Collaborative optimization of high proportion renewable energy system based on Improved PSO algorithm

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Abstract. Due to the uncertainty of renewable energy, the high proportion of renewable energy system has low cooperative scheduling capability and high cost. Therefore, based on the improved PSO algorithm, a high proportion of renewable energy system collaborative optimization method is proposed. Firstly, the framework and decomposition mechanism of transmission and distribution collaborative scheduling of renewable energy system are set up. Then, based on the analysis of the improved PSO algorithm strategy, the reactive power optimization method of renewable energy system is designed based on MSI-PSO algorithm. Firstly, the mathematical model of high proportion renewable energy system is proposed and solved, so as to complete the collaborative optimization. Finally, the simulation analysis shows that the design method has higher collaborative scheduling ability and lower cost, which proves that the collaborative optimization method of high proportion renewable energy system based on Improved PSO algorithm is effective.

1. Introduction
The extensive access of high proportion renewable energy has fundamentally changed the operation and control mode of traditional power system. A key scientific and technical problem to be solved urgently in power system discipline is how to realize the optimal allocation of energy from production, transmission to use in a more safe, reliable, cost-effective and environment-friendly way under the multiple uncertainty environment of Distributed Renewable Energy and energy load [1]. With a large number of distributed generation connected to the distribution system, the operation of distribution network presents a more flexible trend. The traditional distribution network is gradually transformed into active distribution network (ADN), and the interaction between transmission network and distribution network is increasingly close. At the same time, the proportion of renewable energy such as wind and power in the grid is increasing, and both centralized and distributed renewable energy are facing the problem of consumption [2]. In the future, it is inevitable to change the focus of multi-level coordinated dispatching of renewable power grid from multi-level coordinated dispatching to multi-level coordinated dispatching.

Reference [3] points out that renewable energy (RE) can be integrated into the independent third generation CCHP system to achieve zero environmental emissions and higher energy efficiency. However, in order to overcome the inherent intermittent availability of renewable energy and improve the performance of renewable energy CCHP system, it is necessary to include thermal energy and power storage mechanisms. The purpose of this study is to establish a simulation model to optimize different configuration schemes of automatic re-cchp system to meet cold, heat and power loads, based on photovoltaic thermal (PVT) panel, wind turbine (WT), thermal energy storage (TES), electric energy storage (EES), absorption chiller (chabs), electric refrigerator (chelec) and electric heater (EH).
For the operation of autonomous re-cchp system, two operation strategies are adopted: following electric load (FEL) and following thermal load (FTL). In the aspect of optimization, a newly developed evolutionary particle swarm optimization (e-pso) algorithm is tested and verified. The results show that PVT + wt + EES + tes + chabs + eh based on FTL operation strategy is the most cost-effective configuration scheme in autonomous re-cchp system, and chelec is not needed. However, the application effect of this method in high proportion renewable energy system is unknown. Particle swarm optimization (PSO) is a kind of swarm optimization algorithm based on global behavior. Particle swarm optimization has a good effect in dealing with complex multimodal problems [4]. In reference [5], an optimization design method of photovoltaic wind energy hybrid system based on particle swarm optimization (PSO) is proposed. The algorithm uses hourly actual data of wind speed, solar radiation, temperature and power demand of a certain location. The particle swarm optimization algorithm is used to match the power supply with the local demand with a specific reliability index to obtain the minimum generation cost. The algorithm has been tested by a practical case considering the actual situation. The study uses the electricity market price to supply electricity demand from the public grid to estimate the significance of cost saving compared with the actual cost. The results show that the algorithm has a good response to the changes of system parameters and variables, and provides a reliable sizing scheme. According to the operation characteristics of power system in reference [6], it is known that when the load exceeds the generating capacity, the system stability will be affected, leading to the cascading outage of the main components of the power system, resulting in the frequency attenuation effect. Fast load shedding is the best way to avoid cascading blackouts and power system blackouts. Therefore, based on grasshopper optimization algorithm, a novel, accurate, reliable and fast UFLS technology is proposed. In order to verify the effectiveness of the proposed UFLS algorithm based on Goa, different disturbance and adaptation, particle swarm optimization (PSO) and genetic algorithm (GA) UFLS algorithms are compared. Based on DIgSILENT power plant software, the power system under different disturbance levels is simulated. The calculation results verify the accuracy and reliability of the minimum load shedding of Goa under the constraint conditions. In addition, Goa is faster than PSO and GA.

