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Paper Authors **ANARASE BHAU VISHWANATH, DR. RAM MOHAN SINGH BHADORIA**

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A STUDY OF OPTIMISATION METHODOLOGIES FOR OPTIMAL POWER FLOW

CANDIDATE NAME- ANARASE BHAU VISHWANATH
DESIGNATION- RESEARCH SCHOLAR SUNRISE UNIVERSITY ALWAR
GUIDE NAME- DR. RAM MOHAN SINGH BHADORIA
DESIGNATION- ASSOCIATE PROFESSOR SUNRISE UNIVERSITY ALWAR

ABSTRACT

The OPF techniques may be broken down into two broad categories: Intelligent and Conventional. The prominent Newton method, Gradient method, Quadratic Programming method, Interior point method, and Linear Programming method are only few of the typical procedures. OPF seeks to maximize some criterion within the constraints of the network power flow equations and the capabilities of the system and its components. By changing the available controls to minimize an objective function under strict operational and security constraints, the ideal situation is achieved. This chapter discusses the methods already in use and those that have been suggested to address the OPF issue. Formulation of the OPF issue, restrictions, objective function, applications, and detailed reporting of many well-known OPF approaches are all part of this. Particle swarm optimization and the Genetic Algorithm are two examples of the recently created and widely used approaches that are part of intelligent techniques. In this study, both evolutionary and metaheuristic algorithms are taken into account to analyze optimum power flow. PSO and GA are preferred over single-point methods like simulated annealing and tabu search due to the multi-parent effect they produce. When compared to existing metaheuristic algorithms, the Bat method performs much better across a variety of use cases.

KEYWORDS: Optimisation Methodologies, Optimal Power Flow, OPF techniques, Linear Programming method

INTRODUCTION

The social behavior of fish schools and bird flocks served as inspiration for Particle Swarm Optimization (PSO), a population-based stochastic optimization approach. Particle swarm optimization (PSO) employs a population of particles, each of which represents a potential solution to the optimization issue, to conduct the search for the optimum solution. Particles fly about in a multidimensional space, following the paths of the ideal ones, until they either stabilize in a somewhat stable place or run out of computational margins. In order to return to its previous best position and advance toward the global best position obtained up to that point, each particle modifies its trajectory. PSO has lately received a lot of attention in power system applications due to its ease of implementation and speedy convergence for a variety of optimization issues.

The system is initiated with a population of random solutions, and it iteratively looks for optimal solutions by adjusting its generational parameters. Potential solutions, which are represented as particles in PSO, are guided across the solution space by the optimal particles at the moment. Each every atom forms an opinion based on its own experience and that of its neighbours. In contrast to GA, PSO does not make use of genetic operators like crossover and mutation. Particles contain a memory that is crucial to the algorithm and can update them based on its internal velocity. The PSO process flow is shown in Figure 1.

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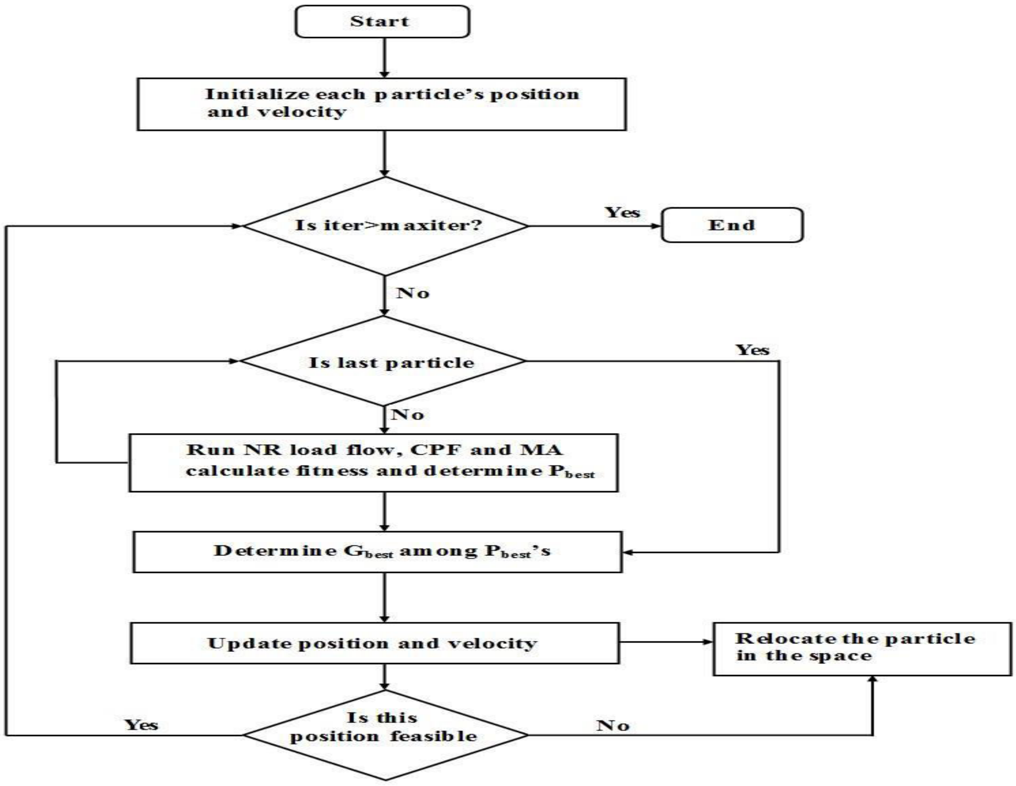

