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Multi-Objective Optimization Scheduling of Microgrids Using an Improved Crow Search Algorithm with Levy Flight Strategy

Ronan Hawke

Department of Electrical and Computer Engineering, University of Massachusetts, Amherst, USA

ronan98@umass.edu

Abstract: With the depletion of traditional energy sources and the rising significance of renewable energy systems, optimizing the scheduling of microgrids has emerged as a critical area of research to ensure safe, stable, and cost-effective operation. This paper presents a multi-objective optimization scheduling model for microgrids, addressing both economic cost minimization and environmental benefits. To overcome the limitations of traditional optimization algorithms, an improved crow search algorithm (PCSA) integrating dynamic sensing probability and the Levy flight strategy is proposed. The enhancements improve the parameter and position update mechanisms of the standard CSA, resulting in increased global search efficiency, faster convergence, and avoidance of local optima. Simulation results demonstrate that the proposed method significantly enhances the global optimization performance, reduces load peak-valley differences, and achieves superior economic and environmental outcomes compared to traditional methods.

Keywords: Microgrid; Optimal Scheduling; Crow Search Algorithm; Levi Flight Strategy.

1. Introduction

It is an inevitable trend that traditional energy sources are increasingly exhausted. Compared with the non-renewable traditional energy sources, the characteristics of green, efficient and sustainable development of distributed energy have gradually attracted the attention of scholars and experts [1- 2].In order to ensure the safe, stable, and efficient operation of microgrids, improve the utilization rate of renewable energy, and alleviate the load pressure during peak electricity consumption, the optimization and scheduling of microgrids has become a research hotspot [3-4]. This not only ensures the safe and economic operation of the microgrid, but also effectively reduces the occurrence of large- scale power outages caused by natural disasters.

The range of load power fluctuations that microgrid systems can withstand is relatively narrow, therefore, a large number of literatures has conducted comprehensive and in-depth research on the optimization and scheduling of microgrids. Xiao et al. [5] considered the needs of intraday optimization and pre day optimization, and established optimization scheduling models to improve the ability of microgrids to respond to demand. Sun et al. [6] uses the split control method to achieve active reactive power coordination under the two models of day ahead scheduling plan and real-time scheduling. Peng et al. [7] transformed the operating cost, sewage treatment cost, and comprehensive benefit cost into a single objective nonlinear optimization problem through the maximum fuzzy membership degree.

Traditional optimization algorithms such as ant colony algorithm, bat algorithm, particle swarm algorithm, whale algorithm can achieve optimal scheduling of microgrids, but their search ability is limited and there is a risk of falling into local optima. To improve the limitations of traditional optimization algorithms, a large number of experts have conducted relevant research. Zhou et al. [8] introduces the longicorn whisker search algorithm in improving the ant colony individual update rules of the bee colony algorithm to increase the individual's global search ability. According to the fitness function and constraint conditions. Fathi et al. [9] minimized the fuel consumption and power loss of island microgrid. In order to solve the problem of slow convergence speed of the algorithm and easy to fall into local optimization, this paper proposes a multi-objective optimization strategy for microgrid of crow algorithm under Levy flight strategy, which comprehensively considers the lowest economic cost and environmental optimization of microgrid, and comprehensively covers photovoltaic, wind power, energy storage and diesel generator.

In this paper, the raven search algorithm (PCSA) based on Levy flight strategy is adopted. In order to solve the difficult optimization problem under engineering constraints, dynamic sensing probability and Levy flight strategy are introduced into the traditional raven search algorithm, which increases the algorithm diversity and improves the global search ability of the algorithm. In the grid-connected mode, the simulation results show that PCSA can improve the global optimization performance of the model, optimize the scheduling system and reduce the load peak valley difference effectively, and reduce the economic loss.

2. Microgrid Model and Microgrid Optimization Model

2.1 Microgrid Structure

The micro grid studied in this paper is composed of wind power generation system, photovoltaic power generation system, diesel generator, energy storage device and micro gas turbine unit.

2.1.1 Photovoltaic Power Generation System

The output power model of photovoltaic cells (PV) is shown in eq. (1).

$$P_{PV} = P_{STC} \cdot \frac{G_C}{G_{STC}} \left[1 + k(T_C - T_{STC})\right] \tag{1}$$

Here, $P_{WT,rate}$ is the rated output power of the fan; u_r Is the rated wind speed, u_0 represents the cut-out wind speed, and u_i represents the cut-in wind speed.

