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Metaheuristic Methods for Optimal Power Flow: A Comparative Analysis of Various Objective Functions

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It is essential to have a solid understanding of the non-linear solution known as optimal power flow (OPF) in order to comprehend how the power system operates. In order to solve the problem of achieving optimal power flow in power systems, the purpose of this study is to provide an examination of a variety of metaheuristic methodologies. These strategies can solve nonlinear issues. The performance and fundamental elements that are used to compare various metaheuristic search algorithms are discussed here. These metaheuristic search approaches are compared to one another. Various optimization techniques, such as the Gravitational Search Algorithm (GSA), Particle Swarm Optimization (PSO), Fire Fly Algorithm (FFA), and Artificial Bee Colony (ABC) algorithms, are examined here. The objective functions of these algorithms vary, but they all aim to minimize fuel cost, active power losses, and voltage fluctuations. The use and analysis of these optimization algorithms on standard IEEE 14-bus test systems in MATLAB is the subject of this study. The purpose of this study is to explore the fundamental variables that need to be taken into consideration when selecting metaheuristic approaches in order to address the OPF problem that arises during the operation of power systems.
Keywords: Problem formulation using OPF, Metaheuristic Techniques, GSA, PSO, FFA, ABC, objective functions, Flow chart for OPF using Metaheuristic Techniques.

1. Introduction

When it comes to planning the economic scheduling, security, and operation of a power system, the optimal power flow issues are absolutely necessary. The solution to optimal power flow problems aims to satisfy various system operations while simultaneously optimizing a specific fitness function by adjusting control variables effectively [1]. With the use of traditional and metaheuristic optimization techniques, the OPF problem has been resolved [2,3].The classical method of optimization is premised on the identification of the global optimal solution. Several OPF difficulties with various objective functions as well as difficult restricted optimization issues have been solved using metaheuristic optimization techniques. The fundamental principle of metaheuristic techniques is the utilization of stochastic search operators on individuals to iteratively refine solutions within a given population. The most important qualities of metaheuristics are the ability to search through huge solution spaces in a short amount of time, to find answers that are applicable globally, and to avoid local optimal [3]. In order to deliver a high-quality optimal solution within a reasonable timeframe, various population-based heuristic search strategies, including GSA, PSO, FFA and ABC are applied on IEEE 14-bus test systems in MATLAB in this study. The goal of this research is to investigate the essential variables that must be considered when selecting metaheuristic approaches to handle the OPF problem that occurs during the operation of power systems.

2. FORMULATION OF PROBLEMS THROUGH OPTIMAL POWER FLOW:

It is common practice for the OPF to minimize the function, which is also referred to as the fitness function. In order to reduce the overall expenses of production, the OPF problem is utilized to ascertain the optimal settings for the transformer taps, bus voltage settings, and generator taps in every given system [4,5]. Optimization refers to the process of modifying the inputs to the qualities of a device, a mathematical formula, or an experiment in order to determine the output that is either the lowest or the highest possible value.

In order to lower the system objective function while adhering to system equality and inequality limitations, a simple OPF issue may be developed. This issue can be expressed as [1]:

$$\text{Minimize,} \quad j\,(a,b) \tag{1}$$

$$\text{Subject to} \quad k\,(a,b) \leq 0 \tag{2}$$

$$l\,(a,b) = 0 \tag{3}$$

a = The state (dependent) variables, b = The control (independent variables), j (a,b) = fitness functions, k (a,b) = a group of inequality constraints, l (a, b) = a group of equality constraints.

The cost function, the target function, and the fitness function are all examples of terms that are utilized in the process of optimization to define the procedure or function.