Based on the above research, considering the uncertainty of renewable energy, this paper proposes a high proportion of renewable energy system collaborative optimization technology based on Improved PSO algorithm.

2. The framework of cooperative scheduling and decomposition mechanism of transmission and distribution

Under the background of power market reform, the separation of transmission and distribution is the trend of power grid development in the future. At the same time, conditional power generation enterprises are allowed to enter the electricity selling side [7-9]. In order to meet the scheduling requirements of various types of autonomous agents, the hierarchical distributed scheduling framework of transmission and distribution network is proposed according to the structure and function. As shown in Figure 1, it is divided into three layers: transmission network scheduling layer, distribution network scheduling layer and local scheduling layer. Among them, the local dispatching layer refers to the internal dispatching unit of a distribution network, which optimizes the joint output of distributed renewable generation (RDG) and energy storage system (ESS). It is oriented to a large number of distributed generation invested and constructed by new energy suppliers in the distribution network, forming an independent stakeholder. Different from the traditional partition control, the local scheduling layer emphasizes the self optimization ability rather than simply executing the scheduling instructions of the centralized mechanism.
Conventional unit Renewable energy Traditional distribution network

Transmission network

Active distribution network 1 Controllable distributed generation Load

Active distribution network 2 Controllable distributed generation Load

RDG Energy storage RDG Energy storage

Local scheduling layer

Figure 1. Distribution Co-scheduling Framework

Under the "hierarchical distributed" scheduling framework, the high proportion of renewable energy system collaborative optimization technology based on Improved PSO algorithm independently schedules the power generation equipment within its jurisdiction, and cooperatively arranges the power transmission plan according to the boundary price of transmission and distribution. The generation plan should take into account the generation resources in the transmission and distribution network, meet the overall operation constraints, and ensure the stability of the system Safe and economic operation.

3. Reactive Power Optimization of Renewable Energy System Based on Improved PSO Algorithm

3.1. Basic Principle of PSO Algorithm

The position of the i particle in the D-dimensional space is expressed as \( x_i = (x_{i1}, x_{i2}, \ldots, x_{id}, \ldots, x_{iD}) \) vector, and the flight speed is expressed as \( v_i = (v_{i1}, v_{i2}, \ldots, v_{id}, \ldots, v_{iD}) \) vector. The fitness value of each particle is brought into the value calculated by the optimization function. In the optimization process, each particle has a best position in history (pbest, also known as individual extremum) and its current position (xi). pbest is the historical position of the particle corresponding to the minimization of particle fitness. By comparing the fitness values of pbest among particles, the position with the lowest fitness value is called gbest, which is called the best position in global history (also known as global extremum), and gbest is the best value of pbest among all particles. In the search space, the
update speed of particles will point to the best value of individual history and the best value of global history, and the search direction of particles will be indicated by these two values.

In the next iteration, the update formulas of particle velocity and position are shown in equations (1) and (2):

\[
\begin{align*}
v_y(t) &= w v_y(t) + c_1 r_1(t) [p_y(t) - x_y(t)] + c_2 r_2(t) [p_y(t) - x_y(t)] \quad (1) \\
x_y(t+1) &= x_y(t) + v_y(t+1) \quad (2)
\end{align*}
\]

Where, \( i = 1,2,\ldots,N \) is the number of particles; \( j = 1,2,\ldots,D \) is the dimension of particles; \( t \) is the number of iterations; \( x_y(t) \) is the \( j \) component of particle \( i \) position in the \( t \) iteration; \( v_y(t) \) is the \( j \) component of particle \( i \) velocity in the \( t \) iteration; \( p_y(t) \) is the \( j \) component of particle \( i \) individual extremum (pbest) in the \( t \) iteration; \( p_y(t) \) is the \( j \) component of the global extreme value (gbest) at the \( t \) iteration; \( r_1(t), r_2(t) \) is the random function between \([0,1]\); \( c_1, c_2 \) is the acceleration factor (also known as the learning factor); \( w \) is the inertia weight.

