Research on economic dispatch based on improved firefly algorithm

Xingang Wang¹, Saijiang Kai¹, Feng Zhang¹, Licheng Sun¹ and Ping Huang²*

¹ Xinjiang Power Grid Co. Ltd of State Power Grid, Urumqi, Xinjiang, 830000, China
² Cross-strait Tsinghua Research Institute, Xiamen, Fujian, 361000, China
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Corresponding author’s e-mail: huangping@qdkj999.onexmail.com

Abstract: An improved firefly algorithm for solving the economic dispatch problem of power system is proposed. The algorithm considers the climbing rate, the dead zone and other constraints, and calculates the network loss. This algorithm is based on the firefly algorithm, a new repair strategy for active correction of the violation of the constraint condition of all kinds of fireflies, and combined with the penalty function technique, the fireflies in the feasible region or as close as possible to the feasible solution search in the area. The accuracy and speed of the algorithm can be effectively improved by greatly reducing the probability of finding the optimal location of the firefly in the infeasible solution region. The simulation results show that the algorithm has the characteristics of high speed, high accuracy and good convergence.

1. Introduction
Economic Dispatch problem of power system is to determine the output distribution of each unit under the condition of satisfying the operation constraints of the unit and the power supply balance of the power system in order to achieve the goal of minimum total power generation cost. There are many methods to study this kind of problem, among which the traditional methods are λ-iterative method [1], gradient method [2] and so on. These traditional methods have a basic assumption that the cost micro-increase curve of the unit has the characteristic of monotone increasing, but in engineering practice, this assumption is often not true, such as the unit has a working dead zone, the cost curve is non-convex. The quadratic programming method [3] can accurately consider the nonlinearity of the model, the objective function is generally required to be continuously differentiable and defined in the convex feasible domain, and the results depend on the selection of the initial value to a certain extent. Dynamic programming method [4] has no strict restriction on objective function, and it is easy to consider constraints, but there are dimension disasters. Recently, artificial intelligence algorithms have also been used to solve ED problems, including neural network method [5], genetic algorithm [6], and simulated annealing algorithm [7], evolutionary programming algorithm. They have their own advantages and disadvantages and have achieved good results.

2. Mathematical Model of Economic Scheduling
ED problem is to optimize the output of generating units in the system to minimize the total power generation cost under the condition of satisfying the system operation constraints.

Its objective function can be described as:

\[
\min F = \sum_{i=1}^{N} C_i(P_i)
\]
The constraints to be met are:
1) Power balance constraint
\[ \sum_{i} P_i = P_{in} + P_L \] (2)

2) The upper and lower limits of the unit output
\[ P_{i,\text{min}} \leq P_i \leq P_{i,\text{max}} \] (3)

3) Constraints on Climbing Rate of Unit
\[ -D_{R,i} \leq P_i - P_0^i \leq U_{R,i} \] (4)

4) Unit dead zone constraints
\[ P_i \in \begin{cases} P_{i,\text{min}} \leq P_i \leq P_{i,\text{max}} \\ P_{i,(j-1)w} \leq P_i \leq P_{i,w}^{j,\text{up}} \\ P_{i,w}^{j,\text{down}} \leq P_i \leq P_{i,\text{max}} \end{cases} \] (5)

Of which: \( N \) is number of units; \( F \) is total generation costs; \( P_i \) is force of the unit \( i \); \( CP_i \) is generating costs of the unit \( i \), usually expressed as a quadratic function, \( CP_i = \alpha_i + \beta_i P_i + \gamma_i P_i^2 \). Of which, \( \alpha_i, \beta_i, \gamma_i \) are fuel cost factor of the unit \( i \); \( P_L \) is system load; \( L_{i,j} \) is load contribution of the unit \( i \); \( R_{j} \) is working dead zone of the unit \( i \); \( u_i \) is upper boundary of the working dead zone of the unit \( i \); \( l_i \) is lower boundary of the working dead zone of the unit \( i \); \( m_j \) is number of working dead zones of the unit \( i \).

3. Firefly algorithm

Firefly algorithm is a new natural heuristic algorithm inspired by firefly's social behavior. About 2 in nature most fireflies emit short, rhythmic fluorescence, and most fireflies emit signals that attract other fireflies. By idealizing and abstracting some of the fly fluorescence, Cambridge University Dr. Yang invented the firefly algorithm [9-10].

The basic firefly algorithm is as follows.
1) Attraction
In the firefly algorithm, the main form of attraction function can be any monotone decreasing function, usually:
\[ \beta(r) = \beta_0 e^{-\gamma r^m}, m \geq 1 \] (6)

Type: \( r \) is the distance between two fireflies; \( \beta_0 \) is the initial attraction; \( \gamma \) is the absorption coefficient; \( m \) usually takes 2.

2) Distance between fireflies
Two Fireflies \( p \) and \( q \) in separate positions \( x_p \) and \( x_q \), the distance between the two can be defined as Cartesian or Euclidean distance.
\[ r_{pq} = \|x_p - x_q\| = \sqrt{\sum_{i=1}^{d} (x_{p,i} - x_{q,i})^2} \] (7)

Type: \( x_{p,i} \) is \( i \) dimension coordinates of the firefly \( p \); \( d \) is total coordinate dimension; \( q \in \{1,2,\ldots,F_q\} \). While \( q \) is a random choice, it is not equal to \( p \). \( F_q \) represents total number of fireflies.

