Parameter Identification of Generator Excitation System based on Improved Grey Wolf Optimization

Hengming Liu* and Lu Cao
East Branch of State Grid Corporation of China, Shanghai, 200120, China

*Corresponding author email: liu_hm@ec.sgcc.com.cn

Abstract. In order to ensure the accuracy of power system modelling and the reliability of safety and stability analysis, it is important to confirm the true parameters of the excitation system. This paper proposes that using hunting group division strategy and convergence factor non-linear decreasing strategy to improve the standard grey wolf optimization algorithm, and applied it to the identification of the generator excitation system. The simulation results show that the identification of the excitation system based on the improved grey wolf optimization algorithm has higher identification accuracy and stability, which provides an effective new method for the parameter identification of the nonlinear.

1. Introduction
Creating a ubiquitous electric power Internet of Things (IoT) with comprehensive status perception, efficient information processing, and convenient and flexible application is a new concept adapted to the development of China's electric power industry[1-3]. From the division of “generation-transmission-distribution-utilization” of traditional power grids, the IoT on the power sources should be resolved first Therefore, the realization of in-depth data collection and monitoring on the power generations is the solid foundations that supports the power IoT.

The generator excitation system provides the excitation voltage for a generator set. It can adjust the generator terminal voltage and control the reactive power, which is an effective means to improve the stability and the dynamic quality of the power system[4-5]. In the calculation and analysis of power system stability, the accuracy of the excitation system model parameters directly determines the accuracy and credibility of the electromechanical transient process simulation. Thus, to make the simulation conclusions closer to the real system, accurately grasping the parameters of the excitation system of each grid-connected unit is of vital importance for studying the stability of the power grid and making a reasonable grid operation manner.

The parameter identification methods for excitation system include traditional identification algorithms and artificial intelligence algorithms[6-7]. Compared with traditional identification algorithms, the artificial intelligence algorithms can effectively solve nonlinear system identification problem. Literature[6-7] applied artificial intelligence algorithms to parameter identification of excitation system, and have achieved some results. However, the identification result is unstable, and these algorithms exist the problem of the optimization effect depending on the selection of the initial value of the parameter settings. The grey wolf optimization (GWO) adopts cooperation and communication among individuals in the group to achieve the purpose of optimization. And the GWO algorithm requires few parameters to be adjusted, and has been proved that its accuracy and stability is better than PSO, DE and GSA algorithms[8].
This paper proposes to apply grey wolf optimization to the parameter identification of the excitation system of the generator. Meanwhile, the standard grey wolf optimization has been improved to increase the accuracy and stability. The main contributions of this article are:

(1) Based on the standard GWO, a non-linear decreasing strategy of convergence factors and a hunting group division strategy are proposed, which enhance the capability of global searching and local searching, as well as the population diversity. (2) Apply improved GWO to the identification of the generator excitation system, and achieve the identification of excitation system successfully. The simulation shows the accuracy and stability of improved GWO are higher than that of standard GWO.

2. Principle of Improved Grey Wolf Optimization

2.1. Principle of standard Grey Wolf Optimization

The GWO algorithm simulates the hierarchy and hunting behavior of grey wolves in nature. The entire wolf group is divided into four groups: $\alpha$, $\beta$, $\delta$, $\omega$. Define the wolf group with the best fitness as the head wolf $\alpha$, the second best as the subordinate wolf $\beta$, and the third best as the universal wolf $\delta$. The other individuals in the population are other wolves $\omega$. $\alpha$, $\beta$, $\delta$ guide other wolves $\omega$ to search for the target. In the process of intelligent optimization, the wolf pack continuously updates the positions of $\alpha$, $\beta$, $\delta$, $\omega$.

$$D = |C \cdot X_\alpha(t) - X(t)|$$  \hspace{1cm} (1)

$$X(t+1) = X_\rho(t) - A \cdot D$$  \hspace{1cm} (2)

Where $D$ is the distance between the individual and the target; $t$ is the number of current iterations; $X_\rho$ is the target position; $X$ is the position vector of the grey wolf; $A$ is the enclosing step size. And $A$, $C$ are determined by equations (3-4):

$$A = 2a \cdot \text{rand}_1 - a$$  \hspace{1cm} (3)

$$C = 2 \cdot \text{rand}_2$$  \hspace{1cm} (4)

$$a = 2 - 2 \cdot \frac{t}{\text{max}}$$  \hspace{1cm} (5)

$\text{max}$ is the maximum number of iterations; $a$ is the convergence factor; $\text{rand}_1$ and $\text{rand}_2$ are random numbers between [0,1].

$$X_\omega(t+1) = (X_\alpha + X_\beta + X_\delta) / 3$$  \hspace{1cm} (7)

$X_\alpha$ indicates the current position of $\alpha$, $X_\beta$ indicates the current position of $\beta$, and $X_\delta$ indicates the current position of $\delta$. $C_1$, $C_2$, $C_3$ represents a random vector. Equation (6) defines the length and direction of $\omega$ wolves’ forward progress towards $\alpha$, $\beta$, $\delta$. And Equation (7) defines the final position of the wolf.

