An Optimal Dispatch of Microgrid Based on Improved Particle Swarm Algorithm

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Abstract. The complex multi-constraint and multi-objective nonlinear optimization problem of optimal dispatching of micro-grid are paid much attention to the studies. This study suggests the optimized dispatching of the micro-power grid based on the improved particle swarm optimization algorithm (IPSO) for full playing to the power generation advantage of distributed energy. A multi-objective micro-grid model under photovoltaic power generation prediction and load prediction is modeled mathematically for the objective function for optimization. The battery's service life and the lowest economic cost are considered multi-objective criteria for solving the optimization problem by the IPSO algorithm. The experimental results' validity confirmed that the proposed scheme works well with the micro-power grid through case analysis.

Keywords: Microgrid; Particle swarm optimization; Optimal operations.

1 Introduction

A microgrid is a group of micro-systems composed of distributed power supply, load, energy storage system, and control device. Most of the power sources are small-capacity distributed power sources, mainly including photovoltaic cells, small-scale wind turbines, micro-gas turbines, fuel cells, and batteries, etc., which are characterized by low cost, low voltage, and low pollution [1]. The micropower grid is the purpose of the operation optimization strategy based on distributed energy output forecasting, micropower grid load demand forecasting, power market information, such as data, according to the different optimization operation objectives and constraints of decision, thus make the microgrid operation scheduling plan, based on the distributed energy, energy storage equipment, and controllable load flexible scheduling to achieve optimal operation of the system of [2-4].

This paper optimizes the operation of micro-grid under grid-connected operation mode. Based on establishing the multi-objective mathematical model for optimal dispatching of micro-grid, an improved particle swarm optimization algorithm is proposed to solve this multi-objective optimization problem. The experimental results show that the proposed method is effective and practical.

2 A mathematical model for optimal dispatching of microgrid

The optimal dispatching mathematical model under the grid-connected operation mode of microgrid includes two parts: objective function and constraint condition. The main objectives of optimal dispatching of microgrid include the lowest operating cost of microgrid; Least affected by the environment; Battery life loss minimum; To meet the demand of heat and electricity in the micro-grid [5-6].

2.1 The objective function

The operation optimization problem of micro-grid is a multi-objective and multi-constraint minimum optimization problem. In this chapter, according to the actual situation, four sub-functions are selected to form a multi-objective function. In considering the microgrid economic benefit and environmental benefit, technical benefit factors, based on the objective function in this paper, the son has chosen the microgrid operation cost minimum, environmental cost minimum, battery life loss minimum, comprehensive cost minimum, the micropower supply of fuel cost and operation maintenance cost belong to a part of the micropower grid economic costs.

The operation cost of microgrid is the lowest

The operating cost of the micro-grid is mainly the fuel cost and operation and maintenance cost of each micro-power source, and its objective function is:

$$min\, C_O = min \sum_{t=1}^{T} \left(\sum_{i=1}^{N} (C_i[P_i(t)] + O_i[P_i(t)]) + C_g\left[P_g(t)\right] \right) \tag{1}$$

where, C_O is the operation cost of microgrid; $P_i(t)$ is the output power of the i-th micropower in t period; $C_i[P_i(t)]$is the fuel cost function of the i-th micropower; $O_i[P_i(t)]$ is the function of the operation and maintenance cost of the ith micropower supply; $P_g(t)$ is the interactive active power between the power grid and the micro-grid in time period T. The power purchased from the power grid is positive, while the power sold to the power grid is negative. $C_g\left[P_g(t)\right]$ is the electricity price of the transaction between the microgrid and the main network in time period T;N is the total number of micropower sources; T is the scheduling period, which is generally set as T=24h.

Battery life loss is the lowest

The lowest battery life loss objective function is:：

$$min\, C_B = min \sum_{t=1}^{T} \left(\lambda P_B(t)\right) \qquad P_B(t) > 0 \tag{2}$$

Where: C_B is battery life loss cost; $P_B(t)$ is the discharge quantity of the battery in time period t; λ is the loss factor corresponding to accumulative battery discharge 1kWh, take λ=0.075.

