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Stability Dispatch of Microgrid Based on Improved Dimensional Learning Particle Swarm Optimization Algorithm

Zeyu Wang[1*], Xizheng Zhang[1,2]

1 The Innovative Center of Wind Equipments and Energy Conversion, Hunan Institute of Engineering, Xiangtan 411104, China
(Correspondence: 1745665498@qq.com)

2 School of Electrical and Information Engineering, Hunan University, Changsha 410082 China

ABSTRACT

The stability dispatch of the microgrid has an important impact on the safety of the power system, so the research on the stability dispatch of the microgrid is necessary. We have established a microgrid model with diesel engines, microturbines, fuel cells, wind turbines and photovoltaic arrays targeting the system load variance. The scheduling algorithm uses an improved particle swarm optimization algorithm based on dimensional learning. The global extremum in the algorithm is derived from the individual extremum of dimensional learning. Firstly, 13 standard test functions are applied to test the performance of the improved dimensional learning algorithm. The simulation results show the effectiveness of the improved algorithm. Then the algorithm and model are combined, and as a result the safety of the system with distributed power generation is better than the system without distributed power generation by comparing the two strategies with or without distributed power generation strategies.

Keywords: Microgrid; stability dispatch; load variance; dimensional learning; particle swarm optimization algorithm

1. INTRODUCTION

Energy is the core key to the development of human society. At present, as the main energy sources for industrial development — coal and petroleum [1], they are non-renewable energy sources and will pollute the environment during use. In order to deal with the shortage of non-renewable resources and environmental pollution that may appear in the future, people have begun to focus on renewable energy and clean energy [2].

Wind energy and solar energy are both renewable energy and clean energy. They have received people's attention for long time, and the related power generation technology is quite developed. However, because of their own characteristics, these two energy sources are seriously affected by the region, leading to scattered use of sites, and the quality of the directly generated power is not as good as that of thermal power [3]. Natural gas, which belongs to clean energy, has also attracted much attention. In recent years, due to various reasons, the demand for natural gas in various countries has increased sharply, and the corresponding price has also skyrocketed.

The microgrid (MG) can make good use of these clean energy sources to relieve the load pressure of large power grids and reduce environmental pollution and electricity cost. Li et al. proposed a decomposition and coordination calculation method to reduce the dimension of the problem for reduce the economic dispatch problem of the MG [4]. Chen et al. proposed a distributed coordinated control method to reduce the voltage fluctuation of the MG, thereby facilitating the realization of the economic dispatch of the MG [5]. Hou et al. established a MG model for study the impact of the charging behavior of electric vehicles on the MG. The economic cost is the main goal of the model [6]. These studies are mainly to reduce the operating cost of the MG, and rarely pay attention to the load fluctuation of the MG. For achieve this aim, this paper established a MG optimization model with diesel engines (DEs), microturbines (MTs), fuel cells (FCs), wind turbines

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(WTs) and photovoltaic arrays (PVs) with the goal of minimizing load fluctuations. Then an improved particle swarm optimization algorithm (PSO) based on dimensional learning is proposed as a model scheduling algorithm.

2. MODEL

2.1 Output power model of distributed generation (DG)

(1) PV

The PV is carried out under the conditions of sunlight and when the light intensity changes, the output power of the PV (P_{PV}) [6] also changes, and no electricity is produced at night. Its specific formula is:

$$P_{PV} = P_{STC}\frac{G_T}{G_S}\left[1+\alpha\left(T_{Cell}-T_{Cell,STC}\right)\right] \tag{1}$$

where P_{STC} is the maximum test power of PV cells under STC (kW), G_I is the measured light temperature at the surface level (kW/m²), G_S is the luminosity under standard test conditions (kW/m²), α is the temperature coefficient (%/℃), T_{Cell} is the current surface temperature of the PV cell (℃), and $T_{Cell,STC}$ is the temperature of the PV cell under STC (℃).

