Application of Moth-fire Optimization Algorithm in Parameter Identification of Photovoltaic System

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Abstract. In order to deeply study the influence of PV on the stability of power system, it is necessary to accurately reflect the external dynamic response characteristics of the PV system, and accurate PV system parameters are the key factors. For this reason, the moth-fire optimization algorithm is introduced to solve the PV system parameters value. This paper models the PV system and find out the key parameters of it. The active power and reactive power response curves of the grid are measured to identify the parameters of the PV based on the moth-fire optimization algorithm. The results of the example show that the curve fitting effect is better, and the feasibility of the proposed identification algorithm is verified.

1. Introduction

Due to the randomness and intermittent nature of PV, the stability of power systems has been increasingly challenged [1]. In order to study the impact of PV system on the stability of power systems, it is necessary to accurately reflect its external dynamic response characteristics. To make the simulation results closer to the actual system, it is necessary to identify the parameters of PV system.

The research on the transient model of photovoltaic power generation system is very mature. The power system electromechanical transient simulation software PSD-BPA, PSASP and PSS/E also have photovoltaic power generation system model. PSD-BPA is widely used in power grid simulation and stability analysis in China, so this paper uses its photovoltaic model as the object of parameter identification. In recent years, intelligent algorithms have gradually emerged, such as PSO [2], GA [3], which is easy to program, strong in parallel search, and good in optimization. It is widely used in parameter identification and other fields. However, most algorithms have insufficient balance between global search performance and local development capabilities, and are easy to fall into local optimal solutions. The moth-fire optimization algorithm is a new bionic intelligent optimization algorithm proposed by Seyedali Mirjalili in 2015 [4], which has good global search performance and local development ability in optimizing the placement and size of capacitors [5] and solving the distribution of the power system FACTS device [6].

This paper proposes to introduce the MFO algorithm into the parameter identification problem of PV system. Firstly, the PV system model is analyzed to determine the parameters to be identified.
Secondly, the basic principle of the MFO algorithm is expounded. Finally, an example is given to verify the feasibility of the identification method.

2. PV System Modeling

2.1. Overall structure of PV system
The PV system model is mainly composed of a PV cell array model and a VSC grid-connected converter and its control system model, as shown in figure 1. The PV cell array converts light energy into DC power, and the VSC converter converts DC power into AC power.

![Figure 1. Structure of PV system.](image)

2.2. Mathematical model for PV cell engineering
Researchers use mathematical parameters provided by PV manufacturers based on standard test environments (25°C, 1000W/m²) to build PV cell mathematical engineering model [7]. The parameters of this model include short-circuit current $I_{sc}$, open circuit voltage $U_{oc}$, maximum power point current $I_{mp}$, maximum power Point voltage $U_{mp}$. The engineering mathematical model is as shown in equations (1) to (3).

$$I_L = I_{sc}[1-C_1(\exp\frac{U}{C_2U_{oc}}-1)]$$  \hspace{1cm} (1)

$$C_1 = (1-\frac{I_{mp}}{I_{sc}})\exp(-\frac{U_{mp}}{C_2U_{oc}})$$  \hspace{1cm} (2)

$$C_2 = (\frac{U_{mp}}{U_{oc}}-1)[\ln(1-\frac{I_{mp}}{I_{sc}})]^{-1}$$  \hspace{1cm} (3)

2.3. Grid-connected converter and its control system model
In the PV system, the grid-connected converter is the core part, which realizes the process of converting direct current into alternating current. In order to improve the active and reactive control performance, the control part often uses the double loop control structure in the dq0 coordinate system, as shown in figure 2. In figure 2, $T_{mU}$, $T_{mV}$, and $T_{mQ}$ are measurement time constants, and $K_{PU}$, $K_P$, $K_{PV}$, $K_{PQ}$, $K_{IU}$, $K_I$, $K_{IV}$, and $K_{IQ}$ are the PI link proportional magnification and integral magnification, respectively.

The outer loop controller mainly exhibits the external characteristics of the inverter, and realizes DC voltage, reactive power or AC voltage control. The current reference value obtained by the outer loop control of the inner loop is used as a reference, and after decoupling, the inverter is finally connected to the grid. Photovoltaic grid-connected inverters can adopt a variety of control strategies, and in this paper, the DC voltage control is used, the reactive power is controlled by constant voltage.
2.4. Selection of parameters to be identified
For the photovoltaic cell arrays, the four parameters I_{sc}, U_{oc}, I_{m}, U_{m} required for their engineering mathematical model can be obtained from the nameplate of the product, so no identification is required.