Like most iterative algorithms, PSO algorithm mainly includes three steps: initialization, iteration and return result, as shown in Figure 2.

![PSO Flowchart](image)

Figure 2.PSO Flowchart

3.2. Improved PSO Algorithm Strategy

On the basis of various existing algorithms [10], this paper comprehensively improves the PSO algorithm. According to the speed update formula of basic particle swarm optimization algorithm,
acceleration factor $C_1$ and $C_2$ is used to adjust the "self experience" and "group experience" of particles to update the speed of the next moment. The standard PSO algorithm usually takes the two values as the same, when the particles move towards the two "best positions" (guided by the best position in the history of the individual and the best position in the history of the population respectively), the weight is the same, and does not highlight the focus of the particles in different search stages. Based on this, the MSI-PSO algorithm used in this paper adopts different acceleration factor combinations according to the particle in different search stages. Because the particle mainly follows the historical best position $p_i$ in the early stage of the optimization search, the individual guidance factor of the particle plays a major role in the whole search share. At this stage, the particle needs to fully explore the area around itself, and at the same time, it needs to keep the search speed. In the later stage of the search, the particles mainly track the best position in the history of the population, and focus on the search in the whole region, so as to speed up the convergence speed and maintain the global search accuracy, so the global guidance of particles plays a major role in this stage.

The inertia weight $w$ keeps the inertia of particle motion and represents the inheritance proportion of particle velocity at the previous time, so as to make it have the trend of exploring space expansion. When the inertia weight is relatively small, the development ability of the particle is strong, so the inertia weight can be modified according to the relationship between the historical best position of the individual and the historical best position of the population, so as to balance the relationship between the global search and local development of the particle. The calculation method of inertia weight is as follows:

$$w(i) = \frac{1}{N} \sum_{j} f_{pi}(t) - f_{best}(t)$$

Among them, $f_{pi}(t)$ is the fitness value of the best historical position of the $i$ particle, $f_{best}(t)$ is the fitness value of the best historical position of the population, $N$ is the number of particles in the population, and $r$ is a constant between $(0,1)$, which is used as a regulator. In this method, the strategy of dynamically adjusting inertia weight in reference [11] is to take the "distance" between the fitness value of individual's historical best position and that of population's historical best position as the basis of inertia weight adjustment, which makes full use of the historical best information of particles in the optimization process, and inherits and continues it. The "distance" represents the closeness between the individuality and commonness of particles. The smaller the distance is, the smaller the inertia weight will be, and the particles will search intensively to increase their local development ability; the larger the distance is, the larger the inertia weight will be, and the global development ability will be expanded.

3.3. Reactive Power Optimization Technology of Renewable Energy System Based on MSI-PSO Algorithm

The intermittence and fluctuation of renewable energy output bring great difficulties to the prediction and analysis of the operation situation of distribution system. One of the difficulties is how to optimize the system structure, improve the system security, and maximize the output of renewable energy through the network reconfiguration and active island autonomous operation of distribution network; the distribution system with electric vehicles, energy storage and intermittent renewable energy is one of the most difficult problems. The control elements of the system are various, and the coordination mechanism of the multi elements is complex. How to realize the collaborative optimal operation of the distribution system through the multi scenario network reconfiguration strategy is also a work with technical challenges. It is necessary to develop and introduce new mathematical optimization algorithms and theories for the increasingly complex multi-objective reconfiguration and coordinated optimal operation of intelligent distribution network in multiple scenarios.
3.3.1 Mathematical Model of Reactive Power System Optimization. Generally speaking, reactive power optimization of power system is a multi-objective mathematical model with the minimum system network loss $P_{loss}$ and the maximum system static voltage stability margin $V_{stab}$, which is established when the active power flow of power grid is known and the operation constraints such as system voltage and generator output are met [12]. Static voltage stability margin $V_{stab}$ can be measured by the minimum singular value component of conventional convergence power flow Jacobian matrix. The larger the value is, the larger the static voltage stability margin is. In order to simplify the calculation and facilitate the comparison, this paper transforms the problem of maximizing the static voltage stability margin into the problem of minimizing it:

$$F_1 = \min \sum_{k \in N} P_{loss} = \sum_{k \in N} g_k(V_i^2 + V_j^2 - 2V_iV_j \cos \theta_i)$$

$$F_2 = \min(\frac{1}{\delta_{min}})$$  

(4)

