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An Analytical Review of Multi-objective Optimal Power Flow Techniques

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Abstract

Power systems are becoming larger and complex with rise in electricity demand. This increases complexity of a system for finding the optimal solution of power flow problem. Solution of optimal power flow (OPF) problem has now become necessity for electrical utilities because of the objectives of minimum fuel cost, power loss, emission and voltage deviation, which are non-convex, non-linear and non-smooth in nature. Consequently, system can cause severe damage both physically and economically if operated without any power flow analysis. This paper reviews different optimization techniques for solution of OPF problems with one or more objectives subject to balanced and unbalanced constraints.

Keywords: Conventional methods, classification of optimization techniques, heuristic methods, multi-objective optimal power flow, optimization techniques.

INTRODUCTION

Optimal power flow (OPF) has now become important tool for power system which is used broadly in power system planning and operation. An optimization problem includes objective function to be optimized, a set of decision variables and balanced and unbalanced constraints. The objective function in case of OPF is traditionally a sum of linear or quadratic generation costs which are calculated from the decision variables, which are typically generator output power values in the system [1]. The constraints can simulate various power system phenomena, such as thermal limits of lines and generators, as well as control policies. In the 1960's, a method was developed to investigate non-deterministic in feeds and their effects on line flows in a power system [2]. However, many of the equations developed were non-linear and therefore very difficult to compute with the hardware available at the time. As the consumption of electricity is increasing day by day, more energy power plants are being established and connected to power grid. Therefore, this increases the instability in the power system. The solution of non-linear equations within optimization problems has now become feasible because of availability of faster equipment. OPF problem can be solved by conventional or heuristic methods. Many researchers have shown that conventional methods in present scenario cannot give reliable solution because of poor convergence, local optima entrapment and slower speed. If the numbers of variables are large, their computational speed for optimizing a solution becomes too slow and expensive for solution of a large system [3]. Therefore, the conventional deterministic methods are not enough for finding a desired optimal solution. To overcome the limitations of conventional methods, a probabilistic, learning or goal discovery based approach or heuristic approach is used. In the next section, a brief idea of OPF problem and different optimization techniques used for solving OPF problem is presented.

OPTIMAL POWER FLOW AND CLASSIFICATION OF OPTIMIZATION TECHNIQUES

The OPF problem as discussed in earlier section contains large scale optimization problem, non-linear objectives having both discrete and continuous variables. Optimization of multiple objectives like minimum of generation cost, voltage deviation, power losses and emission can be done by controlling flow of power in an electrical system without breaching network constraints or system operating limits. OPF determines voltage, current and power injected for the system similarly as conventional power flow analysis but works with under constrained system, so that, multiple solutions are possible [4]. In present scenario, system requires not only economic operation but also environmental friendly and feasible operating system. This increases complexity and non-linearity of the system for solving OPF problem. Many objectives need to be optimized in a single run. Many researchers have come up with several techniques or methods to solve the multi-objective problems.

Optimization techniques are classified in two parts conventional methods and heuristic methods. There are several techniques for optimization purpose. Fig.1 shows different optimization techniques including some popular techniques for solution of OPF problem. Conventional methods have limited capability of handling large scale system constraints and require initial starting point for optimization. They are poor in convergence and may trap in local optimum. They are mostly suitable for single objective at single run and become slow if there is large number of variables. Consequently, these methods are computationally not suitable for finding solution of multiple objectives with several variables [5]. To overcome these drawbacks from analytical methods, heuristic based methods have been flourished in recent past. The main advantage of these methods is that they are versatile for handling large qualitative constraints. They are more suitable to find global optimum solution as well as local optimum solution.

