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Research Article

SOLVING DYNAMIC OPTIMAL POWER FLOW PROBLEMS USING PSO AND DE ALGORITHMS

Linga Murthy S.B and Vaisakh K

Department of Electrical Engineering, AU College of Engineering (A) Andhra University, Visakhapatnam-530003, AP, India

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ABSTRACT

This paper proposes two population based computing techniques such as particle swarm optimization and differential algorithm to solve the dynamic optimal power flow (DOPF) problem with the prohibited zones, valve-point effects, ramp rates and security constraints. In the static optimal power flow, the system total load is constant and the problem is solved for just one period, but in the proposed approach, the multi-period OPF which is termed as dynamic OPF is considered. The, nonlinear characteristics of the alternative current power flow as well as technical constraints, such as valve-point effect and transmission constraints, are all considered for the realistic operation, and they further complicate the proposed problem. These features make the DOPF as a complicated nonlinear and non-convex optimization problem. This paper proposes two population based computing techniques such as particle swarm optimization and differential evolution algorithm to solve the DOPF problem. The IEEE 30-bus test system is implemented to illustrate the application of the proposed modeling framework. The results obtained on the IEEE 30-bus system are also compared with the results reported in the literature.

INTRODUCTION

Optimal power flow (OPF) is one of the key tools for optimal operation and planning of present day power systems [1]. The usefulness of OPF is progressively being recognized, and it has become the most important tool used by the system operator in power systems operation and planning[2]. In the literature number of OPF models have been developed and have been used to formulate different kinds of OPF problems, objectives, and constraint types [3].

The OPF is as an optimization problem which aims to obtain control variables for optimizing a predefined objective function while satisfying operational equality and inequality constraints. However, the traditional OPF is mainly concerned with the minimization of total generating cost. Nowadays, increase in electricity consumption forces the power systems to operate closer to their secure limits because of economical reasons. Also the OPF mathematical formulation has the capability to integrate the economic and security aspects of the concerned system and has become an attractive tool for many researchers [4].

In the present day power system operation, the power demand is continually changed during the entire day, therefore, it has become necessary to solve the OPF problem in each hour considering economic and security aspects and is termed as dynamic optimal power flow (DOPF). The DOPF is actually the extended formulations of the original OPF problem and it is more difficult to solve because of its large dimensionality[5].

Several classical (deterministic) optimization techniques were employed successfully to solve the OPF problem [6]. Surveys of various traditional methods used to solve the OPF problem are given in [7-9]. The classical methods rely on some assumptions such as convexity, smoothness, continuity and differentiability. The classical techniques such as linear programming (LP), quadratic programming (QP), and non-linear programming (NLP), have been developed to solve the OPF problems with the theoretical assumptions, like convexity, differentiability, and continuity, which are difficult to incorporate in the actual OPF formulations. In addition, the convergence to the global optimal solution is highly dependent on the selected initial guess[10]. Moreover, continuous LP, QP, and NLP formulations cannot accurately model discrete control variables, such as transformer tap ratios or switched capacitor banks.

Due to the high complexity in OPF formulation with continuous and discrete control variables, modern heuristic

***Corresponding author: Linga Murthy S.B**
Department of Electrical Engineering, AU College of Engineering (A) Andhra University, Visakhapatnam-530003, AP, India

optimization algorithms have been widely used for solving the OPF problems with different constraints. To overcome these drawbacks, heuristic optimization algorithms such as genetic algorithm (GA)[11], evolutionary programming (EP)[12], simulated annealing (SA)[13], tabu search (TS)[14], harmony search algorithm [15], and enhanced genetic algorithm [16], particle swarm optimization (PSO)[17], differential evolution (DE)[18], etc., have been employed for the solution of the OPF problem.

Currently, powerful evolutionary algorithm such as PSO has been applied in many power system optimization problems. The major advantages of the PSO algorithm compared with classical and many mathematical algorithms and other evolutionary optimization techniques are simple concept, easy implementation mechanism, and minimal storage requirements.

In the recent past, the DE approach, proposed in 1995 [19] is a population-based method and is generally considered a parallel stochastic direct search optimizer that is simple yet powerful algorithm. It is a stochastic population based optimization algorithm with real parameters and real-valued functions. In comparisons to most other heuristic optimization algorithms, the DE algorithm is much simpler and more straightforward to implement.

The main body of the differential evolution algorithm takes few lines of code in any programming language. Despite its simplicity and the gross performance of DE in terms of accuracy, convergence rate and robustness, its an attractive algorithm for applications to various real-world optimization problems [20-22],. The spatial complexity of DE is less than that of some highly competitive real parameter optimization techniques. This feature helps in extending DE to handle expensive and large-scale optimization problems.

