A multi-objective scheduling method for smart grid loads based on improved GSO algorithm

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Abstract. When the traditional scheduling method is applied to the smart grid, it is difficult to adapt to the characteristics of fast changing grid load and multiple scheduling objectives, which leads to problems such as low economy and slow scheduling response rate. In order to improve the above problems, a multi-objective scheduling method for smart grid loads based on the improved GSO algorithm is studied. After predicting the short-term load changes of the smart grid using the maximum Lyapounov exponent method, a grid load scheduling model is established with the objectives of economy, environmental protection and reliability. The GSO algorithm is improved by using simulated annealing algorithm to solve the grid load scheduling model to achieve multi-objective scheduling of grid loads. The comparison experiment verifies that the scheduling method improves the scheduling response rate by at least 37.5%, and effectively reduces the scheduling cost with reliability.

1. Introduction

There is a certain diversity of power loads in smart grids, and in addition to the rigid loads of some traditional grids, the addition of flexible loads makes the dynamic changes of grid power loads more prominent[1-2]. When the power system has a shortage of power supply, the situation can be effectively improved by reasonable scheduling of the flexible load of the smart grid, so as to achieve the stability requirements of the power system.[3-4]

The dispatching method in the literature [5] uses a single-objective optimal dispatching method, i.e., with the goal of pursuing the minimum total energy consumption or the maximum economic benefit of the grid, the units are scheduled in advance according to some sequencing rules, and then the units are switched in order until the total load demand of the power system is satisfied. This method is a static sequencing strategy with very fast calculation speed; however, the results obtained by this algorithm are rough and often do not meet the needs of solving the optimal scheduling of units containing large capacity. The literature [6] combines dynamic planning with genetic algorithm by integrating the constraints with the original scheduling objective function through penalty factors into a comprehensive objective function, which is then solved. Although this method draws on the characteristics of genetic algorithm with wider applicability and flexible application, and is theoretically easy to obtain the global optimal solution, it is very dependent on the computational power, requires high hardware configuration of the grid, and is less economical. Based on the above analysis content, in order to improve the problems such as poor stability, low economy and slow dispatch response rate in multi-objective scheduling of smart grid load, this paper will study the multi-objective scheduling method of smart grid load by improving and optimizing the GSO algorithm, and verify the feasibility of this scheduling method.
2. A multi-objective scheduling method for smart grid loads based on improved GSO algorithm

2.1. Smart grid short-term load change prediction

The power load series is a set of nonlinear time series, and the chaos theory is introduced into the nonlinear time series analysis by the maximum Lyapounov exponent method to realize the short-term prediction of the grid load by the chaotic phase space reconstruction theory[7-8]. In the phase space reconstruction, the most important thing is the selection of delay time $\tau$ and embedding dimension $m$. The selection of the values will largely affect the error range of load prediction, so the proper selection of delay time and embedding dimension is especially important. The autocorrelation function approach is used to find the delay time. The method focuses on the extraction of linear correlations between series, and for a continuous time series variable $x(t)$, the autocorrelation function $C(\tau)$ is expressed as.

$$C(\tau) = \lim_{T \to \infty} \frac{1}{T} \int_{0}^{T} x(t) x(t + \tau) dt$$

(1)

$\tau$ in the above equation represents the amount of change in the time interval, which characterizes the degree of similarity from moment $t$ to moment $t + \tau$. And when the autocorrelation function $C(\tau)$ first decreases to $1 - \frac{1}{e}$ of its initial value, the corresponding time $t$ is the delay time. Phase space reconstruction of grid load data requires only observing any of the many components and recording its value at some fixed delay point to be processed as new data. This process is repeated to record the delay quantities at different times, when the collected information preserves many features in the original sequence[8]. Let there exist a time series $x_1, x_2, \cdots, x_n$, and based on the delay times and embedding dimensions obtained above, the reconstructed phase space is shown in equation.

$$Y(t_1) = [x(t_1), x(t_1 + \tau), x(t_1 + 2\tau), \cdots, x(t_1 + (m-1)\tau)]$$

$$Y(t_2) = [x(t_2), x(t_2 + \tau), x(t_2 + 2\tau), \cdots, x(t_2 + (m-1)\tau)]$$

$$\vdots$$

$$Y(t_n) = [x(t_n), x(t_n + \tau), x(t_n + 2\tau), \cdots, x(t_n + (m-1)\tau)]$$

(2)

Take the initial point as $Y(t_0)$, find the nearest neighbor $Y_0(t_0)$ of $Y(t_0)$, let $L_0$ be the distance from $Y(t_0)$ to $Y_0(t_0)$, and reach $Y(t_1)$ after a certain time evolution to find its nearest neighbor $Y_0(t_1)$. Let $L' = \|Y(t_1) - Y_0(t_1)\|$, when $L' > \varepsilon$, keep the point $Y(t_1)$, and find another point $Y_1(t_1)$, so that $L' = \|Y(t_1) - Y_0(t_1)\| < \varepsilon$, and satisfy its angle less than 45°, and iterate the above process in turn until the end of the time series end moment, then the Lyapounov maximum index is.

