quad (12)$$

where I_G, I_L are the complex currents and V_G, V_L are the complex voltages vectors at the generator and load buses. Y_{GG}, Y_{LL}, Y_{GL}, Y_{LG} are submatrices of system Y_{bus} by making some manipulation in Eq. (12)

$$\begin{bmatrix} V_L \\ I_G \end{bmatrix} = \begin{bmatrix} Z_{LL} & F_{LG} \\ K_{GL} & Y_{GG} \end{bmatrix} \begin{bmatrix} I_L \\ V_G \end{bmatrix} \quad (13)$$

where, $F_{ij} = [F_{LG}] = -[Y_{LL}]^{-1}[Y_{LG}]$.

(6) Real power losses minimization

The required objective function is minimizing the active power loss which can be formulated as follows:

$$P_{loss} = \sum_{i=1}^{NTL} G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\delta_{ij}\right) \tag{14}$$

where, G_{ij} the conductance of a transmission, *NTL* is number of transmission lines, and δ_{ij} is phase difference of voltages.

(7) Emission minimization

Reducing the pollution of the environment can be achieved by minimizing the emission gases from thermal power plants. The objective function for these emission gases can be formulated as follows:

$$E_m = \sum_{i=1}^{NG} \gamma_i P_{Gi}^2 + \beta_i P_{Gi} + \alpha_i + \zeta_i exp(\lambda_i P_{Gi}) \tag{15}$$

where, $\gamma_{i,}$ $\beta_{i,}$ α_i, ζ_i, and λ_i are the emission coefficient of the *i*th generator.

3.1.2 Multiobjective Functions

The main purpose of solving multiobjective problems is to optimize several independent objective functions simultaneously.

The multiobjective problem can be defined as follows:

$$Min\, F(x,u) = [F_1(x,u), F_2(x,u)\ldots, F_i(x,u)] \tag{16}$$

where "*i*" is the number of objective functions. Solving the multiobjective functions can be accomplished by Pareto optimization method or weight factors as:

$$F(x,u) = \omega_1\left(\sum_{i=1}^{NG}\left(a_i + b_iP_{Gi} + c_i{P^2}_{Gi}\right)\right) + \omega_2\left(\sum_{i=1}^{NPQ}|(V_i - 1)|\right) \tag{17}$$

$$F(x,u) = \omega_1\left(\sum_{i=1}^{NG}\left(a_i + b_iP_{Gi} + c_i{P^2}_{Gi}\right)\right) + \omega_2\left(\sum_{i=1}^{NTL}G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\delta_{ij}\right)\right) \tag{18}$$

$$F(x,u) = \omega_1\left(\sum_{i=1}^{NG}\left(a_i + b_iP_{Gi} + c_i{P^2}_{Gi}\right)\right) + \omega_2(max(L_n)) \tag{19}$$

$$F(x,u) = \omega_1\left(\sum_{i=1}^{NPQ} |(V_i - 1)|\right) + \omega_2\left(\sum_{i=1}^{NTL} G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\,cos\,\delta_{ij}\right)\right)$$
$$+ \omega_3(\,max\,(L_n)) \tag{20}$$

where, ω_1, ω_2, and ω_3 are weight factors which are selected based on relative important of one objective to others. Usually, the values of weight factors are selected as follows:

$$\sum_{i=1}^{n} \omega_n = 0 \tag{21}$$

3.1.3 Constraints

The transmission system has several constraints which can be categorized as follows:

(1) *Equality constraints*

The equality constrains represent the balanced load flow equations as follows:

$$P_{Gi} - P_{Di} = |V_i| \sum_{j=1}^{NB} \left|V_j\right| \left(G_{ij}\,cos\,\delta_{ij} + B_{ij}\,sin\,\delta_{ij}\right) \tag{22}$$

$$Q_{Gi} - Q_{Di} = |V_i| \sum_{j=1}^{NB} \left|V_j\right| \left(G_{ij}\,cos\,\delta_{ij} + B_{ij}\,sin\,\delta_{ij}\right) \tag{23}$$

where, P_{Gi} and Q_{Gi} are the generated active and reactive power at bus i, respectively. P_{Di} and Q_{Di} are the active and reactive load demand at bus i, respectively. G_{ij} and B_{ij} are the conductance and susceptance between bus i and bus j, respectively.

(2) *Inequality constrains*

The inequality constrains can be classified as follows:

I. Generators active power output

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \quad i = 1, 2, \ldots, NG \tag{24}$$

II. Generators bus voltages

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max} \quad i = 1, 2, \ldots, NG \tag{25}$$

III. Generators reactive power output

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \quad i = 1, 2, \ldots, NG \tag{26}$$

IV. Transformer tap settings

$$T_i^{min} \leq T_i \leq T_i^{max} \quad i = 1, 2, \ldots, NT \tag{27}$$

V. Shunt VAR compensator

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} \quad i = 1, 2, \ldots, NC \tag{28}$$

VI. Apparent power flow in transmission lines

$$S_{Li} \leq S_{Li}^{min} \quad i = 1, 2, \ldots, NTL \tag{29}$$

VII. Voltage magnitude of load buses

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max} \quad i = 1, 2, \ldots, NPQ \tag{30}$$

The dependent control variables can be easily considered in an optimization solution by using the quadratic penalty formulation of objective function which can be expressed as follows:

$$F_g(x,u) = F_i(x,u) + K_G(\triangle P_{G1})^2 + K_Q \sum_{i=1}^{NPV} (\triangle Q_{Gi})^2 + K_V \sum_{i=1}^{NPQ} (\triangle V_{Li})^2 + K_S \sum_{i=1}^{NTL} (\triangle S_{Li})^2 \tag{31}$$

where, K_G, K_Q, K_V, and K_S are the penalty factors, these values are high positive $\triangle P_{G1}$, $\triangle Q_{Gi}$, $\triangle V_{Li}$ and $\triangle S_{Li}$ are penalty terms which can be defined as follow:

$$\triangle P_{G1} = \begin{cases} \left(P_{G1} - P_{G1}^{max}\right) & P_{G1} > P_{G1}^{max} \\ \left(P_{G1} - P_{G1}^{min}\right) & P_{G1} < P_{G1}^{min} \\ 0 & P_{G1}^{min} < P_{G1} < P_{G1}^{max} \end{cases} \tag{32}$$