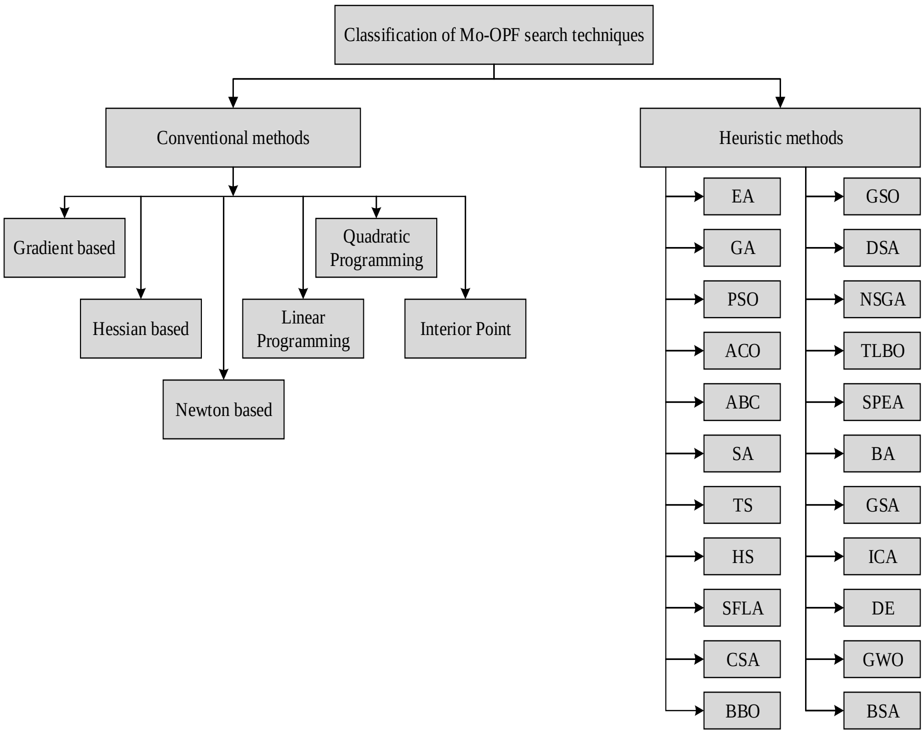

Figure 1: Classification of Optimization Techniques

In the tables below, there are several methods for multiple objective optimization of the OPF problem which have already been proposed. Here, some of the techniques briefly explained which are largely used by the searchers and shown in table 1 and 2. Optimization of active and reactive power dispatch problem while maximizing voltage security is done by using interior point method along with goal programming and linearity combined objective functions [6]. In [7], an improved real and reactive power control technique using linear programming proposed which partitioned Jacobian matrix in a unified way, consequently common sensitivity matrices for both real and reactive power can be achieved. An evolutionary programming based OPF algorithm enhanced by the inclusion of gradient information to speed the search in areas local to candidate solutions and less sensitive to starting points proposed in [8]. In [9], genetic algorithm (GA) is used for solving OPF problem in feasible and reliable way satisfying the equality constraints with the desired precision. In [10], a Non-dominated Sorting Genetic Algorithm (NSGA) technique is proposed for solving environment/emission dispatch optimization problem with diversity preserving mechanism. In [11], a modified Improved NSGA (NSGA-II) algorithm presented for economic and emission dispatch problem which overcomes the drawbacks of NSGA-II for lacking uniform diversity and absence of lateral diversity among the non-dominated solutions. In [12], a mathematical model for solving multi-objective OPF (Mo-OPF) problem considering uncertainties modeled by fuzzy numbers and a model developed for analyzing trade-off between profit and security constraint. A Mo-OPF solution proposed by parallel elitist NSGA-II with innovative weight assuming technique based on fuzzy membership variance considering fuel cost and transient stability as objective function. In [3], a novel particle swarm optimization (PSO) based approach to OPF problem is presented with flexibility to control the balance between the global and local search space and avoids premature convergence of the search process. In [13], this paper proposed chaotic improved PSO (CIPSO) based optimization technique to minimize power losses and L-index in power systems for multi-objective reactive power dispatch (MORPD) problem. In [14], the Mo-OPF problem considering fuel cost and losses as objective function solved by stochastic weighted turn-off chaotic PSO (SWTCPSO). This paper used mechanism of stochastic weighted turn-off and dynamic coefficients factors to overcome the premature convergence. The DE algorithm presented for the solution of Mo-OPF under contingent operations stated considering multiple shunt FACTS devices [15]. A solution of Mo-OPF implemented using DE algorithm demonstrated effectiveness and robustness over evolutionary based NSGA-II and classical weighted summation approach in [16]. The Efficient EA proposed with the concepts from simple evolutionary algorithm and classical algorithms to solve the OPF problem in [17]. The Strength Pareto Evolutionary Algorithm (SPEA) proposed for solution of OPF problem to get optimal cost and voltage profile for the system [18]. In [19], the improved SPEA (SPEA2) technique presented to overcome the drawbacks of multiple runs, inability to find Pareto optimal solutions for non-convex optimal front. The modified teaching learning based optimization (TLBO) presented aiming to solve the multiple objective problems by self-adaptive wavelet technique to deal with search capability, population diversity and convergence speed [20]. In [21], non-dominated sorting multi-objective opposition based GSA (NSMOGSA) proposed to solve different single and multiple OPF problems by improving the current population toward optimal solutions and accelerating the convergence of the solutions.

Table 1 shows some of the conventional optimization methods for solving OPF problems and Table 2 shows some heuristic methods and applied methods on these heuristic techniques in subsection. These tables also show the controlling parameters of methods and power flow constraints used in particular.

Table 1. Brief summary of solution of OPF problem by conventional methods

Techniques	Controlling parameters	Objective function	Constraints	Remark
Newton based Mathematical method [22]	-	-	V_{g1}=[0.915,1.14] V_{g2}=[0.95,1.05]	A practical Solution for power flow problem considering control variables to minimize system costs or losses
Hessian method [23]	ρ_L = [0,1]	$Min\sum_{i=1}^{N_g}\left(a_i P_{g_i}^2 + b_i P_{g_i} + c_i\right)$	-	A reduced hessian based optimization method for solving economic dispatch problem
PQ decomposition [24]	λ_0 = [0,1]	$Min\sum_{i=1}^{N_l} g_k\left(V_i^2 + V_j^2 - 2V_iV_j\cos\left(\theta_{ij}\right)\right)$	V_1=[0.9,1.1] V_3=[0.9,1.1]	Cost and transmission real power losses are considered as objective function
Quadratic Programming [25]	-	$Min\sum_{i=1}^{N_g}\left(a_i P_{g_i}^2 + b_i P_{g_i} + c_i\right)$ $Min\sum_{i=1}^{N_l} g_k\left(V_i^2 + V_j^2 - 2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i - V_{ref}\rvert$	-	Extension of basic Kuhn-Tucker conditions and employing a quadratic model
Quasi-Newton Approach [26]	-	-	-	Used explicit Newton method for OPF problem solution. Employing Special sparsity technique
Interior point method [6]	λ_p = [0.8,1.6]	$Min\sum_{i=1}^{N_g}\left(a_i P_{g_i}^2 + b_i P_{g_i} + c_i\right)$	-	Goal programming and linearly combined objective functions
Interior Point Method [27]	-	$Min\sum_{i=1}^{N_g}\left(a_i P_{g_i}^2 + b_i P_{g_i} + c_i\right)$	V = [0.95,1.1]	A versatile, efficient and faster method among the gradient based methods
Linear Programming [7]	-	$Min\sum_{i=1}^{N_g}\left(a_i P_{g_i}^2 + b_i P_{g_i} + c_i\right)$	V_g=[0.9,1.15] V=[0.95,1.05] T_p=[0.9,1.1] Q_c=[0,15.5]	Uniformly partitioned Jacobian matrix for common sensitivity matrices for both real and reactive power