Figure 1 Flow Chart of proposed PSO algorithm

Solution Algorithm

Below is a representation of the fundamental building blocks required for the operation of the Solution Algorithm.

X(t) = X(t) = 0 An m-dimensional vector, where m is the number of optimized parameters, defines this possible solution. To represent the jth particle at time t, we write Xj(t) = [xj,1(t),.........xj,m (t)], where xs are the optimised parameters and xj, k(t) represents the location of the jth particle with respect to the kth dimension, i.e. the value of the kth optimised parameter in the jth candidate solution.

Populace, nabes (t): Pop (t)= [Xi(t),....] is a collection of n particles at time t. Xn(t)T. Swarm: It is an inherently disordered collection of moving particles that prefer to cluster together, even if each particle seems to be traveling in a different direction.

The speed of a moving particle is denoted by the m-dimensional vector V(t), where m is the number of dimensions. The velocity of the jth particle at time t is defined as Vj(t) = [vj,1(t),.............vj, m (t)], where vj,k(t) is the component of the jth particle's velocity with respect to the kth dimension.

w (t) = moment of inertia. The effect of past velocities may be modulated by adjusting this parameter, which affects the current velocity. By doing so, it manipulates the trade-off between the particles' local and worldwide exploration capacities, with earlier stages recommending a high inertia weight to aid in global exploration and later stages recommending a lower inertia weight to aid in local exploration.

Uniquely superior X* (t): During the time it spends searching, the particle compares the fitness it has at its present place to the highest fitness it has ever had. The optimal position, X* (t), is the one that corresponds to the greatest fitness thus far. This allows the optimal location, X* (t), to be determined for each particle in the swarm and updated during the search. In the case of an objective function J in a minimization problem, the best jth particle can do is

X*(t) is find such that $J\left(\left(\hat{X}_j^{*}((t))\right)\right) \le J\left(\left(\hat{X}_j^{*}((\tau))\right)\right), \tau \le t$.

For straightforwardness, it is understood that $J_j^* = J(X^*_j(t))$.

For the jth particle, individual best can be expressed as $X^*_j(t) = [x_j, 1(t) \ldots\ldots\ldots\ldots x^*_j, m(t)]$.

Global best X** (t): Among all best positions (i.e., the greatest of all) achieved up to this point, it is the best. Therefore, the best in the world may be identified as

$J\left(\left(X_j^{\wedge(**}()(t)\right)\right) \le J\left(\left(\hat{X}_j^{*}((\tau))\right)\right)$, $j=1,\ldots\ldots.n$.

For straight
forwardness, consider that J**= J(X** (t)).

Criteria for when to call it quits on a search operation. If any of the following holds true, we may call this search off.

After more iterations than you care to count, the optimal answer hasn't changed.

or

The maximum number of iterations has been reached. The Solution algorithm is developed as shown below, with the essential parts explained as above.

Annealing is used to provide a unified search in the early stages and a highly localized search in the latter stages. Here, we think about a decrement function for reducing the inertia weight provided by w(t)=w(t-1) where is a decrement constant less than but close to 1.

After the location update, the search area is checked for feasibility to ensure that the particles don't go shooting off into unreachable reaches.

There is an upper bound, denoted vkmax, on the speed of particles in the kth dimension. By setting this limit, local exploration space is expanded and the gradual evolution of human learning is more accurately simulated.

To optimize m parameters, the PSO method uses a population of n particles, each of which is a vector with m dimensions. The computational flow of the PSO approach, after incorporating the aforementioned changes, may be summarized as follows.

Step 1 (Initialization)

Start the clock at t=0 and produce n random particles.