$$\triangle Q_{Gi} = \begin{cases} \left(Q_{Gi} - Q_{Gi}^{max}\right) & Q_{Gi} > Q_{Gi}^{max} \\ \left(Q_{Gi} - Q_{Gi}^{min}\right) & Q_{Gi} < Q_{Gi}^{min} \\ 0 & Q_{Gi}^{min} < Q_{Gi} < Q_{Gi}^{max} \end{cases} \tag{33}$$

$$\triangle V_{Li} = \begin{cases} \left(V_{Li} - V_{Li}^{max}\right) & V_{Li} > V_{Li}^{max} \\ \left(V_{Li} - V_{Li}^{min}\right) & V_{Li} < V_{Li}^{min} \\ 0 & V_{Li}^{min} < V_{Li} < V_{Li}^{max} \end{cases} \tag{34}$$

$$\triangle S_{Li} = \begin{cases} \left(S_{Li} - S_{Li}^{max}\right) & S_{Li} > S_{Li}^{max} \\ \left(S_{Li} - S_{Li}^{min}\right) & S_{Li} < S_{Li}^{min} \\ 0 & S_{Li}^{min} < S_{Li} < S_{Li}^{max} \end{cases} \tag{35}$$

4 CONVENTIONAL OPTIMIZATION METHODS FOR OPTIMAL POWER FLOW

The conventional methods were based on linearized objective functions and these methods apply sensitivity analysis and gradient based optimization algorithms. The conventional methods that have been applied for the OPF problem are illustrated as follows.

4.1 Linear Programming Method

Linear programming (LP)-based method is used to linearize nonlinear power system optimization problems. This method is reliable and has a good convergence characteristic, however the main shortage is it could be trapped in local minima. Moreover, errors could appear, especially in constraints, due to rounding by digital computers [5–7].

4.2 Nonlinear Programming Method

The nonlinear programming (NLP) method is more accurate compared to linear programs where it can be applied for the nonlinear objective functions and constraints. The NLP techniques are based on reduced gradient method utilizing the Lagrange multiplier or use the penalty function optimization approach. In this method, the first partial derivatives of the equations (the reduced gradient) is used to choose a search direction in the iterative procedure. The merits of this method are it can be applied in a large-scale system while the drawbacks of this method are that some system components are not considered [8–12].

4.3 Quadratic Programming Method

The quadratic programming (QP) can be considered a special form of nonlinear programming method where the objective function is quadratic, and the constraints are in linear form. This method doesn't require the determination of the gradient steps. The obtained solution using the QP method is more accurate compared with LP and NLP and it can be applied in ill conditions, moreover it has fast convergence characteristic [13,14].

4.4 Newton's Method

Newton's method is commonly used in power flow problems based on the creation of the Lagrangian or decomposition approach by applying second-order partial derivatives (the Hessian). The advantages of Newton's method are that it can be applied for different optimal power flow problems, it has fast convergence characteristics, and it can handle inequality constraints efficiently. The disadvantage of Newton's method is that its convergence characteristics are very sensitive for the initial condition [15–18].

4.5 Interior Point Method

Interior point (IP) method is usually applied for large problems and has been employed to solve the optimal power problem. However, the results obtained using IP result are better and need less iteration compared with LP, and it can be trapped in local minima [19,20].

5 RECENT OPTIMIZATION METHODS FOR OPTIMAL POWER FLOW

The OPF problem is a multimodal, nonlinear, or nonconvex problem; hence, application of conventional methods is not always suitable and can't guarantee a global solution. To overcome the shortages of conventional methods, several heuristics optimization techniques have been developed to solve the OPF problem. The merits of recent optimization techniques can be summarized as follows:

(1) These methods can be applied in small and large-scale systems
(2) High reliability to obtain the optimal solutions
(3) These methods rarely suffer from stagnations or trapped in local minima solutions
(4) These methods converge rapidly to the optimal solution compared to conventional methods.

In this section, we offer a comprehensive survey of the application of the recent (nondeterministic) heuristic optimization techniques for optimal power flow. The heuristic optimization algorithms that applied for OPF problem can be classified based on inspiration methods as follows:

5.1 Swarm and Bio-inspired Optimization Techniques

Nature-inspired and bio-inspired optimization techniques are inspired from motion and searching behavior of swarms of animals or birds for food sources. Table 1 summarizes the nature-inspired techniques that have been applied to the OPF problem.

5.2 Human-Inspired Optimization Techniques

Several optimization techniques mimic human behavior, especially in thinking or decision-making. The human-inspired algorithms that have been employed to solve the OPF problem are listed in Table 2.

5.3 Physics-Inspired Optimization Techniques

Physics-inspired algorithms are conceptualized from physics laws or natural phenomena in space. The applied physics-inspired optimization methods for OPF are listed in Table 3.

TABLE 1 Summary of the Literature Review Regarding Nature Inspired Algorithms for OPF Problem

Algorithm	Objective Function	System	Year	Ref.
Improved artificial bee colony	Fuel cost & fuel cost with valve effect & P_{loss}	IEEE 30-bus, IEEE 118-bus	2017	[22]
Moth swarm algorithm	Fuel cost & fuel cost with valve effect & emission & L-index & P_{loss} & piecewise cost & VD	IEEE 30-bus, IEEE-57, IEEE-118 bus	2017	[24]
Adaptive partitioning flower pollination	Fuel cost & P_{loss} & VD	IEEE 30-bus, IEEE 57-bus	2016	[27]
Glow-worm swarm optimization	Fuel cost & emission	IEEE 30-bus, Indian 75-bus	2016	[28]
Best-guided artificial bee colony algorithm	Fuel cost	IEEE 30-bus, IEEE 57-bus	2016	[30]
Oppositional krill herd algorithm	Fuel cost & fuel cost with valve effect emission & P_{loss}	IEEE 30-bus, IEEE-57	2016	[32]
Chaotic krill herd algorithm	Fuel cost & fuel cost with valve effect & P_{loss} & VD	IEEE-26-, IEEE 57-bus	2015	[36]
Improved group search optimization	Fuel cost with valve effect	26-bus, IEEE 30-bus, IEEE 118-bus	2015	[39]
Chaotic artificial bee colony algorithm	Fuel cost & transient stability	IEEE 30-bus, New England 39-bus systems	2015	[41]
Adaptive clonal selection	Fuel cost & P_{loss} & L-index & VD	IEEE 30-bus	2014	[45]