The below analysis illustrates the conventional objective functions for the OPF:

(a) Minimization of fuel cost:

The OPF approach seeks to reduce the system's generation cost as:

$$\min_{a} J(a,b) = \min_{a} Jcost(a,b) = \min_{a} \sum_{I=1}^{ng} j_I(P_{gI}) \tag{4}$$

$$= \min_{a} \sum_{I=1}^{ng} (x_I + y_I \cdot P_{gI} + z_I \cdot P^2{}_{gI}) \tag{5}$$

J_{cost} = overall fuel cost of the system, j = a cost function of the generator output power (P_g), a= vector of regulating variables, n_g = count of generators; x_I, y_I, and z_I = cost coefficients.

(b) Reduction in active power loss: For this objective, the fitness function is written as:

$$\min_{a} J(a,b) = \min_{a} Ploss(a,b) = \min_{a} \sum_{l=1}^{ntl} Ploss,l \tag{6}$$

$Ploss,_l$ = l^{th} line active power loss and the total number of lines denotes by ntl.

(c) Reduction in voltage deviation:

In this scenario, the goal is to reduce the bus voltage deviation written as:

$$\min_{a} J(a,b) = \min_{a} VD(a,b) = \min_{a} \sum_{I=1}^{nl} \left| V_I - V_I^{ref} \right| \tag{7}$$

nl denotes number of load buses., V_I = I^{th}-bus voltage, and V_{Iref} = I^{th} bus reference voltage.

3. METAHEURISTIC TECHNIQUES THAT ARE BASED ON POPULATION:

The methodologies for population-based stochastic search are referred to as metaheuristic optimization techniques. The iterative adjustment of solutions is the essential element of metaheuristic methodologies. The efficiency and effectiveness of metaheuristic optimization strategies are directly proportional to the correct configuration of the key algorithmic parameters [6]. The capacity of such algorithms to apply optimization strategies to various issues is detailed below:

3.1 Gravitational Search Algorithm (GSA):

They developed the gravitational search algorithm (GSA) approach, which was devised by Rashedi and multiple other authors [7]. An assembly of masses that are able to communicate with one another through the application of Newtonian gravity and the principles of motion are known as the GSA Seekers. For the purpose of computing the gravitational and inertial masses, a fitness function is utilized, and the placements of these masses are in accordance with the manner in which the problem was resolved.

Upon completion of the evaluation of the fitness of the existing population, the mass of each agent is determined by the following formula:

$$M_i(T) = \frac{m_i(T)}{\sum_{j=1}^{N} m_j(T)} \tag{8}$$

$$m_i(T) = \frac{fit_i(T) - worst(T)}{best(T) - worst(T)} \tag{9}$$

In this scenario, $fit_i(T)$= i^{th} agent's fitness at T iteration, best(T) = best fitness, worst(T) = worst fitness.

According to Newton's theory of gravitation, the force exerted on the i^{th} agent during the T iteration can be described as follows:

$$F_i(T) = \sum_{j \in Kbest,\, j \neq i} r.G(T) \frac{Mj(T).M_i(T)}{Ri.j(T) + \varepsilon} \left(u_j(T) - u_i(T)\right) \tag{10}$$

In this case, r = random number, G(T) = constant of gravitation at T iteration, Mi(T) = i^{th} agent's mass, Mj(T) = j^{th} agent's mass, ε = tiny constant, and $R_{ij}(T)$ = their distance in Euclid's triangle. Kbest = first collection of K-agents having the highest fitness and largest masses.

The representation of the acceleration of the i^{th} agent at the T iteration can be found in the following equation:

$$a_i(T) = \frac{F_i(T)}{M_i(T)} \tag{11}$$

Following are updates to an agent's position and velocity:

$$v_i(T + 1) = r_i.v_i(T) + a_i(T) \tag{12}$$

$$u_i(T + 1) = u_i(T) + v_i(T + 1) \tag{13}$$

r_i = uniform random variable.

