Research on Efficient and Economical Power System Optimization Algorithm

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Abstract. The paper proposes to apply the particle swarm optimization algorithm to the dynamic optimization power flow calculation in the power system with distributed power generation, which takes all periods of time into consideration. The specific implementation method of the algorithm is given. According to the principle of nearby reactive power compensation, distributed power sources do not absorb reactive power from the system as much as possible. The reactive power required by distributed power sources is mainly provided by distributed power reactive power compensation devices. In order to verify the effectiveness of the algorithm, the economic load distribution of the power system with different unit numbers was tested, and compared with other optimization algorithms. The result proves that the algorithm can find the optimal solution efficiently and accurately, effectively avoiding the problem of falling into the local optimal, and ensuring a faster running speed.

Key words: Efficient economy, power system, particle swarm optimization algorithm, economic load.

1. Introduction
Economic load distribution ELD is a typical optimization problem of power system that reasonably distributes the load of each unit in the power system or power plant under the premise of meeting the system load and operating constraints, and minimizes the power generation cost. In the calculation methods of economic dispatch optimization problems, intelligent algorithms have been widely used and recognized in solving nonlinear, non-convex, and discontinuous optimization problems because they do not require continuous differentiability for variables and functions. However, the calculation results are more random and the algorithm has poor global convergence [1]. Therefore, based on the basic intelligent algorithm, a hybrid algorithm is formed that combines the advantages of genetic algorithm with strong global search ability and strong tabu search ability. However, this kind of hybrid algorithm has a large amount of calculation, a long time, and randomness problems are difficult to obtain. Improvements make it difficult to handle real-time online scheduling optimization problems. The particle swarm optimization PSO algorithm is gradually applied and improved due to its speed and simplicity. The introduction of random mutation operators, the integration of tabu search ideas, the use
of self-adjustment of adaptive mutation operators, random black hole processing and clustering introduce global search information to increase the diversity of understanding; and the improved chaotic particle swarm optimization algorithm By modifying the iterative action strategy of particle swarms and introducing chaotic mapping, the global search ability of particles with better fitness values is strengthened. These particle swarm optimization algorithms and their improvements all optimize and modify multi-dimensional control variables through two types of parameters: speed and position. The optimization process is just like in a rolling mountain group. Standing on each mountainside, it is easy to get the top of the mountain. The vantage point is the local best point; but if you want to find the highest point of the entire mountain range, you need to look down in the air and change the optimal perspective.

Therefore, it is possible to explore a new type of space particle swarm optimization SPSO algorithm by adding a type of parameter, namely the height parameter, to form an optimization space together with height, speed and position. This paper proposes to apply an improved particle swarm algorithm to the ELD optimization problem [2]. This method has global convergence, makes the particles less likely to fall into the local optimum, and has a better convergence effect. By comparing with other particle swarm optimization algorithms under different dimensional conditions, and simulating the 3-unit, 13-unit and 40-unit systems considering the valve point effect, the results verify that the method is successful and feasible.

2. Mathematical model

In order to establish a dynamic optimization power flow mathematical model for power systems with distributed power sources, the active power output of distributed power sources and the reactive power absorbed by generators are first discussed [3]. The generator output power in the t period can be replaced by its expected value $P_{tw,av}$. Predicting the load can obtain the expected value of the load in the t period. In this way, in each period of dynamic optimization, the output and load of the generator set can be treated as definite values.

2.1. Equality constraints

The equation constraint is the power flow balance constraint, that is, the balance equation of active and reactive power at each node. The research hotspot of power flow calculation in power systems with distributed power generation lies in the calculation model of distributed power generation. For the over-limit situation of the active power output of the balanced unit obtained by the power flow calculation, this paper proposes a method for the over-limit detection of the active output of the balanced unit [4]. After the over-limit detection of the balanced unit takes the limit, the following equation constraints must be satisfied. If not, add the objective function is treated as a penalty function.

$$\Delta P^t = \sum_{i=1}^{N_{gen}} P_i^t + P_{sl}^t + P_{w,av}^t - P_{ls}^t - P_{ld}^t = 0$$

In the formula, $\Delta P^t$ is the active power unbalance in the t period, $N_{gen}$ is the number of conventional generators in the system, and $N_{gen-1}$ is the number of conventional generators excluding the balanced units; $P_i^t$ is the output of the conventional unit i during the t period, and $P_{sl}^t$ is the balanced unit over the t period. The limit detection takes the active output after the limit, $P_{ls}^t$ is the network loss in the t period, and H is the total load in the t period.