TABLE 1 Summary of the Literature Review Regarding Nature Inspired Algorithms for OPF Problem—cont'd

Algorithm	Objective Function	System	Year	Ref.
Multihive bee foraging algorithm	Fuel cost with valve effect & emission & P_{loss}	IEEE 30-bus	2014	[47]
Artificial bee colony algorithm	Fuel cost & fuel cost with valve effect & emission & L-index & P_{loss} & piecewise cost & VD	IEEE 9-bus, IEEE 30-bus, IEEE 57-bus	2013	[50]
Moth-flame algorithm	L-index & P_{loss} & VD	IEEE 30-bus	2016	[53]
Modified artificial bee colony algorithm	Fuel cost with valve effect & emission & P_{loss} & piecewise cost & VD	IEEE 30-bus, IEEE 118-bus	2013	[55]
Modified shuffle frog leaping algorithm	Fuel cost & emission	IEEE 30-bus	2011	[60]
Chaotic invasive weed optimization algorithms	Fuel cost & fuel cost with valve effect & fuel cost considering the prohibited zones & piecewise cost	IEEE 30-bus	2014	[65]
Particle swarm optimization	Fuel cost & L-index & piecewise cost & VD	IEEE 30-bus	2002	[68]
Group search optimization	Fuel cost with valve effect & emission & L-index & piecewise cost & VD	IEEE 30-bus, 57-bus, 118-bus	2016	[72]
Gray wolf optimizer	Fuel cost with valve effect & P_{loss} & Q_{loss}	IEEE 30-bus, 118-bus	2016	[74]
Moth-flame optimizer	Fuel cost & L-index & P_{loss} & VD	IEEE 30-bus	2016	[77]
Stud krill herd algorithm	Fuel cost & fuel cost with valve effect & emission & L-index & P_{loss}	IEEE 14-bus, IEEE 30-bus, IEEE 57-bus	2016	[78]
Artificial bee colony algorithm	Fuel cost & fuel cost with valve effect & piecewise cost	IEEE 30-bus	2014	[82]

Continued

TABLE 1 Summary of the Literature Review Regarding Nature Inspired Algorithms for OPF Problem—cont'd

Algorithm	Objective Function	System	Year	Ref.
Enhanced ant colony optimization	Fuel cost & emission	IEEE 30-bus, IEEE 118-bus	2012	[86]
Biogeography-based optimization	Fuel cost & fuel cost with valve effect & VD & L-index	IEEE 30-bus	2010	[89]
The modified flower pollination	Fuel cost & P_{loss} VD	IEEE 30-bus	2017	[92]
Modified honey bee mating optimization	Fuel cost & fuel cost with valve effect	IEEE 14, IEEE 30-bus, IEEE 118-bus	2011	[96]
Particle swarm	Fuel cost & emission & L-index & P_{loss}	IEEE 30-bus	2015	[99]

TABLE 2 Summary of the Literature Review Regarding Human Inspired Algorithms for OPF Problem

Algorithm	Objective Function	System	Year	Ref.
Biogeography-based optimization	Fuel cost & emission & L-index & P_{loss} & VD	IEEE 30-bus, IEEE 57-bus	2015	[35]
Imperialist competitive algorithm	Fuel cost & Emission & P_{loss} & VD	IEEE 30-bus, IEEE 57-bus	2014	[40]
The league championship algorithm	Fuel cost & fuel cost with valve effect & emission & L-index & P_{loss} & VD	Algerian power system network	2014	[42]

TABLE 2 Summary of the Literature Review Regarding Human Inspired Algorithms for OPF Problem—cont'd

Algorithm	Objective Function	System	Year	Ref.
Modified imperialist competitive algorithm	Fuel cost & P_{loss} & VD	IEEE 57-bus	2014	[44]
Teaching learning based optimization	Fuel cost & L-index & P_{loss} & piecewise cost & VD	IEEE 30-bus, IEEE 118-bus	2014	[46]
Quasioppositional teaching learning-based optimization	Fuel cost with valve effect & emission & L-index & P_{loss}	IEEE 30-bus, Indian utility 62-bus, IEEE 118-bus	2014	[48]
Modified teaching-learning based optimization	Fuel cost with valve effect & emission	IEEE 30-bus, IEEE 57-Bus	2013	[50]
Improved harmony search algorithm	Fuel cost with valve effect	6-bus, 14-bus, 30-bus, 57-bus,118-bus	2013	[54]
Tabu search algorithm	Fuel cost & fuel cost with valve effect & VD	30-bus	2002	[71]
Symbiotic organisms search algorithm	Fuel cost & fuel cost with valve effect & fuel cost considering the prohibited zones	IEEE 30-bus	2016	[87]
Improved teaching-learning	Fuel cost & fuel cost with valve effect & emission & piecewise cost & VD	IEEE 30-bus, IEEE 57-bus	2015	[100]

TABLE 3 Summary of the Literature Review Regarding Physics Inspired Algorithms for OPF Problem

Algorithm	Objective Function	System	Year	Ref.
Improved colliding bodies optimization algorithm	Fuel cost & fuel cost with valve effect & emission & L-index & P_{loss} & piecewise cost & VD	IEEE 30-bus, IEEE 57- IEEE 118-bus	2016	[33]
Opposition based gravitational search algorithm	Fuel cost & fuel cost with valve effect & emission & L-index & P_{loss} & piecewise cost & VD	IEEE 30-bus	2015	[38]
Black-hole-based optimization approach	Fuel cost & L-index & P_{loss} & VD	30-bus, Algerian 59-bus system	2014	[43]
Gravitational search algorithm	Fuel cost & fuel cost with valve effect & L-index & P_{loss} & piecewise cost & VD	IEEE 30-bus, 57-bus	2012	[58]
Simulated annealing	Fuel cost	IEEE 6-bus, IEEE 30-bus	2003	[67]
Improved electromagnetism-like mechanism method	Fuel cost & L-index & P_{loss} & Q_{loss} & piecewise cost & VD	IEEE 30-bus, IEEE 57-bus	2016	[37]

5.4 Evolutionary-Inspired Optimization Techniques

The evolutionary optimization algorithms are derived from the mechanics of natural selection and genetics or living organism or creatures. The evolutionary-based optimization techniques that applied for OPF problem are listed in Table 4.

