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Parameters tuning of power system stabilizers using improved ant direction hybrid differential evolution

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ABSTRACT

The tuning of the PSS parameters for a multi-machine power system is usually formulated as an objective function with constraints consisting of the damping factor and damping ratio. A novel mixed-integer ant direction hybrid differential evolution algorithm, called MIADHDE, is proposed to solve this kind of problem. The MIADHDE is improved from ADHDE by the addition of accelerated phase and real variables. The performances of three different objective functions are compared to the MIADHDE in this paper. Both local and remote feedback signals of machine speed deviation measurements can be selected as input signals to the PSS controllers in the proposed objective function. The New England 10-unit 39-bus standard power system, under various system configurations and loading conditions, is employed to illustrate the performance of the proposed method with the three different objective functions. Eigenvalue analysis and nonlinear time domain simulation results demonstrate the effectiveness of the proposed algorithm and the objective function with a remote signal.

1. Introduction

The dynamic stability of power systems is an important factor for secure system operation. Low-frequency oscillation modes have been observed when power systems are interconnected by weak tie lines [1,2]. The low-frequency oscillation mode, which has poor damping in a power system, is also called the electromechanical oscillation mode and usually occurs in the frequency range of 0.1–2.0 Hz [3–6]. The power system stabilizer (PSS) has been widely used for mitigating the effects of low-frequency oscillation modes [7]. The construct and parameters of PSS have been discussed in many studies [3–6]. Currently, many plants prefer to employ conventional lead-lag structure PSSs, due to the ease of online tuning and reliability [7–9]. Over the last two decades, various parameter tuning schemes of PSS have been developed and applied to solve the problem of dynamic instability in a power system. The parameter tuning of PSSs in the power system has two major methods, sequential tuning and simultaneous tuning [8]. In order to obtain the set of optimal PSS parameters under various operating conditions, the tuning and testing of PSS parameters must be repeated under various system operating conditions. Therefore, if the sequential tuning method is applied to tuning PSS parameters, the parameters tuning will become more complicated, and the tuned result maybe not a locally or globally optimal solution. On the other hand, in the case that the simultaneous tuning method is employed in tuning of PSS parameters, which can simultaneously relocate and coordinate the eigenvalues of various oscillation modes under different operating conditions, the set of PSS parameters solutions can quite close to the globally optimal solution. However, the drawback of the simultaneous tuning method is the longer computation time required for large power systems. The simultaneous tuning of PSS parameters is usually formulated as a very large scale nonlinear non-differentiable optimization problem. This kind of optimization problem is very hard, if not impossible, to solve using traditionally differentiable optimization algorithms. Instead, we propose a stochastic optimization approach.

Abdel-Magid and Abido [8,10–13] have employed the tabu search (TS), simulated annealing (SA), particle swarm optimization (PSO), evolutionary programming (EP), and genetic algorithm (GA) to optimize the parameters of the PSSs in the New England ten-machine system. In the system, all PSSs are simultaneously designed to take into account mutual interactions. The objective function is devised to optimize the desired damping factor (σ) and/or the desired damping ratio (ξ) of the lightly damped and undamped modes. In this way, only the unstable or lightly damped oscillation modes are relocated. Hongesombut et al. [9] used hierarchical and parallel micro genetic algorithms in a multi-machine system. Do Bomfim et al. [14] used genetic algorithms to simultaneously tune

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Nomenclature

General

σ	damping factor
$\Delta\omega$	speed deviation
T_1, T_2, T_3, T_4	lead/lag time constants of PSS
n	amount
ϖ	weight constant
X	real variables
ϑ_i, χ	random number
τ_i	pheromone information
object	objective function value
η_i	heuristic information
α	influence factor of pheromone information
$\tilde{I}_{jk}$	difference vector between individual j and k for integer variables
κ	scaling factor
$\breve{I}_{ih}^{G+1}$	h^{th} gene of i^{th} trial individual vector of $(G+1)^{th}$ generation
ε_1	desired tolerance for the population diversity
$(\bar{I}_b^{G+1}, \bar{X}_b^{G+1})$	best individual
ξ	damping ratio
δ	rotor angle
K_S	gain of the PSS
σ_0	expected damping factor
ζ_0	expected damping ratio
I	integer variables
N_P	number of individuals
PH	proportion constant of pheromone
ρ	constant coefficient
p_i	probability of choosing a mutation operator
β	influence factor of heuristic information
$\hat{I}_i^{G+1}$	perturbed individual vector of i^{th} individual for integer variables
C_r	crossover factor
arg min	the argument of the minimum
ε_2	desired tolerance for the gene diversity
$\bar{\alpha}$	step size

