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Grey Predictor reference model for assisting particle swarm optimization for wind turbine control

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ABSTRACT

This paper proposes an approach of forming the average performance by Grey Modeling, and use an average performance as reference model for performing evolutionary computation with error type control performance index. The idea of the approach is to construct the reference model based on the performance of unknown systems when users apply evolutionary computation to fine-tune the control systems with error type performance index. We apply this approach to particle swarm optimization for searching the optimal gains of baseline PI controller of wind turbines operating at the certain set point in Region 3. In the numerical simulation part, the corresponding results demonstrate the effectiveness of Grey Modeling.

1. Introduction

The applications of intelligent optimization have been proposed and shown the strengths in literature [1–14,17]. Unlike the gradient-based optimization methods, these random optimization methods less likely get trapped at the local optimum. Compared with other optimization algorithms, Particle Swarm Optimization (PSO) is better suited for some applications. First, PSO consists of a simpler concept and elegant paradigm, which means PSO is more computationally efficient. Moreover, PSO has memory and knowledge of optimum which is kept by all particles. Thanks to the advantages of PSO, we choose PSO assisted by Grey Predictor to solve the optimization problems of control systems design. The applications of the combination of PSO and Grey Predictor can also be seen [6,7].

In general, Integral of Square Error (ISE), Integral of Absolute Error (IAE), Integral of Time Weighted Absolute Error (ITAE) and Integral of Time Weighted Square Error (ITSE) are commonly used performance indexes to evaluate the performance of control systems [8–10]. However, following these error-integral type performance indexes, the performance of control systems suffer long sustained oscillation. To overcome these drawbacks, different performance indexes are proposed. In 1958 M. A. Aizerman introduced a new type of performance index, the general performance index [16], with differential equations to define the desired system models:

$$I = \int_0^{\infty} \left\{ e(t)^2 + \tau_1^2 \left(\frac{de(t)}{dt}\right)^2 + \cdots + \tau_n^{2n} \left(\frac{d^n e(t)}{dt^n}\right)^2 \right\} dt \tag{1}$$

Z. V. Rekasius utilized the general performance index for analytical design of control systems in 1961 [16]. Nevertheless, it is a tough task to derive the ideal model of the performance index of the type of (1) for higher-order models, complex systems and systems with stochastic elements. There are also limitations imposed on the ideal model and the performance index also burdens some restrictions on deriving ideal model.

Due to the disadvantages of the general performance index, Z. V. Rekasius presented another way to form the performance index as [16]:

$$I = \int_0^{\infty} \left\{ x(t) + \sum_{i=1}^{k} \tau_i \left[\frac{d^i x(t)}{dt^i}\right] \right\}^2 dt, \quad k < n \tag{2}$$

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In order to minimize the performance index above, the optimum system would be consequently derived as:

$$x(t) + \sum_{i=1}^{k} \tau_i \left[\frac{d^i x(t)}{dt^i}\right] = 0, \quad k < n \tag{3}$$

As a result, the transfer function of the closed-loop system (Fig. 1 bellow) can represent the ideal model as:

$$C(s)/R(s) = 1 \Bigg/ \left[1 + \sum_{i=1}^{k} \tau_i s^i\right] \tag{4}$$

Even though this type of performance index makes it possible to obtain ideal dynamic system model, there is no rule for determining how many terms should be used and what values the variable τ_i is.

Another type of performance index which shares the same concept with Linear Quadratic Regulator (LQR) is described as [11]:

$$I = \int_0^{\infty} \left[(y(t) - z(t))^2 + \alpha u(t)^2\right] dt \tag{5}$$

where y(t) is the real output, z(t) is the desired output, and u(t) is the input. Since this type of performance index comprises a desired function z(t) and undetermined variable α, control engineers need to construct the desired function and determine the optimal α before going through the optimization process. See for instance Refs. [10–15]. Some researchers presented another approach [19] in order to take the overshoot, settling time and robustness simultaneously into account.