5.5 Hybrid Optimization Techniques

Several hybrid optimization algorithms have been proposed to capture merits of several techniques and to gain superior results compared to singular technique. Hybrid optimization techniques that have been applied for OPF are listed in Table 5.

TABLE 4 Summary of the Literature Review Regarding Evolutionary Inspired Algorithms for OPF Problem

Algorithm	Objective Function	System	Year	Ref.
Enhanced self-adaptive differential evolution	Fuel cost & emission& L-index & P_{loss}	IEEE 30-bus, IEEE 57-bus	2017	[21]
Improved evolutionary algorithm	Fuel cost & emission	IEEE 30-bus, IEEE 57-bus	2017	[23]
Backtracking search optimization	Fuel cost & fuel cost with valve effect emission & L-index & piecewise cost & VD	IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus	2016	[25]
Modified evolutionary algorithm based decomposition	Fuel cost emission & L-index & VD & P_{loss}	IEEE 30-bus	2016	[26]
Differential search algorithm	Fuel cost & emission & L-index & P_{loss} & VD	IEEE 9-bus, IEEE 30-bus IEEE 57-bus	2016	[29]
Enhanced charged system search algorithm	Fuel cost with valve effect & piecewise cost with valve effect	IEEE 30-bus, IEEE 118-bus	2012	[57]
Multiagent-based differential evolution approach	Fuel cost & fuel cost with valve effect & piecewise cost with valve effect	6-bus, IEEE 30-bus	2012	[59]
Differential evolution algorithm	Fuel cost & VD & L-index & piecewise cost	IEEE 30-bus	2010	[61]
Enhanced genetic algorithm	Fuel cost & L-index & P_{loss}	IEEE 30-bus	2010	[62]
Modified differential evolution algorithm	Fuel cost & piecewise cost & fuel cost with valve effect	6-bus, IEEE30-bus	2008	[63]
Evolutionary programming	Fuel cost	IEEE 30-bus	2004	[64]
Differential search algorithm	Fuel cost & emission & L-index & P_{loss} & VD	IEEE 30-bus	2014	[69]

Continued

TABLE 4 Summary of the Literature Review Regarding Evolutionary Inspired Algorithms for OPF Problem—cont'd

Algorithm	Objective Function	System	Year	Ref.
Improved evolutionary programming	Fuel cost & piecewise cost & fuel cost with valve effect	IEEE 30-bus	2014	[70]
Adapted genetic algorithm	Fuel cost & VD	IEEE 30-bus	2012	[75]
Evolutionary programming	Fuel cost & piecewise cost	IEEE 30-bus, Indian utility 62-bus	2005	[76]
Differential evolution	Fuel cost with valve effect emission & L-index & piecewise cost & P_{loss}	IEEE 30-bus, IEEE 118-bus	2012	[79]
Backtracking search algorithm	Fuel cost & fuel cost with valve effect & fuel cost considering the prohibited zones	IEEE 30-bus	2015	[81]
Differential evolution	Fuel cost & fuel cost with valve effect & L-index & P_{loss}	IEEE 30-bus	2017	[83]
Forced initialized differential evolution algorithm	Fuel cost & VD & L-index & P_{loss}	IEEE 30-bus, IEEE 57-bus	2016	[88]
Enhanced genetic algorithm	Fuel cost	IEEE 30-bus, IEEE RTS96	2002	[90]
Evolutionary programming	Fuel cost & piecewise cost & fuel cost with valve effect & VD	IEEE 30-bus	1999	[91]
Genetic-algorithm	Fuel cost & severity index	IEEE 30-bus, IEEE 118-bus	2005	[93]
Improved genetic algorithms	Fuel cost	IEEE 30-bus	1997	[97]
Genetic algorithm	Fuel cost	IEEE 6-bus	2004	[98]
Faster evolutionary algorithm	Fuel cost & fuel cost with valve effect	IEEE 30-bus, IEEE 118-bus, IEEE 300-bus	2014	[101]

TABLE 5 Summary of the Literature Review Regarding Hybrid Inspired Algorithms for OPF Problem

Algorithm	Objective Function	System	Year	Ref.
Fuzzy logic system with harmony search algorithm	Cost & severity index	IEEE 30 bus, IEEE 57 bus, IEEE 118 bus	2016	[31]
Particle swarm optimization with an aging leader and challengers algorithm	Fuel cost & fuel cost with valve effect & P_{loss} & VD	IEEE 30 bus, IEEE 118 bus	2016	[34]
Artificial bee colony algorithm with quantum theory	Fuel cost & fuel cost with valve effect	IEEE 30-bus, IEEE 118-bus	2015	[37]
Fuzzy particle swarm optimization and Nelder-Mead algorithm	Fuel cost & fuel cost with valve effect & emission & L-index & piecewise cost & VD	IEEE 30-bus	2014	[49]
Fuzzy evolutionary and swarm optimization	Fuel cost	IEEE 30-bus	2013	[52]
Particle swarm optimization and the shuffle frog leaping algorithms	Fuel cost with valve effect & piecewise cost with valve effect & emission	IEEE 30-bus, IEEE 57-bus, IEEE 118-bus	2013	[56]
Imperialist competitive algorithm and teaching learning algorithm	Fuel cost & fuel cost with valve effect & fuel cost considering the prohibited zones & piecewise cost	IEEE 30-bus, IEEE 57-bus	2014	[66]
GA-fuzzy and PSO-fuzzy	Fuel cost	IEEE 30-bus	2014	[80]
Genetic evolving ant direction	Fuel cost & fuel cost with valve effect & piecewise cost	IEEE 30-bus, IEEE 118-bus	2012	[84]

Continued

TABLE 5 Summary of the Literature Review Regarding Hybrid Inspired Algorithms for OPF Problem—cont'd

Algorithm	Objective Function	System	Year	Ref.
Hybrid genetic algorithm and particle swarm	Fuel cost & fuel cost with valve effect	IEEE 30 bus	2017	[85]
Harmony search algorithm and an ant system	P_{loss} & VD & performance index	IEEE 30-bus and Taiwan Power Company 345 kV simplified systems	2014	[94]
GA with SA	Fuel cost & P_{loss} & security margin index & emission	IEEE 30-bus, IEEE 118-bus	2003	[95]
Shuffle frog leaping algorithm and simulated annealing	Fuel cost & fuel cost with valve effect & fuel cost considering the prohibited zones	IEEE 30-bus	2012	[102]

5.6 Artificial Neural Networks (ANN) and Fuzzy Logic Approach

Artificial neural networks (ANNs) are computational methods mimic the operation of biological neural networks while the fuzzy set theory is a natural and suitable tool to represent inexact relations. The optimizations methods based on ANNs and fuzzy logic approach are listed in Table 6.