Generally speaking, in the multi-objective model of reactive power optimization, due to the different dimensions of each sub objective function, it cannot be directly weighted. In order to make the West numbers of different sub objectives comparable, the objective functions are normalized:

$$F'_1 = \frac{F_1}{F_0}$$

$$F'_2 = \frac{F_2}{(1/\delta_0)}$$  

(5)

Where $F_0$ is the initial active power loss and $\delta_0$ is the minimum singular value of the initial Jacobian matrix.

Since generator terminal voltage, transformer ratio and compensation capacitor capacity of each node are control variables [13], their constraints can be satisfied by the search space of the algorithm. PQ node voltage and reactive power are state variables, which are written as penalty function:

$$f_1 = F'_1 + \sum_i \lambda_{V_i} (V_i - V_{i,lim})^2 + \sum_i \lambda_{Q_{Gl}} (Q_{Gl} - Q_{Gl,lim})^2$$

$$f_2 = F'_2 + \sum_i \lambda_{V_i} (V_i - V_{i,lim})^2 + \sum_i \lambda_{Q_{Gl}} (Q_{Gl} - Q_{Gl,lim})^2$$  

(6)

Where $\lambda_{V_i}$, $\lambda_{Q_{Gl}}$ is the penalty factor and $V_{i,lim}$, $Q_{Gl,lim}$ is the penalty factor:

$$V_{i,lim} = V_{i,max}; V_i > V_{i,max}$$

$$V_{i,lim} = V_{i,min}; V_i > V_{i,min}$$  

(7)

$$V_{i,lim} = V_{i}; others$$

$$Q_{Gl,lim} = Q_{Gl,max}; Q_{Gl} > Q_{Gl,max}$$

$$Q_{Gl,lim} = Q_{Gl,min}; Q_{Gl} > Q_{Gl,min}$$  

(8)

$$Q_{Gl,lim} = Q_{Gl}; others$$

Where, $V_{i,max}$, $V_{i,min}$ is the upper and lower limits of node voltage; $Q_{Gl,max}$, $Q_{Gl,min}$ is the upper and lower limits of reactive power generated by each generator.

3.3.2 Multi-objective Problem Solving Method. Usually, multi-objective problems are transformed into single objective problems, such as weighting method, fuzzy membership function method, etc.

1) Weighting method

The multi-objective optimization model is transformed into the following single objective optimization model:
In the formula, \( w_i \) is the multi-objective weight value, which is a weight measure of economy and voltage stability, called preference factor, and \( m \) is the number of objective functions, usually \( \sum_{i=1}^{m} w_i = 1 \).

(2) Fuzzy membership function method

The objective values are transformed into fuzzy membership functions:

\[
\min F = \sum_{i=1}^{m} u(F_i) \quad (10)
\]

Where \( u(\cdot) \) is a membership function. Membership functions include convex index, linear, hyperbolic, concave index and other functions [14]. In this paper, the membership function is linearized.

For the system network loss, the membership function \( u(F_1) \) adopts the function that increases with the network loss, that is:

\[
u(F_1) = \begin{cases} 
0 & F_1 < F_{1\text{min}} \\
\frac{F_1 - F_{1\text{min}}}{F_{1\text{max}} - F_{1\text{min}}} & F_{1\text{min}} \leq F_1 < F_{1\text{max}} \\
1 & F_{1\text{max}} \leq F_1 
\end{cases} \quad (11)
\]

In the formula, \( F_{1\text{min}} \) is the minimum network loss, \( F_{1\text{max}} \) is the maximum network loss.