Table 2. Review of heuristic methods for solving OPF problem

Techniques	Applied method, year and reference	Controlling parameters	Objective Function	Constraints	Remarks
GA (Genetic Algorithm)	GA, 2004, [9]	$P_m = 0.9$, $P_c = 0.01$, $\delta = [0,1]$, $\mu = [0,1]$	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_l}g_k\left(V^2{}_i+V^2{}_j-2V_iV_j\cos\left(\theta_{ij}\right)\right)$	V_g=[0.95,1.05] V=[0.9,1.1] Q_c=±75%	Satisfying the equality constraints with the desired precision
	Enhanced GA, 2002, [28]	P_c=0.9, P_m=0.01	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	V_g=[0.95,1.05] T_p=[0.9,1.1] Q_c=[0.0,0.05]	Using problem specific operators to get faster operation
	Modified NSGA-II, 2011, [11]	P_c=0.85, P_m=1/6, η_C=5, η=15, rr=0.65	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_iP_{g_i}}\right)$	-	Overcomes the uniform diversity and absence of a lateral diversity among the Pareto-optimal solutions
	Multi-objective GA, 2013, [12]	P_c=0.7, P_m=0.061, λ_l=[1,2]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$ $Min\sum_{i=1}^{N_g}\left(\alpha P^2{}_{g_i}+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_iP_{g_i}}\right)$	V_g=[0.95,1.05] T_p=[0.9,1.1]	Considering uncertainties modelled by fuzzy numbers and a model developed for analyzing trade-off between profit and security constraints
	Parallel NSGA-II, 2015, [29]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Max\sum_{i=1}^{N_g}\sum_{k=1}^{N_f}\sum_{n=k}^{\frac{T}{\Delta t}}\left\{\left[\phi\left(\left\lvert\delta_n^i(k)-\delta_n^{GOI}(k)\right\rvert,\delta^{'}\right)\lambda\right]\right\}$	-	Algorithm with innovative weight assuming method based on fuzzy membership variance
	NSGA, 2003, [10]	α_C=0.5, r=[0,1], β=5, λ_f=3000, w=$rand$[0,1], P_c=0.9, P_m=0.1	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\lvert d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\rvert\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{g_i}}\right)$	-	Proposed algorithm applied with diversity preserving mechanism
	Modified NSGA-II, 2011, [30]	-	$Min\sum_{k=1}^{N_l}g_k\left(\mathrm{V}_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Max\left(L_{index}\right)$	V_g=[0.95,1.1] Q_c=[0,0.01]	Incorporating controlled elitism and dynamic crowding distance for solving ORPD problem
	EGA-DQLF, 2010, [31]	P_c=1.0, P_m=0.006, C_1=C_2=2.05, ω=1.2	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{k=1}^{N_l}g_k\left(\mathrm{V}_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Max\left(L_{index}\right)$	V_g=[0.95,1.1] V=[0.95,1.05] T=[0.9,1.1] Q_c=[0,0.01]	Better optimal solution and calculate recommended set points for power system controls
	NSGA-II, 2010, [32]	w_v=w_q=0.5	$Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$	-	Robust MORPD includes information of load increase directions to assist the stability of most favourable solutions in the presence of load irregularities

Techniques	Applied method, year and reference	Controlling parameters	Objective Function	Constraints	Remarks
PSO (Particle Swarm Optimization)	PSO, 2002, [3]	ω=1.0, α_d=0.98, C_1=C_2=2	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	V=[0.95,1.1] V_g=[0.95,1.1] T=[0.9,1.1] Q_c=[0.0,0.05]	Flexible technique. Avoids premature convergence
	Modified PSO, 2005, [33]	$\omega_{min,}$ =[0.1,0.5], ω_{max}=[0.5,1.0], C_1,C_2=[1,2], Δ=[0.01,0.8]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	-	Dynamic search space reduction strategy to improve the convergence speed
	Improved PSO, 2012, [34]	ω=[0.9,0.4]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Max\left(L_{index}\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$	T_p=[0.9,1.1]	Allows several non-dominated solutions
	CIPSO, 2014, [13]	ω_{max}=0.9, ω_{min}=0.4, r_1,r_2=(0,1), λ_{CP}=[0,4], c_1,c_2=2, P_C=0.8	$Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Max\left(L_{index}\right)$	V=[0.94,1.06] V_g=[0.9,1.1] T_p=[0.9,1.1] Q_c=[0.0,0.3]	Minimization of power losses and voltage stability index improvement as objective function
	SWTCPSO, 2015, [14]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{k=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$	V=[0.95,1.05] T=[0.95,1.05] Q_c=[0,0.05]	-
	Multi-objective PSO, 2011, [35]	C_1,C_2=[0,4]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{gi}}\right)$	-	PSO technique with dynamic velocity control
DE (Differential Evolution)	Tribe Modified DE, 2013, [36]	η_1,η_2=1	$Min\sum_{i=1}^{N_g}(a_iP_{g_i}^2+b_iP_{g_i}+c_i)$ $Min\sum_{i=1}^{N_g}\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_iP_{gi}}$	-	-
	Multi-objective DE, 2012, [37]	N_p=100, P_m=0.5, P_C=0.98	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\|d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\|\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V^2{}_j-2V_iV_j\cos\left(\theta_i-\theta_j\right)\right)$ $Min\sum_{i=1}^{N_l}\|V_i-V_{ref}\|$	V_g=[0.95,1.1] V=[0.95,1.05] T=[0.9,1.1] Q_c=[0,5]	Cluster based technique to deal with the size of Pareto optimal set and obtain finest balance solution for assisting the decision maker
	Enhanced self-adaptive DE, 2017, [38]	W_p=W_r=W_q= W_s=200000, P_m=[0.5,1], P_C=[0.5,1], N_Ω=21	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{g_i}}\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2-V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$	V=[0.9,1.1] T_p=[0.9,1.1] Q_c=[0,0.05]	-