TABLE 6 Summary of the Literature Review Regarding ANNs and Fuzzy Approach Inspired Algorithms for OPF Problem

Algorithm	Objective Function	System	Year	Ref.
Neural network	P_{Loss}	22-bus system	1997	[103]
Artificial neural network	Fuel cost & maximize the voltage stability margin	IEEE 30-bus	2003	[104]
Fuzzy logic model	Fuel cost & emission	IEEE 14-bus	2010	[105]

TABLE 6 Summary of the Literature Review Regarding ANNs and Fuzzy Approach Inspired Algorithms for OPF Problem—cont'd

Algorithm	Objective Function	System	Year	Ref.
Fuzzy logic approach	Fuel cost	IEEE 14-bus	1997	[106]
Fuzzy mathematical programming	P_{Loss}	IEEE 14-bus	1988	[107]
Hopfield neural network	Minimum deviations in real power generations and loads at buses	IEEE 6-bus	1996	[108]
Fuzzy linear programming	Fuel cost & maximizing the generation reserve	IEEE 5-bus, IEEE 14-bus	2005	[109]

6 CONCLUSIONS

This chapter has presented a survey related to the optimal power flow (OPF) problem. However, the chapter has described the following:

- OPF problem formulation, including the common objective functions of power system, control variables and operating constraints.
- The conventional methods that have been employed to solve OPF problem, including the pros and cons of these methods.
- The recent optimization techniques that have been applied for OPF. In addition, the recent optimization algorithms have been categorized based on inspiration methods such as evolutionary, human, nature, bio-inspired, and physics inspired techniques.

However, the recent optimization techniques have a superiority than the conventional techniques due to the following merits:

- These methods can be applied in both small and large-scale systems
- High reliability to obtain the optimal solutions
- These methods rarely suffer from stagnations or trapped in local minima solutions
- These methods converged rapidly to the optimal solution compared with conventional methods.

REFERENCES

[1] J. Carpentier, Contribution a l'etude du dispatching economique, Bull. Soc. Franc. Elec. 3 (1962) 431–447.

[2] J.A. Momoh, R. Adapa, M. El-Hawary, A review of selected optimal power flow literature to 1993. I. Nonlinear and quadratic programming approaches, IEEE Trans. Power Syst. 14 (1999) 96–104.
[3] J.A. Momoh, M. El-Hawary, R. Adapa, A review of selected optimal power flow literature to 1993. II. Newton, linear programming and interior point methods, IEEE Trans. Power Syst. 14 (1999) 105–111.
[4] J. Zhu, Optimization of Power System Operation, vol. 47, John Wiley & Sons, Hoboken, 2015.
[5] D. Wells, Method for economic secure loading of a power system, Proc. Inst. Electr. Eng. 115 (1968) 1190–1194.
[6] B. Stott, E. Hobson, Power system security control calculations using linear programming, part I, IEEE Trans. Power Appar. Syst. 5 (1978) 1713–1720.
[7] C. Shen, M. Laughton, Power-system load scheduling with security constraints using dual linear programming, Proc. Inst. Electr. Eng. 117 (1970) 2117–2127.
[8] C. Shen, M. Laughton, Determination of optimum power-system operating conditions under constraints, Proc. Inst. Electr. Eng. (1969) 225–239.
[9] A.M. Sasson, Combined use of the Powell and Fletcher-Powell nonlinear programming methods for optimal load flows, IEEE Trans. Power Appar. Syst. 10 (1969) 1530–1537.
[10] A.H. El-abiad, F.J. Jaimes, A method for optimum scheduling of power and voltage magnitude, IEEE Trans. Power Appar. Syst. 4 (1969) 413–422.
[11] H.W. Dommel, W.F. Tinney, Optimal power flow solutions, IEEE Trans. Power Appar. Syst. 10 (1968) 1866–1876.
[12] A.M. Sasson, Decomposition techniques applied to the nonlinear programming load-flow method, IEEE Trans. Power Appar. Syst. 1 (1970) 78–82.
[13] G. Contaxis, C. Delkis, G. Korres, Decoupled optimal load flow using linear or quadratic programming, IEEE Trans. Power Syst. 1 (1986) 1–7.
[14] N. Nabona, L. Freris, Optimisation of economic dispatch through quadratic and linear programming, Proc. Inst. Electr. Eng. 120 (1973) 574–580.
[15] G.A. Maria, J. Findlay, A Newton optimal power flow program for Ontario Hydro EMS, IEEE Trans. Power Syst. 2 (1987) 576–582.
[16] A. Monticelli, W.-H. Liu, Adaptive movement penalty method for the Newton optimal power flow, IEEE Trans. Power Syst. 7 (1992) 334–342.
[17] D.I. Sun, B. Ashley, B. Brewer, A. Hughes, W.F. Tinney, Optimal power flow by Newton approach, IEEE Trans. Power Appar. Syst. 10 (1984) 2864–2880.
[18] S.-D. Chen, J.-F. Chen, A new algorithm based on the Newton-Raphson approach for real-time emission dispatch, Electr. Power Syst. Res. 40 (1997) 137–141.
[19] K. Ponnambalam, V. Quintana, A. Vannelli, in: A fast algorithm for power system optimization problems using an interior point method, Power Industry Computer Application Conference, 1991. Conference Proceedings, 1991, pp. 393–400.
[20] J. Momoh, R. Austin, R. Adapa, E. Ogbuobiri, in: Application of interior point method to economic dispatch, IEEE International Conference on Systems, Man and Cybernetics, 1992, pp. 1096–1101.
[21] H. Pulluri, R. Naresh, V. Sharma, An enhanced self-adaptive differential evolution based solution methodology for multiobjective optimal power flow, Appl. Soft Comput. 54 (2017) 229–245.
[22] W. Bai, I. Eke, K.Y. Lee, An improved artificial bee colony optimization algorithm based on orthogonal learning for optimal power flow problem, Control. Eng. Pract. 61 (2017) 163–172.