3) Firefly moves
When the firefly \( p \) is attracted by another more attractive (brighter) firefly \( q \), it will move.
\[ x_p = x_p + \beta(r) \times (x_q - x_p) + \alpha \times (\text{rand} - \frac{1}{2}) \] (8)
Part 2 of the formula is determined by the attraction between fireflies, and part 3 introduces random parameters 'rand' is a uniformly distributed random number between 0 and 1.

4. Improved Firefly Algorithm

In this paper, based on the firefly algorithm, a new repair strategy is adopted to produce particles to ensure that all particles are optimized in the feasible solution region or as close as possible to the feasible solution region, thus improving the accuracy and speed of the algorithm.

4.1. Coding representation

Each firefly consists of a set of real numbers, which represent the output distribution of each unit. For example, there are d units, then a firefly is represented by a d dimensional row vector, and each value in the vector represents the output force of each unit.

4.2. Adaptation function

The fitness function of fireflies is taken:

$$ f = F + \sigma \left[ \sum_{i=1}^{N} (P_i - P_{0i} - P_{	ext{L}}) \right] $$

In the formula: F is (1) form which expressed objective function, \( \sigma \) as a punishment factor. When the total generation cost is smaller and the power balance error is smaller, the fitness value of firefly is lower, and the solution is closer to the optimal solution. The penalty function is only added to the power balance constraint because the later patch strategy can adjust the position of the meet other constraints.

4.3. Repair Strategy

How to deal with various constraints when applying PSO to the solution of such constrained optimization problems [12] is as follows: One is to transform the optimization problem into an unconstrained optimization problem, and then solve it by particle swarm optimization algorithm, but it is very difficult to transform the complex constrained optimization problem into an equivalent unconstrained optimization problem; One is to introduce the concept of Pareto graph in the solution of multi-objective optimization problem, adopt multi-level information sharing strategy, the algorithm is more complex, and another is a relatively simple method. That is, only particles that meet the constraints are retained when initializing and updating particles. The firefly algorithm in this paper is similar to the particle swarm optimization algorithm. In this paper, the third method is adopted to improve the fireflies, not only to retain the fireflies that meet the constraints, but to give up or renew the fireflies that do not meet the constraints.

If output value of each unit exceeds upper and lower value of each unit exceeds the upper and lower limit of the output, it is limited to the corresponding boundary value, which is expressed as follows:

$$ x_{ij}^{k} = \begin{cases} \text{max}_{ij} & \text{if } x_{ij}^{k} < \text{min}_{ij} \\ \text{min}_{ij} & \text{if } x_{ij}^{k} > \text{max}_{ij} \\ x_{ij}^{k} & \text{otherwise} \end{cases} $$

If the unit climbing rate constraint is violated, it is adjusted according to similar principles:

$$ x_{ij}^{k} = \begin{cases} \text{P}^{0} - \text{DR} & \text{if } x_{ij}^{k} < \text{P}^{0} - \text{DR} \\ \text{P}^{0} + \text{UR} & \text{if } x_{ij}^{k} > \text{P}^{0} + \text{UR} \\ x_{ij}^{k} & \text{otherwise} \end{cases} $$

If the force value of the unit violates the constraints of the working dead zone, it is limited to the nearest boundary value, expressed by the following formula:

$$ x_{ij}^{k} = \begin{cases} \text{P}^{0} & \text{if } 0 < x_{ij}^{k} - \text{P}^{0} \leq (\text{P}_{\text{max}}^{0} - \text{P}_{\text{min}}^{0}) / 2 \\ \text{P}_{\text{min}}^{0} & \text{if } 0 < \text{P}_{\text{max}}^{0} - x_{ij}^{k} < (\text{P}_{\text{max}}^{0} - \text{P}_{\text{min}}^{0}) / 2 \\ x_{ij}^{k} & \text{otherwise} \end{cases} $$

When the force value of the unit violates the power balance constraint, the deviation value must be calculated first

$$ \Delta_{\text{p}} = \sum_{i=1}^{N} (P_{i} - P_{0i} - P_{L}) $$

If the absolute value is greater than a small positive number, then the
output distribution value of each unit cannot meet the power balance constraint, \( \Delta P_{\text{err}} \) values need to be redistributed to each unit. Be careful not to violate the previous constraints when redistributing. The specific steps are as follows:

- **Seek** 
  \[ \Delta P_{\text{err}} = \sum_{i=1}^{N} P_i - P - \Delta P_{\text{err}}, \]
  if \( |\Delta P_{\text{err}}| < \epsilon \) (\( \epsilon \) for a small positive number, turn 7)

- According to the initial force value of each unit, the corresponding micro-increase rate is obtained and queued in a certain order (\( \Delta P_{\text{err}} \) in the order from big to small, and in the order from small to large).