$[X_j(0), j = 1, \ldots . n]$, where $X_j(0) = [x_{j,1}(0), \ldots . . x_{j,m}(0)]$

$X_{j,k}(0)$ is formed by picking a random probability-weighted value from the set of all possible values for the kth optimized parameter $[x_{k\ max}, x_{k\ min}]$

In a similar vein, have all particles' starting velocities be completely arbitrary,

$[V_j(0), j = 1, \ldots . n]$, where $V_j(0) = [v_{j,1}(0), \ldots . . v_{j,m}(0)]$

$V_{j,k}(0)$ uses a uniform probability distribution across the k-th dimension to obtain a random number $[-x_{k\ max}, x_{k\ min}]$

The goal function J is applied to each particle in the seed population.

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For each particle, set $X_j^*(0) = X_j(0)$ and $J_j^* = J_j, j = 1, \dots n.$ Search for the best value of the objective function J_{best}

Set the particle associated with J_{best} as the global best $X^{**}(0)$, with an objective function of J^{**}

Set the initial value of the inertia weight $w(0)$

Step 2 (Time updating)

Update the time counter t = t + 1.

Step 3 (Weight updating)

Update the inertia weight w(t)=αw(t-1)

Step 4 (Velocity updating)

The following equation is used to update the jth particle's velocity in the kth dimension based on the global best and individual best of each particle:

$$v_{j,k}(t) = w(t)v_{j,k}(t-1) + c_1 r_1 \left(x_{j,k}^*(t-1) - x_{j,k}(t-1)\right) + c_2 r_2 \left(x_{j,k}^{**}(t-1) - x_{j,k}(t-1)\right) \quad (4.2)$$

Where c_1 , c_2 is a uniformly distributed random integer between 0 and 1, where both and are positive constants. Importantly, the second term symbolizes the PSO's ability to think and remember, allowing the particle to adjust its velocity in response to new information. The third term indicates the PSO's social component, in which the particle's velocity modifies itself in response to the social-psychological adaption of information. If a particle's velocity exceeds the allowed range, it should be corrected to the range.

Step 5 (Position updating)

Each particle's location is updated according to the following equation using the new velocities:

$$x_{j,k}(t) = V_{j,k}(t-1) + x_{j,k}(t-1) \quad (4.3)$$

If a particle's location exceeds the allowed range in either direction, restore it to the appropriate range.

Step 6 (Individual best updating)

Each particle is evaluated according to its updated position. If $J_j < J_j^*, j = 1, \dots\dots n.$ then update individual best as $X_j^*(t) = X_j(t)$ and $J_j^* = J_j$ and go to step 7; else go to step 7.

Step 7 (Global best updating)

Search for the minimum value J_j among J_j^*, where min is the index of the particle with minimum objective function, i.e. $\min \in \{j; j = 1, \dots . n\}$. if $J_{min} < J^{**}$, then update global best as and go to step 8; else go to step 8.

Step 8 (Stopping criteria)

Proceed to Step 2 unless one of the Stopping Criteria has been met.

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OBJECTIVE FUNCTION FOR PSO

Adjusting the on-load tap changing ratio, the capacity of the reactive power compensation capacitor, and the voltage at the generator's terminals are all examples of control variables that can be used in conjunction with voltage integrated control and reactive power to decrease active power losses and boost power factor. The objective function, state variables (generator reactive power and nodes' voltages), control variables (on-load tap changing ratio, reactive power compensation capacitor capacity, and generator terminal voltage), and mathematical model

SIMULATION ANALYSIS OF PSO IN OPTIMAL POWER FLOW CONTROL

Cost Optimization of PSO

PSO: 1/50 iterations, G_{Best} = 7927773.0219071107.

PSO: 10/50 iterations, G_{Best} = 7919868.2389082452.

PSO: 20/50 iterations, G_{Best} = 7915334.1705612.

PSO: 30/50 iterations, G_{Best} = 7898649.0694836471.

PSO: 40/50 iterations, G_{Best} = 7893281.6893112473.

PSO: 50/50 iterations, G_{Best} = 7828249.4674299723.

GBest represents the optimal cost-benefit ratio for the cycle. Cost optimization using PSO may be observed to be achieved as costs continue to drop. As seen in Figure 2, the minimum value occurs at the 50th repetition. The optimal cost sets a limit on PSO's dimensionality. Since the optimal value is found at the 50th iteration, this study restricts the dimension to 53.