For the grid-connected inverter, the parameters of its control part are mainly identified. Since the switching frequency of photovoltaic grid-connected inverters is often high and there are no mechanical parts, the time constant is often small and has little effect on engineering applications, so the typical values are directly used. But the PI link is the core of the control part and has a great impact on the system output. Therefore, the parameters to be identified selected in this paper are shown in Table 1.

| Variables to be identified                      | Parameters symbol |
|------------------------------------------------|-------------------|
| Active outer loop proportional link magnification | $K_{PU}$          |
| Active outer loop integral link magnification    | $K_{IU}$          |
| Reactive outer loop proportional link magnification | $K_{PV}$          |
| Reactive outer loop integral link magnification  | $K_{IV}$          |
| Current inner loop proportional link magnification | $K_{P}$           |
| Current inner loop integral link magnification   | $K_{I}$           |

3. Moth-fire optimization algorithm

3.1. MFO algorithm principle
In the MFO algorithm, assuming that the candidate solution is a moth, the variable of the problem is the position of the moth in space. Since the MFO algorithm is a population-based algorithm, this group of moths can be represented by the equation (4) in the matrix.

\[
M = \begin{bmatrix}
M_1 & M_2 & \cdots & M_n
\end{bmatrix}
= \begin{bmatrix}
m_{1,1} & m_{1,2} & \cdots & m_{1,d} \\
m_{2,1} & m_{2,2} & \cdots & m_{2,d} \\
\vdots & \vdots & \ddots & \vdots \\
m_{n,1} & m_{n,2} & \cdots & m_{n,d}
\end{bmatrix}
\]

(4)

Where \(n\) is the number of moths and \(d\) is the number of variables.

For all moths, suppose there is an array for storing the appropriate fitness values as follows:

\[
O_M = [O_{M_1}, O_{M_2}, \cdots, O_{M_n}]
\]

(5)

The fitness values are the return value of the fitness function of moths. The position vector of each moth is passed to the fitness function, and the output of the fitness function is assigned to the corresponding moth as its fitness value. Another key part of the algorithm is the flame, which has a similar matrix representation to the moth, as shown in equation (6).

\[
F = \begin{bmatrix}
F_1 & F_2 & \cdots & F_n
\end{bmatrix}
= \begin{bmatrix}
f_{1,1} & f_{1,2} & \cdots & f_{1,d} \\
f_{2,1} & f_{2,2} & \cdots & f_{2,d} \\
\vdots & \vdots & \ddots & \vdots \\
f_{n,1} & f_{n,2} & \cdots & f_{n,d}
\end{bmatrix}
\]

(6)

As can be seen from equations (4) and (6), the dimensions of matrices \(M\) and \(F\) are the same. For flames, it is also assumed that there is an array for storing the corresponding fitness values as follows:

\[
O_F = [O_{F_1}, O_{F_2}, \cdots, O_{F_n}]
\]

(7)

Moths and flames are solutions, and the difference between them is how we process and update them in each iteration. The moth is the actual search agent that moves around the search space, and the flame is the best place for moths to date. In other words, when searching for space, the flame can be seen as a sign or point where the moth falls. Therefore, if a better solution is found, each moth will search and update around the flame.

In this paper, we choose logarithmic spiral as the main update mechanism of moth, as shown in equation (8).

\[
S(M_i, F_j) = D_i \cdot e^{bt} \cdot \cos(2\pi t) + F_j
\]

(8)

Where \(M_i\) represents the \(i\)-th moth, \(F_j\) represents the \(j\)-th flame, \(D_i\) represents the distance between the \(i\)-th moth and the \(j\)-th flame, \(b\) is a constant defining the logarithmic spiral shape, \(t\) is a random number in \([-1,1]\). The calculation method of \(D_i\) is as follows:

\[
D_i = \left| F_j - M_i \right|
\]

(9)

Equation (8) simulates the spiral flight path of the moth. As can be seen from this equation, the next position of the moth is determined relative to the flame. As shown in figure 3, the \(t\) in the spiral equation defines the distance at which the moth’s next position should be close to the flame (\(t=-1\) is the closest to the flame and \(t=1\) is the farthest). Spiral motion is a major component of this method because it determines how the moths update their position around the flame. The spiral equation allows moths to fly around the flame without necessarily flying in the space between them. Therefore, the global search capability and local development capability of the algorithm can be guaranteed.

To illustrate the problem, figure 4 shows a conceptual model of the positional update of the moth around the flame in a one-dimensional space, but this method can be used for all variables of higher dimensional problems. As can be seen from the arrows labeled 1, 3, 4, when the next position (black...
dotted line) is outside the space between the moth (brown horizontal line) and the flame (green horizontal line), the moth searches. When the next position is in the space between the moth and the flame, the position of the moth will be selected as the position of the next generation of flame, as indicated by the arrow labeled 2 in the figure.