(2) WT

Since the WT of the place where the wind speed (v) is generated is not stable, the output power of WT (P_{WT}) [6] is not stable either.

$$P_{WT} = \begin{cases} 0, & v < v_{ci}, v \geq v_{co} \\ \frac{P_R}{v_r^3 - v_{ci}^3}v^3 - \frac{v_{ci}^3}{v_r^3 - v_{ci}^3}P_R, & v_{ci} \leq v < v_r \\ P_R, & v_r \leq v < v_{co} \end{cases} \tag{2}$$

where v, v_{ci}, v_R and v_{co} are the actual wind speed (m/s), the cut-in wind speed (m/s), the rated wind speed (m/s) and the cut-out wind speed (m/s) respectively, P_R is the rated output power.

(3) DE

The relationship between the fuel cost of DE (C_{DE}) [7] and the output power of DE (P_{DE}) is as follows:

$$C_{DE} = o + pP_{DE} + qP_{DE}^2 \tag{3}$$

where o, p, and q are coefficients.

(4) MT

The fuel cost of a MT (C_{MT}) [8] is inversely proportional to its working efficiency η_{MT}, and its functional relationship is as follows:

$$C_{MT} = \frac{C \times P_{MT}}{LHV \times \eta_{MT}} \tag{5}$$

where C is the price of fuel gas (¥/m³), P_{MT} is the output power of MT (kW) and LHV is the low calorific value of fuel gas (kWh/m³).

(5) FC

The calculation formula of FC power generation cost (C_{FC}) [8] can be expressed as follows:

$$C_{FC} = C \times \frac{1}{LHV} \times \sum_J \frac{P_{FCJ}}{\eta_{FCJ}} \tag{6}$$

where P_{FCJ} is the net output power in J time interval (kW), and η_{FCJ} is the total efficiency of the battery in the J time interval.

2.2 Objective function

This paper uses the load variance of the MG to represent the load fluctuation of the MG.

$$\min F = \frac{1}{T}\sum_{t=1}^{T}\left(P_{grid,t} - \frac{1}{T}\sum_{t=1}^{T}\left(P_{grid,t}\right)\right)^2 \tag{7}$$

where T is the total number of cycles in the dispatch period, and $P_{grid,t}$ is the transmission power (kW) of the MG and grid in cycle t.

2.3 Constraints

(1) System power balance

$$\sum_{i=1}^{N} P_{i,t} + P_{grid,t} = P_{load,t} \tag{8}$$

Where $P_{i,t}$ is the output power (kW) of the i-th DG in cycle t, $P_{load,t}$ is the original load (kW).

(2) Power limit of DGs

$$P_i^{\min} \leq P_{i,t} \leq P_i^{\max} \tag{9}$$

where P_i^{min} / P_i^{max} is the lower / upper limit of the ith DG output power (kW).

3. IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM BASED ON DIMENSIONAL LEARNING

The (PSO) is very suitable to solve the non-convex optimization problem, and the power system problem belongs to the non-convex optimization problem.

3.1 PSO

The (PSO) [9] was proposed by J. Kennedy and R. Eberhart in 1995. However, the performance of the PSO is relatively inferior to that of other intelligent optimization algorithms that have just been proposed. Yuhui Shi and Russell Eberhart added an inertia weight ω [10] to the speed update formula on the original basis in 1998 to improve the performance of the algorithm. After that, most of the researchers conducted research on this basis. The general update formula is:

$$v_{(i+1)d} = \omega * v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{10}$$

$$x_{(i+1)d} = x_{id} + v_{id} \tag{11}$$

PSO first initializes a group of random particles (potential solution) in the scope of the solution, and then iterates to find the optimal solution in combination with the update formula. Suppose that in a D-dimensional target search space, there are N particles forming a community, where the *i*-th particle is represented as a D-dimensional vector $X_i=(x_{i1},x_{i2},..., x_{iD})$, $i=1, 2, ..., N$. The "flying" speed of the i-th particle is also a D-dimensional vector, denoted as $V_i=(v_{i1}, v_{i2}, ..., v_{iD})$. The best value searched by the *i*-th particle so far is called the individual extreme value, denoted as $p_{best}=(p_{i1}, p_{i2}, ..., p_{iD})$. The optimal position searched by the entire particle swarm so far is the global extremum, denoted as $g_{best}=(p_{g1}, p_{g2}, ..., p_{gD})$. c_1 and c_2 are learning factors (acceleration constants), r_1 and r_2 are uniform random numbers in the range of [0, 1].