Techniques	Applied method, year and reference	Controlling parameters	Objective Function	Constraints	Remarks
	Efficient DE, 2017, [39]	P_m=0.9, P_c=0.5, w_1,w_2=(0,1)	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\|d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\|\right)$ $Min\sum_{i=1}^{N_l}\sum_{j=1}^{N_l}R_{ij}\frac{\left(\|V_i^2\|+\|V_j^2\|-2\|V_i\|\|V_j\|\cos\left(\delta_{ij}\right)\right)}{\|z_{ij}^2\|}$ $Min\sum_{i=1}^{N_l}\sum_{j=1}^{N_l}Q_{ij}\frac{\left(\|V_i^2\|+\|V_j^2\|-2\|V_i\|\|V_j\|\sin\left(\delta_{ij}\right)\right)}{\|z_{ij}^2\|}$ $Min\sum_{i=N_g+1}^{n}\left[\frac{\|V_i\|-V_{avg}}{dV}\right]^{2n}$	V_g=[0.95,1.1] T_P=[0.95,1.1] Q_C=[0,0.05]	Multi-objective problem solution using Tchebycheff decomposition approach
	DE, 2017, [16]	P_m=0.9, P_c=0.5, w_1,w_2=(0,1)	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$	V_g=[0.95,1.1] T_P=[0.95,1.1] Q_C=[0,0.05]	Demonstrating effectiveness and robustness over evolutionary based NSGA-II and classical weight summation approach
	Forced initialised DE, 2016, [40]	P_m=0.6, P_C=0.9	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_l}\|V_i-V_{ref}\|$ $Max\left(L_{index}\right)$	V_g=[0.95,1.1] V=[0.95,1.05] Q_c=[0,5] T_P=[0.9,1.1]	DE algorithm combined with epsilon constraint approach
	Modified DE, 2008, [41]	P_C=0.75, P_m=0.7	$Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$	V_g=[0.9,1.1] V=[0.95,1.05] Q=±75%	-
	Simple DE, 2013, [15]	P_m=0.6, P_C=0.4	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_l}\|V_i-V_{ref}\|$ $Max\left(L_{index}\right)$	V_g=[0.95,1.1] V=[0.95,1.05] T=[0.9,1.1] Q_c=[0, 0.05]	OPF solution under contingent operations stated considering multiple shunt FACTS devices
EA (Evolutionary Algorithm)	Improved SPEA, 2017, [42]	P_c=0.8, P_m=0.2, Ne=50	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{g_i}}\right)$	V=[0.95,1.05] T_P=[0.9,1.1]	Improved environment selection strategy and external elite population update strategy

Techniques	**Applied method, year and reference**	**Controlling parameters**	**Objective Function**	**Constraints**	**Remarks**
	Modified Multi-objective EA based decomposition, 2016, [43]	P_m, P_C = 0.5	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$	V_g= [0.95,1.1] V_L=[0.9,1.05] T_p=[0.9,1.05]	Solution for single and multi-objective power flow problem
	Efficient EA, 2014, [44]	P_c=0.95, P_m=0.001, C_1=C_2=2.05, ω=1.2, E_i=0.15	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\lvert d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\rvert\right)$	V_g=[0.95,1.1] V=[0.95,1.05] Q_c=[0,0.05] T_p=[0.9,1.1]	Efficient and effective than Classical algorithm and simple evolutionary algorithm
	SPEA, 2004, [18]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Max\left(L_{index}\right)$	-	Optimal cost and voltage profile for the system
	SPEA2, 2011, [19]	P_c= 0.9, P_m= 0.01	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Max\left(L_{index}\right)$	V=[0.95,1.05]	Overcome the drawbacks of multiple, inability to find Pareto-optimal solutions for non-convex optimal front
	MOEA, 2017, [17]	W_1=[0,1]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Max\left(L_{index}\right)$	V=[0.95,1.1] T_P=[0.9,1.1] Q_c=[0,0.05]	Using lower and upper bounds for determining cost of generation in order to reduce computational burden
TLBO (Teaching Learning Based Optimization)	Improved TLBO, 2015, [20]	γ_S=1, α_S=0.8	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$	V=[0.95,1.05] T_P=[0.9,1.1] Q_C=[0,0.3]	Used self-adaptive wavelet technique to handle search capability, population diversity and convergence speed
	Simple TLBO, 2014, [45]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	V_g=[0.95,1.1] T_P=[0.9,1.1] Q_c=[0,5]	-
GSA (Gravitational Search Algorithm)	GSA, 2012, [46]	G_o=100, α=20	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\lvert d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\rvert\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$	-	Required less memory. Accurate, Efficient than NSGA-II, MODE, PDE, SPEA