Microgrid has the lowest comprehensive cost

Considering the above three objectives of optimal dispatching of microgrid comprehensively, and assigning different weights to each objective, the lowest objective function of comprehensive cost of microgrid is obtained as follows:

$$min\, C_P = min(\omega_1 C_o + \omega_2 C_E + \omega_3 C_B) \tag{3}$$

Where, C_P is the comprehensive cost of microgrid; ω_1、ω_2、ω_3 as the weight of each objective function, $\omega_1 \geq 0$，$\omega_2 \geq 0$，$\omega_3 \geq 0$, and ω_1+ω_2+$\omega_3 = 1$.

2.2 Constraints

1) Power balance constraints:

$$P_L(t) = \sum_{i=1}^{N} P_i(t) + P_g(t) \tag{4}$$

2）Generation capacity constraints:

$$W_i^{min} < W_i < W_i^{max} \tag{5}$$

3）Horizontal constraint of battery charge:

$$H^{min} < H < H^{max} \tag{6}$$

4）Transmission power constraints:

$$G^{min} \leq G \leq G^{max} \tag{7}$$

Where: $P_L(t)$ is the total active load in the system at time t; W_i is the power of the i-th micro-power supply; W_i^{min}、W_i^{max} are the upper and lower limits of the power of the i-th set of micropower, respectively. H is the actual charge level of the battery; H^{min}、H^{max} are the upper and lower limits of battery charge level respectively. G is the exchange power between the microgrid and the power grid; G^{min}、G^{max} are the upper and lower limits of the power exchange between the microgrid and the power grid respectively.

3 particle swarm optimization algorithm

3.1 Basic particle swarm optimization

Optimal dispatching of microgrid is a nonlinear multi-objective optimization problem. There are two requirements for optimal dispatching of microgrid, one is to find the global optimal point, the other is to have a fast convergence speed. The basic particle swarm optimization (PSO) algorithm is proposed to solve the multi-objective optimization problem. The basic particle swarm optimization algorithm has the advantages of fast convergence, high precision, strong stability, simple and universal, easy to implement, etc. It has a strong optimization ability for complex nonlinear optimization problems, and is more suitable for solving complex multi-dimensional optimization problems [7-8].

In particle swarm initialization, the flight speed and position of each particle are randomly distributed. In the calculation, the particle's own flight speed and corresponding position are dynamically adjusted according to the global extreme value and individual extreme value.

In a D-dimensional search space, suppose there are U particles in the group, where the position x_j of the j-th particle is $[x_{j1}, x_{j2}, \ldots, x_{jD}]$,j=1,2,…,U, the position of each particle Corresponds to a potential solution. The D-dimensional velocity v_j of the j-th particle is $[v_{j1}, v_{j2}, \ldots, v_{jD}]$, and the current optimal position p_j^b of the j-th particle is $[p_{j1},p_{j2},\ldots,p_{jD}]$, which is the current optimum of the entire particle swarm The position g_g^b is $[g_{g1},g_{g2},\ldots,g_{gD}]$.

After the k-th flight, the update speed of the j-th particle is:

$$v_j^{k+1} = \omega v_j^k + c_1 rand_1\left(p_j^b - x_j^k\right) + c_2 rand_2\left(g_g^b - x_j^k\right) \tag{8}$$

The updated location is:

$$x_j^{k+1} = x_j^k + v_j^{k+1} \tag{9}$$

where: v_j^k is the velocity of the j-th particle after the k-th flight; v_j^{k+1} is the velocity of the j-th particle after the k+1 flight; x_j^k is the speed of the j-th particle The position after k flights; x_j^{k+1} is the position of the j-th particle after the k+1 flight; c_1、c_2 are learning factors; ω is the inertia weight; $r_{\text{and}1}$、$rand_2$ are random number between 0 and 1.

3.2 Improved particle swarm algorithm

The performance of the particle swarm optimization algorithm depends to a large extent on the control parameters of the algorithm, that is, the number of particles, the fastest speed, the learning factor, the inertia weight, etc. This paper proposes an improved particle swarm optimization algorithm to dynamically optimize and calculate two important control parameters, learning factor and inertia weight.