2.2. Improvement of Grey Wolf Optimization

2.2.1. Hunting Group Division Strategy

The wolves, in the reality hunting process, are often scattered around the prey to surround it, and then some wolves start chasing the prey. During the chasing process, the wolves originally surrounded by the prey constantly participate in chasing the target, and some wolves initially participated in the chase
will slow down their speed to restore their physical strength and ambush in the direction of the prey’s escape. This hunting behavior makes it easier for the wolves to hunt successfully. Therefore, a wolf group can be divided into a chasing group and a surrounding group. The chasing group continuously participates in calculation, and the surrounding group does not participate in calculation. After each iteration, the individual with the lowest fitness in the chasing group ($P_w$) exits from the chasing group to the surrounding group, and the most adaptive individual in the surrounding group ($\mu$) participates in the chasing group.

The individual of surrounding group is $\mu = (z_1, z_2 \cdots z_{\text{dim}})$, $z_i$ is the attribute of the surrounding wolf. The initialization process of $\mu$ is shown in equation (8):

$$z_i = I_i + \lambda (u_i - I_i)$$

Where $I_i$ and $I_i$ are the upper and lower bounds of the variable, and $\lambda$ are random numbers between 0 and 1. The $N$ individuals of the population before replacing can be expressed as: $X = (P_1, P_2 \cdots P_N)$, The $N$ individuals of the population after replacing can be expressed as:

$$X = (P_1, P_2 \cdots P_{i-1}, \mu, P_{i+1} \cdots P_N)$$

2.2.2. Convergence Factor Nonlinear Decreasing Strategy

According to article [6], the grey wolf optimization relies on $A$ and $C$ to balance the global search ability and local search ability of the algorithm. When $|A| > 1$, the grey wolf group will expand the enclosing circle, corresponding to the global search. When $|A| < 1$, the grey wolf group will shrink the enclosing circle, corresponding to local exact search. According to equations (3) and (5), it can be seen that the value of $A$ is changed with the convergence factor $a$, and $a$ decreases linearly from 2 to 0 as the number of iterations increases. It is hoped that the global search ability of the algorithm will be enhanced to adapt to the parameter identification of complex systems. Construct exponential function with base $e$ to get the nonlinear linear decreasing strategy of the convergence factor:

$$a' = e^{-\left(\frac{t}{t_{\text{max}}}\right)}$$

(10)

Mapping $a'$ into the $[0, 2]$:

$$a = 2 \left( e^{-\left(\frac{t}{t_{\text{max}}}\right)} - 1 \right) / (e - 1)$$

(11)

As shown in Figure 2, on the one hand, the attenuation degree of $a$ in the early stage of the algorithm is reduced, which enhances the algorithm's random search ability in the early stage. When $t_{\text{max}} \approx 0.62$, the value of $a$ equals 1, what means that there is a probability to carry on global searching when $t_{\text{max}} < 0.62$, not limited to $t_{\text{max}} < 0.5$. On the other hand, the late attenuation degree of $a$ is enhanced so that the speed of finding a local optimal solution at the end of the
algorithm is increased. Thereby the improved algorithm has more effective capability to balance the
global searching and local searching.

2.2.3. Improved Grey Wolf Optimization Flow

Based on the content above, the flow of the improved GWO is as figure 3:

![Improved Grey Wolf Optimization flow](image)

**Figure 3.** Improved Grey Wolf Optimization flow.

3. Parameter Identification of Excitation System

3.1. Excitation System Model

Take a power plant in East China as an example, its excitation system is a self-excitation static
excitation system. The control block of its excitation system is shown in Figure 4.

![Generator no-load excitation system](image)

**Figure 4.** Generator no-load excitation system.

3.2. The Flow of System Parameter Identification

According to the influence of the excitation system parameters on the large-disturbance and small-
disturbance step responses of the generator, the parameters identification can be divided into two steps. The square of the deviation between the measured output response and the simulated output of the
generator terminal voltage is used as the objective function for identification. When the generator receives a small disturbance signal, the system response does not enter the non-
linear region. The model parameters that affect the step response of the generator are $K_p, K_i, K_d, T_s, T_a, T_r$. When the generator receives a large disturbance signal, the system response enters the non-
linear region. The model parameters that affect the step response of the generator are $U_{R_{max}}, U_{R_{min}}$. The identification steps are as follows:

a) Build the original excitation system model and the actual system model under the Matlab/Simlink;
b) Add small disturbance(5%) to the original model and the actual system model at the same time;
c) Call the identification algorithm program to get the values of $K_p, K_i, K_d, T_s, T_a, T_r$;
d) Substitute the identification values of $K_p, K_i, K_d, T_s, T_a, T_r$ into the actual system model;
e) Add large disturbance(10%) to the original model and the actual system model at the same time;
f) Call the identification algorithm program to get the values of $U_{R_{max}}, U_{R_{min}}$;
g) Output the identification result.
4. Simulation and Analysis