Techniques	Applied method, year and reference	Controlling parameters	Objective Function	Constraints	Remarks
	NSMOGSA, 2015, [21]	-	$Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$ $Min\sum_{i,j=1}^{N_l} g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Max\left(L_{index}\right)$	V=[0.95,1.1] T_P=[0.9,1.1] Q_C=[0,30]	Improved current population toward optimal solutions and accelerating convergence speed
GSO (Group Search Optimization)	Adaptive GSO, 2016, [47]	r=(0,1)	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{g_i}}\right)$ $Max\left(w_l\sum_{l=1}^{nl}\left(\frac{s_l}{s_{l\max}}\right)+w_v\sum_{i=1}^{nb}\left(\Delta V_i\right)\right)$	V_g=[0.94,1.06] T_p=[0.9,1.1] Q_c=[0,0.3]	Feasible operating ranges of the generators with fuzzy decision maker
ABC (Artificial Bee Colony)	ABC, 2010, [48]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	-	Faster computation time and convergence than GA and PSO
	Efficient ABC, 2013, [49]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_iP_{g_i}}\right)$ $Min\sum_{i,j=1}^{N_l} g_k\left(V_i^2+V_j^2-2t_kV_iV_j\cos\left(\theta_i-\theta_j\right)\right)$ $Max\left(L_{index}\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$	V_g=[0.95,1.1] V=[0.95,1.05] Q_c=[0,0.05] T_p=[0.9,1.1]	Gives efficient and effective solution. Satisfying all the constraints
	BFA (Bee Foraging Algorithm), 2011, [50]	P=6, S=100, N_c=50, N_{ed}=15, P_{ed}=0.1, P_g=0.2, $c(i)$=0.1, M=2	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{g_i}}\right)$	-	Using some performance matrices to improve convergence and diversity of the solution
GWO (Grey Wolf Optimization)	Wolf algorithm, 2015, [51]	-	$Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_iP_{g_i}}\right)$ $Min\sum_{i,j=1}^{N_l} g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$	-	Inspired by exploration and social behaviour of grey wolf
	Hybrid GWO, 2016, [52]	ω=[0.4,1] P_m=[0,0.2]	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\lvert d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\rvert\right)$	-	Enhanced mutation and crossover parameters better performance

Techniques	**Applied method, year and reference**	**Controlling parameters**	**Objective Function**	**Constraints**	**Remarks**
	GWO-DE, 2015, [53]	-	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\|d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\|\right)$ $Min\sum_{i=1}^{N_l}\sum_{j=1}^{N_l}R_{ij}\frac{\left(\|V_i^2\|+\|V_j^2\|-2\|V_i\|\|V_j\|\cos\left(\delta_{ij}\right)\right)}{\|z_{ij}^2\|}$ $Min\sum_{i=1}^{N_l}\sum_{j=1}^{N_l}X_{ij}\frac{\left(\|V_i^2\|+\|V_j^2\|-2\|V_i\|\|V_j\|\sin\left(\delta_{ij}\right)\right)}{\|z_{ij}^2\|}$ $Min\sum_{i=N_g+1}^{n}\left[\frac{\|V_i\|-V_{avg}}{dV}\right]^{2n}$	V_g=[0.95,1.1] T_P=[0.9,1.1] Q_C=[0,5.0]	Hybrid GWO and DE algorithms to check viability for the small and large systems with different scenarios
HS (Harmony Search)	Improved HS, 2013, [54]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	V_g=[0.9,1.05] T_P=[0.9,1.1]	Refined the intervals of design parameters to achieve better optimization
	Multi-objective HS, 2011, [55]	*Consideration rate*= 0.8, *range*=0.2	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{k=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Max\left(L_{index}\right)$	V_g=[0.9,1.05] T_P=[0.95,1.05] Q_C=[0,0.05]	Crowded comparison operator used for finding Pareto optimal solutions
	Differential HS, 2014, [56]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Max\left(L_{index}\right)$	T=[0.9,1.05] V=[0.95,1.1] Q_c=[0,5]	Enhancing the exploitation ability and strengthened the exploration ability of the algorithm
ACO (Ant Colony Optimization)	Ant Colony Search, 2011, [57]	α_w=2.50, β_w=1.89, ρ_P=0.15, τ_{min}=0.05, τ_{max}=10	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	-	Algorithm used in as middle phase between the UC and ED phases
	OPF-Security constraint ACO, 2013, [58]	α_P=9, β_P= 11, ρ_e=0.5, q_0= 0.1	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\|d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\|\right)$	-	Checking viability to counter the non-convex, non-linear behaviour of OPF problem
BA (Bat Algorithm)	BAT Algorithm, 2013, [59]	A=0.9, r=0.1, f_{min}=0, f_{max}=2	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	-	-
	Theta-modified BA, 2016, [60]	*Constant Parameters* (α=0.5, γ=0.2)	$Min\sum_{i=1}^{N_g}\left(\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)+\left\|d_i\sin\left(e_i\left(P_{g_i}^{\max}-P_{g_i}\right)\right)\right\|\right)$	-	Phase angle vectors used for updating bat position to get better convergence and solution
Trust Region strategy	Multi-objective optimal Economic and Emission Load Dispatch, 2014, [61]	ρ_1=1, σ=1, r_0=1, β=0.1, ε_1=10^{-8}, ε_2=10^{-8}, W_1,W_2=[0.4,0.6]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_iP_{g_i}}\right)$	-	More efficient strategy for less or ill-defined, non-convex systems

