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Eigenvalues Optimization Method of Low Frequency Oscillation for Multi-machine System based on Genetic Algorithm

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Abstract. This paper presents a method that simultaneously tunes the control parameters using genetic algorithms (GAs) to optimize the eigenvalues of multi-machine system, thereby achieving the effect of suppressing low frequency oscillation of the system. Due to the complexity and scale of the multi-machine system, it is necessary to rationally and efficiently optimize the algorithm for the parameter setting of this grid. In this article, the method of adjusting the population size and mutation rate and adopting several improved eigenvalues optimization objective functions is proposed to improve the performance of the genetic algorithm. These improvement measures are applied for control parameters tuning to the modified IEEE-39 system that contains DFIG-based wind farms and energy storage devices. The optimization results show that the efficiency and convergence of the genetic algorithm have indeed improved.

1. Introduction

Oscillation is one of the main features of power system operation. Small disturbances, such as load changes, may cause system oscillations. Because of the lack of damping of the system or the negative damping of the system, the power fluctuation frequency on the transmission line is generally between 0.1 and 2.5 Hz, which is usually called low frequency oscillation. With the development of the size of the power system and large-scale application of the rapid excitation system, the low frequency oscillation of the power system is causing more and more concern. And low frequency oscillation affects the stability of the power system and the reliability of the relay device. From the analysis of the single-machine infinity bus system and the analysis of the damping torque of some devices, it is possible to configure that some devices can improve the stability of the system, such as power system stabilizers (PSS), energy storage devices. However, the control effect of the above equipment is very dependent on the control parameters. Reasonable control parameters can suppress the low-frequency oscillation, but unreasonable control parameters will intensify the oscillation of the power system.

Energy storage system plays an important role in penetrating renewable energy. And energy storage device can theoretically increase the system damping, making the system tends to be stable. However due to the phenomenon of eigenvalues drifting[1], it may occur that after adding the energy storage device to the system, regardless of how the energy storage control parameters and access points are adjusted, the system eigenvalues are always existing positive real part. Therefore, in this paper a solution is presented for simultaneously setting the control parameters of synchronous machines, wind motors and energy storage systems. And the genetic algorithm is applied to the joint setting parameters of multi-machine system.

2. The study method of frequency oscillation in multi-machine system

Modal analysis is often used in parameter setting of power system stabilizers. The eigenvalues of the state matrix are used to describe the stability of the system. If the real part of the eigenvalue is positive, the system is unstable. If the real part of the eigenvalue is negative, then the system is in a steady state.

First, establish a mathematical model of the power system. The model of the synchronous generator is simplified Heffron-Phillips model, and the automatic voltage regulator uses the simplest transfer function:

$$TE(s) = \frac{K_A}{1+sT_A} \tag{1}$$

The detailed mathematical model and physical meaning of specific parameters can be found in the reference[2].

The simplified seventh-order model is adopted to describe the doubly-fed wind generator (DFIG). The first three orders are dynamic equations of DFIG, expressed on the d-q coordinate system of the DFIG. The other four equations present the machine-side converter control system, the expressions are as follows:

$$\begin{cases} I_{swq}^{ref} = K_{pwq}(s)(P_s^{ref} - P_s) \\ I_{swd}^{ref} = K_{pwd}(s)(Q_s^{ref} - Q_s) \\ V_{rwd} = K_{iwd}(s)\left(I_{rwd}^{ref} - I_{rwd}\right) + s_w(\frac{X_m^2}{X_{ss}} - X_{rr})I_{rwq} \\ V_{rwq} = K_{iwq}(s)\left(I_{rwq}^{ref} - I_{rwq}\right) - s_w\left(X_{rr} - \frac{X_m^2}{X_{ss}}\right)I_{rwd} + s_w\frac{X_m}{X_{ss}}V_s \end{cases} \tag{2}$$

The detailed mathematical model physical meaning of specific parameters can be found in the reference[3].

The energy storage model uses a simplified equivalent model, and the mathematical model[4] is as follows:

$$\begin{cases} I_{dc} = \tilde{I}_{dc} - \frac{V_{dc}-V_{ESS}}{r_{ESS}} \\ \bar{V}_c = mkVdc(cos\phi + jsin\phi) = mkV_{dc}\angle\phi \\ \dot{V}_{dc} = \frac{1}{C_{dc}}I_{dc} = \frac{1}{C_{dc}}[mk\left(I_{sd}\,cos\phi + I_{sq}sin\phi\right) - \frac{V_{dc}-V_{ESS}}{r_{ESS}}] \end{cases} \tag{3}$$

The mathematical model of the controller is:

$$\begin{cases} m = m_0 + (K_{mP} + \frac{K_{mI}}{s})(V_{sref} - V_s) \\ \phi = \phi_0 + (K_{\phi P} + \frac{K_{\phi I}}{s})(V_{dc} - V_{dcref}) \end{cases} \tag{4}$$

Then, linearize the above dynamic equation, a 64-order small-signal model of multi-machine system was established. Finally, system state matrix is obtained.

