Research on Parameter Identification Method of Generator Excitation System Based on Differential Evolution Algorithm

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Abstract. In order to solve the problem of large parameter identification error caused by non-linear links of excitation system being triggered easily when transient stability is under fault state, an improved differential evolution algorithm for system parameter identification is proposed by using the characteristic of artificial intelligence algorithm that the nonlinear link is approximated infinitely through optimization. The improvement of the algorithm solves the problems of slow convergence speed, poor fine optimization ability and easily to produce local optimum when classical artificial intelligence algorithm identifies the parameters of non-linear links. At the same time, in order to solve the problem of inaccurate parameters in the whole identification, a decomposition link identification strategy is proposed. The example analysis shows that the algorithm improves the convergence speed, avoids local optimum and improves the convergence accuracy. According to the proposed parameter identification strategy, the excitation system is decomposed and identified, which improves the accuracy of generator excitation system parameter identification, and provides an accurate model and method for power system stability analysis.

1. Introduction
In recent years, many scholars have done a lot of research work in the field of parameter identification of excitation system in [1]. Literature [2] uses genetic algorithm to identify the non-linear link of excitation system, which proves the feasibility of using artificial intelligence algorithm to identify the parameters of excitation system. In [3], the improved genetic algorithm is used to identify the non-linear excitation system, and the identification accuracy is improved by combining the genetic algorithm with the gradient descent BP neural network. In [4], the adaptive particle swarm optimization (APSO) algorithm is applied to identify the parameters of excitation system to improve the convergence speed. But there are many problems in practical application. For example, genetic algorithm, particle swarm optimization and other algorithms have many control parameters, complex implementation and slow convergence speed.
Differential evolution algorithm has the characteristics of less control parameters and strong robustness. It has a good effect on multi-parameter optimization problem. But it also has the problems of slow convergence, local optimum and poor ability of fine optimization. In order to improve the convergence speed and the ability of fine optimization, the classical differential evolution algorithm is improved and applied to parameter identification of generator excitation system. In view of the high order of generator excitation system and the large number of parameters to be identified, a strategy to improve the accuracy of parameter identification based on link decomposition is proposed. According to the actual observation points and parameter sensitivity, the decomposition identification results show that the accuracy of parameter identification is improved.

2. Excitation System Model
We use self-shunt static excitation system model for parameter identification in [5], and the type model is FV. The block diagram of its transfer function is shown in Figure 1.

\[ V_i(t+1) = x_1(t) + F \times (\lambda \times (x_1(t) - x_2(t)) + (1-\lambda) \times (x(t)_\text{best} - x_3(t))) \]  

(1)

Where, \( \lambda = e^{\text{-GM}(\text{GM-1})} \), GM is the maximum number of iterations, \( x(t)_\text{best} \) is the best individual in the current population, and \( r_1, r_2, r_3 \) are three different index numbers that are not equal to \( i \). \( t \) is the current number of iterations, and \( F \) is the scaling factor. The optimization effect is better when the value is between \([0.4, 1]\). The larger the value of \( F \), the faster the convergence speed, the smaller the value of \( F \), the narrower the search range, and the higher the identification accuracy. During the operation of the algorithm, both convergence speed and identification accuracy need to be taken into account. Therefore, the random oscillation value with 0.6 as the center and 0.4 as the amplitude is chosen, as shown in formula (2):

\[ F = 0.6 + (-1)^k \times 0.4 \times \text{rand} \]  

(2)

Where, \( k \) is a random positive integer.
3.1.2. For the Current Optimal Individual. For the current population optimization, small step oscillation fine-tuning mutation is carried out to enhance the local optimization ability. The specific operation is shown as follows:

\[ v_i(t+1) = x_i(t)_{best} + (-1)^k \times (x_i^l - x_i^u) / 100 \]  

(3)

Where, \( k \) is a random positive integer, and \( x_i^l \) and \( x_i^u \) are upper and lower bounds of parameters.