Therefore, the differential evolution is a best algorithm to solve DOPF, which is a complicated problem and has a lot of local optima. The remainder of this paper is organized as follows: Section 2 describes the formulation of DOPF problems. Section 3 explains the PSO and differential algorithms, Section 4 gives the implementation steps of both PSO and differential evolution algorithm and Section 6 gives the numerical examples of solving the DOPF problem. Finally Section 6 explains the conclusions.

Problem formulation of dynamic optimal power flow

The main objective function of the DOPF is the minimization of the total fuel cost over total time horizon. The adjustable system quantities such as controllable real power generations, controllable voltage magnitudes, and transformer tap ratios are taken as control variables in the proposed scheme. Accordingly, the objective function of the DOPF problem can be written as follows:

$$Min \quad F(\mathbf{X}) = \sum_{t=1}^{T}\sum_{i=1}^{N} F_{it}(P_{it}) \quad (\$) \tag{1}$$

where $F(\mathbf{X})$ is the total generating cost over the whole dispatch period, T is the number of intervals in the scheduled horizon, N is the number of generating units, and $F_{it}(P_{Git})$ is the fuel cost in terms of its real power output P_{Git} in megawatts at time t.

Considering the valve-point effects, the fuel cost function of i^{th} thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form

$$F_{it}(P_{it}) = a_i P_{it}^2 + b_i P_{it} + c_i + \left| \; e_i \sin(f_i (P_{i\min} - P_{it})) \; \right| \quad (\$/h) \tag{2}$$

where

a_i, b_i and c_i are cost coefficients,

e_i and f_i are constants from the valve point effect of the i^{th} generating unit.

$$\mathbf{X} = \left[\mathbf{P_G}, \mathbf{V_G}, \mathbf{T_{TP}}, \mathbf{Q_c}\right]_{1*NV} \tag{3}$$

$$\mathbf{P_G} = \left[P_{G1}, P_{G2}, ..., P_{GNg-1}\right]_{1*((N_g-1)*T} \tag{4}$$

$$P_{Gi} = \left[P_{Gi,1}, P_{Gi,2}, ..., P_{Gi,t}, ..., P_{Gi,T}\right]_{1*T} \tag{5}$$

$$\mathbf{V_G} = \left[\mathbf{V_{G1}}, \mathbf{V_{G2}}, ..., \mathbf{V_{gNg}}\right]_{1*(Ng*T)} \tag{6}$$

$$V_{Gi} = \left[V_{Gi,1}, V_{Gi,2}, ..., V_{Gi,t}, ..., V_{Gi,T}\right]_{1*T} \tag{7}$$

$$\mathbf{T_{TP}} = [\mathbf{T_{TP1}}, \mathbf{T_{TP2}}, ..., \mathbf{T_{TPNtran}}]_{1*(NT*T)} \tag{8}$$

$$T_{TPi} = [T_{TPi,1}, T_{TPi,2}, ..., T_{TPi,t}, ..., T_{TPi,T}]_{1*T} \tag{9}$$

$$NV = (N_{tran} + N_{cap} + N_{gen} + (N_{gen} - 1)) * T \tag{10}$$

This objective function minimizes the total system generation cost, where $F(\mathbf{X})$ is the total generation cost, X is the control vector of the presented problem, $\mathbf{P_G}$ is a vector related to the power generation of all generator except slack generator. $\mathbf{P_{Gi,t}}$ is the real power generation of i^{th} unit at t^{th} interval, $\mathbf{V_G}$ is a vector related to the voltage of generator bus (PV buses), and $\mathbf{V_{Gi,t}}$ is the voltage magnitude of i^{th} generator at t^{th} interval, $\mathbf{T_{TP}}$ is a vector related to the tap of transformers and $\mathbf{T_{TPi,t}}$ is the tap of i^{th} transformer at t^{th} interval, which is a discrete control variable, meanwhile, it is considered as continuous variable in this paper.

Similarly, Ng is the total number of generation units, NT is the number of tap transformers, and T is the number of intervals, respectively. NV is the number of control variable in the proposed optimization problem.

The minimization of the generation cost is subjected to the following equality and inequality constraints:

Prohibited operating zones. Units can have prohibited operation regions due to faults in the machines themselves or the associated auxiliaries, such as boilers, feed pumps etc.

Generators ramp rate: The ramp rate is the amount of load you can add to the turbine per unit of time.