According to the manufacturer's excitation system structure, set $K_p = 0$. The algorithm uniformly sets 50 search agents, and runs the experiment 10 times with 100 iterations per experiment. The average value of 10 results represents the parameter identification result, and the standard deviation of the 10 results represents the stability of the result.

| Parameter | Real value | GWO | Improvised GWO | Errors |
|-----------|------------|-----|----------------|--------|
| $K_p$     | 120        | 121.0048 | 119.9714 | 0.8373% |
| $K_i$     | 100        | 101.8766 | 100.5001 | 1.8766% |
| $T_a$     | 0.003      | 0.0030  | 0.0030  | 0.0043% |
| $T_r$     | 0.02       | 0.0199  | 0.0199  | 0.0791% |
| $U_{Rmax}$ | 8.64      | 8.6414  | 8.6398  | 0.0100% |
| $U_{Rmin}$ | -6.05     | -6.0586 | -6.0517 | 0.0142% |

Table 1. Identification results and errors.

From Tables 1 and 2, it can be seen that the identification errors of the improved GWO are smaller than the standard GWO. Meanwhile, the stability of improved GWO is obviously better than standard GWO. Particularly, the stability of the $K_p$ identification value has been reduced from 2.06086 to 0.3282, and the stability of the $K_i$ identification value has been reduced from 5.8187 to 1.3526, which means that there is not much differences in the identification results of $K_p$ and $K_i$ during 10 times.

The dynamic curve of the terminal voltage output and the output of the limiting link during the small disturbance signal (5%) are shown in Figure 5.

![Figure 5](image.png)

(a) Terminal voltage output   (b) Limiting link output

**Figure 5.** The output of 5% Step response.

### Table 2. Identification stability.

| Parameter | GWO | Improved GWO | Errors |
|-----------|-----|--------------|--------|
| $K_p$     | 2.6086 | 0.3282 | 0.0024% |
| $K_i$     | 5.8187 | 1.3526 | 0.5010% |
| $T_a$     | 3.3972e-4 | 6.3259e-4 | 0.0041% |
| $T_r$     | 2.4193e-4 | 4.3695e-4 | 0.0683% |
| $U_{Rmax}$ | 6.1847e-4 | 7.3619e-4 | 0.0003% |
| $U_{Rmin}$ | 8.9983e-4 | 4.4611e-4 | 0.0281% |

### Table 3. The output of 5% Step response.

| Parameter | Real value | GWO | Errors | Improved GWO | Errors |
|-----------|------------|-----|--------|--------------|--------|
| maximum of Terminal voltage output | 0.053778 | 0.05384 | 0.0112% | 0.05374 | 0.0074% |
| maximum of Limiting Link output | 5.7999 | 5.846 | 0.0810% | 5.797 | 0.0034% |
| minimum of Limiting Link output | -0.1340 | -0.1386 | 3.4328% | -0.1303 | 2.7612% |

The dynamic curve of the terminal voltage output and the output of the limiting link during the large disturbance signal (±10%) are shown in Figure 6.
Through Figures 5-6 and Tables 3-4, it is clear that, the maximum (minimum) value of the terminal voltage obtained by using the improved GWO is closer to the real-value system than that of the terminal voltage obtained by using the standard GWO.

Through Figure 6 and Table 4, it can be seen that both GWO and improved GWO can realize the identification of the non-linear parameters of the excitation system. But the errors of limiting link output obtained by using the improved GWO is smaller compared to using standard GWO. And under the 3 amplitude step responses, the fitting effect using improved GWO is obviously better than that of using standard GWO.

5. Conclusion

This paper proposes to apply the improved grey wolf optimization to the parameter identification of generator excitation system. The main conclusions are as follows:

1) Based on the original algorithm's linear decrement strategy of convergence factor, a nonlinear decrement strategy of convergence factor is proposed, which balances the global search and local search capabilities of the algorithm.

2) Inspired by the hunting method of the grey wolf, a hunting division strategy is proposed, which increases the diversity of the grey wolf population and improves the algorithm's vulnerability to local optimization.

3) The accuracy and stability of the excitation system parameter identification based on the improved grey wolf algorithm are better than the standard grey wolf algorithm. The new algorithm effectively achieves the parameter identification of the nonlinear generator excitation system.
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