3.2 Dimensional learning

Xu et al. [11] proposed a dimensional learning strategy. Based on the dimensional learning strategy, each p_{best} learns from g_{best} to generate individual extreme value pbestdl with better quality than p_{best}, and replace p_{best} with p_{best}^{dl}. This is the dimensional learning PSO (DLPSO), the update formula is as follows:

$$v_{(i+1)d} = \omega * v_{id} + c_1 r_1 (p_{id}^{dl} - x_{id}) + c_2 r_2 (p_{gd}^{dl} - x_{id}) \quad (12)$$

3.3 Algorithm steps

Step 1: Initialize the parameters of the algorithm, the population;
Step 2: Combine the fitness function to calculate the fitness value of each particle;
Step 3: Combine formulas (11) and (12) to update the position and velocity of the particles;
Step 4: Generate new individual extremum and global extremum by comparing the pros and cons of each particle fitness value of the new initial population;
Step 5: Determine whether the population reaches the maximum number of iterations, if it reaches the maximum number of iterations, jump out of the loop, otherwise re-execute step 3.

3.4 Algorithm performance test

In order to understand whether the proposed algorithm can improve the performance of the algorithm, 13 benchmark functions [12] are used in the study to verify the performance of the algorithmthe algorithms are run independently 20 times. In order to distinguish DLPSO, this article will use DLPSO-V to denote the improved DLPSO. The algorithm parameter settings are shown in Tab. 1. The comparison results are shown in Tab. 2.

Tab. 1 Parameter settings

Algorithms	Parameter settings	References
PSO	w: 1, c_1: 2, c_2: 2	[9]
DLPSO	w: 0.7298, c_1: 1.5, c_2: 0.5~2.5	[11]
DLPSO-V	w: 0.7298, c_1: 1.5, c_2: 0.5~2.5	-

It can be known from Tab. 2 that the convergence accuracy of DLPSO-V is higher than that of DLPSO on most functions. Even if it is not high, the convergence accuracy is equivalent. Therefore, we believe that the new changes in DLPSO are beneficial.

4. SCHEDULING RESULTS AND ANALYSIS

In the micro-grid system established in this paper, there is one DE, MT, FC, WT and PV. The structure of the microgrid system model established in this paper is shown in Fig. 1. The relevant parameters are shown in Fig. 2, 3 and 4.