In Eq. (10), gravitational constant G(T) which is function of starting value G_0 passing of T time is written as:

$$G(T) = G_0 \cdot \exp\left(\frac{-\alpha \cdot T}{T_{max}}\right) \tag{14}$$

3.2 Particle Swarm Optimization Algorithm (PSO):

The PSO method was created by Kennedy [8], which is based on a simulation of a flock of birds in two dimensions. It makes use of a swarm of particles that flit around the search region in order to find the solution that is most suitable for the situation [9]. In the meantime, all of the particles are focusing their attention on the particle that best represents the path. As a consequence of this, particles investigate their own best choices and the resolution that has been determined to be the finest so far. The position of the particle shifts in response to an assortment of factors, including its current position, velocity, distance from p_{best} & g_{best}, and the distance between the present location and p_{best}.

To determine the particle velocities following equation used in each iteration:

$$v_i(T + 1) = w \cdot v_i(T) + C_1 \cdot r_1 \cdot \{pbest_i(T) - u_i(T)\} + C_2 \cdot r_2 \cdot \{gbest(T) - u_i(T)\} \tag{15}$$

The particle locations can be determined by updating the velocities as follows:

$$u_i(T+1) = u_i(T) + v_i(T+1) \quad (16)$$

$v_i(T)$ = i^{th} particle's current position at T iteration, p_{besti} = i^{th} particle's best individual at T iterations, g_{best} = best outcome so far, w = weight function, C_1 and C_2 = positive constants, r_1 and r_2 = uniform random values.

The initial section of equation (15), gives PSO the capacity to explore. The second and third sections depict individual thought and particle cooperation, respectively.

3.3 Firefly Algorithm (FFA):

Xin-She Yang created the "firefly algorithm," which was motivated by fireflies' flickering lights [10]. The attraction of all fireflies is inversely correlated with the power of their flash, making them all unisexual. Therefore, if a firefly particle had the option of travelling in the direction of any one of two fireflies, it would be drawn to the brighter firefly and would go in this direction. If other fireflies around not available, then the firefly will fly in an arbitrary direction. Firefly's attractiveness (β) is a function of distance between the fireflies, which depends on the lightning intensity seen by nearby fireflies [10,11] and it is expressed by:

$$\beta = \beta_0 \exp\left(-\gamma r^2\right) \quad (17)$$

γ = absorption coefficient and β_0 = attraction at r = 0, r = Cartesian distance.

When one firefly i approaches another alluring firefly j can be find by:

$$u_i(T+1) = u_i(T) + \beta_0 \exp\left(-\gamma r_{ij}^2\right)\left\{u_j(T) - u_i(T)\right\} + \alpha\varepsilon \quad (18)$$

(α)= random parameter and (ε)= random values vector.

The firefly having the maximum brightness is determined to be the best result to the issue at the conclusion of every generation.

3.4 Artificial Bee Colony Algorithm (ABC):

This algorithm was created by Karaboga after being impressed by the intelligence behavior of bees [12]. There are three categories of bees in the ABC algorithm: working bees, observer bees and scout bees. A proposed answer to the optimization problem is the location of a food source.

The bees are in charge of determining the nectar content of each potential new food sources in the vicinity of potential new food sources during the employed bee phase [13]. The steps taken to pinpoint the new food sources is:

$$u_i(T+1) = u_i(T) + \varnothing \cdot \left\{u_i(T) - u_k(T)\right\}, \quad i = 1,2,\ldots..N; \;\; k \in \{1,2,\ldots...N\} \quad (19)$$

$u_k(T)$= a solution picked at random that is distinct from $u_i(T)$ and $u_i(T+1)$ = new solution, Ø= uniform random number between [-1, 1].

By employing equation (19), observers try for a better food supply nearby their current food source. The previous resource is eliminated if the new nectar yield is greater than the previous one's yield. In such case, a single increment is added to the abandonment counter of the food resource. Repeat this procedure until all spectator is scattered among the food sources. [13]. Without receiving any direction from the search space, this scout begins haphazardly searching a new food source. The algorithm is helped to avoid local optimal conditions by this abandoning and scouting technique [14].

4. GENERAL FLOW CHART FOR OPF USING METAHEURISTIC TECHNIQUES:

The following figure illustrates the general process flow for the OPF solution using metaheuristic optimization techniques [3].