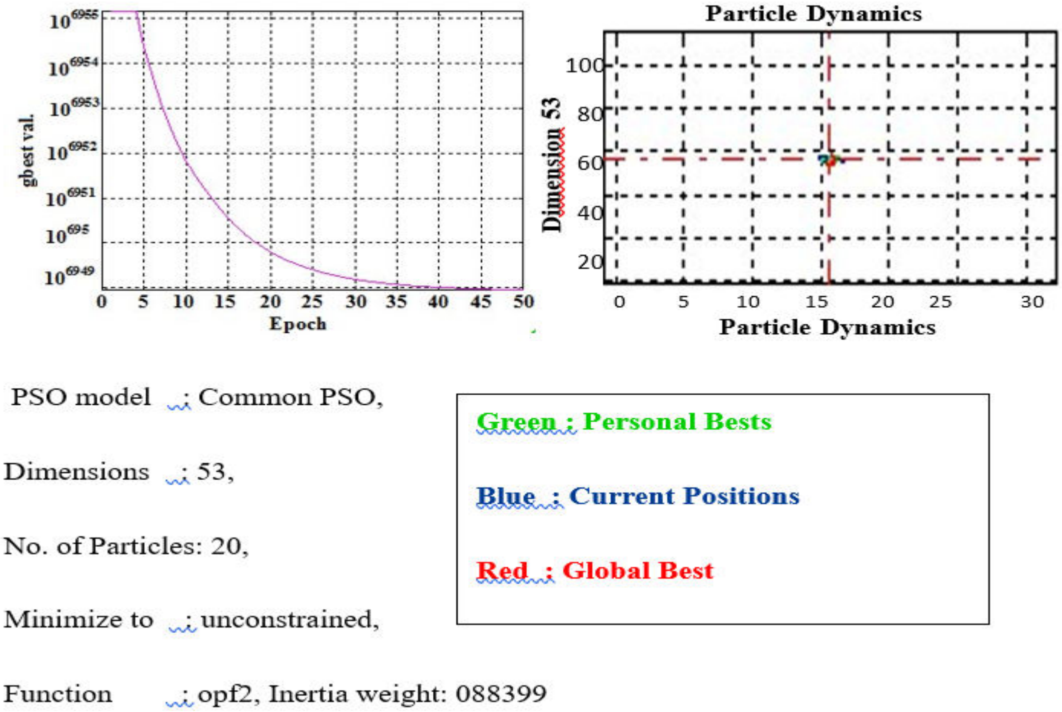

Figure 2 Simulation analysis of PSO

BAT ALGORITHM

The BAT algorithm is a kind of optimization theory that takes its cues from bats' echolocation. Using echolocation, bats can constantly adjust their location. Bats use a method called echolocation to navigate by emitting a succession of loud ultrasonic waves and listening to the resulting echoes. Bats use the variations in the latency and volume of the reflected waves to zero in on a specific prey item. Each pulse in echolocation barely lasts milliseconds at most (8-10 ms). However, its frequency is always the same, ranging from 25 to 150 kHz (or 2 to 14 mm in wavelength).

The normal frequency range for most bat species is 25 kHz to 100 kHz, while some may emit frequencies up to 150 kHz. The numerous bat-inspired algorithms are designed by idealizing certain bat echolocation properties. The following guidelines best describe how bats use echolocation:

I. All bats utilize echolocation to gauge distance, and for some unknown reason, they can distinguish between obstacles and prey.
II. Bats use a set frequency fmin, a changing wavelength, and a constant loudness A0 to fly about in random patterns while they look for prey. They emit pulses at a rate r [0,1], which they may control based on how close they are to their intended target.
III. Even though there is a wide range of possible loudness values, we will suppose that the range is from a very loud (positive) A0 to a very quiet (constant) Amin.

CONCLUSION

Optimal power flow for voltage regulation using several controllers like PSO, BAT, and GA are explored in this research. The efficacy of GA in OPF is confirmed by comparative study. Utilizing UPFC broadens the scope of voltage regulation in the power grid. Using the novel SA algorithm and comparing it to PI based UPFC, we explore the importance of DC link voltage regulation in terms of voltage stability. The IEEE 30 bus system is used for all of the following analyses. For greater voltage stability and reactive power regulation, this method may be used to larger IEEE bus systems. In addition, the UPFC FACTS device for regulating power flow and improving system stability is incorporated in this study. To regulate the voltage and the reactive power injected by the UPFC, the shunt control's voltage controller is crucial. Performances of UPFCs using PI and simulated annealing (SA) approaches were evaluated with regards to Maintained voltage and Harmonics reduction. There is a 5% voltage loss with a PI controller, but it is eliminated with SA. While the PI controller can achieve a reduction in harmonics of around 85%, the SA can achieve a reduction of about 95%. Therefore, improved outcomes may be shown in Maintained voltage and Harmonics when SA is decreased in UPFC. As a result, IEEE 30 bus systems are a good fit for SA based UPFC.

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