Subscripts

Z=1,2,...,n_Z	index of local machines
RZ=0,1,...,n_Z	index of remote machines
q=1,2,...n_q	index of eigenvalues in the system
present	present generation
h = 1,...,n	index of integer variable
N	N^{th} PSS
y=1,2,...,n_y	index of system operating conditions
i=1,2,...,N_P	index of individuals
j	index of the genes
g = (n + 1),...,m	index of real variable

Superscripts

0	initial value
G	index of the generation
best	best value

multiple power system damping controllers with the objective function of the sum of the spectrum damping ratios for all operating conditions. These studies did not consider the remote feedback signals, which are available from synchronized phasor measurement units [15–17]. Kamwa et al. [18,19] used a decentralized/hierarchical control system with two global signals and one local signal as input of PSSs. The global signals obtained the highest controllability of these oscillation modes. Hasanović and Feliachi [20] used a genetic algorithm to accomplish simultaneous tuning of multiple power system damping controllers. Both local and remote measurement signals have been considered as input signals to the damping controllers. However, the remote measurements are considered only in a 4-machine system, and that remote signal is not determined from the computational results. Su and Lee [21,22] used improved mixed-integer hybrid differential evolution to solving network reconfiguration and capacitor placement problems of a distribution system, but those problems only contain integer decision variables.

Chiou et al. [23] developed the ant direction hybrid differential evolution (ADHDE) method, which utilizes the concept of an ant colony search to find a suitable mutation strategy in the HDE method [24,25] to accelerate the search for the global solution. The ADHDE has proved that it can obtain excellent computation results to the optimization problems of integer variables in the capacitor placement problem [23], but it has not been investigated in terms optimization problems consisting of both integer and real variables. In order to rapidly find a global solution by ADHDE, the accelerated phase is added in this algorithm. In this study, the machine numbers of remote feedback signals are regarded as the integer variable. Therefore, the proposed optimization algorithm must have the ability to search out the set of optimal solutions of integer and real variables at the same time. The optimization problems of both real and integer variables are generally called mixed-integer nonlinear programming problems. The original ADHDE algorithm gives it the ability to search out a set optimal solution of integer and real variables at the same time, so the algorithm is called the mixed-integer ant direction hybrid differential evolution algorithm (MIADHDE). The MIADHDE algorithm in this study is proposed to determine the optimal gain, time constants, and machine numbers of remote feedback signals of PSSs for the multi-machine system by three different objective functions. The three objective functions will be compared in terms of performance by the degree of system damped.

2. Problem formulation

2.1. Power system model

In this study, each generator is modeled as a two-axis model, which is a six-order model. The state vector of the generator is given as $[\Delta\omega, \delta, \phi_{fd}, \phi_{1d}, \phi_{1q}, \phi_{2q}]$, where $\Delta\omega$ and δ are the speed deviation and rotor angle, respectively, and $\phi_{fd}, \phi_{1d}, \phi_{1q}$ and ϕ_{2q} are the contribution to the rotor flux linkage as a result of field winding, one d-axis and two q-axis amortisseur circuits, respectively [26]. These device models of a power system include generators, PSSs, and excitation systems, and can be formulated by:

$$\dot{x} = f(x, r, t) \tag{1}$$

where x is the vector of all state variables, and r is the vector of input variables. In the PSS design, the power system is usually linearized in terms of a perturbed value in order to perform the small signal analysis. Therefore, Eq. (1) can be represented as:

$$\begin{cases} \Delta\dot{x} = A\Delta x + B\Delta v \\ \Delta u = C\Delta x + D\Delta v \end{cases} \tag{2}$$

where A is the power system state matrix, B is the input matrix, C is the output matrix, D is the feedforward matrix, v is the vector of the