In this paper, a Grey Modeling approach is presented for predicting the performance based on the behavior of the optimized system by PSO with error-integral type performance indexes. Following the predicted performance, the control system is then optimized by PSO again. We apply this methodology to control design of wind turbine, as an example. The paper is organized as follows. Section 2 describes the Particle Swarm Optimization (PSO), Section 3 introduces Grey Predictor (GP), Section 4 summarizes dynamic model, control structure and the simulation environment, and finally Section 5 describes the control example and numeric simulation indicating significant improvement in the turbine control.

2. Particle swarm optimization

Particle Swarm Optimization, PSO, is a stochastic optimization method originated from the description of the social behaviors of bird flocking or fish schooling. It was first proposed by Kennedy, Eberhart and Shi in 1995 [4,5]. Unlike conventional optimization approaches, PSO relies on the trajectories of a group of potential solutions known as "particles" in search of the optimum. PSO uses velocity vector of each particle to update the position of each particle in the swarm [1].

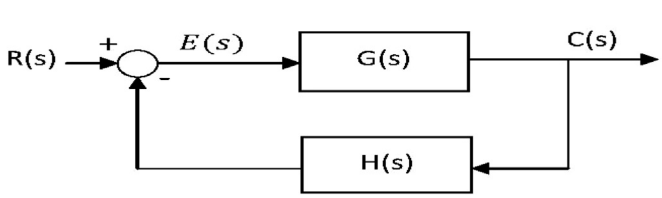

Fig. 1. Block diagram of general feedback system.

The PSO algorithm is described by the following steps:

1. Start with an initial set of particles, usually randomly distributed throughout the design space.
2. Determine the velocity v of each particle based on the following equation:

$$v^i_{k+1} = K[wv^i_k + c_1 r_1 (p^i - x^i_k) + c_2 r_2 (p^g_k - x^i_k)] \tag{6}$$

where K is the constriction parameter, x is the position, w is called inertial weight, p^i is current local optimum of particle i and $p^g{}_k$ is current global optimum in the swarm at iteration k. The coefficients c_1 and c_2 are called cognitive and social parameters, respectively, and r_1 and r_2 are uniform random numbers between 0 and 1.

3. Update the position x of particle i by the following equation:

$$x^i_{k+1} = x^i_k + v^i_{k+1} \tag{7}$$

4. Go back to step 2 and repeat until some convergence criteria is met or total iterations are completed.

To improve the performance of PSO, Eberhart and Shi suggested the inertia weight which linearly changes from 0.9 to 0.4 [2,3]. The inertia weight can be represented as:

$$w = w_{max} - k\ (w_{max} - w_{min})/k_{max} \tag{8}$$

where w_{max} and w_{min} denote the maximum and minimum of w, respectively, with k_{max} is the maximum number of iterations and k is the current iteration. The constriction parameter K can be represented as:

$$K = 2 \Big/ \left|2 - \varphi - \sqrt{(\varphi^2 - 4\varphi)}\right|, \quad \varphi = c_1 + c_2 > 4 \tag{9}$$

K is generally considered to be 0.729 with $c_1 = c_2 = 2.05$.

3. Grey Predictor

The first reference to "Grey" was initiated by Ju-Long Deng in 1982, in the research entitled "The Control Problem of Grey Systems" in the journal, Systems and Control Letters [30–36]. For simplicity, the "Black" is usually represented as lack of information and the "White" represented as known information. Hence, the information that is either incomplete or partly known is called "Grey". We can roughly conclude the incomplete information as four possible categories [18]:

1. The information on parameters is incomplete
2. The information on structure is incomplete
3. The information on boundary conditions is incomplete
4. The behavior information of movement is incomplete

In general, the Grey Modeling is performed through building GM(β,γ) model known as Grey Model, where β is the order of the differential equation and γ is the number of variables. Grey theory has been successfully applied for solving control problems [19,20] and in wind energy industry [21–24].

Grey Prediction process is described in Fig. 2, as:

1. Accumulated Generation Operation (AGO)

This step is to map the original set of data $x^{(0)}$ into a new set $x^{(1)}$ with less noise and randomness than original data set; therefore,