Techniques	Applied method, year and reference	Controlling parameters	Objective Function	Constraints	Remarks
	Mo-OPF, 2017, [62]	δ_{min}=10^{-3}, δ_{max}=10^{5}, γ_1=10^{-4}, η_2=0.5, α_1=0.5, α_2=2, ε_1=10^{-10}, η=0.1	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$ $Min\sum_{i,j=1}^{N_l} g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$	-	Tchebychev approach for local optimization, Coleman-Li scaling matrix for global Optimization, Hessian technique for handling the feasible trust region sub-problems
Imperialist Comparative Algorithm	Modified ICA, 2014, [63]	λ_S=1000, λ_V=λ_Q= 50000, λ_P= 100000000	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l} g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$	V=[0.95,1.05] V_g=[0.95,1.1] T_P=[0.9,1.1] Q_C=[0,0.05]	Allowing decision maker to obtain a better informed decision regarding the cooperation of objective
	MOMICA, 2014, [64]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l} g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$	V_g=[0.95,1.1] V=[0.95,1.05] T_p=[0.9,1.1] Q_c=[0,0.05]	-
EP (Evolutionary Programming)	EP, 1999, [8]	u =[0,1]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	V_g=[0.95,1.1] V=[0.95.1.05] T_p= [0.9,1.05]	Used gradient information to speed up the local search. Less sensitive to starting points
	PSO, GA, EP, 2015, [65]	C_1=C_2=2, ω_1=0.9, ω_2=0.4, λ_1,λ_2=[0,1], P_m =0.01, P_c=0.9	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l} g_k\left(V_i^2+V_j^2-2V_iV_j\cos\left(\theta_{ij}\right)\right)$ $Max\left(L_{index}\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$	V,V_g= [0.95,1.1]	Comparison of algorithms on the basis of better solution, convergence speed, time taken to complete the operation and quality of solution
	SA (Simulated Annealing), 2003, [66]	T_o=500, M_o=30, ρ_o=0.90, α_w=100, β_w=1	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	V_g=[0.95,1.1] V=[0.9,1.1]	Global optimum achieved by adequate selection of annealing parameters and weighting factors
	TS (Tabu Search), 2002, [5]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	V_g=[0.95,1.1] T_p=[0.9,1.1] V=[0.95,1.05]	Flexible memory of search history to prevent cycling and to avoid jumbling in local search

Techniques	Applied method, year and reference	Controlling parameters	Objective Function	Constraints	Remarks
	WCA (Water Cycle Algorithm), 2016, [67]	r=[0,1], c=[1,2]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	V_g=[0.94,1.06] T_p=[0.9,1.1] Q_c=[0,30]	Inspired by the surface run-off phase strategy
	Hybrid CSA (Cuckoo Search Algorithm), 2014, [68]	λ_{lf}=[1,3], α_{lf}=[-1,1]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_l}g_k\left(V^2{}_i+V^2{}_j-2V_iV_j\cos(\theta_{ij})\right)$ $Max(\mathrm{L}_{index})$	V_g=[0.95,1.1] T_p=[0.9,1.1] Q_c=[0,5]	Employed levy flights and crossover operations to find the steady state operating point
	DSA (Differential Search Algorithm), 2016, [69]	-	$Min\sum_{k=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos(\theta_{ij})\right)$ $Max(L_{index})$	Q_g = ±75% V_g=[0.95,1.1] V=[0.95,1.05] Q_c=[0,0.05] T_p=[0.9,1.05]	Applied successfully to various complex OPF problems
	BBO (Bio-geography Based Optimization), 2010, [70]	P_{mod}=1, P_m=0.05, I=1, E=1, $elitism$ =4	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos(\theta_{ij})\right)$	V_g=[0.95,1.1] V=[0.95,1.05] T=[0.9,1.1] Q_c=[0,5]	Employed to small and large systems having linear/non-linear constraints and smooth/ non-smooth cost curves with different OPF problems
	KHA (Krill Herd Algorithm), 2015, [71]	V_i^{max}= 0.01, V_i^{max}= 0.05, ω_n, ω = 0.9, Position constant vector(C_t) = 0.3	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i,j=1}^{N_l}g_k\left(V_i^2+V_j^2-2V_iV_j\cos(\theta_{ij})\right)$ $Min\sum_{i=1}^{N_l}\lvert V_i-V_{ref}\rvert$ $Max(L_{index})$	V=[0.95,1.05] T=[0.95,1.05] Q_c=[0,0.05]	Algorithm inspired by herding behaviour of krill individuals
	Epsilon constraint based OPF solution, 2010, [72]	w_1=w$_2$=0.5	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$	-	A fuzzy based decision maker is used to get best solution from Pareto-optimal set
	Game Theory based EED, 2015, [73]	θ=[0,1], w_1=w_2=w_3=1/3, w=[0,1]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha P_{g_i}^2+\beta P_{g_i}+\gamma_i+\xi e^{\lambda_i P_{g_i}}\right)$	-	Considering additional practical limitation like budgetary and maximum consumer load
	Hybrid ACO-ABC-HS method. 2016, [74]	Φ=$rand$[-1,1]	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_i P_{g_i}}\right)$	-	Hybrid method provide better features of these techniques in a single framework for better solution
	Game Theory formulation based, 2015, [75]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$	-	Converts unbalanced constraints into viable action sets and engulf equality constraints by penalty factors

Techniques	Applied method, year and reference	Controlling parameters	Objective Function	Constraints	Remarks
	GSO (Glowworm Search Optimization), 2016, [76]	γ=0.95, β=0.0005, ρ= 0.95, n_t =4, r_s=0.005, r_d=0.0005	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{g_i}}\right)$	V=[0.95,1.1] T_p=[0.9,1.1] Q_c=[0,0.05]	Comparison of GSO to PSO in terms of convergence, solution quality and computational time
	SFLA (Shuffle Frog Leaping Algorithm), 2011, [77]	P=2	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{g_i}}\right)$	V=[0.95,1.05]	Proposed algorithm does not impose any limitations on the number of objectives to achieve a set of solutions
	BSA (Back-tracking Search Algorithm), 2016, [78]	-	$Min\sum_{i=1}^{N_g}\left(a_iP_{g_i}^2+b_iP_{g_i}+c_i\right)$ $Min\sum_{i=1}^{N_g}\left(\alpha_iP_{g_i}^2+\beta_iP_{g_i}+\gamma_i+\xi_ie^{\lambda_iP_{g_i}}\right)$	V=[0.9,1.1]	Solution by this algorithm compared with DE, PSO, ABC, GA and BBO