Real power balance constraint: The total generation should be able to satisfy the given load demand at any interval.

***AC power flow equalities*:** The power flow constraints are satisfied by running the load flow solution techniques.

The inequality constraints: For the safety purposes of the generating units as well as the stable operation of the system, all the generating units are firmly limited to operate within their minimum and maximum generation capacity;

***System spinning reserve constraint*:** A minimum system spinning reserve is required to be considered to satisfy the system load demand and be responsible for any frequency changes due to load fluctuations in real-time systems

Security constraints: The OPF security constraints ensure that the optimal solution is secure, preventively secure or correctively secure with respect to the steady operational state of the power system.

Overview of optimization algorithms

The proposed solution methodology comprises the application of PSO and DE algorithms. Firstly, the DOPF problem is solved separately through the PSO algorithm and DE algorithm.

Particle swarm optimization algorithm

Particle swarm optimization is is modeled by social behavior of birds flocking or fish schooling [23,24] and is a population-based optimization tool, where the initialization is carried out with a population of random particles and it searches for optima by updating generations. This algorithm maintains a swarm of candidate solutions, referred to as particles with each particle being attracted towards the best solution found by the particle's neighborhood and the best solution found by the particle. During this iterative process, the agent position is realized by the position and velocity information. The position and velocity of each particle are updated, as follows:

$$V_e^{k+1} = \omega * V_e^k + C1 * rand1() * (P_{beste}{}^k - X_e^k) + C_2 * rand2() * (G_{best}^k - X_e^k) \quad (11)$$

$$X_e^{k+1} = X_e^k + V_e^{k+1} \quad (12)$$

where V_e^k is the velocity of eth particle at kth iteration, V_e^{k+1} is the velocity of eth particle at k+1th iteration, o is an inertia weight, C1 and C2 are positive coefficients between 0 and 2 such that C1 + C2≤4, and rand1() and rand2() are random numbers selected between 0 and 1. $P_{best}{}^k$ and G_{best}^k best are the personal best and global best experiences of eth particle at kth iteration, respectively. X_e^k and X_e^{k+1} are the control vectors of eth particle at kth and k+1th iteration, respectively.

Differential evolution algorithm

DE uses mutation and crossover to generate new individuals. One population consists of NP individuals. One individual $X_{i,G}$ consists of D variables which are constrained by search range. The initial individuals are randomly determined, then mutation and crossover are used to generate the new individuals and selection is applied to determine whether the new individual or the original one will survive into the next generation[25].

***Mutation*:** According to the strategy DE/rand/1/bin, the mutation vector $v_{i,G+1}, i = (1, 2, 3, ..., NP)$, is generated by using three randomly chosen target vectors $x_{r1,G}, x_{r2,G}, x_{r3,G}$ and a mutation parameter F. The formula is represented as:

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}), \quad r1 \neq r2 \neq r3 \neq i \quad (13)$$

From the formula above, we can see that it contains 4 vectors, so the number of population (NP) must be at least 4. $F > 0$ is a mutation control parameter which affects the disturbance added by two individuals.

***Crossover*:** Crossover means to swap the dimensions between the target vectors and its offspring mutant vector controlled by crossover parameter CR. Usually the binomial crossover is accepted, which is described as:

$$u_{i,G+1}^j = \begin{cases} v_{i,G+1}^j & if\ r(j) \leq CR\ or\ j = n_j \\ x_{i,G}^j & otherwise \end{cases} \quad (14)$$

where $u_{i,G+1}^j$ means the jth number of trial vector $u_{i,G+1}$, $r(j)$ is a random number between [0, 1], and n_j is a randomly generated dimension to make sure that at least one dimension of the trial vector is closed from the mutant vector.

***Selection*:** The operation of selection determines whether the trail vector or the target vector survives into the next generation on the basis of the vectors' fitness. Greedy selection is used:

$$x_{i,G+1} = \begin{cases} u_{i,G+1}^j & if\ f(u_{i,G+1}) < f(x_{i,G}) \\ x_{i,G} & otherwise \end{cases}$$

(15)

where $f(u_{i,G+1})$ and $f(u_{i,G})$ are the objectives of $u_{i,G}$ and $x_{i,G}$ and $f(u_{i,G+1}) < f(x_{i,G})$ is used to solve minimization problems.

Implementation steps of PSO and DE algorithms on DOPF problem

In this section, the application of PSO and DE on the DOPF problem is presented step by step.