[23] X. Yuan, B. Zhang, P. Wang, J. Liang, Y. Yuan, Y. Huang, et al., Multi-objective optimal power flow based on improved strength Pareto evolutionary algorithm, Energy 122 (2017) 70–82.

[24] A.-A.A. Mohamed, Y.S. Mohamed, A.A. El-Gaafary, A.M. Hemeida, Optimal power flow using moth swarm algorithm, Electr. Power Syst. Res. 142 (2017) 190–206.

[25] A. Chaib, H. Bouchekara, R. Mehasni, M. Abido, Optimal power flow with emission and non-smooth cost functions using backtracking search optimization algorithm, Int. J. Electr. Power Energy Syst. 81 (2016) 64–77.

[26] J. Zhang, Q. Tang, P. Li, D. Deng, Y. Chen, A modified MOEA/D approach to the solution of multi-objective optimal power flow problem, Appl. Soft Comput. 47 (2016) 494–514.

[27] B. Mahdad, K. Srairi, Security constrained optimal power flow solution using new adaptive partitioning flower pollination algorithm, Appl. Soft Comput. 46 (2016) 501–522.

[28] S.S. Reddy, C.S. Rathnam, Optimal power flow using glowworm swarm optimization, Int. J. Electr. Power Energy Syst. 80 (2016) 128–139.

[29] K. Abaci, V. Yamacli, Differential search algorithm for solving multi-objective optimal power flow problem, Int. J. Electr. Power Energy Syst. 79 (2016) 1–10.

[30] H. Jadhav, P. Bamane, Temperature dependent optimal power flow using g-best guided artificial bee colony algorithm, Int. J. Electr. Power Energy Syst. 77 (2016) 77–90.

[31] K. Pandiarajan, C. Babulal, Fuzzy harmony search algorithm based optimal power flow for power system security enhancement, Int. J. Electr. Power Energy Syst. 78 (2016) 72–79.

[32] A. Mukherjee, V. Mukherjee, Solution of optimal power flow with FACTS devices using a novel oppositional krill herd algorithm, Int. J. Electr. Power Energy Syst. 78 (2016) 700–714.

[33] H. Bouchekara, A. Chaib, M.A. Abido, R.A. El-Sehiemy, Optimal power flow using an improved colliding bodies optimization algorithm, Appl. Soft Comput. 42 (2016) 119–131.

[34] R.P. Singh, V. Mukherjee, S. Ghoshal, Particle swarm optimization with an aging leader and challengers algorithm for the solution of optimal power flow problem, Appl. Soft Comput. 40 (2016) 161–177.

[35] A.R. Kumar, L. Premalatha, Optimal power flow for a deregulated power system using adaptive real coded biogeography-based optimization, Int. J. Electr. Power Energy Syst. 73 (2015) 393–399.

[36] A. Mukherjee, V. Mukherjee, Solution of optimal power flow using chaotic krill herd algorithm, Chaos, Solitons Fractals 78 (2015) 10–21.

[37] X. Yuan, P. Wang, Y. Yuan, Y. Huang, X. Zhang, A new quantum inspired chaotic artificial bee colony algorithm for optimal power flow problem, Energy Convers. Manag. 100 (2015) 1–9.

[38] A.R. Bhowmik, A.K. Chakraborty, Solution of optimal power flow using non dominated sorting multi objective opposition based gravitational search algorithm, Int. J. Electr. Power Energy Syst. 64 (2015) 1237–1250.

[39] Y. Tan, C. Li, Y. Cao, K.Y. Lee, L. Li, S. Tang, et al., Improved group search optimization method for optimal power flow problem considering valve-point loading effects, Neurocomputing 148 (2015) 229–239.

[40] M. Ghasemi, S. Ghavidel, M.M. Ghanbarian, M. Gharibzadeh, A.A. Vahed, Multi-objective optimal power flow considering the cost, emission, voltage deviation and power losses using multi-objective modified imperialist competitive algorithm, Energy 78 (2014) 276–289.

[41] K. Ayan, U. Kılıç, B. Baraklı, Chaotic artificial bee colony algorithm based solution of security and transient stability constrained optimal power flow, Int. J. Electr. Power Energy Syst. 64 (2015) 136–147.