Elite strategy

After the reverse learning mechanism produces a comprehensive set of the original solution vector and the reverse solution vector, the elite strategy is used to make the 20% solution with the best fitness value in the set generate a new 20% solution, adding the original solution and the reverse solution. For the total set of solutions, the fitness values of the solutions in the set are reordered, and the 20% solutions with the worst fitness values in the set are removed, thereby generating a new optimization group [8-9]. Among them, the optimization process for generating a new solution x_{inew} is as follows:

$$Q = R_{istra} \times \frac{rand(-0.5,0.5)}{D} \tag{10}$$

$$x_{inew} = x_i \times Q \tag{11}$$

Where: R_{istra} is the Euclidean distance between the optimal solution and the solution closest to the optimal solution; rand (-0.5,0.5) is a random number with a value between -0.5 and 0.5; Q is the generation of a new solution the change factor of; D is the dimension of the solution space. After sorting the fitness values of the solution vectors in the new set, the 20% D solutions x_{iworst} with the worst fitness values are eliminated to generate a new optimization group.

Improve the learning factor

This paper proposes to use the linear dynamic adjustment method to calculate the learning factors c_1、c_2, which speeds up the learning speed compared with using fixed values. $c_{1\mathrm{i}}$、$c_{2\mathrm{i}}$ are respectively:

$$c_{1i} = c_1^{start} - \frac{(c_1^{end} - c_1^{start})k}{k_{max}} \tag{12}$$

$$c_{2i} = c_2^{start} - \frac{(c_2^{end} - c_2^{start})k}{k_{max}} \tag{13}$$

Where: c_1^{start}、c_1^{end} are the upper and lower limits of $c_{1\mathrm{i}}$, respectively; c_2^{start}、c_2^{end} are the upper and lower limits of $c_{2\mathrm{i}}$, respectively; $c_1^{start} = c_2^{end} = 2.5$, $c_1^{end} = c_2^{start} = 0.5$; k_{max} is the maximum number of flights.

Improve adaptive weight

The inertial weight determines how much the current velocity of the particle is inherited, and the proper selection of the inertial weight can make the particle have a balanced exploration ability and development ability. The adaptive method is adopted to dynamically adjust the inertia weight. The improved inertia weight ω expression is:

$$\omega_i = \begin{cases} \omega_{min} - \dfrac{(\omega_{max} - \omega_{min}) * (f - f_{min})}{f_{avg} - f_{min}}, f \leq f_{avg} \\ \omega_{max} \end{cases} \tag{14}$$

$$\omega_{max} = \mu + \sigma \cdot N(0,1) \tag{15}$$

$$\mu = \mu_{min} + (\mu_{max} - \mu_{min}) \cdot rand(0,1) \tag{16}$$

IPSO Improved formula

After the k-th flight, the update speed of the j-th particle is:

$$v_j^{k+1} = \omega_i v_j^k + c_{1i} rand_1 \left(p_j^b - x_j^k\right) + c_{2i} rand_2 \left(g_g^b - x_j^k\right) \tag{17}$$

The updated location is:

$$x_j^{k+1} = x_j^k + v_j^{k+1} \tag{18}$$

3.3 Improved particle swarm algorithm steps

The steps of the improved particle swarm algorithm proposed in this paper are as follows:

(1) Initialize, calculate the fitness value of each particle. Use the reverse learning method; select (2*N/5) particles with the best fitness value from the total set of forward and reverse solutions to generate new solutions and merge them into the solution set

according to the elite strategy, and adapt the solution set The particles with the worst degree value (2*N/5) are eliminated to form a new solution set.

(2) Calculate the fitness value of all particles, record the extreme value of all particles, update the individual extreme value $F(p_j^b)$ of the particle and the corresponding optimal position p_j^b;

(3) Update and record the global optimal objective function value $F(g_g^b)$ of the particle swarm and the corresponding global optimal position g_g^b;

(4) Update the flight speed and position of all particles;

(5) For the updated particles, update the global optimal position g_g^b and the individual optimal position p_j^b of the particles according to the result of the target value calculation;

(6) Determine whether to converge. If it reaches the maximum number of flights, it ends, otherwise update k to k+1 and return to step (4).

4 Example analysis

This paper uses PSO, adaptive PSO and the proposed method to compare. The maximum number of iterations is 100; the number of particles is 100; c1 and c2 are 0.85 and 0.95, respectively. The convergence curve is shown in Fig. 1. The figure shows that the IPSO Better than basic PSO and APSO, IPSO has a very fast convergence speed, while PSO and APSO are far from each other.

