A Novel Method of Solving Economic Load Dispatch Problem using Differential Evolution Algorithm with Particle Swarm Optimization

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Abstract: **This project presents the design and application of an efficient hybrid heuristic search method to solve the practical economic dispatch problem considering many nonlinear characteristics of power generators, and their operational constraints, such as transmission losses, valve-point effects, multi-fuel options, prohibited operating zones, ramp rate limits.In this paper, a hybrid differential evolution and a particle swarm optimization based algorithms are proposed for solving the problem of scheduling the economic dispatch problems. The efficient scheduling requires minimizing the operating cost of the power system. The effectiveness of the proposed algorithm is demonstrated by solving ELD problems with non-smooth and non-convex solution spaces. The comparative results with some of the most recently published methods confirm the effectiveness of the proposed strategy to find accurate and feasible optimal solutions for practical ELD problems.**

Keywords: Economic Load Dispatch, Differential Evolution, Particle Swarm Optimization, Optimization, Hybrid De With Pso.

I.INTRODUCTION

Effective management of electrical energy generation has become more important. As a part of unit commitment, economic dispatch (ED) determines optimal outputs of committed generating units, subject to unit and system constraints, to achieve the minimal total fuel cost.Economic load dispatch is a fundamental function in modern power system operation and control. The economic dispatch(ED) problem of power generation involves allocation of power generation to different thermal units to minimize the total fuel cost while satisfying load demand and diverse operating constraints of a power system.

The traditional ED considers the power balance constraint apart from the generating capacity limits. Recently, as an alternative to the conventional mathematical approaches, modern stochastic optimization techniques have facilitated solving non-smooth and non-convex ED problems, such as genetic algorithms , evolutionary programming ,neural networks, differential evolution, simulated annealing, tabusearch, particle swarm optimization ,and ant colony optimization. Also, some hybridization and combination of these methods have been widely used to solve more effectively this kind of ED problems. The results reported were promising and encouraging for further research in this direction.

The DE algorithm is a stochastic population based search method successfully applied in global optimization problems. DE improves a population of candidate solutions over several generations using the mutation, crossover and selection operators in order to reach an optimal solution.DE presents great convergence characteristics and requires few control parameters, which remain fixed throughout the optimization process and need minimum tuning.

PSO refers to a relatively new family of algorithms that may be used to find optimal or near optimal solutions to numerical and qualitative problems. PSO inspired by social behaviour of bird flocking and fish schooling. PSO has proven to be both very fast and effective when applied to a diverse set of optimization problems.

In DE, the fitness of an offspring is one-to-one competed with that of the corresponding parent. This one-to-one competition makes convergence speed of DE faster than other evolutionary algorithms. Nevertheless, this faster convergence property yields in a higher probability of searching toward a local optimum or getting premature convergence.

Furthermore, PSO may also be trapped in local minima, because it easily loses the diversity of swarm. To overcome the disadvantages of DE and PSO, an efficient combination strategy of DE and PSO is introduced in this study. The proposed approach combines differential information obtained by DE with the memory information extracted by PSO to create the promising solution.

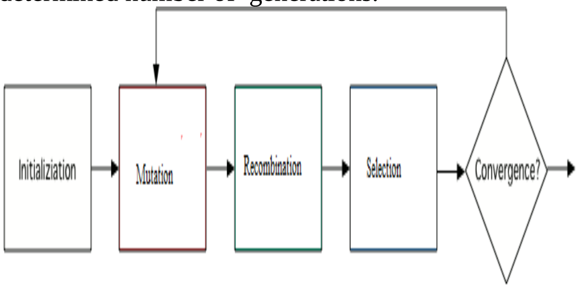
II DIFFERENTIAL EVOLUTION

The differential evolution algorithm (DE) is a population based algorithm like genetic algorithm using the similar operators crossover, mutation and selection. In DE, each decision variable is represented in the chromosome by a real number. As in any other evolutionary algorithm, the initial population of DE is randomly generated, and then evaluated. After that, the selection process takes place. During the selection stage, three parents are chosen and they generate a single offspring which competes with a parent to determine which one passes to the following generation. DE generatesa single offspring (instead of two like in the genetic algorithm)by adding the weighted difference vector between two parents toa third parent. If the resulting vector yields a lower objective function value than a predetermined population member, the newly generated vector replaces the vector to which it was compared. An optimization task consisting of D parameters can be presented by a D-dimensional vector. In DE, a population of NP solution vectors is randomly created at the start. This population is successfully improved over G generations by applying mutation, crossover and selection operators to reach an optimal solution.