2.2. Inequality constraints

Inequality constraints include conventional unit active and reactive power output constraints, node voltage amplitude constraints, and distributed power reactive power compensation capacity constraints. Distributed power reactive power compensation is switched on and off in groups, and its compensation capacity is a whole quantity. In addition, in dynamic optimization, the ramp rate constraints of
conventional generator sets must also be considered. The maximum and minimum range of active power output of the generator sets and the limit of ramp rate constraints after comprehensive consideration are:

\[
\max \left( P_{i,\text{max}}, P_{i}^{-1} + D_{Ri}\Delta T \right) \leq P_{i} \leq \min \left( P_{i,\text{min}}, P_{i}^{-1} - U_{Ri}\Delta T \right)
\]  

This equation is the feasible region of conventional unit output, where \( P_{i} \) is the output of the unit i in the current period (the t period), \( P_{i}^{-1} \) is the output of the unit Bi in the previous period (the t-1 period), and \( D_{Ri} \) and \( U_{Ri} \) are the output of the unit i. The lower limit and upper limit of the slope rate, \( F \) is the sub-period section interval.

### 2.3. Objective function

Taking the minimum cost of conventional unit consumption as the optimization goal, the research period is divided into T time periods. The dynamic optimization of power flow must take into account the coupling of each time section. All time periods should be optimized uniformly, with the minimum cost of all conventional units throughout the period the objective function is expressed as follows:

\[
\min F = \sum_{t=1}^{T} \sum_{i=1}^{N_{\text{gen}}} F \left( P_{i}^{t} \right) \quad \text{(3)}
\]

\[
F \left( P_{i}^{t} \right) = a_{i} + b_{i}P_{i}^{t} + c_{i}P_{i}^{2} + \left| p_{i}\sin(f_{i}(P_{i,\text{min}} - P_{i}^{t})) \right| \quad \text{(4)}
\]

Where \( F \) is the total cost of the entire period T, \( F \left( P_{i}^{t} \right) \) is the cost characteristic function of the conventional unit i in the period t.

### 2.4. Evaluation function

The active power output of conventional generators and the reactive power output of distributed power supply reactive power compensation devices are control variables, and the constraints of regulating output within the feasible region can be satisfied by itself. The over-limit active power output of the balanced unit adopts the method of detecting and taking the limit value of the over-limit active power output (over-limit means exceeding the feasible range), and the load equation constraint is handled by the penalty function. Conventional generator set reactive power output constraints, PQ node and distributed power node voltage constraints are handled by penalty functions.

Distributed power sources must absorb reactive power, and distributed power reactive power compensation devices are mainly used to compensate the reactive power required by distributed power sources. Because the reactive power compensation device is switched in groups, the maximum reactive power that the distributed power supply can absorb from the system is the reactive power capacity of each group [5]. Considering the maximum benefit of the distributed power reactive power compensation device, the reactive power injected into the system by the distributed power can be the maximum output of the distributed power reactive power compensation device minus the remaining reactive power required to compensate the distributed power range. The maximum reactive power that the distributed power source absorbs from the system is handled by the penalty function. The reactive power injected into the system by the distributed power source is not restricted because the output of the distributed power reactive power compensation device is satisfied in the regulation. The paper uses the penalty function method to construct the evaluation function of the dynamic optimization power flow as follows:

\[
\min \left\{ \sum_{t=1}^{T} \sum_{i=1}^{N_{\text{gen}}} F \left( P_{i}^{t} \right) + K_{Q_{r}} \sum_{t=1}^{T} \left( Q_{r}^{t} - Q_{r,\text{min}}^{t} \right)^{2} + \right. \\
K_{Q_{r}} \sum_{t=1}^{T} \left( Q_{r}^{t} - Q_{r,\text{min}}^{t} \right)^{2} + K_{Q_{r}} \sum_{t=1}^{T} \left( Q_{r}^{t} - Q_{r,\text{min}}^{t} \right)^{2} \left\} \quad \text{(5)}
\]
In the formula, $K_V$, $K_Q$, $K_C$ and $K_D$ are the penalty coefficients for variable crossing; $v_i^t$ is the voltage of node i in the t period (except for the balance node and PV node), note that $v_i^t$ contains the distributed power node voltage; $Q_i$ is the conventional power generation in the t period. The reactive output of unit i. $v_i^{lim}$ is the voltage limit of node i. If $v_i^t$ exceeds the upper limit, then $v_i^{lim}$ takes the upper limit; if it crosses the lower limit, then the lower limit is taken; $Q_i^{lim}$ is the limit of the reactive power output of conventional generator set i, and the value method of $Q_i^{lim}$ is the same as $v_i^{lim}$ is the same; $Q_{inj}$ is the reactive power injected into the system by the distributed power node in the t period, and $Q_{inj}^{lim}$ is the limit of its capacity. The value is as follows:

$$Q_{inj}^{lim} = \begin{cases} Q_{inj}^{min}, & Q_{inj}^t < Q_{inj}^{min} \\ Q_{inj}^t, & Q_{inj}^t \geq Q_{inj}^{min} \end{cases}$$  \hspace{1cm} (6)$$

In the formula, $Q_{inj}^{lim}$ is the lower limit value of the reactive power injected into the system by the distributed power node, and this article takes -1Mvar.

3. Example analysis

In order to better evaluate and compare algorithms and analyse the effects of algorithms in solving different problems, researchers have proposed many test functions. These test function sets contain basic knowledge in the field of nonlinear constrained optimization problems and are tested under the same conditions for different test functions. In order to verify the effectiveness of the EPUSPSO algorithm for optimizing the ELD problem of the power system, this paper uses MATLAB 8.1 programming on the Inter Core i7 3.4G PC, and performs simulation verification for typical ELD problems of different dimensions, non-conductive and multi-constraint optimization, simulation examples Both consider the valve point effect of the consumption curve and ignore the network loss. The design algorithm (EPUSPSO) in this paper has also been compared with other two particle swarm algorithms, PSO algorithm and SAPSO algorithm. In the comparison, the number of particles in each algorithm is 64, and the number of iterations is 1000. In order to avoid the existence of the randomness problem of the algorithm, the three algorithms were separately executed 50 times in the verification process [6]. The comparison data includes the following content: Average total cost \( F_{mean} = \sum_{i=1}^{50} F_i / 50 \), lowest total cost \( F_{min} = \min(F_1, ..., F_{50}) \), average time-consuming \( T_{mean} = \sum_{i=1}^{50} t_i / 50 \), shortest time-consuming \( T_{min} = \min(t_1, ..., t_{50}) \), where: \( F_i (i = 1, ..., 50) \) is the optimal solution obtained by the i single execution of the algorithm, that is, the minimum total system power generation cost of the ELD optimization problem; \( t_i (i = 1, ..., 50) \) is the algorithm The time it takes to perform the process of finding the optimal solution alone for the i time.

Figure 1 is a comparison diagram of the convergence of the three particle swarm algorithms in Example 1, Figure 2 is a comparison of the convergence of the three particle swarm algorithms in Example 2, Table 1 is a comparison of the running results of the three particle swarm algorithms in Example 3, Figure 3 is a comparison diagram of the convergence of the three particle swarm optimization algorithms in Example 3.
Figure 1. Convergence comparison diagram of EPUSPSO, SAPSO and PSO in Example 1

Figure 2. Convergence comparison diagram of EPUSPSO, SAPSO and PSO in Example 2

Table 1. Calculation example 3 Comparison of calculation results

| Particle swarm algorithm | $F_{\text{mean}}/\$  | $F_{\text{min}}/\$  | $T_{\text{mean}}/\text{s}$ | $T_{\text{min}}/\text{s}$ |
|--------------------------|----------------------|----------------------|-----------------------------|-----------------------------|
| PSO                      | 128613.47            | 127453.51            | 7.39                        | 7.12                        |
| SAPSO                    | 124985.46            | 124390.72            | 18.56                       | 17.91                       |
| EPUSPSO                  | 123121.78            | 122897.69            | 8.63                        | 8.55                        |
4. Conclusion
Comparing the classic particle swarm optimization algorithm and the improved particle swarm optimization algorithm, the method in this paper is easy to jump out of the premature interval, and can greatly reduce the randomness of the calculation results; the number of iterations has not increased significantly, the convergence time is relatively short, and the optimization variables are different Sexual requirements are not high. Therefore, the proposed spatial particle swarm optimization algorithm is also effective and superior in solving nonlinear, non-convex, and discontinuous optimization problems.

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