Research on MPPT Based on Gray Wolf Algorithm improved by Levy Flight

Su Wang a, Wencheng Cai b, Liang Zeng c

School of Electrical and Electronic Engineering Hubei University of Technology
Wuhan, China

a 1643124698@qq.com, b 2484927771@qq.com, c hbut.zengliang.edu.cn

Abstract. In the late iteration of the gray wolf algorithm, the convergence results will have low accuracy because of the elite retention. When implementing MPPT control, the maximum power point of the photovoltaic array cannot be accurately tracked, and it is easy to fall into the local optimum. Therefore, this paper proposes gray wolf algorithm improved with Levy flight applied to MPPT control. The algorithm introduces the Levy flight to search the head wolf position globally, then uses the group optimization of the gray wolf algorithm and the random walk of Levy flight to improve the tracking speed and accuracy of the MPPT controller. In the simulation experiment, the algorithm is modeled and verified by setting different lighting conditions. Finally, it is compared with the conductance increment method, modified hybrid method of grey wolf optimization and golden-section optimization, the original gray wolf algorithm. The results show that the algorithm meets the requirements of fast tracking speed, high accuracy and stability in MPPT control.

Keywords: PV system, maximum power point tracking, Levy flight, gray wolf optimization algorithm.

1. Introduction
Photovoltaic power generation is the most effective form of using solar energy, and with the continuous advancement of technology, photovoltaic power generation has become one of the most important sources of electrical energy. In order to improve the power generation efficiency of photovoltaic power generation systems and reduce costs, scholars have conducted a lot of research on photovoltaic maximum power point tracking (MPPT) technology.

At home and abroad, scholars have proposed many MPPT algorithms for different lighting environments. Under ideal conditions, when each photovoltaic cell receives the same light intensity, the PV array presents a single-peak P-U characteristic curve. At this time, the mature constant voltage method, disturbance observation method or conductance increment method can be used to achieve the maximum effective photovoltaic power point tracking control[1]. However, in practical applications, due to the existence of obstructions and the gradual aging of the device, the output P-U curve of the photovoltaic cell shows a multi-peak characteristic[2]. In this case, if the above mentioned traditional control method is still used for tracking, because The limitation of its own algorithm principle makes it impossible to track the maximum power point, which causes the photovoltaic cell to output the local
maximum power, leading to the phenomenon of output power loss in the photovoltaic power generation system. Aiming at the problem of the failure of traditional MPPT algorithm under partial shading, literature[3,4] uses fuzzy control to achieve MPPT control, but the fuzzy rules and membership functions are completely empirical in the design process, and the accuracy is not high; literature[5,6] The use of neural neural network to achieve MPPT control, but this method has a great dependence on the choice of samples. Theoretically, all intelligent optimization algorithms can achieve univariate multi-peak optimization. For example, literature[7,8] conducted a design study on particle swarm optimization or improved particle swarm optimization applied to MPPT control, but the experimental results show tracking The speed is slow; literature[9,10] combines evolutionary algorithms and swarm intelligence algorithms to improve the tracking speed and accuracy of MPPT, but there are problems such as power fluctuations.

The gray wolf optimization algorithm is a swarm intelligence optimization algorithm. The algorithm has the characteristics of strong convergence, few parameters, and easy implementation. However, the literature[11,12] pointed out that the gray wolf algorithm is easy to solve complex nonlinear optimization problems. Fall into the local optimum, and the accuracy is low in the later stage of evolution. Based on the ideas of literature[13,14], this paper designs a gray wolf algorithm based on Levy’s flight and applies the algorithm to the MPPT controller to improve the power generation efficiency of photovoltaic cells. In the simulation experiment, by setting different lighting environments and algorithms for comparative analysis, the results show that the algorithm can adapt to different environmental conditions, has strong anti-interference ability, and has faster tracking speed and higher accuracy than the gray wolf algorithm. degree.

2. Photovoltaic cell modeling and MPPT principle

2.1. Establishment of mathematical model

After a lot of experimental research, when modeling a photovoltaic cell, through simplified processing, it can be regarded as a large-area planar diode. From Figure 1, the U-I relationship can be obtained as

\[ I = I_{ph} - I_d - I_{sh} \] (1)

\[ I_d = I_o \left\{ \exp \left[ \frac{q(U + IR)}{AkT} \right] - 1 \right\} \] (2)

\[ I_{sh} = \frac{U + IR}{R_{sh}} \] (3)

In the formula, I is the output current; U is the output voltage; \( I_{ph} \) is the photovoltaic current; \( I_0 \) is the reverse saturation current of the photovoltaic cell; q is the electron charge constant; A is the
semiconductor PN junction coefficient; \( k \) is the Boltzmann constant; \( T \) is temperature; \( R_s \) and \( R_{sh} \) are equivalent resistances.