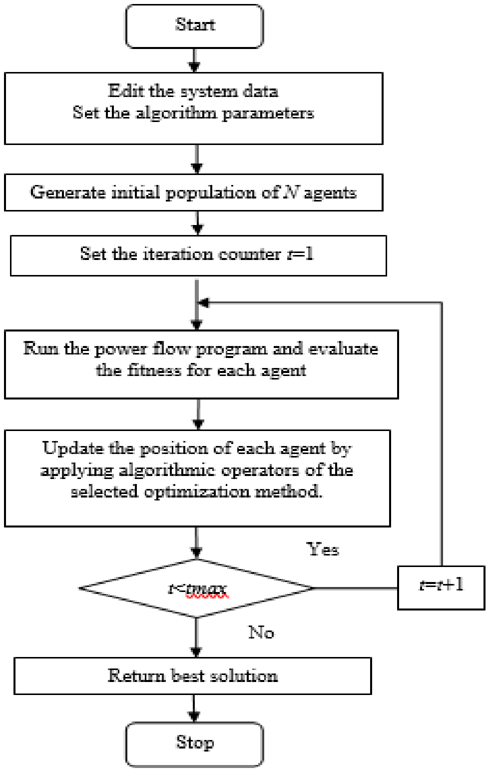


Fig-1: General flow chart for OPF using Metaheuristic Techniques [3]

5. RESULT AND DISCUSSION: (on IEEE 14-bus System)

On common IEEE 14-bus system, suggested methods are applied to the test. Here, bus Number 2, 3, 6, and 8 are generator bus except that remaining are load bus, three transformers are located at lines 4-7, 4-9 and 5-6, Bus number 14 is shunt VAR compensation buses. All the suggested optimization methods with various objective functions has been implemented and tested in MATLAB.

For GSA, the parameters are: number of population (n)=25, maximum iteration (t_{max})=100, gravitational constant (α)=10 and (G_0) =100;

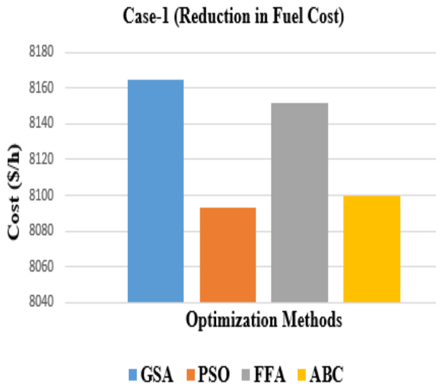
For PSO, the parameters are: number of population (n)=25, maximum iteration (t_{max})=100, constant c_1=2 & c_2=2, weight w_1=0.4 & w_2=0.9;

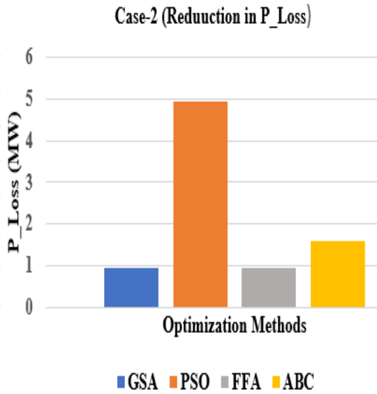
For FFA, the parameters are: number of population (n)=25, maximum iteration (t_{max})=100, randomize parameter (α)=0.5, initial attractiveness (β_0) =0.2, absorption co-efficient(γ)=1.0;

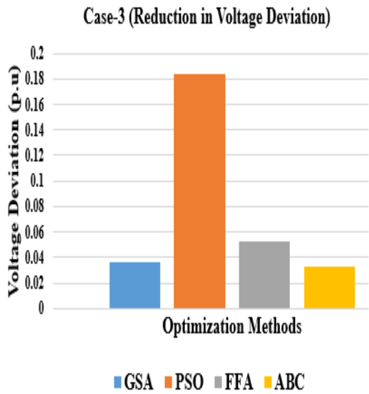
For ABC, the parameters are: total number of food sources (N_S)=25, Maximum cycle number (M_{CN}): 100.