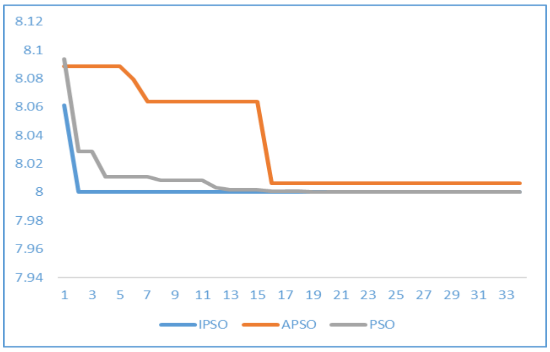

Fig. 1. The comparison of the proposed scheme with the other algorithms

The microgrid system used in this paper includes photovoltaic, diesel generator and storage battery. The maximum power of photovoltaic power generation is 20kW, and the maximum power of storage battery is 100kW. The load demand is relatively small, mainly for lighting and office power. Table 1 shows the operating costs of the microgrid equipment, and Table 2 shows the price of electricity purchased and sold by the microgrid. Among the micropower pollution control costs, the diesel generator cost is 0.7621 yuan/(kWh) and the grid cost is 0.3141 yuan/(kWh). Fig. 2 shows the wind power and photovoltaic power prediction curves and typical daily load curves of the microgrid within 24 hours of a certain day.

Table 1. Operating cost of micro-power equipment

Time Frame	Time	Price/[yuan· $(kWh)^{-1}$]	
		Purchase	Sale
Peak time	8:00~11:00 18:00~21:00	1.058	0.85
Normal time	6:00~8:00 11:00~18:00 21:00~22:00	0.630	0.55
Valley time	22:00~6:00	0.321	0.40

Table 2. Electricity purchase and sale prices of microgrid

Time Frame	Time	Price/[yuan· $(kWh)^{-1}$]	
		Purchase	Sale
Peak time	8:00~11:00 18:00~21:00	1.058	0.85
Normal time	6:00~8:00 11:00~18:00 21:00~22:00	0.630	0.55
Valley time	22:00~6:00	0.321	0.40

The improved particle swarm optimization algorithm is used to solve the optimal dispatching problem of the small grid-connected microgrid system. The algorithm parameters are as follows: the maximum number of iterations is 100; the number of particle populations is 100; c1 and c2 are 0.85 and 0.95, respectively. Using IPSO to solve, the result of microgrid optimization dispatching in grid-connected mode is shown in Fig. 3. Under the new IPSO algorithm, the economy of microgrid dispatching is well realized, and the proposed IPSO method is proved to be feasible.

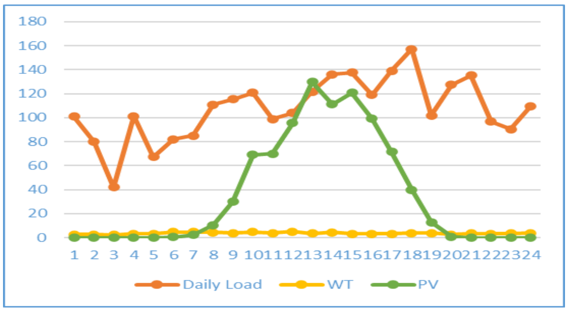

Fig. 2. Microgrid unit prediction curve

5 Conclusion

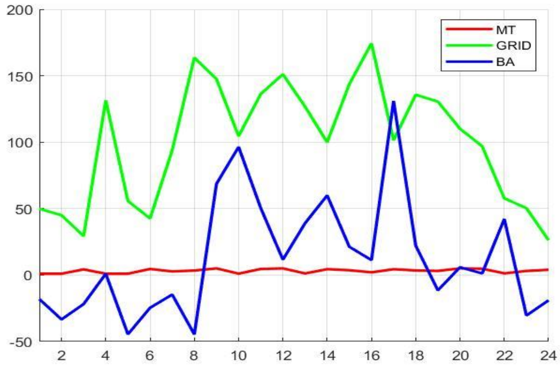

Fig. 3. Model optimization results

This paper proposed a solution to the micro-grid optimization operation meth-od based on the improved particle swarm algorithm (IPSO). The multi-objective, multi-constraint of nonlinear micro-grid optimization of operation scheduling problem was modeled mathematically for suitable with micro-grid optimization operation for the objective function. The IPSO is implemented through the learning factor and inertia weight based on the elite strategy in the particle swarm algorithm (PSO) for enhancing its optimization performance. The calculation effectiveness case of the micro-grid operation optimized is optimized by applying the IPSO. Compared with the other micro-grid operation shows, the proposed scheme provides better economic benefits in the micro-grid obtain.

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