[42] H. Bouchekara, M. Abido, A. Chaib, R. Mehasni, Optimal power flow using the league championship algorithm: a case study of the Algerian power system, Energy Convers. Manag. 87 (2014) 58–70.
[43] H. Bouchekara, Optimal power flow using black-hole-based optimization approach, Appl. Soft Comput. 24 (2014) 879–888.
[44] M. Ghasemi, S. Ghavidel, M.M. Ghanbarian, H.R. Massrur, M. Gharibzadeh, Application of imperialist competitive algorithm with its modified techniques for multi-objective optimal power flow problem: a comparative study, Inf. Sci. 281 (2014) 225–247.
[45] B.S. Rao, K. Vaisakh, Multi-objective adaptive clonal selection algorithm for solving optimal power flow considering multi-type FACTS devices and load uncertainty, Appl. Soft Comput. 23 (2014) 286–297.
[46] H. Bouchekara, M. Abido, M. Boucherma, Optimal power flow using teaching-learning-based optimization technique, Electr. Power Syst. Res. 114 (2014) 49–59.
[47] H. Chen, M.L. Bo, Y. Zhu, Multi-hive bee foraging algorithm for multi-objective optimal power flow considering the cost, loss, and emission, Int. J. Electr. Power Energy Syst. 60 (2014) 203–220.
[48] B. Mandal, P.K. Roy, Multi-objective optimal power flow using quasi-oppositional teaching learning based optimization, Appl. Soft Comput. 21 (2014) 590–606.
[49] M. Joorabian, E. Afzalan, Optimal power flow under both normal and contingent operation conditions using the hybrid fuzzy particle swarm optimisation and Nelder–Mead algorithm (HFPSO–NM), Appl. Soft Comput. 14 (2014) 623–633.
[50] M.R. Adaryani, A. Karami, Artificial bee colony algorithm for solving multi-objective optimal power flow problem, Int. J. Electr. Power Energy Syst. 53 (2013) 219–230.
[51] A. Shabanpour-Haghighi, A.R. Seifi, T. Niknam, A modified teaching–learning based optimization for multi-objective optimal power flow problem, Energy Convers. Manag. 77 (2014) 597–607.
[52] S. Kumar, D. Chaturvedi, Optimal power flow solution using fuzzy evolutionary and swarm optimization, Int. J. Electr. Power Energy Syst. 47 (2013) 416–423.
[53] M. Ebeed, S. Kamel, H. Youssef, Optimal setting of STATCOM based on voltage stability improvement and power loss minimization using Moth-Flame algorithm, 2016 Eighteenth International Middle East Power Systems Conference (MEPCON), 2016, pp. 815–820.
[54] N. Sinsuphan, U. Leeton, T. Kulworawanichpong, Optimal power flow solution using improved harmony search method, Appl. Soft Comput. 13 (2013) 2364–2374.
[55] A. Khorsandi, S. Hosseinian, A. Ghazanfari, Modified artificial bee colony algorithm based on fuzzy multi-objective technique for optimal power flow problem, Electr. Power Syst. Res. 95 (2013) 206–213.
[56] M.R. Narimani, R. Azizipanah-Abarghooee, B. Zoghdar-Moghadam-Shahrekohne, K. Gholami, A novel approach to multi-objective optimal power flow by a new hybrid optimization algorithm considering generator constraints and multi-fuel type, Energy 49 (2013) 119–136.
[57] T. Niknam, R. Azizipanah-Abarghooee, M.R. Narimani, Reserve constrained dynamic optimal power flow subject to valve-point effects, prohibited zones and multi-fuel constraints, Energy 47 (2012) 451–464.
[58] S. Duman, U. Güvenç, Y. Sönmez, N. Yörükeren, Optimal power flow using gravitational search algorithm, Energy Convers. Manag. 59 (2012) 86–95.
[59] S. Sivasubramani, K. Swarup, Multiagent based differential evolution approach to optimal power flow, Appl. Soft Comput. 12 (2012) 735–740.

[60] T. Niknam, M. Rasoul Narimani, M. Jabbari, A.R. Malekpour, A modified shuffle frog leaping algorithm for multi-objective optimal power flow, Energy 36 (2011) 6420–6432.
[61] A.A. El Ela, M. Abido, S. Spea, Optimal power flow using differential evolution algorithm, Electr. Power Syst. Res. 80 (2010) 878–885.
[62] M.S. Kumari, S. Maheswarapu, Enhanced genetic algorithm based computation technique for multi-objective optimal power flow solution, Int. J. Electr. Power Energy Syst. 32 (2010) 736–742.
[63] S. Sayah, K. Zehar, Modified differential evolution algorithm for optimal power flow with non-smooth cost functions, Energy Convers. Manag. 49 (2008) 3036–3042.
[64] P. Somasundaram, K. Kuppusamy, R.K. Devi, Evolutionary programming based security constrained optimal power flow, Electr. Power Syst. Res. 72 (2004) 137–145.
[65] M. Ghasemi, S. Ghavidel, E. Akbari, A.A. Vahed, Solving non-linear, non-smooth and non-convex optimal power flow problems using chaotic invasive weed optimization algorithms based on chaos, Energy 73 (2014) 340–353.
[66] M. Ghasemi, S. Ghavidel, S. Rahmani, A. Roosta, H. Falah, A novel hybrid algorithm of imperialist competitive algorithm and teaching learning algorithm for optimal power flow problem with non-smooth cost functions, Eng. Appl. Artif. Intell. 29 (2014) 54–69.
[67] C. Roa-Sepulveda, B. Pavez-Lazo, A solution to the optimal power flow using simulated annealing, Int. J. Electr. Power Energy Syst. 25 (2003) 47–57.
[68] M. Abido, Optimal power flow using particle swarm optimization, Int. J. Electr. Power Energy Syst. 24 (2002) 563–571.
[69] M. Varadarajan, K.S. Swarup, Solving multi-objective optimal power flow using differential evolution, IET Gener. Transm. Distrib. 2 (2008) 720–730.
[70] W. Ongsakul, T. Tantimaporn, Optimal power flow by improved evolutionary programming, Electr. Power Compon. Syst. 34 (2006) 79–95.
[71] M. Abido, Optimal power flow using tabu search algorithm, Electr. Power Compon. Syst. 30 (2002) 469–483.
[72] M. Basu, Group search optimization for solution of different optimal power flow problems, Electr. Power Compon. Syst. 44 (2016) 606–615.
[73] H.R. El-Hana Bouchekara, M.A. Abido, A.E. Chaib, Optimal power flow using an improved electromagnetism-like mechanism method, Electr. Power Compon. Syst. 44 (2016) 434–449.
[74] A.A. El-Fergany, H.M. Hasanien, Single and multi-objective optimal power flow using grey wolf optimizer and differential evolution algorithms, Electr. Power Compon. Syst. 43 (2015) 1548–1559.
[75] A.-F. Attia, Y.A. Al-Turki, A.M. Abusorrah, Optimal power flow using adapted genetic algorithm with adjusting population size, Electr. Power Compon. Syst. 40 (2012) 1285–1299.
[76] R. Gnanadass, P. Venkatesh, N.P. Padhy, Evolutionary programming based optimal power flow for units with non-smooth fuel cost functions, Electr. Power Compon. Syst. 33 (2004) 349–361.
[77] I.N. Trivedi, P. Jangir, S.A. Parmar, N. Jangir, Optimal power flow with voltage stability improvement and loss reduction in power system using moth-flame optimizer, Neural Comput. Appl. 1 (2016) 1–16.
[78] H. Pulluri, R. Naresh, V. Sharma, A solution network based on stud krill herd algorithm for optimal power flow problems, Soft. Comput. (2016) 1–18.
[79] M. Abido, N. Al-Ali, Multi-objective optimal power flow using differential evolution, Arab. J. Sci. Eng. (2012) 37.
[80] S. Kumar, D. Chaturvedi, Optimal power flow solution using GA-fuzzy and PSO-fuzzy, J. Inst. Eng. (India): Ser. B 95 (2014) 363–368.