For the system voltage stability margin [15], the membership function \( u(F_2) \) increases with \( F_2 \), that is:

\[
u(F_2) = \begin{cases} 
0 & F_2 < F_{2\text{min}} \\
\frac{F_2 - F_{2\text{min}}}{F_{2\text{max}} - F_{2\text{min}}} & F_{2\text{min}} \leq F_2 < F_{2\text{max}} \\
1 & F_{2\text{max}} \leq F_2 
\end{cases} \quad (12)
\]

Where \( F_{2\text{min}} \) is the reciprocal of the calculated maximum \( \delta^* \) and \( F_{2\text{max}} \) is the minimum reciprocal.

After adding the penalty function, the objective function is modified as follows:

\[
\min f = \sum_{i=1}^{m} u(F_i) + \sum_i \lambda_i (V_i - V_{i,\text{lim}})^2 + \sum_i \lambda_{Gl} (Q_{Gl} - Q_{Gl,\text{lim}})^2 \quad (13)
\]

So far, the reactive power optimization technology of renewable energy system based on MSI-PSO algorithm is completed.

4. Simulation Analysis

This paper takes 24h's daily scheduling as an example to verify the effectiveness of the proposed collaborative optimization method based on improved PSO algorithm for high proportion renewable energy system. Based on MATLAB, yalmip is used to solve the problem. CPLEX is selected as the solver. The CPU of the test environment is Intel corei53.2GHz and 8GB memory.

4.1. Optimization Results of Local Scheduling Layer

In this paper, it is assumed that the RDG in the active distribution network is a wind turbine. The power prediction curve, joint selling price and ESS parameters are shown in Figure 3, table 1 and table
2. The penalty coefficients $\lambda_v$, $\lambda_c$ in the objective function are respectively set as 1.2 times of the real-time price. The Monte Carlo sampling method is used to generate 1000 wind power scenarios, and the scene reduction technology based on K-means clustering is used to reduce the number of scenarios to 20.

| Power consumption at all times | Electricity price / (yuan/MWh) | Power consumption at all times | Electricity price / (yuan/MWh) |
|-------------------------------|-------------------------------|-------------------------------|-------------------------------|
| 0:00-8:00                    | 3                             | 8:00-24:00                   | 5                             |

Table 2 ESS Parameters

| $E_{min}$/MWh | $E_{max}$/MWh | $P_{char,max}$/MW | $P_{dis,max}$/MW | Charging efficiency | Discharge efficiency |
|----------------|---------------|-------------------|------------------|--------------------|----------------------|
| 12             | 60            | 10                | 10               | 0.9                | 0.9                  |

4.2. Optimal results of cooperative scheduling of high proportion renewable energy systems

On this basis, the collaborative scheduling optimization results of high proportion renewable energy system are tested, as shown in Figure 4. It can be seen from Figure 4 that the expected output value of RDG is basically consistent with the prediction curve, indicating that the local dispatching layer can make full use of Distributed Renewable Energy in each wind power scenario without abandoning wind; secondly, the output characteristics of RDG and ESS units are relatively flat on the whole At the same time, the combined output is larger when the selling price is higher than when the selling price is lower, which realizes the economic optimization. It should be pointed out that the local dispatching level gives the day ahead plan according to the hour scale in order to keep consistent with the time scale of the power grid.
5. Conclusion

Under the background of high proportion of renewable energy power system, aiming at the problem of insufficient coordination of generation and consumption planning between transmission network and active distribution network, this paper proposes a transmission and distribution collaborative optimization scheduling method based on Improved PSO algorithm. The main conclusions are as follows.

(1) Based on the idea of hierarchical scheduling, a multi-layer optimal scheduling system of transmission and distribution network is constructed, and the msi-pso algorithm is used to realize the optimal solution of the exchange power between levels. The algorithm has fast convergence performance, which not only realizes the independent optimization of each scheduling layer, but also takes into account the coordination of power generation resources between transmission and distribution networks, and can adapt to the scheduling needs of various types of autonomous agents.