Variable Parameters	case-I (Reduction in F_{cost})				case-II (Reduction in Active Power Loss Ploss)				case-III (Reduction in Voltage Deviation)			
	GSA	PSO	FFA	ABC	GSA	PSO	FFA	ABC	GSA	PSO	FFA	ABC
P_{g2} (MW)	28.97	37.13	34.48	38.46	64.95	140.0	58.52	97.12	43.51	140.0	70.15	53.13
P_{g3} (MW)	24.49	34.92	7.313	31.82	66.57	23.95	70.63	84.03	60.67	93.12	90.57	63.64
P_{g6} (MW)	19.77	00.00	0.001	00.00	29.60	100.0	55.14	11.69	61.80	00.00	6.099	43.06
P_{g8} (MW)	17.79	00.00	43.27	2.360	70.60	00.00	75.64	67.57	41.13	00.00	21.96	100.0
V_{g1} (p.u)	1.004	1.060	1.027	1.036	1.049	1.060	0.997	1.029	1.010	1.060	1.024	1.008
V_{g2} (p.u)	0.981	1.040	1.003	1.015	1.042	1.060	0.995	1.031	0.998	1.060	1.011	1.003
V_{g3} (p.u)	0.954	1.011	0.950	0.990	1.026	1.060	0.994	1.017	1.008	1.060	1.003	1.009
V_{g6} (p.u)	0.959	1.060	1.011	0.988	0.989	1.060	0.982	0.980	1.022	1.024	1.013	1.021
V_{g8}(p.u)	1.038	1.060	0.999	1.025	0.997	1.060	0.996	0.989	1.019	0.940	1.043	1.002
T_8(4-7) (p.u)	0.942	0.900	0.998	0.957	1.038	1.100	1.041	0.987	1.014	1.100	1.007	0.976
T_9(4-9) (p.u)	1.057	1.100	1.010	1.100	0.980	0.900	0.962	0.900	0.961	0.966	0.990	0.988
T_{10}(5-6) (p.u)	1.046	0.900	0.949	1.013	1.057	0.980	0.988	1.052	0.972	0.900	0.996	0.961
Qc_{14} (MVAR)	5.6173 e-15	00.00	1.7444 e-14	1.0202 e-14	1.3324 e-14	2.2204 e-14	6.4284 e-15	00.00	5.4804 e-15	2.2204 e-14	1.1344 e-14	8.3739 e-15
Cost ($/h)	8165	8093	8152	8100	9734	12763	10221	10954	9188	12164	9165	10200
Ploss (MW)	8.8071	9.7187	9.6695	9.9366	0.9311	4.9419	0.9609	1.6069	2.2532	4.7225	3.1964	1.0382
Voltage Deviation (p.u)	0.3450	0.2718	0.1473	0.1913	0.2141	0.3311	0.2637	0.1466	0.0368	0.1840	0.0532	0.0334

Table-1: Best solution of different optimization methods for different objective functions







Based on the comparing results obtained by GSA, PSO, FFA and ABC methods, it can be concluded that, for reduction in active power loss objective GSA performs better than other methods. PSO gives the optimal solution for reduction in cost, and for reduction in voltage deviation and improve voltage profile ABC gives better solution compare to others.

6. CONCLUSION:

It is suggested that metaheuristic optimization is a method for using metaheuristic algorithms to solve optimization problems. In this research, The OPF problem with different objective functions has been effectively solved using different optimization methods. On the IEEE 14-bus systems, the proposed methods have been examined and put to the test. The outcomes of the simulations demonstrate that GSA performs better than other methods for reduction in active power loss objective function. PSO gives the optimal solution for reduction in cost. For reduction in voltage deviation and improve voltage profile ABC gives better solution compare to others. The OPF problem was solved using a variety of metaheuristic optimization techniques, which have all been thoroughly reviewed and contrasted in this study.

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