In above tables, following variables are defined as

P_m = Mutation Probability;

P_{mod}=Habitat modification probability;

P_C = Crossover Probability;

I = Maximum immigration rate;

η_{e1}, η_{e2} = Expectation membership values;

E = Maximum emigration rate;

ω = Inertia weight;

V_i^{max} = Maximum induced speed;

η_C = Distribution index for crossover;

V_d^{max} = Maximum diffused speed;

η_m = Distribution index for mutation;

C_t = Position constant factor;

γ = Luciferin enhancement constant;

τ = Pheromone;

ρ = Luciferin decay constant;

A = Loudness Rate;

C_1,C_2 = Acceleration factors;

r = Pulse rate;

r_s = Radial range of luciferin sensor;

f_{min}, f_{max} = Minimum and maximum pulse frequency;

r_d = Variable local decision range;

P = Dimension of search space;

η_t = Threshold parameter to control number of neighbors;

M_0 = Constant temperature;

P_{ed} = Elimination-dispersal probability;

ρ_0 = Cooling factor;

G = Gravitational constant;

rr = Reduction rate;

N_e = External set archive;

W_p, W_s, W_q, W_r = Penalty factors;

N_Ω = Archive set;

λ_S, λ_V, λ_Q, λ_P = Penalty factors;

Δ = Step size;

w, w_1, w_2, w_3, α_w, β_w, w_v, w_q = Weight factors;

δ, μ, r_n, u, λ_1, λ_2, ϕ = Random numbers;

λ_0 = Optimum factor;

α_S = Shape factor;

λ_l = Load factor;

α_P, β_P = Parameters of relative importance of pheromone intensity versus visibility;

λ_{lf}, α_{lf} = Levy flight constant;

ρ_L = Lagrange coefficient;

λ_{Sf}; λ_S = Scaling factor;

ρ_P = Pheromone coefficient;

λ_{CP} = Control parameter;

ρ_e = Evaporation coefficient;

S = Total number of bacteria in the population;

d, e = Cost coefficients considering valve point effect;

v_{ref} = Reference voltage;

α, β, γ, ξ, λ = Generator emission coefficients;

V_g = Generator voltage limit;

T_P = Transformer tap changing limits;

V = Voltage limits of all buses;

Q_C = Transmission line shunt reactive power limit;

θ = Customer type;

N_C = Number of Chromo-tactic steps;

T_0 = Initial Annealing temperature;

N_{ed} = Number of elimination dispersal events;

λ_P = Lagrangian multiplier;

E_i = Elitism index;

α_C = Crossover operator;

α_d = decrement constant;

N_g = Number of generators;

g_k = Line conductance at k^{th} bus;

N_l = Number of line voltages;

R_k, X_k = Resistance, reactance at k^{th} bus;

P_{gi} = Power generated at i^{th} generator bus;

a, b, c = Cost coefficients for quadratic cost function;

v_i; v_l = Voltages at i^{th} and j^{th} buses;

Fig. 2 has the graphical representation between number of publications and publication year for different objectives mostly used in those years. Fig. 3 presents recently proposed literature on different objectives by researchers during year 2010-2017.