PSO Algorithm: The implementation steps of the proposed PSO based algorithm can be written as follows;

Step 1: Input the system data for load flow analysis
Step 2: Run the power flow
Step 3: At the generation Gen =0; set the simulation parameters of PSO parameters and randomly initialize k individuals within respective limits and save them in the archive.
Step 4: For each individual in the archive, run power flow to determine load bus voltages, angles, generator reactive power outputs and calculate line power flows.

- ***Step 5:*** Evaluate the penalty functions
- ***Step 6:*** Evaluate the objective function values and the corresponding fitness values for each individual.
- ***Step 7:*** Find the generation local best xlocal and global best xglobal and store them.
- ***Step 8:*** Increase the generation counter Gen = Gen+1.
- ***Step 9:*** Apply the PSO operators to generate new k individuals
- ***Step 10:*** For each new individual in the archive, run power flow to determine load bus voltages, angles, generator reactive power outputs and calculate line power flows.
- ***Step 11:*** Evaluate the penalty functions
- ***Step12:*** Evaluate the objective function values and the corresponding fitness values for each new individual.
- ***Step 13:*** Apply the selection operator of PSO and update the individuals.
- ***Step 14:*** Update the generation local best xlocal and global best xglobal and store them.
- ***Step 15:*** If stopping criterion have not been met, repeat steps 4-15. Else go to step 16
- ***Step 16:*** Print the results

DE Algorithm: The details of the DE based optimization algorithm are as follows

- ***Step. 1*** Generate an initial population randomly within the control variable bounds.
- ***Step. 2*** For each individual in the population, run power flow algorithm such as Newton Raphson method, to find the operating points.
- ***Step. 3*** Evaluate the fitness of the individuals
- ***Step. 4*** Perform differentiation (mutation) and cross over to create offspring from parents.
- ***Step. 5*** Perform Selection between parent and offspring. While using the penalty method of constraint handling the following criteria are enforced while selecting the individuals for the next generation. Any feasible solution is preferred to any infeasible solution. Among two feasible solutions, the one having better objective function value is preferred.
- ***Step. 6*** Store the best individual of the current generation.
- ***Step. 7*** Repeat steps 2 to 6 till the termination criteria is met (maximum number of generations).

Simulation results

IEEE 30-bus system results

To demonstrate the performance of the proposed PSO and DE algorithms, these methods have been applied on the IEEE 30-bus test system. Detailed data about 30-bus IEEE test system can be obtained from [25]. The IEEE 30-bus system consists of six generators connected at buses 1, 2, 5, 8, 11, and 13, where the bus 1 is treated as the slack bus. The lower and upper voltage magnitude limits of all buses are set to 0.95 and 1.1 p.u. respectively. The system's single-line diagram is shown in Figure 1. This test system has two shunt compensator capacitors installed at buses 10 and 24.. Also, this system has four tap changing transformers connected between the buses 6-9, 6-10, 4-12, and 27-28, and their lower and upper limits are set to 0.9 and 1.1 p.u. respectively. All generators' cost coefficients, power generation limit, ramp rates, and prohibited zones are taken from [5] for the IEEE 30-bus test system.

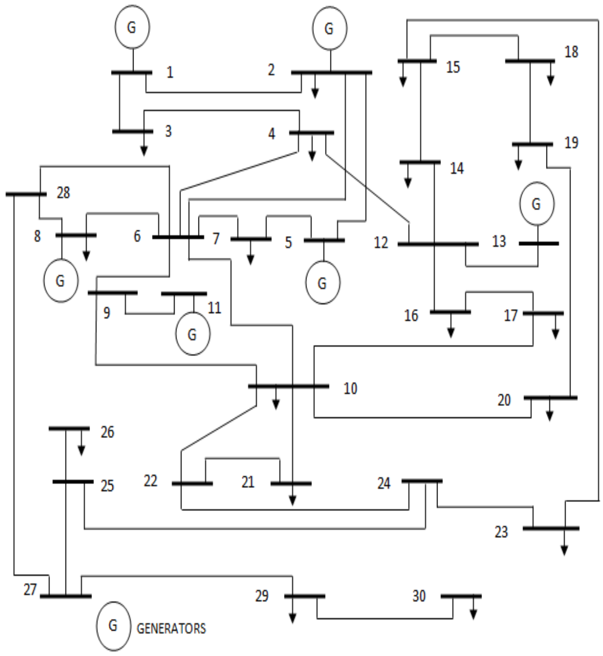

Figure 1 Single-line diagram of IEEE 30-bus test system.

In this paper, MATLAB programming codes for both the PSO and the DE dynamic optimal power flow algorithms are developed and incorporated together for the simulation purposes. In the implementation of the algorithms, several parameters have been tuned for optimal search process and have been extracted from many computer experiments. The settings of the proposed algorithm are as follows: Number of populations is set to 100 and the maximum number of iteration is 300 for the test system.