$$\lambda = \frac{1}{t_M - t_0} \sum_{k=0}^{M} L'_{k}$$

(3)

In the above equation, $t_M$ denotes the moment of the end of the iterative time series. $M$ denotes the total number of iterations, and when the value of the maximum exponent is greater than 0, the time series is proved to be chaotic. And in Lyapounov maximum exponent forecasting, the longest time period $T$ days of the predicted load can be calculated from the obtained maximum exponent and $T$ is $\frac{1}{\lambda}$. Based on the predicted load trend of the power grid, a load scheduling plan is developed in conjunction with the load scheduling model established below to complete the scheduling process.
2.2. Establishing a multi-objective scheduling model for smart grid loads

The intelligent scheduling load multi-objective scheduling economical scheduling objective function is shown in the following equation.

\[
\min C_1 = \sum_{i=1}^{T} \left( \sum_{m=1}^{N} F_i(P_i(t)) + C_{DE}(P_i(t)) \right)
\]

\[F_i(P_i(t)) = C_{fi}(P_i(t)) + C_{OMi}(P_i(t))\]

\[C_{DE}(P_i(t)) = \frac{C_{ADCC}}{8760P_{ni} \times f_i}\]

In the above equation, \(C_1\) is the total cost of smart grid dispatch. \(T\) is the total number of work periods. \(N\) is the total number of distributed power sources in the grid. \(F_i(P_i(t))\) is the generation cost of the output unit. \(C_{DE}(P_i(t))\) is the depreciation cost of the grid system. \(C_{fi}(P_i(t))\) is the fuel cost of the \(i\) th power source. \(C_{OMi}(P_i(t))\) is the maintenance cost of the \(i\) th power supply. \(C_{ADCC}\) is the installed cost of each power supply amortized to an annual cost. \(f_i\) is the capacity factor of the \(i\) th generation source. \(c\) are the parameters of the corresponding power sources. The intelligent scheduling load multi-objective scheduling security scheduling objective function is shown in the following equation.

\[C_3(t) = 1 - \frac{R(t)}{riskP_{wp}} \cdot R(t) < riskP_{wp}\]

In the above equation, \(C_3\) is the operational risk factor of the smart grid. \(risk\) is the coefficient of smart grid response to fluctuations, which is set to 0.2 in this paper. \(R(t)\) is the backup capacity provided by the battery at time \(t\). \(P_{wp}\) is the sum of the power ratings of the power sources of the smart grid auxiliary generation.

2.3. Improving the GSO algorithm solution model for multi-objective scheduling of grid loads

The standard GSO algorithm can be basically divided into: the fluorescein update phase, the search for a better individual phase, the firefly location update phase and the perceptual radius update phase.

(1) Fluorescein update. The fluorescein value of firefly \(i\) is updated according to equation (9), and the fluorescein value shows the fitness size of a potential solution in the function solution space; the higher the value of fluorescein, the better the potential solution, the more attractive the firefly individual is to other firefly individuals in the neighborhood, and the higher the probability of other individuals in the neighborhood moving toward it.

\[l_i(t) = \max \left\{ 0, (1 - \rho) * l_i(t-1) + \gamma * J\left[X_i(t)\right] \right\}\]

In equation (9), \(l_i(t)\) denotes the fluorescein value of individual \(i\) at the \(t\)th iteration. \(l_i(t-1)\) denotes the fluorescein value of individual \(i\) at the \(t-1\)th iteration. \(J[X_i(t)]\) denotes the fitness value of the function for individual \(i\) at the \(t\)th iteration. \(\rho\) is a fluorescein attenuation factor. \(\gamma\) is the fluorescein update rate, which is used to enhance the fluorescein value.

(2) Searching for better individuals. If firefly \(i\) has more than one individual in its neighborhood, it will randomly select an individual firefly and move toward it according to the probability ratio of the luciferin value, and generally the random selection method is roulette. The probability \(P_{ij}(t)\) that firefly \(i\) moves toward firefly \(j\) is calculated as follows.
(3) Firefly position update. Individual $i$ selects an individual by calculating the probability of fluorescein values of the best individuals in its neighborhood, and assuming that the individual is a firefly $j$, then individual $i$ moves toward $j$ and updates the individual position.

(4) Since the GSO algorithm will significantly reduce the global search ability in the face of more local optimal points of multimodal functions and will fall into local optimal solutions, this paper selects the simulated annealing algorithm to improve it. Suppose $i$ is the current solution and $j$ is a new solution in its neighborhood. The SA algorithm is based on a process of neighborhood search strategy to reach the equilibrium state, also known as the inner loop process of the SA algorithm. According to the flowchart shown in figure 1 below, the improved GSO algorithm is used to solve the smart grid load multi-objective scheduling model.