(2) The comparative analysis shows that this method can reduce the wind abandonment rate of transmission network and improve the reserve level of the system under the premise of autonomous operation of distribution network, and improve the overall operation economy of power grid. In this paper, the transmission and distribution collaborative optimization scheduling method is limited to the scenario of distribution network with independent power prediction and scheduling management function. In the future, the structure and dispatching form of distribution network will be diversified. Under the more complex dispatching relationship of transmission and distribution network, it is worth to further explore what kind of transmission and distribution cooperative dispatching system to build.

References

[1] Liu H, Zhai R, Fu J, et al. Optimization study of thermal-storage PV-CSP integrated system based on GA-PSO algorithm[J]. Solar Energy, 2019, 184(05):391-409.

[2] Gong X. Optimization of the Power Generation Control Process of Hydraulic Turbine Set Based on the Improved BFO-PSO Algorithm[J]. Journal of Coastal Research, 2019, 94(01):227-230.

[3] Lorestani A, Ardehali M M. Optimal integration of renewable energy sources for autonomous tri-generation combined cooling, heating and power system based on evolutionary particle swarm optimization algorithm[J]. Energy, 2018, 145(15):839-855.

[4] Mohamed M A, Eltamaly A M, Alolah A I. Swarm intelligence-based optimization of grid-dependent hybrid renewable energy systems[J]. Renewable and Sustainable Energy Reviews, 2017, 77(09):515–524.

Figure 4. Optimal results of cooperative scheduling of high proportion renewable energy systems
[5] Gohari F S, Aliee F S, Haghighi H. A significance-based trust-aware recommendation approach[J]. Information Systems, 2020, 87(01):16-20.

[6] Kargarian A, Fu Y, Wu H. Chance-Constrained System of Systems Based Operation of Power Systems[J]. IEEE Transactions on Power Systems, 2016, 31(5):3404-3413.

[7] Nadjemi O, Nacer T, Hamidat A, et al. Optimal hybrid PV/wind energy system sizing: Application of cuckoo search algorithm for Algerian dairy farms[J]. Renewable & Sustainable Energy Reviews, 2017, 70(04):1352-1365.

[8] Singh S, Chauhan P, Singh N J. Capacity optimization of grid connected solar/fuel cell energy system using hybrid ABC-PSO algorithm[J]. International Journal of Hydrogen Energy, 2020, 45(16):10070-10088.

[9] Godio A, Santilano A. On the optimization of electromagnetic geophysical data: Application of the PSO algorithm[J]. Journal of Applied Geophysics, 2018, 148(11):163-174.

[10] Davood, Azizian, Gevork, et al. Split-winding transformer design using new hybrid optimisation algorithm based on PSO and I-BB-BC[J]. Iet Science Measurement & Technology, 2018, 12(6):712-718.

[11] Rezk H, Fathy A, Abdelaziz A Y. A comparison of different global MPPT techniques based on meta-heuristic algorithms for photovoltaic system subjected to partial shading conditions[J]. Renewable and Sustainable Energy Reviews, 2017, 74(14):377-386.

[12] Manickam C, Raman G R, Raman G P, et al. A Hybrid Algorithm for Tracking of GMPP Based on P&O and PSO With Reduced Power Oscillation in String Inverters[J]. IEEE Transactions on Industrial Electronics, 2016, 63(10):1-1.

[13] Ma K, Yuan C, Xu X, et al. Optimizing Regulation of Aggregated Thermostatically Controlled Loads Based on Multi-Swarm PSO[J]. IET Generation Transmission & Distribution, 2018, 12(10):2340-2346.

[14] Haseena K A, Jeevamma J, Mathew A T. Fractional-Order Lead-Lag Compensator Based Multi-Band Power System Stabilizer Design Using a Hybrid Dynamic GA-PSO Algorithm[J]. IET Generation, Transmission & Distribution, 2018, 12(13):3248-3260.

[15] Ren M, Huang X, Zhu X, et al. Optimized PSO algorithm based on the simplicial algorithm of fixed point theory[J]. Applied Intelligence, 2020, 50(7):2009-2024.

[16] Ren G, Yang R, Yang R, et al. A parameter estimation method for fractional-order nonlinear systems based on improved whale optimization algorithm[J]. Modern Physics Letters B, 2019, 33(07):14-16.