The above location update mechanism ensures that the moth has good local development capabilities around the flame. In order to improve the possibility of finding a better solution, we considered the best position for the flame. Therefore, the matrix $F$ always contains the optimum position of the $n$ flames obtained so far. During the optimization process, the moths need to update their position relative to the matrix. To further enhance local development capabilities, we assume that $t$ is a random number in $[r, 1]$, where the convergence constant decreases linearly from -1 to -2 during the iteration. In this way, moths tend to more accurately utilize the corresponding flame that is proportional to the number of iterations.

$$t = 0.5 \quad t = 0.5 \quad t = -0.5 \quad t = 0 \quad t = -1$$

![Figure 3. Logarithmic spiral, space around the flame, and consider different $t$ locations on the curve](image)

![Figure 4. Conceptual model of position update of moths around the flame](image)

In order to prevent the MFO algorithm from quickly falling into a local optimum, each moth can only use one of the flames to update its position. After each iteration and update of the flame list, the flames are sorted according to their fitness, and the moths update their position relative to the corresponding flame. The first moth always updates its position relative to the best flame, and the last moth updates its position relative to the worst flame in the list. Figure 5 shows the process by which each moth is assigned to a flame in the flame list.

![Figure 5. The process of assigning moths to the flame list](image)
If the moth updates their position relative to $n$ different flames in the search space, the local development capability of the algorithm may be reduced. Aiming at this problem, a mechanism of flame quantity adaptation is proposed, as shown in equation (10). The gradual reduction in the number of flames balances the global search capability and local development capabilities of the algorithm in the search space.

$$\text{flame.no} = \text{round}(N - l \cdot \frac{N - 1}{T})$$

(10)

Where $l$ is the current number of iterations, $N$ is the maximum number of flames, and $T$ is the maximum number of iterations.

3.2. Parameter identification based on MFO

In order to apply the MFO algorithm to the parameter identification of photovoltaic system, this paper takes the root mean square error as its fitness (target) function:

$$f(X) = \text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (R_i - C_i)^2}$$

(11)

Where $X = (K_{PL}, K_{IL}, K_{PV}, K_{PV}, K_{P}, K_{I})$ is the position vector of moth, representing the parameter value of the grid-connected photovoltaic power generation system, $N$ is the number of samples of the sample, and $R_i$ is the true measurement value, $C_i$ represents the simulated calculation value. The smaller the fitness, the more accurate the parameters that are identified.

The basic idea of using MFO optimization algorithm to identify parameters is to search for a set of $X$ that minimizes the value of equation (11) within the parameter optimization range. The strategy for PV system parameter identification is shown in figure 6.

4. Case analysis

When a short circuit occurs in the northwest region of China, it is measured that the voltage of the grid connection point of a photovoltaic power station drops to 0.5pu during the period from 0.35s to 0.43s and restores the steady state value. The photovoltaic system shown in figure 1 is established using the electric system electromechanical transient simulation software PSD-BPA. Because MATLAB has flexible programming language and friendly programming environment, this paper writes MFO optimization algorithm in MATLAB, co-simulation by PSD-BPA and MATLAB, and identifies the parameters of photovoltaic power generation system model based on the measured data of PV. The identification results are shown in the table 2 is shown. The identification results are reapplied to the PSD-BPA, and the obtained active power and reactive power fitting curves are shown in figure 7 and 8.
Table 2. PV system parameter identification results.

| Variables to be identified | Identification results |
|---------------------------|------------------------|
| $K_{PU}$                  | 1.144                  |
| $K_{IU}$                  | 0.182                  |
| $K_{PV}$                  | 0.858                  |
| $K_{IV}$                  | 1.659                  |
| $K_P$                     | 5.632                  |
| $K_I$                     | 2.374                  |

Figure 7. Active power fitting curve

Figure 8. Reactive power fitting curve

It can be seen from figure 7 and figure 8 that compared with the typical value parameters, the parameters obtained by using the identification method can be used to fit the measured active power and reactive power curves, thus simulating the photovoltaic power generation system. Provide more accurate parameters.

5. Conclusion

In this paper, the moth-fire optimization algorithm is introduced into the field of parameter identification of photovoltaic power generation system, and the parameters of photovoltaic power generation system are identified according to the measured active and reactive power curves of the power grid. The results show that the fitting effect is better, and the validity of the parameter identification method proposed in this paper is verified.

Reference

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