3.2. Improved mutation operation Improving cross-over operation

In this paper, the difference vectors between the individual and the optimal individual of the current population are introduced, so that the evolutionary direction of the population tends to the optimal individual of the current population. This paper takes \( CR \) as the center and 0.6 as the amplitude, taking into account the evolution speed and the diversity of the population. As shown in formula (4):

\[ CR = 0.6 + (-1)^k \times 0.3 \times \text{rand} \]  

(4)

4. Parameter identification based on improved differential evolution algorithm

Artificial intelligence algorithms such as Differential Evolution Algorithms can identify the model parameters as a whole, that is, the values of all the parameters to be identified at one time. Let the transfer function of the excitation system be:

\[ G(s) = \frac{a_0 + a_1s + \ldots + a_m s^m}{1 + b_1s + \ldots + b_n s^n} \]  

(5)

Where, \( a_0, a_1, \ldots, a_m, b_1, b_2, \ldots, b_n \) are the parameters to be identified.

Because the excitation system is a high-order system, there are many sets of parameters to be identified. Even in accordance with the general practice of engineering, using multiple identification to obtain the average value, there will still be large errors, and the correct results cannot be obtained. In this paper, a parameter identification strategy based on link decomposition is proposed. The system is decomposed into several sub-modules to reduce the order of the system and improve the accuracy of parameter identification.

The parameter identification strategy of link decomposition is as follows:

- For both input and output signals, a simple sub-module with clear observation points can be established and identified directly.
- For modules with nested relationships, the parameters of simple links with clear structure and close distance to the observation point are identified in order from small to large and from inside to outside.
- The parameters with high error sensitivity are identified first, and then the parameters with low error sensitivity are identified.
- Nonlinear link parameters can be identified only when triggered, that is, they can only be identified in the non-linear state.

5. Example analysis

5.1. Simulation analysis

The model of FV self-shunt excitation system is used as the model to be identified. Let the actual system parameter \( K = 400, T_1 = 1, T_2 = 7, T_3 = 3.83 \), Take \( t \) as a known parameter, Identification \( K, T_1, T_2 \). The step disturbance with a unit value of 0.05 is taken as input and the output of generator terminal is taken as system output. The identification results are shown in Table 1.
Table 1. Identification result of linear link parameter of excitation system

| Parameters | K  | T1 | T2  |
|------------|----|----|-----|
| unit       | /  | s  | s   |
| Truth value| 400| 1  | 7   |
| Identification value | 398 | 1.05 | 6.97 |
| deviation  | 0.5% | 0.5% | 0.42% |

Let the limiting link $V_{\text{AMAX}} = 7$, $V_{\text{AMIN}} = 2$; Linear link parameters $K = 400$, $T_1 = 1$, $T_2 = 7$, $T_s = 3.83$. The linear link parameters are known, the step disturbance with a unitary value of 0.2 is taken as the input of the system. The VAMAX and VAMIN can be identified, and the results are shown in Table 2.

Table 2. Nonlinear link identification results of excitation system.

| Parameters | VAMAX | VAMIN |
|------------|-------|-------|
| unit       | P.u.  | P.u.  |
| Truth value| 7     | 2     |
| Identification value | 6.98 | 2.01 |
| deviation  | 0.28% | 0.5%  |

The improved DE algorithm can not only identify the linear link of excitation system effectively, but also identify the parameters of non-linear link effectively. In order to verify the superiority of the improved DE algorithm, three different artificial intelligence algorithms, namely, differential evolution algorithm, PSO and improved differential evolution algorithm, are used to identify the second-order linear system. The convergence comparison chart of the algorithm is shown in Figure 2, and the identification results are shown in Table 3.

Figure 2. Objective function curves of three algorithms.