2.1 Differential EvolutionAlgorithm :

i. Initialization
ii. Evaluation
iii. Repeat
iv. Mutation
v. Crossover
vi. Selection
vii. Until (Termination criteria are met)

The termination criteria are the conditions under which the search process will stop. In this work, the search procedure will terminate whenever the predetermined maximum number of generations Gmax is reached, or whenever the global best solution does not improve over a predetermined number of generations.



III PARTICLE SWARM OPTIMIZATION

The particle swarm optimization (PSO) is a swarm intelligence method that differs from well-known evolutionary computation algorithms, such as genetic algorithms , in that the population is not manipulated through operators inspired by the human DNA procedures. Instead, in PSO, the population dynamics simulate the behaviourof a "birds' flock", where social sharing of information takes place and individuals profit from the discoveries and previous experience of all other companions during the search for food. Thus, each companion, called 'particle', in the population, which is called 'swarm', is assumed to "fly" over the search space looking for promising regions on the landscape. For a minimization case, such regions possess lower function values than others previously visited. In this context, each particle is treated as a point into the search space, which adjusts its own flying according to its flying experience as well as the flying experience of other particles.

Therefore, each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) that it has achieved so far. This implies that each particle has a memory, which allows it to remember the best position on the feasible search space that it has ever visited. This value is commonly called Pbest. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighborhood of the particle. This location is commonly called Gbest. The basic idea behind the particle swarm optimization technique consists, at each iteration, updating the velocity and accelerating each particle towards Pbest and Gbest locations.

The velocity of each particle can be modified by using the following Equation

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (Pbest_i^k - X_i^k) + c_2 r_2 (Gbest^k - X_i^k)$$

Where , V_i^k is velocity of particle i at iteration k , X_i^k is position of particle i at iteration k, $Pbest_i^k$ is the best position of particle i ,$Gbest^k$ is the best position of the group ,ω is inertia weight parameter ,*c1*, *c2* are positive constants ,*r1*, *r2* are random numbers within the range [0,1].

The position of each particle is updated by the following equation $X_i^{k+1} = X_i^K + V_i^{k+1}$

The positive constants c1, c2 provide the correct balance between exploration and exploitation, and are called the cognitive parameter and the social parameter, respectively. The random numbers provide a stochastic characteristic for the particles velocities in order to simulate the real behaviour of the birds in a flock. The weight parameter ω is a control parameter which is used to control the impact of the previous history of velocities on the current velocity of each particle. Hence, the parameter ω regulates the trade-off between global and local exploration ability of the swarm . The recommended value of the inertia weight ω is to set it to a large value for the initial stages, in order to enhance the global exploration of the search space, and gradually decrease it to get more refined solutions facilitating the local exploration in the last stages.

In general, the inertia weight factor is set according to the following equation

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} iter$$

Where ,ω_{min}, ω_{max} are initial and final weights, $Iter_{max}$ is the maximum number of iterations and iter is the current iteration number.

The velocity of each particle is limited by a maximum value .which facilitates local exploration of the problem space and it realistically simulates the incremental changes of human learning .This limit is given by

$$V_i^{\max} = \frac{X_i^{\max} - X_i^{\min}}{N}$$

Where, $X_i^{min}$and$X_i^{max}$are the minimum and maximum position limits of the particle i,*N*is a defined number of intervals.

IV OPTIMAL POWER FLOW-CONVENTIONAL METHODS

The OPF methods are broadly grouped as Conventional and Intelligent. The conventional methodologies include the well known techniques like Gradient method, Newton method, Quadratic Programming method, Linear Programming method and Interior point method. Intelligent methodologies include the recently developed and popular methods like Genetic Algorithm, Particle swarm optimization.The following bus system is solved economically by Gradient method.

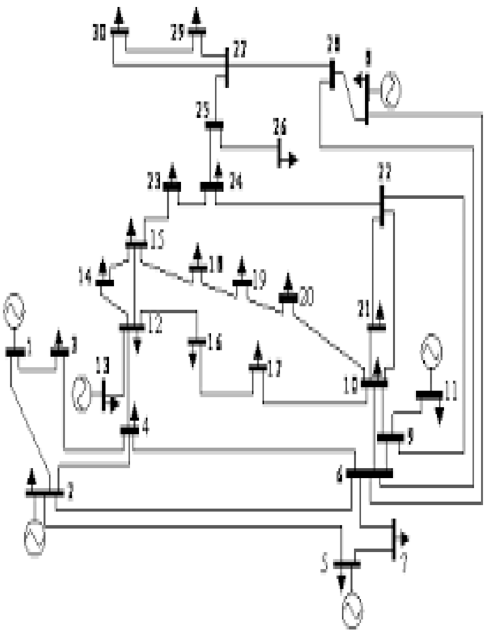


Fig 2. 30 bus system

V RESULT for OPF of the above 30 bus system by conventional method:

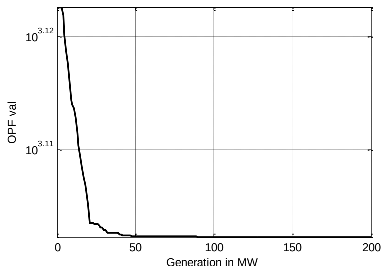


Fig 3 Graph for minimization of fuel cost

VI DE WITH PSO

The proposed DE with PSO consists essentially in a strong co-operation of the two evolutionary algorithms described above, since it maintains the integration of the two techniques for the entire run. The general structure of the proposed DE with PSO algorithm is similar to that of DE. The main difference is in the mutation operation.Instead of manipulating a single mutant vector in DE, we use two mutant vectors in DE with PSO. The first is the classical mutant vector of DE, and the second is generated using the PSO updating rules for particle position. Therefore, in the crossover operation, two different trial vectors are created for each parent or target vector. The selection operator form a new individual by choosing among the trial vectors and the parent vector, i.e. the individual that presents abetter fitness or are more optimal.

This efficient combination strategy of DE and PSO improves the global search capability, avoiding convergence to local minima and at the same time accelerates the convergence.

VII HYBRID DE with PSO ALGORITHM

The proposed DE with PSO algorithm applied in this study for ED problem can be described as follows:

Step 1: Initialize the vectors of candidate solutions of the parent population (particles), between the maximum and minimum operating limits of the generating units.
Step 2: Generate the particle velocities randomly.
Step 3: Evaluate the fitness function of each particle.
Step 4: Obtain the first mutant vector using DE rule (4.2).
Step 5: Compute the particle velocity using (4.5).
Step 6: Obtain the second mutant vector using the PSO updating rule (4.6).
Step 7: Crossover of control variables to generate two trial vectors.
Step 8: Evaluation of new solution fitness.
Step 9: Selection operation.
Step 10: If one of the stopping criteria is met, than stop. Otherwise, go to step 4.

The stopping criteria are the conditions under which the search process will stop. In this work, the search procedure will terminate whenever the predetermined maximum number of generations Gmax is reached, or whenever the global best solution does not improve over a predetermined number of generations.

A penalty function approach is used to handle the power balance constraint and inequality constraints. The extended objective function FT (or fitness function) is defined by

$$F_T = F + K\left(\sum_{i=1}^{ng} Pi - PD - PL\right)^2 + \sum_{j=1}^{nc} PFj$$

(b$/h)

Where, K denotes the penalty factor of the equality constraint; nc represents the number of inequality constraints and PFj is the penalty function for the jth inequality constraint; given as

$$PF_j = \begin{cases} Kj(Uj - Uj\text{lim})2 & \text{if violated} \\ 0 & otherwise \end{cases}$$

Where, K_j is the penalty factor for the jth inequality constraint; $U_j^{lim}$is the

limit value of the variable U_j.

parameters for t

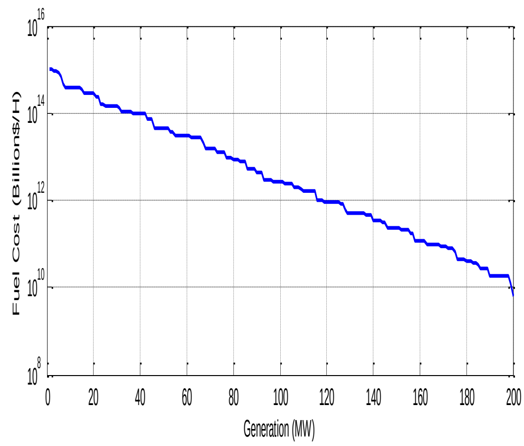


Fig 4.Output of DEPSO

For all above mentioned parameter combinations, performance of DEPSO is evaluated. These results reveal that the proposed hybrid approach is robust under various parameter combinations when applied to solve economic dispatch problems.

VIII RESULT AND CONCLUSION

The proposed hybrid approach is robust under various parameter combinations when applied to solve non-smooth/non-convex economic dispatch problems. The most noticeable observation from this groundwork is that the optimal settings are found .Once optimal values of CR have been obtained, the effect of population size is explored. The optimum population size is found to be related to the dimension and the complexity. In this project, efficient hybrid differential evolution based particle swarm optimization strategy was successfully implemented to solve practical economic dispatch problems. The PSO process was incorporated as a supplementary mutation operator into the conventional DE algorithm to improve the global search capability. In this, generator equality and inequality constraints are considered in economic dispatch problem. Hence the effectiveness of the proposed strategy of Hybrid DE with PSO is used to find accurate and feasible optimal solutions for practical ED problems.

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