In practical applications, the series resistance \( R_s \) of the general photovoltaic cell is close to zero, and the parallel resistance \( R_{sh} \) tends to infinity. So the equation (1) can be simplified as

\[
I = I_{ph} - I_0 \left[ e^{\frac{q(U + IR_s)}{kT}} - 1 \right] \tag{4}
\]

Then the output power of the photovoltaic cell is

\[
P = UI_{ph} - UI_0 \left\{ \exp \left[ \frac{q(U + IR_s)}{kT} \right] - 1 \right\} \tag{5}
\]

It can be seen from (5) that the output power of photovoltaic cells is related to light intensity and temperature, and has a nonlinear relationship with voltage.

2.2. MPPT principle

According to the relationship between voltage and current and the law of conservation of energy when the Boost circuit is working, the relationship between the equivalent input impedance \( R_{in} \) of the Boost circuit and the connected load can be obtained.

\[
R_{in} = R(1-D)^2 \tag{6}
\]

It can be seen from (6) that when the load is unchanged, the value of \( R_{in} \) can be adjusted by adjusting the duty cycle. When \( R_{in} \) matches the photovoltaic output impedance, the maximum power of the photovoltaic cell can be achieved according to the principle of maximum power transmission, the maximum power output of photovoltaic cells can be achieved.

3. Gray wolf algorithm based on Levy flight

3.1. Introduction to Gray Wolf Algorithm

The GWO algorithm is an optimized search method developed to simulate the predation activities of gray wolves. In the gray wolf society, there is a strict social hierarchical relationship between gray wolves and gray wolves, as shown in Fig 2.

In Fig 2, the wolf at the first level of the social hierarchy is called the head wolf, which is recorded as the \( \alpha \) wolf, and has the highest social level. During the iteration process, the remaining gray wolves approach the \( \alpha \) wolf, and the fourth level of social hierarchy marked as \( \omega \) wolf.

The gray wolf algorithm is optimized according to the following steps,

1) Social hierarchy: The three individuals with the best fitness in the population are marked as \( \alpha, \beta, \) and \( \delta \) in turn, and all the remaining individuals are marked as \( \omega \);

2) Surrounding the prey: In the iterative process, the gray wolf will gradually move closer to the prey. The mathematical model of this behavior can be expressed by formulas (7)-(10),

\[
\vec{X}(t+1) = \vec{X}_{ph}(t+1) - \vec{A} \cdot \vec{D} \tag{7}
\]

\[
\vec{D} = \left| \vec{C} \cdot \vec{X}_{ph}(t) - \vec{X}(t) \right| \tag{8}
\]
\[ \overline{A} = 2 \cdot a \cdot r_i - a \]  
(9)

\[ C = 2 \cdot r_i \]  
(10)

In equation, \( \overline{X}_p(t) \) represents the position vector of the t generation prey; \( \overline{X}(t) \) represents the position vector of the t gray wolf; \( \overline{A} \) is the convergence factor; \( C \) is the swing factor; in the entire iteration process, a linearly decreases in the interval \([0,2] \); \( r_1, r_2 \) is \([0,1]\) the random vector.

3) Hunting: During each iteration, the positions of \( \alpha, \beta \) and \( \delta \) wolves will be reserved, and then updated according to their position information to gradually surround the optimal solution. The mathematical model of this behavior can be expressed as follows,

\[ \overline{D}_\alpha = \left| \overline{C}_1 \cdot \overline{X}_\alpha - \overline{X}(t) \right| \]  
(11)

\[ \overline{D}_\beta = \left| \overline{C}_2 \cdot \overline{X}_\beta - \overline{X}(t) \right| \]  
(12)

\[ \overline{D}_\delta = \left| \overline{C}_3 \cdot \overline{X}_\delta - \overline{X}(t) \right| \]  
(13)

\[ \overline{X}_1 = \overline{X}_\alpha - \overline{A}_1 \cdot \overline{D}_\alpha \]  
(14)

\[ \overline{X}_2 = \overline{X}_\beta - \overline{A}_2 \cdot \overline{D}_\beta \]  
(15)

\[ \overline{X}_3 = \overline{X}_\delta - \overline{A}_3 \cdot \overline{D}_\delta \]  
(16)

When the local iteration is completed, the final position of the gray wolf is

\[ \overline{X}(t+1) = \left( \overline{X}_1 + \overline{X}_2 + \overline{X}_3 \right) / 3 \]  
(17)

In the equation, \( \overline{X}_\alpha, \overline{X}_\beta, \overline{X}_\delta \) respectively represent the position vector of \( \alpha \) wolf, \( \beta \) wolf, and \( \delta \) wolf during this iteration; \( \overline{X} \) represent the position vector of gray wolf; \( \overline{D}_\alpha, \overline{D}_\beta, \overline{D}_\delta \) respectively represent the distance between the current candidate gray wolf and the best three wolves.