![Flow chart of the improved GSO algorithm for solving the load scheduling model](image)

Figure 1. Flow chart of the improved GSO algorithm for solving the load scheduling model

3. Scheduling method feasibility validation study

3.1. Experiment content

The experiment is in the form of comparison experiments, and the grid load scheduling methods mentioned in literature [5] and literature [6] are selected as comparison group 1 and comparison group 2, and the multi-objective scheduling method proposed in this paper is used as the experimental group. The experiments compare the solution performance of the scheduling solution algorithm and the practical application effect of the scheduling method, respectively, to comprehensively verify whether the method proposed in this paper is feasible and reliable.

3.2. Experimental results and analysis

The experimental results of experiment 1 on the solution performance of the algorithm are shown in figure 2 below, where the genetic algorithm, GSO algorithm, and improved GSO algorithm are solved for three cases with different amounts of operations. The convergence curves of each algorithm in figure 2 are analyzed to compare the solution performance of the algorithms.
From (a), (b), and (c) in figure 2, it can be concluded that the improved GSO algorithm converges extremely well for the three cases, and the strong merit-seeking ability of the improved GSO algorithm enables it to search for the theoretical lower bound in a small number of iterations. The convergence curve of the genetic algorithm is higher than that of the improved GSO algorithm and lower than that of the classical GSO algorithm when solving two cases, example 1 and example 2. When solving example 3, the initial convergence of the genetic algorithm is worse than that of the classical GSO, and with the increase of iterations, the convergence curve decreases rapidly and the convergence is gradually stronger than that of the classical GSO algorithm. The convergence of the improved GSO algorithm is significantly better than that of the classical GSO algorithm when solving different cases. The maximum completion time of the improved GSO algorithm is significantly smaller than the other two algorithms. The above results show that the improved GSO algorithm has better convergence, faster solution speed, and better solution performance when solving the arithmetic cases.

Experiment 2 uses three load scheduling methods to schedule the same smart grid, changing different parameters in the grid to set 10 different sets of load scheduling backgrounds, and comparing the scheduling cost and scheduling response time of the scheduling methods. The data recorded in the experiment are shown in table 1 below.

| Number | Comparison group 1 | Comparison group 2 | Experimental group |
|--------|--------------------|--------------------|--------------------|
|        | Scheduling costs/¥1000 | Scheduling response time /s | Scheduling costs/¥1000 | Scheduling response time /s | Scheduling costs/¥1000 | Scheduling response time /s |
| 1      | 74.85               | 49.4               | 68.05              | 36.0 | 35.68 | 24.9 |
| 2      | 73.76               | 47.8               | 66.03              | 36.7 | 35.84 | 22.2 |
| 3      | 73.75               | 45.7               | 67.56              | 35.6 | 36.21 | 23.1 |
| 4      | 74.61               | 48.9               | 69.25              | 36.5 | 35.76 | 25.6 |
| 5      | 74.59               | 48.6               | 70.47              | 37.9 | 35.73 | 21.5 |
| 6      | 74.78               | 49.2               | 66.36              | 37.8 | 35.92 | 23.4 |
| 7      | 73.93               | 46.5               | 69.15              | 36.1 | 35.44 | 23.2 |
| 8      | 73.32               | 49.2               | 69.48              | 36.3 | 35.39 | 23.7 |
| 9      | 73.79               | 46.3               | 66.82              | 36.4 | 36.15 | 25.3 |
| 10     | 73.94               | 48.1               | 66.19              | 38.2 | 35.28 | 22.8 |

Analysis of the data in Table 1 above shows that when dispatching the grid with different parameters, the dispatching cost of the comparison group 1 method is the highest, followed by the comparison group 2 method, and the dispatching cost of the experimental group method is the lowest and is about 50% of the comparison group 2 method. In detailed analysis, when applying the experimental group method for dispatching, the clean energy supply is reasonably invoked based on the grid load forecast results, effectively reducing the grid’s emission cost while also reducing the grid generation cost. Further processing of the data in table 1 above shows that the dispatch response time of the experimental group is on average about 5/8 of that of the comparison group 2 method and 1/2 of
that of the comparison group 1 method. This indicates that the high dispatch response rate of the experimental group method shortens the time difference of grid execution and further reduces the energy consumption of the grid. In summary, the multi-objective scheduling method for smart grid loads based on the improved GSO algorithm proposed in this paper has a fast processing response rate and can effectively reduce the grid scheduling cost with reliability.

4. Conclusion

Smart grid is a new type of grid based on the physical grid, integrating advanced sensing and measurement technology, communication technology, information technology, computer technology and control technology with the physical grid. Smart grid optimizes resource allocation while fully satisfying customers' electricity demand, ensures the safety and economy of power supply, guarantees the quality of electricity while meeting environmental constraints, and provides reliable, economic, clean, interactive power and value-added services to customers. Reasonable scheduling of smart grid loads can reduce grid operating losses while improving the efficiency of the smart grid. To address the problems of traditional grid load scheduling methods, this paper proposes a multi-objective scheduling method for smart grid loads based on improved GSO algorithm. The feasibility and reliability of the method are verified through comparison experiments with the traditional scheduling method. As the new energy generation technology continues to mature, the smart grid scheduling also needs to be continuously optimized. Therefore, the load scheduling method should be continuously improved in the future research by combining with the actual demand.

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