Table 3. Identification results of three algorithms.

| Algorithm | Each iteration time consuming(s) | T1 (True value is 7) | T2 (True value is 2) | Mean deviation |
|-----------|----------------------------------|----------------------|----------------------|----------------|
| PSO       | 12.15                            | 7.15                 | 1.95                 | 2.32%          |
| DE        | 7.87                             | 7.17                 | 2.03                 | 1.81%          |
| IDE       | 8.06                             | 6.98                 | 2.01                 | 0.35%          |
From Figure 2, it can be seen that the improved DE algorithm converges to zero in about 50 generations, and the convergence speed is obviously faster than other algorithms. In order to verify the validity of the decomposition link identification strategy, the linear and non-linear parameters of FV self-shunt static excitation system are identified step by step according to the identification process of the decomposition link identification strategy. The identification results are compared with the overall identification results, as shown in Table 4.

### Table 4. Comparison of integral and link decomposition identification results.

| Parameters | unit | Truth value | Decomposition Identification results | Decomposition identification bias | Global identification results | Global identification bias |
|------------|------|-------------|--------------------------------------|----------------------------------|-------------------------------|---------------------------|
| K         | /    | 400         | 380.5                                | 0.5%                             | 350.48                        | 12.5%                     |
| T1        | s    | 1           | 1.01                                 | 0.5%                             | 2.13                          | 113%                      |
| T2        | s    | 7           | 6.97                                 | 0.42%                            | 8.96                          | 28%                       |
| Tg        | s    | 8.38        | 8.37                                 | 0.1%                             | 20.5                          | 114%                      |
| VAMAX     | p.u. | 7           | 7.01                                 | 0.28%                            | 8.05                          | 15%                       |
| VAMIN     | p.u. | 2           | 1.98                                 | 0.5%                             | 2.3                           | 15%                       |

5.2. Measured data identification

According to the actual data measured on site, the parameters of excitation system are identified by using improved DE algorithm and link decomposition identification strategy. The disturbance signal unit of measured data is divided into 0.05 and 0.2 step signals. The sampling frequency is 1600 Hz. The identification results of the measured data are shown in Table 5. The output of the system in case of small interference and large interference is shown in Figure 3 and Figure 4.

![Figure 3. System output under small disturbance.](image1)

![Figure 4. System output under large disturbance.](image2)

### Table 5. Identification results of measured data.

| Parameters | unit    | Truth value | Identification results | Mean deviation |
|------------|---------|-------------|------------------------|----------------|
| K         | /       | 400         | 360.6                  | 10%            |
| T1        | s       | 1           | 0.95                   | 5%             |
| T2        | s       | 7           | 6.73                   | 3%             |
| Tg        | s       | 8.38        | 8.5                    | 1.4%           |
| VAMAX     | p.u.    | 7           | 7.21                   | 3%             |
| VAMIN     | p.u.    | 2           | 1.9                    | 5%             |
PSO, DE and IDE are used according to the decomposition strategy. The identification results and deviations are shown in Table 6. The system outputs processed by the differential evolution algorithm and the output of the actual system are compared in Figure 5 and Figure 6.

![Figure 5. System output under small perturbations.](image1)

![Figure 6. System output under large disturbances.](image2)

**Table 6.** Data identification results of different algorithms.

| Parameter | Truth value | PSO | PSO bias (%) | DE | DE bias (%) | IDE | IDE bias (%) |
|-----------|-------------|-----|--------------|----|-------------|-----|-------------|
| K         | 400         | 338.5 | 15.5         | 450 | 12.5        | 360.5 | 10          |
| T1        | 1           | 1.13  | 13           | 0.91 | 9           | 0.95  | 5           |
| T2        | 7           | 7.43  | 6.1          | 6.1  | 12.9        | 6.73  | 3           |
| Tg        | 8.38        | 6.3   | 14.7         | 8.97 | 7.9         | 8.5   | 1.4         |
| VAMAX     | 7           | 6.35  | 9            | 7.81 | 11.5        | 7.21  | 3           |
| VAMIN     | 2           | 1.83  | 9.15         | 2.2  | 10          | 1.9   | 5           |

From Table 6, it can be seen that the improved differential evolution algorithm and link decomposition identification strategy proposed in this paper can effectively identify the linear and non-linear link parameters of the actual excitation system of power grid.

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