3.2. Grey Wolf Algorithm Design Based on Levy Flight

In the original gray wolf optimization algorithm, since the position of the \( \alpha \) wolf represents the optimal solution, it is particularly important. In the later iteration of the algorithm, all gray wolf individuals in the group must approach the optimal individual \( \alpha \) wolf, which will lead to the loss of the population diversity, easy to fall into local convergence\([13,14]\). Aiming at this drawback, this paper uses Levy's random walk strategy to search the gray wolf individual alpha wolves in the group globally. In Levy’s flight, the new generation of \( \alpha \) wolf calculation formula is as follows:

\[ \overline{X}_\alpha(t+1) = \overline{X}_\alpha(t) - a \oplus \text{Levy}(\beta) \]  
(18)

Where \( \overline{X}(t) \) is the position of the \( \alpha \) wolf individual; \( a \) is the random number representing the position of the \( \alpha \) wolf, determined by equation (19); \( \text{Levy}(\beta) \) represents the random search path, determined by equation (20)

\[ a = \text{random(size(\alpha_{\text{position}}))} \]  
(19)

\[ \text{Levy}(\beta) \sim 0.01 \frac{u}{|v|^\beta} \]  
(20)

\[ u \sim N(0, \sigma_u^2) \quad v \sim N(0, \sigma_v^2) \]  
(21)

The values of \( \sigma_u \) and \( \sigma_v \) are as follows,
\[
\sigma_r = \begin{cases} 
\Gamma(1 + \beta) \sin \frac{\pi \beta}{2} & \text{for } \beta \neq 1 \\
\Gamma\left(\frac{1 + \beta}{2}\right) \beta \cdot 2^{(\beta-1)/2} & \text{for } \beta = 1
\end{cases}
\]

According to the above analysis, the designed algorithm steps are as follows:

1) Numerical initialization: Initialize the position and objective function value of all population individuals;
2) Select the first wolf: Select the best individual according to the fitness value of the individual and record it as \(\alpha\) wolf;
3) Update head wolf position: update alpha wolf position according to formulas (7) ~ (8), and use formulas (19) ~ (22) to perform global search for \(\alpha\) wolf. Calculate the values of the corresponding parameters such as \(A\), \(C\) in each iteration;
4) Surround prey: According to formulas (11) ~ (16), iteratively update the positions of \(\alpha\) wolves, \(\beta\) wolves, and \(\delta\) wolves.
5) If the iteration termination condition is reached, output the position of the first wolf, otherwise go to step 2).

4. Gray wolf algorithm MPPT control based on Levy flight
The gray wolf algorithm of Levy’s flight is applied to the MPPT control method of photovoltaic power generation system, and the group optimization of the gray wolf algorithm and the random walk of Levi’s flight are used to solve the problems of MPPT control accuracy and tracking speed.

4.1. Selection of the initial population
Literature [15] generates the duty cycle by random placement method. Due to the strategy of elite retention, there will obviously be low accuracy problems in the later iterations. Therefore, this paper uses Levi flight to perform a global search on randomly generated head wolf positions to enhance the global Search ability.

4.2. Fitness function
According to the MPPT control principle, the power of the main circuit is selected as the fitness function. Through real-time detection of the voltage and current of the main circuit as the input of the algorithm, the value of the duty cycle is changed every iteration to compare the size of the output power to achieve the goal of maximum power output.

4.3. Termination criteria
In order to reduce the fluctuation of output power, the algorithm is set to terminate when the maximum position difference between gray wolves is less than the threshold or the iteration is completed.

5. Simulation experiment
In order to verify the effect of the gray wolf algorithm based on Levy’s flight (LGWO) in tracking the maximum power under different environmental conditions, this paper connects 4 photovoltaic cells in series and sets three different environmental conditions, each of which is as follows
1) The light intensity received by each photovoltaic cell is 500 W/m² and the temperature is 25 °C;
2) The light intensity received by the photovoltaic cell is 500 W/m², 1000 W/m², 800 W/m², 1000 W/m², and the temperature is 25 °C;
3) The light intensity of each photovoltaic cell will change in different time periods, and the temperature will not change.