In order to avoid the phenomenon of eigenvalues drifting, simultaneously setting the control parameters of synchronous machines, doubly-fed induction wind motors and energy storage systems is a feasible solution. The optimization variables are control parameters K_A, T_A for each 10 synchronous machine. The transfer functions of DFIG are: $K_{pwq}(s)$, $K_{pwd}(s)$, $K_{iwd}(s)$, $K_{iwq}(s)$, and PI control is adopted, so 3 DFIGs totally have 24 parameters. And there are 5 energy storage devices control parameter: K_{mP}, K_{mI}, $K_{\phi P}$, $K_{\phi I}$, and access point parameters. Above all, a total of 49 control parameters need to be set.

Because of the stability of the system depends only on the stabilization effect of the energy storage and the coordination of the controller parameters, and the grid side variable introduced by the energy storage controller is the amplitude of voltage, so the effect on suppressing the low-frequency oscillation is not ideal, and the system is on the stable edge. In this case, it needs high requirements on the performance of algorithm.

3. Control parameter coordination setting method

The parameter setting process is the process of moving all the eigenvalues of the system state matrix to the left half plane of the complex plane. At present, there is no accurate analytic method for eigenvalues optimization, it is common to use intelligent algorithms to optimize the eigenvalues.

Genetic algorithm is a kind of optimization intelligent algorithm that simulates the evolution of nature[5]. The genetic algorithm has a very powerful global search capability. However, the genetic algorithm still faces many problems. The most prominent and unconfirmed problem is the premature problem. In addition, genetic algorithm as a black box algorithm, lacking theoretical support of analytic solutions, can be optimized or not, whether the optimization results are good enough affected by the algorithm process.

Due to the complexity and scale of the multi-machine system, it is necessary to rationally and efficiently optimize the algorithm for the joint setting control parameter of this grid. In the process of joint setting, the following problems are mainly faced and need to be improved:

3.1. Population size

Too large a population is not only difficult for computer to support, but also affects the calculation speed. However, too small a population will lead to the problem of "premature". The impact of population size on optimization is shown in the case analysis part.

3.2. Mutation rate

Increasing the mutation rate can improve the global searching ability of the algorithm, but excessive mutation rate will lead to the difficulty of inheriting the excellent genes to the offspring. So the mutation rate should be increased to find if there is positive effect on eigenvalue optimization.

3.3. The stability of the optimization results

There are a large number of random processes in the genetic algorithm, whether the optimization result of the same optimization process is reproducible is also a concerning problem. Carrying out repeated experiments is a solution.

3.4. The selection of objective function and penalty function

The most important and most critical problem of genetic algorithm is the selection of objective function. About modal analysis of low frequency oscillation for power system, the earliest objective function is as follows[6]:

$$\beta_a = \begin{cases} \beta_0 & if \text{ any } (\lambda) \geq \bar{\lambda}_0 \\ \beta_1 & if\ all(\lambda) < \bar{\lambda}_1\ and\ if\ any(\lambda) \geq \bar{\lambda}_2 \\ \beta_2 & if\ all(\lambda) < \bar{\lambda}_2\ and\ if\ any(\lambda) \geq \bar{\lambda}_3 \\ \beta_3 & if\ all(\lambda) < \bar{\lambda}_3\ and\ if\ any(\lambda) \geq \bar{\lambda}_4 \\ \beta_4 & if\ all(\lambda) < \bar{\lambda}_4\ and\ if\ any(\lambda) \geq \bar{\lambda}_5 \\ F & if\ all(\lambda)\ < \bar{\lambda}_{min} \end{cases} \tag{5}$$

Among them λ means the real part of the eigenvalue, $\bar{\lambda}$ means reference value, β mesas objective function value which can be incremented or decreed according to different optimization objectives. Because the objective function is discontinuous, the convergence is not strong. And this method which maps eigenvalues to another ascending or decreasing series is equivalent to find the maximum value of the real part of the eigenvalue. Document[7] simplifies it and takes the maximum value of the real part of the eigenvalue directly as the optimization objective. As shown below.