2.1.2 Wind Power Generation System

The wind power generation system (WT) is mainly composed of wind turbines, and its output power model is shown in eq. (2).

$$P_{WT} = \begin{cases} 0 & 0 \le u \le u_i \\ P_{WT,rate} \dfrac{u - u_i}{u_r - u_i} & u_i \le u \le u_r \\ P_{WT,rate} & u_r \le u \le u_0 \\ 0 & u_0 \le u \end{cases} \tag{2}$$

2.1.3 Energy Storage Device Model

The energy storage system (BSS) stores electricity related to the state of charge (SOC) of the battery, and its charging and discharging model at time t is shown in eq. (3).

$$\begin{cases} SOC(t) = SOC(t-1) - P_k(t)\eta_c P_k(t) \ge 0 \\ SOC(t) = SOC(t-1) - P_k(t)\eta_d P_k(t) \le 0 \end{cases} \tag{3}$$

Here, $SOC(t)$, $SOC(t-1)$ represents the remaining electricity at time t and t-1; $P_k\ (t)$ represents the charging and discharging power of the energy storage device, ≤ 0 represents the discharging state, ≥ 0 represents the charging state; η_c represents charging efficiency, and η_d represents discharge efficiency.

2.1.4 Diesel Generator

The power generation cost of diesel generator (DE) adopts quadratic function, and the expression is shown in eq. (4).

$$C_{DE} = a + bP_{DE} + cP_{DE}^2 \tag{4}$$

Here, C_{DE} is the cost of fuel; P_{DE} is the generating power of diesel generator; a , b , c is the coefficient of fuel cost.

2.1.5 Fuel Cell

The output power of a fuel cell (FC) is directly related to the fuel consumption, and the cost can be approximately expressed as:

$$C_{FC} = cT\,\frac{1}{LHV} \cdot \sum_j \frac{P_j}{\eta_j} \tag{5}$$

Here, c represents the unit price of natural gas, which is taken as 2.02 yuan$/m^3$ in this article. T represents time, represents the low calorific value of natural gas, taken as 9.73 kwh/m^3 . P_j and η_j represent the output power and total efficiency of the fuel cell during the j time period, respectively.

2.1.6 Micro Gas Turbine

The model used in this article is the Capstone C65 gas turbine (MT). The power generation cost can be approximately calculated using eq. (6).

$$C_{MT} = c_{MT} \cdot \frac{P_{MT}^t . \Delta t}{\eta_e . \mathrm{LHV}} \tag{6}$$

2.2 Objective Function

In this paper, we consider the dual objectives of the lowest system operating cost and the optimal environment, and the objective function is shown in Eq. (7).

$$\mathrm{F} = \min(\mathrm{F}_1) + \min(\mathrm{F}_2) \tag{7}$$

Where, F is the total operation cost of microgrid; F1 and F2 are economic cost and environmental cost respectively.

The economic cost mainly considers the depreciation of batteries and the costs of operation, maintenance, fuel, and electricity purchase. The target is shown in eq. (8):

$$F_1 = C_{Fuel}(x) + C_{Mn}(x) + C_{Ec}(x) + C_{Bss}(x) \sum_{i,pbss,i>0}^{H} P_{bss,i} \tag{8}$$

Where, C_{Fuel} represents fuel cost, C_{Fuel} represents operation and maintenance cost, C_{Ec} is power purchase cost, C_{Bss} is battery depreciation cost; $P_{bss,i}$ represents the charge and discharge power of the battery in period i, and H is the total time during the scheduling period. Environmental benefits mainly consider the emission of polluting gases and the impact of particulate matter on the environment. The formula for calculating environmental benefits is as follows:

$$F_2(x) = \sum_{i=1}^{n}(V_{e,i}Q_i(x) + V_i) \tag{9}$$

Where, $V_{e,\,i}$ are the cost of pollutant treatment; n is the type of pollutant, $Q_i(x)$ is the emission of pollutant, V_i is the treatment cost.

2.3 Constraint Condition

Power constraints for microgrids:

$$P_{BSS} + P_{WT} + P_{PV} + P_{DE} = P_L \tag{10}$$

Here, P_{BSS} , P_{WT} , P_{PV} , P_{DE} respectively represent battery power, wind power generation power, photovoltaic power generation power, and micro gas turbine power; P_L is the total power. The power balance constraints of each system are as follows:

$$\begin{gathered}
P_{PV_{\min}} << P_{PV} << P_{PV_{\max}} \\
P_{WT_{\min}} << P_{WT} \le P_{WT_{\max}} \\
P_{BSS_{\min}} << P_{BSS} << P_{BSS_{\max}} \\
SOC_{\min} << SOC << SOC_{\max} \\
P_{DE_{\min}} << P_{DE} \le P_{DE_{\max}} \\
P_{FC_{\min}} << P_{FC} \le P_{FC_{\max}} \\
P_{MT_{\min}} << P_{MT} \le P_{MT_{\max}}
\end{gathered} \tag{11}$$

3. Algorithm Optimization

3.1 Traditional Crow Search Algorithm

The Crow Search Algorithm (CSA), as an emerging intelligent algorithm, mainly imitates the behavior of crows hiding food. After the crow hides its excess food, it remembers the location of the food. At the same time, they will follow other crows to find their hidden food and steal it [10-11].