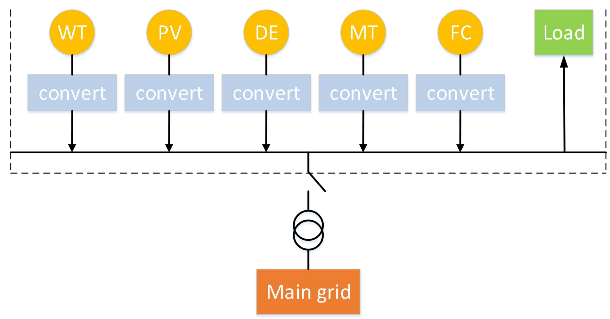

Fig. 1. The structure of the MG system model

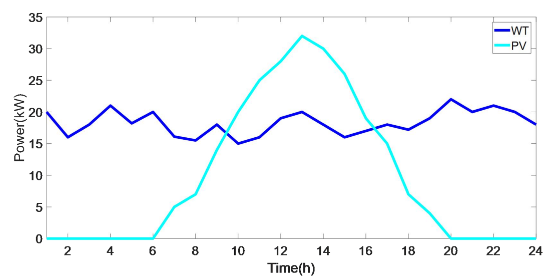

Fig. 2. Daily output power of WT and PV

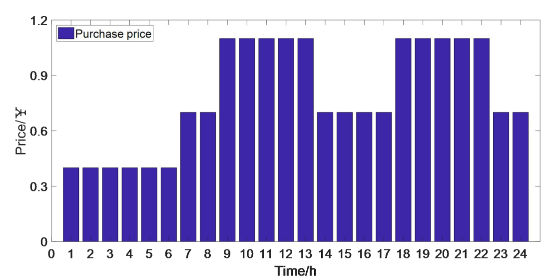

Fig. 3. Electricity price

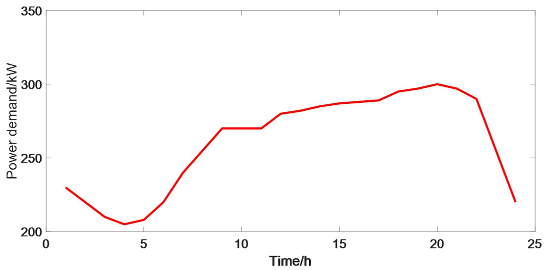

Fig. 4. System load demand

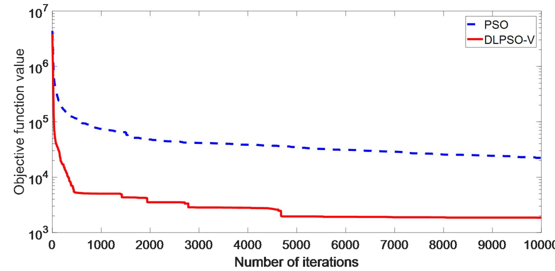

Fig. 5. The iterative curves of the two PSOs

In order to analyze the role of distributed power generation in the system, this paper establishes two different scenarios.

Scenario 1: Dispatch scenario where only the original load and the large power grid participate;

Scenario 2: Add distributed power generation based on scenario 1.

4.1 Scheduling result

Both algorithms are run for 20 times, the average value represents the average of the final results obtained after 20 runs, and the optimal value represents the best result obtained after 20 runs. The running results of the two PSOs are shown in Tab. 3.

Tab. 3 The running results of the two PSOs

Indexes	PSO	DLPSO-V
Number of runs	20	20
Average value	2.23e+04	1.86e+03
Optimal value	2.02e+03	1.39e+03

The results of DLPSO-V are less than PSO regardless of the average value or the optimal value, indicating that DLPSO-V is better than PSO in the current system model. Combined with the iterative curves of the two PSOs in Fig. 5, it is found that the convergence speed of DLPSO-V is also faster than that of PSO, so this paper uses DLPSO-V as the system's scheduling algorithm.

4.2 Discussion of scheduling results

The results of load variance for different scenarios are shown in Tab. 4. In Table 4, the load variance of Scenario 2 is 98.28% smaller than Scenario 1, indicating that the use of algorithms to dispatch distributed power generation output power can effectively improve the safety of the system.

	Load variance
Scenario 1	6.44e+04
Scenario 2	1.11e+03

Tab. 4. The results of load variance for different scenarios

5. CONCLUSIONS

In order to improve the stability of the MG system, this paper established a microgrid model containing diesel engines, microturbines, fuel cells, wind turbines and photovoltaic arrays. At the same time, an improved particle swarm optimization algorithm based on dimensional learning is proposed. Firstly, the algorithm was tested with 13 standard test functions, which proved that the improvement of the particle swarm optimization algorithm based on dimensional learning was effective; then the algorithm was applied to the system with distributed power generation, and the

Functions	DLPSO Average value	DLPSO Standard deviation	DLPSO Optimal value	DLPSO-V Average value	DLPSO-V Standard deviation	DLPSO-V Optimal value
F1	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
F2	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
F3	3.45e+03	4.82e+03	0.00e+00	3.16e+00	1.41e+01	0.00e+00
F4	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
F5	9.61e+01	2.10e+02	2.82e+01	2.87e+01	1.86e-01	2.81e+01
F6	3.42e+00	1.37e+00	1.57e+00	2.56e+00	1.93e+00	3.93e-01
F7	2.90e-03	3.40e-03	4.97e-05	3.47e-04	6.00e-04	2.43e-05
F8	-9.29e+03	9.97e+02	-1.06e+04	-1.16e+04	3.69e+02	-1.21e+04
F9	1.45e+00	6.47e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
F10	8.88e-16	0.00e+00	8.88e-16	8.88e-16	0.00e+00	8.88e-16
F11	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00	0.00e+00
F12	1.17e-01	8.93e-02	2.18e-02	2.62e-02	1.80e-02	1.80e-03
F13	2.06e+01	6.85e-01	4.41e-01	1.50e+00	6.89e-01	8.94e-02

Tab.2. Experimental results of DLPSO and DLPSO-V

simulation results showed that it is effective for distributed power generation. The effective management of the output power can reduce the load variance of the system, that is, it can improve the stability of the system.

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