$$\beta_b = \lambda_{max} \tag{6}$$

The goal of eigenvalue optimization is to move all the real parts of the eigenvalue to a specific area of the complex plane. The maximum value of the real part of the eigenvalue does not fully represent our optimization goal. Therefore, a new objective function is proposed here, in which the real part of the eigenvalue is greater than the sum of the objective value as our objective function, as shown below.

$$\beta_c = \sum \lambda(\lambda > \bar{\lambda}) \tag{7}$$

However, when the eigenvalue real part approaches the target value, lacks of motivation to further optimize the real part of the eigenvalue. When the real part of the maximum eigenvalue decreases, the real part of the eigenvalue near the target value may increase and become the new real part of the maximum eigenvalue. Therefore, the range of summation is further expanded, and the revised objective function is:

$$\beta_d = \sum \lambda(\lambda > \bar{\lambda} - \varepsilon) \tag{8}$$

Among them, ε is a positive value which is relatively small, for example 0.1.

Further, combine the objective function β_b and β_d by weighted ratios a and b. Taking into account the leading role of the maximum objective function and the global role of the summation objective function, the efficiency and convergence of the optimization algorithm are improved. The function is:

$$\beta_e = a\beta_b + b\beta_d \tag{9}$$

The following case is used to verify the effect of the above improved method.

4. Case analysis of eigenvalues optimization of multi-machine system including wind farms and energy storage devices

In this paper, the power grid IEEE-39 system is analyzed. The IEEE-39 system parameters are standard per unit value parameters. On the basis of it, 3 DFIGs with injection power of 0.75 (p.u.), 0.65 (p.u.), and 0.7 (p.u.) is respectively connected to the 10, 20, and 31 bus lines. Parameters of the 3 DFIGs are the same: X_m=2.4012, X_s=0.1784, X_r=0.1225, R_r=0.002, J=8s, access impedance is 0.005+0.0272i. The type of energy storage device is battery energy storage, rated power is 1p.u. Fixed parameters in the format of per unit are: R_{ESS}=0.01, V_{ESS}=1.

In order to study the influence of the design of genetic algorithm on the optimization result, the default settings are: population size is 500, maximum genetic algebra is 100, mutation function is mut, mutation rate is default, and objective function is the maximum real part of eigenvalues.

4.1. Optimization results under the same optimization design

In order to verify the stability of genetic algorithm and prevent the influence of random process on the experiment, the optimization objective values of five optimization processes under default settings were selected.

The table 1 shows: After the experiment was repeated 5 times, the optimization objective is stable at about 0.05, which can be used as an evaluation index to evaluate the calculation efficiency and global search ability of genetic algorithm.

Table 1. Five repeated experiments results comparing.

Test number	1	2	3	4	5
Optimized result	0.0521	0.0534	0.0483	0.0547	0.0506

4.2. Effects of different population sizes on optimization results

As seen from the table 2, with the increasing size of population, the result of optimization keeps getting better, because the bigger size of the population, the stronger global search ability. At the same time, it can avoid the premature phenomenon and make the results more in line with objectives.

However, the population size cannot be increased indefinitely. In the process of increasing the number of population from 50 to 2000, the calculation time also increased from 3 minutes to 20 hours.

Table 2. Optimized results under different population sizes.

Population size	50	200	500	2000	5000	20000
Optimized result	0.1303	0.1063	0.0521	0.0563	-0.0158	-0.1062

4.3. Effects of different mutation rates on optimization results

From the table 3, it can be seen that increasing the mutation rate has no positive effect on the efficiency and convergence of eigenvalue optimization. The default mutation rate can meet the needs.

Table 3. Optimized results under different mutation rates.

Mutation ratio	default	0.1	0.2	0.3	0.4	0.5
Optimized result	0.0521	0.0707	0.0803	0.1295	0.1322	0.2797

4.4. Objective function selection

Adopting the five objective functions described in the previous section, the following results are obtained. (In the objective function β_d, ε=0.1; in the β_e, a=b=1.)

This case verify that it can truly improves the efficiency of the optimization algorithm by modify the objective function. And function β_e is the best of all the objective functions.

Table 4. Optimized results under different objective function.

Objective function	β_a	β_b	β_c	β_d	β_e
Optimized result	0.2683	0.0521	0.5838	0.0988	-0.0191

5. Conclusion

(1) The population size of the genetic algorithm used to tune the control parameters of multi-machine systems should be as large as possible considering the calculation speed.

(2) The mutation rate of eigenvalue optimization genetic algorithm should not be too high.

(3) The efficiency and convergence of genetic algorithm can be improved by combining the eigenvalue maximum function with the summation of eigenvalue real part larger than the target value function as the objective function.

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