In CSA, the position of the i-th crow is represented by $x^{i,iter} = [x^{i,iter}, x^{i,iter}, x^{i,iter}, ..., x^{i,iter}]$,i=1 , 2,…Q, $iter$=1,2,…N. Among them, Q represents the number of crows, d is the dimension of the decision variable, and N is the number of iterations.Every crow has the best food location $m^{i,iter}$ in memory, and in the iteration, In the iteration, crow x randomly follows a crow j to steal food, and there are two situations based on the perception probability (AP): Status 1: Crow j is unaware that he is following Crow i behind him. At this point, Crow i updates its position to [12]:

$$\begin{aligned}
&x^{i,iter+1} = x^{i,iter+1} + r_i \times fl^{i,iter} \times (m^{j,iter} - x^{i,iter}) \\
&r_i >> \mathrm{AP}
\end{aligned} \tag{12}$$

3.2 Improved Crow Search Algorithm (PCSA)

3.2.1 Dynamic Perceived Probability

In conventional crow search algorithms, the flying position of crows is updated by eq. (10), and the search method chosen by crows to forage depends on the setting of the perception probability AP. If the AP is small, the crow's tracking behavior is difficult to detect, and the crow approaches the optimal hiding point, effectively promoting the intensification of the crow population. The algorithm is more prone to convergence and is used for local search; On the contrary, by selecting a larger AP, the crow will randomly fly within the search range, increasing the complexity of the population for global search. Select a dynamic AP and set a larger AP during the initial search phase to enhance the global search ability of the crow population; And during the iteration process, reduce AP, enhance the algorithm's local search ability, and enable the algorithm to quickly converge to the extreme point. The dynamic perception probability is a ConvexDescending Form (CvDF) function, expressed as:

$$\mathrm{AP} = \mathrm{AP}_{\max} - (\mathrm{AP}_{\max} \times iter^3 / iter_{\max}^3) \tag{13}$$

Here, $\mathrm{AP}_{\max}$ is the maximum perception probability, $iter_{\max}$ represents the maximum number of iterations.

3.2.2 Levy Flight Search Strategy

When the crow is in state 2, it randomly selects a new location to confuse the tracker. When there are no headed crows to lead, the direction of crow group optimization is relatively blind. Therefore, the introduction of the Levy flight search mechanism further enhances the algorithm's global search ability. Levi's flight is essentially a process of random walk. Levi's flight is added to the crow search algorithm. At the beginning of the iteration, a long-distance walk mode is used, so that the crow has a larger search range when flying, and does not stay in the local optimum; In the later stage of the iteration, the close-range walk method is used to make the algorithm tend to converge. The improved formula is as follows:

$$x^{i,iter+1} = x^{i,iter} \times (1 + Levy(n)) \tag{14}$$

here,

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$$Levy(n) = a \times \frac{r_a \times \sigma}{|\gamma|^{\frac{1}{\beta}}}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{(\frac{\beta-1}{2})}} \right)^{1/\beta} \tag{15}$$

r_a represents the random number in the interval (0,1); γ、σ follows normal distribution; *n* is the dimension; *a* represents a step factor of 0.01, and β represents a constant of 1.5; Γ is the standard gamma function.

In summary, the improved update formula is as follows:

$$x^{i,iter+1} = \begin{cases} x^{i,iter} + r_i \times fl^{i,iter} \times (m^{j,iter} - x^{i,iter}) \\ r_i >> AP \\ \quad x^{i,iter} \times (1 + Levy(n)) \end{cases} \tag{16}$$

4. Example Analysis

4.1 Parameter Settings

This paper takes MATLAB as the simulation platform. Table 1 lists the specific parameters of each distributed power supply. The emission coefficient of pollutants is shown in Table 2.

Table 1. Parameters of Distributed Power Sources in Microgrid

DG type	Lower power limit(kw)	Lower upper limit(kw)	Operating cost (yuan/kg)	Fuel cost(yuan/kg)
WT	0	150	0.045	0
PV	0	100	0.0096	0
DE	0	60	0.0789	0.211
BSS	-60	60	0.055	0
MT	0	60	0.0419	0.409
FC	0	60	0.02933	0.2435

Table 2. Treatment costs and emission coefficients of pollutants

Pollutant type	DE emission factor(g/kw)	MT emission factor(g/kw)	FC emission factor(g/kw)	Management cost(yuan/kg)
CO_2	4.33	1.078	0.454	0.02805
NO_x	2.32	0.03	1.432	8.5
SO_2	464	0.06	2.18	5.95

This simulation takes one day as a cycle, and the unit period is 1 hour. The data source is the power consumption of users in a region of Guangdong, and the power variation curve of the day and load is shown in Figure 1.