[81] U. Kılıç, Backtracking search algorithm-based optimal power flow with valve point effect and prohibited zones, Electr. Eng. 97 (2015) 101–110.
[82] S.S. Jadon, J.C. Bansal, R. Tiwari, H. Sharma, Artificial bee colony algorithm with global and local neighborhoods, Int. J. Syst. Assur. Eng. Manag. 8 (2014) 1–13.
[83] S.S. Reddy, P. Bijwe, Differential evolution-based efficient multi-objective optimal power flow, Neural Comput. Appl. (2017) 1–14.
[84] K. Vaisakh, L. Srinivas, K. Meah, Genetic evolving ant direction PSODV hybrid algorithm for OPF with non-smooth cost functions, Electr. Eng. Arch. Elektrotech. 95 (2012) 1–15.
[85] A. Gacem, D. Benattous, Hybrid genetic algorithm and particle swarm for optimal power flow with non-smooth fuel cost functions, Int. J. Syst. Assur. Eng. Manag. 8 (2017) 146–153.
[86] V. Raviprabakaran, R.C. Subramanian, Enhanced ant colony optimization to solve the optimal power flow with ecological emission, Int. J. Syst. Assur. Eng. Manag. 5 (2012) 1–8.
[87] S. Duman, Symbiotic organisms search algorithm for optimal power flow problem based on valve-point effect and prohibited zones, Neural Comput. Appl. (2016) 1–15.
[88] A.M. Shaheen, R.A. El-Sehiemy, S.M. Farrag, Solving multi-objective optimal power flow problem via forced initialised differential evolution algorithm, IET Gener. Transm. Distrib. 10 (2016) 1634–1647.
[89] A. Bhattacharya, P. Chattopadhyay, Application of biogeography-based optimisation to solve different optimal power flow problems, IET Gener. Transm. Distrib. 5 (2011) 70–80.
[90] A.G. Bakirtzis, P.N. Biskas, C.E. Zoumas, V. Petridis, Optimal power flow by enhanced genetic algorithm, IEEE Trans. Power Syst. 17 (2002) 229–236.
[91] J. Yuryevich, K.P. Wong, Evolutionary programming based optimal power flow algorithm, IEEE Trans. Power Syst. 14 (1999) 1245–1250.
[92] E. Barocio, J. Regalado, E. Cuevas, F. Uribe, P. Zúñiga, P.J.R. Torres, Modified bio-inspired optimisation algorithm with a centroid decision making approach for solving a multi-objective optimal power flow problem, IET Gener. Transm. Distrib. 11 (2016).
[93] D. Devaraj, B. Yegnanarayana, Genetic-algorithm-based optimal power flow for security enhancement, IEE Proc. Gener. Transm. Distrib. 152 (2005) 899–905.
[94] C.-M. Huang, Y.-C. Huang, Hybrid optimisation method for optimal power flow using flexible AC transmission system devices, IET Gener. Transm. Distrib. 8 (2014) 2036–2045.
[95] D.B. Das, C. Patvardhan, Useful multi-objective hybrid evolutionary approach to optimal power flow, IEE Proc. Gener. Transm. Distrib. 150 (2003) 275–282.
[96] T. Niknam, M. Narimani, J. Aghaei, S. Tabatabaei, M. Nayeripour, Modified honey bee mating optimisation to solve dynamic optimal power flow considering generator constraints, IET Gener. Transm. Distrib. 5 (2011) 989–1002.
[97] L.L. Lai, J. Ma, R. Yokoyama, M. Zhao, Improved genetic algorithms for optimal power flow under both normal and contingent operation states, Int. J. Electr. Power Energy Syst. 19 (1997) 287–292.
[98] M. Osman, M.A. Abo-Sinna, A. Mousa, A solution to the optimal power flow using genetic algorithm, Appl. Math. Comput. 155 (2004) 391–405.
[99] S. Kahourzade, A. Mahmoudi, H.B. Mokhlis, A comparative study of multi-objective optimal power flow based on particle swarm, evolutionary programming, and genetic algorithm, Electr. Eng. 97 (2015) 1–12.
[100] M. Ghasemi, S. Ghavidel, M. Gitizadeh, E. Akbari, An improved teaching–learning-based optimization algorithm using Lévy mutation strategy for non-smooth optimal power flow, Int. J. Electr. Power Energy Syst. 65 (2015) 375–384.
[101] S.S. Reddy, P. Bijwe, A. Abhyankar, Faster evolutionary algorithm based optimal power flow using incremental variables, Int. J. Electr. Power Energy Syst. 54 (2014) 198–210.

[102] T. Niknam, M.R. Narimani, R. Azizipanah-Abarghooee, A new hybrid algorithm for optimal power flow considering prohibited zones and valve point effect, Energy Convers. Manag. 58 (2012) 197–206.

[103] T.T. Nguyen, in: "Neural network optimal-power-flow" Australia, Proceedings of the 4th International Conference on Advances in Power System Control, Operation and Management, APSCOM-97, Hong Kong, November, 1997.

[104] B. Venkatesh, Online ANN memory model–based method for unified OPF and voltage stability margin maximization, Electr. Power Compon. Syst. 31 (2003) 453–465.

[105] V.C. Ramesh, X. Li, Optimal power flow with fuzzy emissions constraints, Electr. Mach. Power Syst. 25 (1997) 897–906.

[106] V.C. Ramesh, X. Li, A fuzzy multiobjective approach to contingency constrained OPF, IEEE Trans. Power Syst. 12 (1997) 1348–1354.

[107] Y. Terasawa, S. Iwamoto, Optimal power flow solution using fuzzy mathematical programming, Electr. Eng. Jpn. 108 (1988) 46–54.

[108] S. Ghosh, B.H. Chowdhury, Security-constrained optimal rescheduling of real power using Hopfield neural network, IEEE Trans. Power Syst. 11 (1996) 1743–1748.

[109] A.A. Abou El-Ela, et al., Optimal preventive control actions using multi-objective fuzzy linear programming technique, Electr. Power Syst. Res. 74 (2005) 147–155.

[110] P. Kessel, H. Glavitsch, Estimating the voltage stability of a power system, IEEE Trans. Power Deliv. 1 (1986) 346–354.