5.1. Power tracking under uniform illumination
Under environmental condition 1, the photovoltaic array receives uniform light, and the maximum power is 493.2W. The original gray wolf algorithm, the improved gray wolf-golden section hybrid
algorithm, and the gray wolf algorithm based on Levi's flight were used to track and optimize the photovoltaic maximum power point. The simulation convergence results are shown in Figure 3. According to the convergence curve in the figure, it can be seen that at about t=0.1s, the gray wolf algorithm based on Levy's flight tracks the maximum power, which is 484.7 W, which is 1.72% different from the theoretical maximum power value. The improved gray wolf-golden section hybrid algorithm is only at 0.2s, the maximum power tracked is 472 W, which is 4.29% different from the theoretical maximum power value. In contrast, the maximum power found by the original gray wolf algorithm is only 367.4 W, which is 25.5% different from the theoretical value, which shows that this article proposes Compared with the gray wolf algorithm used in MPPT, the tracking speed is faster and the tracking accuracy is higher.

![Fig.3 Simulation result by LWGO, GWO and MGWO-GSO under uniform illumination](image)

5.2. Power tracking under partial shading

In practical applications, in order to increase the output power of the photovoltaic system, multiple photovoltaic cells are usually connected in series and parallel to form a large-area photovoltaic array, in order to prevent the "hot spot" effect due to local shading, resulting in local photovoltaic cells To generate heat, or even damage the entire photovoltaic array, a diode must be connected in parallel to the bypass of a single photovoltaic cell to form a unit. At this time, the PV output curve of the photovoltaic array exhibits multi-peak characteristics. In order to improve the accuracy and stability of MPPT, this paper applies the gray wolf algorithm based on Levi's flight to MPPT control. The photovoltaic array is composed of 4 batteries connected in series, and the received light intensity is 500 W/m2 and 1000 W/m2, 800 W/m2, 1000 W/m2, and the temperature is 25 °C. The simulation result shows that in this case, the photovoltaic array The maximum power is 637.8W. In order to verify the superiority of the proposed algorithm, compared with the original gray wolf algorithm and the improved gray wolf-golden section hybrid algorithm, the simulation results are shown in Fig4.

![Fig.4 Simulation result base on LWGO, MGWO-GSO and GWO under partial shading](image)
After 10 simulation experiments, the best output curve is selected. According to the simulation results in Fig. 7, it can be seen that the MPPT device controlled by the LGWO algorithm stops working at 0.1s, and the maximum power found is 635.7W, which is equivalent to the theoretical maximum power. The difference is 0.33%, the convergence time is fast, and the tracking accuracy is high, which verifies the feasibility of the algorithm for MPPT control. In contrast, the maximum power found by the improved gray wolf-golden section hybrid algorithm is 511.9W, which is the maximum The power difference is 19.7%. Although the algorithm jumps out of the local optimal step before convergence, the convergence result is still only tracking to the local highest peak. The maximum power tracked by the original gray wolf algorithm is 394.8W, and the power loss is huge.

In order to verify the conclusion that the traditional MPPT algorithm fails under the multi-peak output characteristic curve, this paper uses the conductance increment method to track the maximum power of the photovoltaic array. After 10 simulation experiments, the best simulation result is selected, as shown in Figure 5. It can be seen from the figure that although the power of the conductance incremental method rises rapidly and the convergence speed is very fast, the maximum power found is only 77.68W, which is 87.8% different from the theoretical maximum power.

5.3. Power tracking under changing illumination

In order to further verify the adaptability of the algorithm, assume that the light intensity received by the photovoltaic cell under condition 3 is shown in Table 1. The LGWO algorithm is used for MPPT control. The output curve obtained after simulation is shown in Figure 6. From the simulation results, it can be seen that the algorithm can quickly react to changes in lighting conditions and tends to be stable.

| Battery | 0-2s | 2-4s | 4-6s | 6-8s |
|---------|------|------|------|------|
| Battery1 | 500  | 800  | 1000 | 750  |
| Battery2 | 500  | 750  | 900  | 600  |
| Battery3 | 500  | 800  | 900  | 700  |
| Battery4 | 500  | 600  | 850  | 900  |

Fig.5 Simulation result by INC algorithm under partial shading

Fig.6 Simulation results of MPPT based on LWGO under dynamic conditions
6. Conclusion
In the case of partial shading, the output power of the photovoltaic system will be greatly reduced. In order to improve the power generation efficiency, this paper proposes an MPPT control method based on Levi flight. By introducing Levi flight, the global search capability of the gray wolf algorithm is improved. The simulation experiment shows:

1) The gray wolf algorithm based on Levy's flight proposed in the article effectively solves the problem that the gray wolf algorithm is easy to fall into local optimality, and retains the speed of the original algorithm;
2) The algorithm proposed in the article can effectively track the PV maximum power point in various modes, the power output is stable, and the power generation efficiency of the system is improved.

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