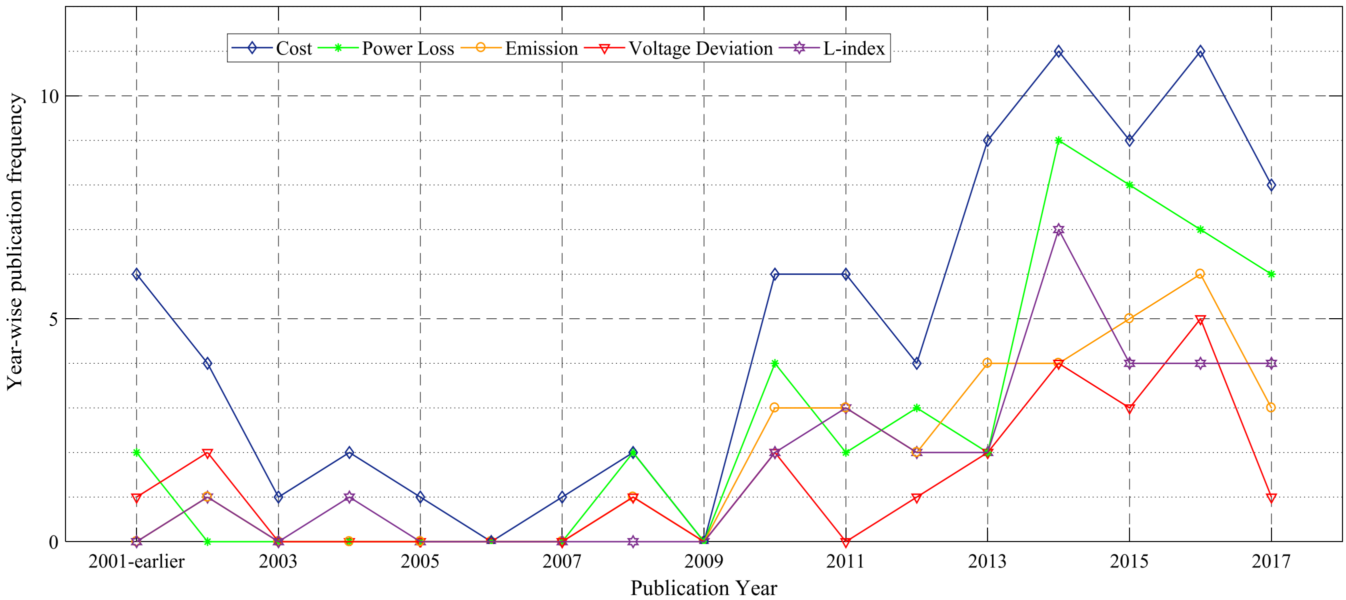

Figure 2: Number of literature in previous years for solving OPF problem

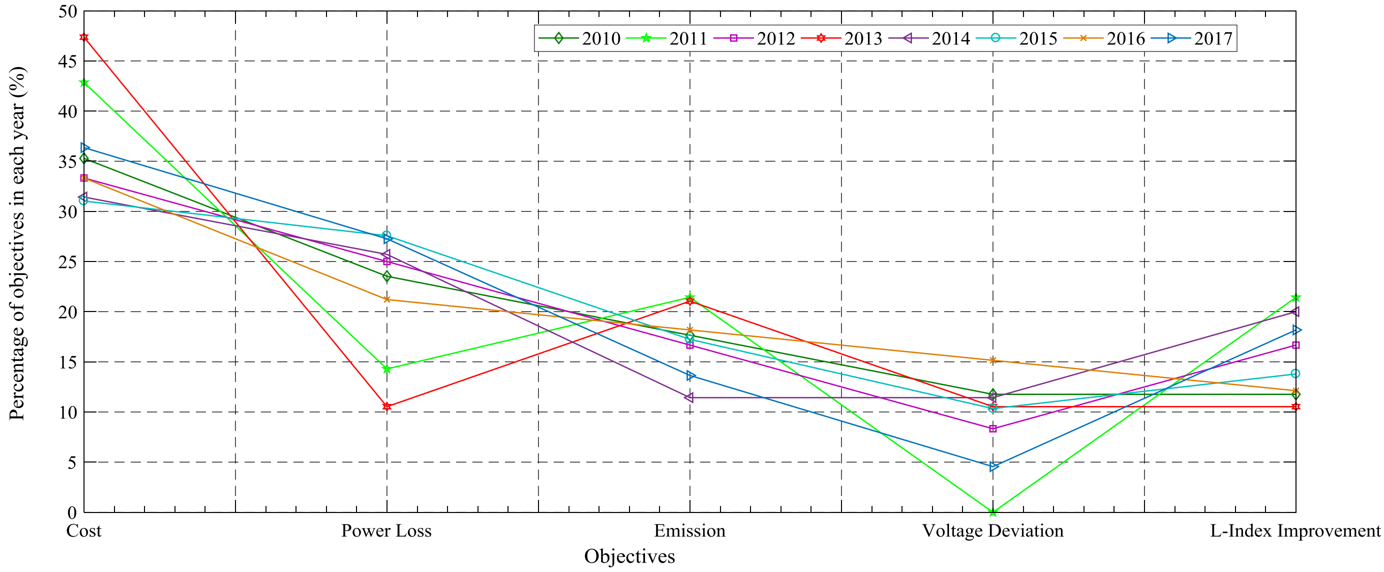

Figure 3: Different objective function during recent years

From the above discussion, it is found that there are some opportunities to do further work related to OPF problem. Some of the research opportunities are shown in the next section.

RESEARCH OPPORTUNITY

In recent year, there is a requirement of clean energy to tackle pollution problem caused by fossil fuel. So that power utilities are now using renewable energy sources to generate electric power. However, integration of renewable energy in the power system is very difficult because the power generated from these sources is uncertain and not reliable, that increases complexity of the system. In above literatures, researchers did comprehensive work to optimize different objectives in order to get suitable power flow. But, the effect of renewable energy on the environment and cost of power generated from these sources needs to be done by using different optimization techniques. Also, while determining the effect of renewable sources on a power system with the help of optimization techniques or methods, it has become necessary to fulfill these requirements shown below.

- Effect on generation cost and emission from generator due to integration of these sources in the power system.
- Effect of renewable energy on environment and economic due to uncertain generation of electric power from renewable energy sources
- Voltage profile possesses an improvement because of uncertain behavior of renewable energy sources in a power system.
- Power system requires less power loss so that the solution from OPF problem should have minimum power losses.
- For optimization purpose, the technique should have less computation time, reliable operation, viable for continuous and discrete operation and solvable for non-linear, non-convex objective function.
- The optimization technique should avoid premature convergence and local optima entrapment.

CONCLUSION

In this paper, optimal power flow problem using single objective and multi-objective based algorithms are briefly reviewed. It has been reviewed that gradient based algorithm was first introduced to solve OPF problem which requires initial information about the problem. This may cause premature convergence and may confine to local optimum. To solve these problems, the meta-heuristic based optimization techniques are introduced which don't require initial set point to process the problem. But it may take time if more than one objective functions are optimized. To overcome this problem, hybrid optimization technique and Pareto optimal front are produced. In Pareto optimal front solution, two objectives are combined into one objective in order to save computational time. Hybrid optimization techniques can deal with more difficulties with the help of two or more different optimization techniques in single framework. As the future work, the effect of renewable energy over cost and emission objective will be analyzed and difficulty in handling controlling variables or constraints while optimizing renewable energy sources based cost and emission functions.

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