- Established \( i = 1 \), Here i the unit number after queuing.

- Established \( P_{\text{avg}} = P_i, P_i = P_i - \Delta P_{\text{err}} \), then the values of \( P_i \) are adjusted according to formula (10)-(12) to satisfy various constraints.

- Established \( \Delta P_{\text{err}} = \Delta P_{\text{err}} + P - P_{\text{avg}} \), if \( |\Delta P_{\text{err}}| < \epsilon \), turn 7, or turn next.

- if \( i < N \), established \( i = i + 1 \), then turn around 4, or take the next step.

- Over.

If all units are redistributed, the deviation cannot be compensated \( \Delta P_{\text{err}} \), the solution obtained by this iteration is not feasible. Because penalty function of power balance constraint is added in the definition of adaptive value function, the adaptive value of this non-feasible solution will be larger, and the possibility of being selected as extreme value when the firefly is selected. Thus, the penalty function is a necessary supplement to the redistribution process, which can attract fireflies to the feasible solution. In addition, the redistributed fireflies have been as close as possible to the feasible solution area.

It should be noted that the calculation of the micro-increase rate can be completed in advance before the firefly iteration, which can avoid recalculation at each iteration and save the calculation time.

To sum up, after each firefly iteration, the location of the firefly needs to be checked. If the constraints such as the upper and lower limit of the unit output force, the climbing rate and the working dead zone are violated, it is set on the adjacent boundary value; if the power balance constraint is violated, the redistribution steps need to be performed to correct it.

### 4.4. Algorithm steps

The firefly algorithm has Yang Xinshe invention [11] based on the following ideal characteristics of firefly fluorescence:

- All fireflies have no gender differences; such a firefly is not attracted to another firefly for gender reasons;
- Attraction is proportional to the distance between fireflies, so for any two fireflies with less brightness, it moves in a more luminous direction. The degree of attraction is proportional to the brightness, and both are inversely proportional to the distance. If no firefly is brighter than a particular firefly, it will move randomly;
- The brightness or intensity of fireflies is affected or determined by the optimized objective function.

The algorithms are as follows:

**Objective function** 
\[ f(x), x = (x_1, ..., x_d)^T \]

**Initialize a firefly population** 
\[ x_i(i = 1, 2, ..., n) \]

**Definition of light absorption coefficient** \( \gamma \)

While \( (t < \text{Maximum number of iterations}) \)

for \( i = 1:n \)

for \( j = 1:n \)

The intensity of light \( I_i \) at \( x_i \) is determined by the \( f(x) \)

if \( I_j > I_i \)
Move the d firefly i to the j
end if
Attraction with distance r change rate is $\gamma r^2$
Evaluate new results and update light intensity
end j
end i
Arrange all the fireflies and find the best
end while
Visualization of post-processing results

During the above process, if the output value after iteration violates the constraints such as the upper and lower limits of the unit output, the climbing rate and the working dead zone, it is corrected according to (10)–(12), etc. At the same time, it is necessary to check whether the force value meets the power balance constraint, and if not, step.

5. Simulation experiment
Examples of 15 units used in literature [12] are used in this paper. Unit parameters, dead zone and B coefficient matrix are detailed in [12] literature. 2630 MW system load. Algorithm is written and run by Matlab2014a, the number of fireflies is set to 20, the number of iterations is 200, and the number of independent calculations is 30. Table 1 lists the processing assignments of each unit obtained by the optimal solution in 30 calculations. Table 2 lists the performance statistics of the optimized solutions and the comparison with the optimized solutions [13] the literature. It can be seen from the table that the optimized solution has the advantages of high speed and good effect compared with the particle swarm optimization algorithm, which proves the effectiveness of the algorithm in solving economic scheduling problems.

Table 1. FA algorithm solves the economic scheduling result of 15 machine system

| Units | Contributions (MW) | Units | Contributions (MW) |
|-------|--------------------|-------|--------------------|
| 1     | 455                | 9     | 58.92              |
| 2     | 380                | 10    | 160                |
| 3     | 130                | 11    | 80                 |
| 4     | 130                | 12    | 80                 |
| 5     | 170                | 13    | 25                 |
| 6     | 460                | 14    | 25                 |
| 7     | 430                | 15    | 15                 |
| 8     | 71.74              |       |                    |
| Losses (MW) | 30.66 | Cost of electricity generation ($/h) | 32704.45 |

Table 2. Performance and comparison of optimization results

| Algorithm                  | Best solution ($) | Worst solution ($) | Average solution ($) | Average time (s) |
|----------------------------|-------------------|--------------------|----------------------|-----------------|
| Particle swarm optimization| 32858             | 33331              | 33039                | 26.59           |
| This algorithm             | 32704             | 37175              | 32856                | 5.5             |

6. Conclusion
The traditional method of solving economic scheduling is to add various inequality constraints to the penalty function. The repair strategy proposed in this paper actively corrects fireflies that violate various constraints. The fireflies can search in or near the feasible domain as much as possible, which ef-
fectively improves the accuracy and speed of calculation. The simulation results show the effectiveness and good convergence of this algorithm.

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