Referring to the electricity price of a certain region in Guangdong Province, the dynamic prices for selling and purchasing electricity are shown in Table 3.

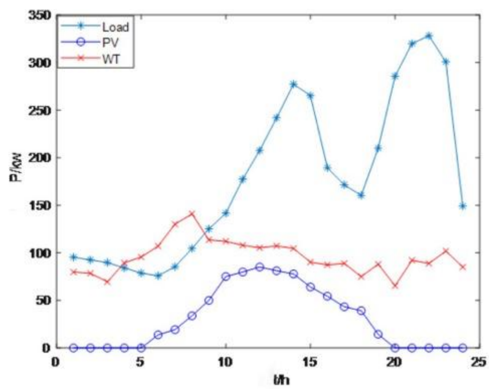

Fig 1. Variation curve of residential load, PV and WT power

Table 3. Dynamic electricity purchase price

Period of time	Peak period	bottom period	off-peak period
	10:00-14:00	07:00-09:00	00:00-06:00
Time (h)	18:00-20:00	15:00-17:00	23:00-24:00
		21:00-22:00	
Electricity purchase price (yuan)	0.69	0.46	0.31
Electricity selling price (yuan)	0.64	0.38	0.23

4.2 Analysis of Grid Connection Examples

In this paper, only single-day optimal scheduling of micro-grid is considered, and the unit period is set as 1 hour, and the interactive power is 200kw. In the grid-connected mode, considering the purchase and sale of electricity to the grid, the system optimized scheduling arrangement is shown in Fig.2. The convergence curves of PCSA and CSA are shown in Fig.3, and the economic benefit pairs are shown in Table 4.

As can be seen from Fig.2, when the microgrid is connected to the grid, PV and WT belong to clean energy and are used in priority. With the increase of load, the output of other distributed power sources is increased. At this time, if the demand cannot be met, it is considered to purchase electricity from the power grid and charge the battery with the surplus. If there is still surplus, it can be sold to the power grid.

Fig. 3 shows the optimization comparison between PCSA algorithm and CSA algorithm. From the figure, it can be seen that PCSA algorithm is superior to CSA algorithm in terms of convergence speed and search accuracy. The specific results are shown in Table 4. It is obvious that PCSA algorithm has a higher convergence speed than CSA algorithm, and the convergence results are good, reducing economic costs by 10%. Therefore, it can be seen that dynamic perception probability and Levi flight search strategy are introduced into traditional crow algorithm, It can effectively improve the convergence speed of the algorithm and enhance its global optimization ability.

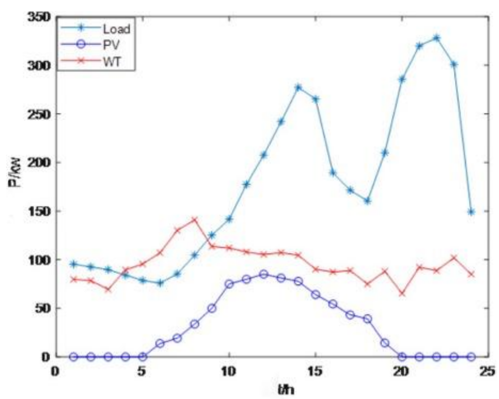

Fig 2. Multi-objective optimization scheduling results in grid connection mode

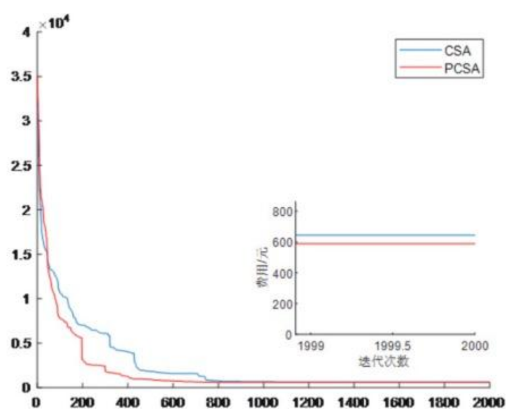

Fig 3. Comparison of convergence between PCSA and CSA

Table 4. Comparison of Economic Benefits

Algorithm	cost (yuan)	convergence time (s)
CSA	644	5.86
PCSA	588	7.28

5. Summary

In this paper, the multi-objective optimization scheduling model of microgrid is established under the requirement of the objective function of the lowest economic cost and the best environmental benefit. This paper proposes an improved algorithm based on the crow search algorithm, which introduces dynamic sensing probability and Levy flight strategy, improves the parameter and position update mechanism of the standard CSA, so as to improve the search efficiency of each crow individual, improve the optimization performance, and avoid the algorithm falling into the local optimal in the iterative process. The example analysis shows that the improved crow algorithm has better scheduling ability, faster convergence speed, and more environmental protection and economy.

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