In this case, all the constraints such as the valve-point effect, ramp rate, and prohibited zones are considered simultaneously. Fig. 2 shows the variation of fitness function against the number of generations during the PSO and DE evolutionary process. From this figure it is clearly seen that the convergence property of the DE method is better than those achieved by the PSO algorithm. Fig. 3 gives the best real power generation levels of each generator during each period. The results of implementing DOPF over the IEEE 30-bus test system using the proposed PSO and DE algorithms along with the other methods are presented in Tables 1. The results show the superiority of the proposed method over other methods. The cost obtained by the proposed technique is found to be less than the existing results while satisfying all the equality and inequality constraints. From Table 1, it can be inferred that the proposed algorithms can converge to the better solution, which proves the ability of the proposed algorithm for solving the complex DOPF problems.

Figure 4 compares the real power loss obtained after optimization with the proposed DE and IMDE methods on the 30-bus test system. According to Fig.4, the real power loss of the system in each period with the proposed IMDE algorithm is higher than DE due the further reduction in the cost of generation.

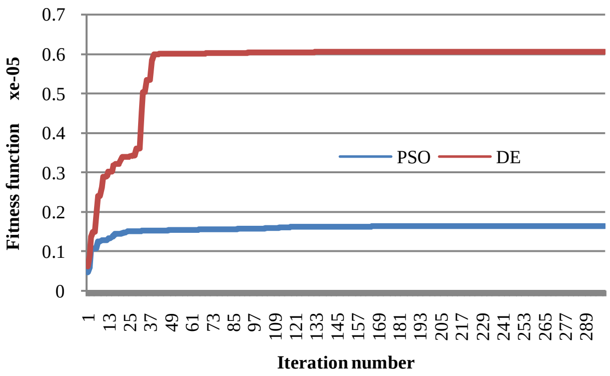

Figure 2 Convergence of fitness function of the IEEE 30-bus system

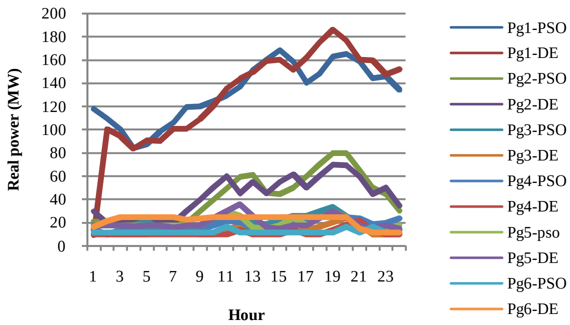

Figure 3 Real power generation levels of IEEE 30-bus system

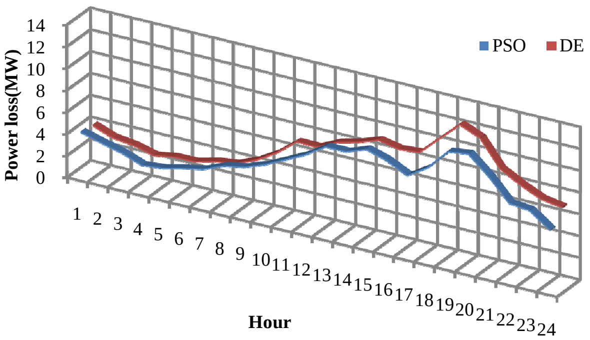

Figure 4 Real power loss of the IEEE 30-bus system

Table 1 Comparing generation cost obtained with different algorithms on IEEE 30-bus system

Method	Cost($/24h)
SA[NIK]	16,703.81
PSO[ ]	16,619.92
PSO-SA[ ]	16,486.85
Proposed PSO	16,601.00
Proposed DE	16,506.00

CONCLUSION

This paper has been proposed two population based techniques to solve the dynamic optimal power flow problems. The simulation results have shown the superiority of the proposed algorithms over the previous methods reported in the literature. The proposed DOPF which, is a complex, non-convex, non-smooth, and nonlinear optimization problem with constraints like ramp rate, prohibited zones, and valve-point effect has been formulated and solved effectively. Despite the complicated structure of the DOPF problem, the results prove the applicability and validity of the proposed techniques as efficient tools for solving complicated problems such as DOPF. The results have been compared with those obtained by other evolutionary algorithms reported in the literature. It is seen from the comparisons that the proposed methods such as particle swarm optimization and differential evolution algorithms provide better solutions.

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