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Swarm Size and Inertia Weight Selection of Particle Swarm Optimizer in System Identification

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***Abstract*—The performance of Particle Swarm Optimizer (PSO) is not only related with the inertia weight, but also with the swarm size. In a typical second-order discrete transfer function case, an analysis about swarm size and inertia weight selection on PSO optimizing performance in system identification is given. Through simulations of different sets of the two parameters, this paper gives a selection of the two parameters witch make PSO a better performance on convergence rate and identification accuracy in system identification.**

***Keywords*—PSO ; swarm size ; inertia weight ; system identification**

I. INTRODUCTION

Particle Swarm Optimization (PSO) algorithm is an evolutionary computation technique developed by Dr. Eberhart and Dr. Kennedy [1] in 1995, inspired by social behavior of bird flocking. Compared with conventional identification methods, PSO method has many advantages such as simple computation, rapid convergence capability and without any requirement for the input and output data, and has been extended to many fields such as portfolio optimization and system identification.

In PSO, different parameters have different impact on performance, such as swarm size and inertial weight. Wang Weibo and Lin Chuan [2] proposed that for standard test functions swarm size should be between 20 and 50. Carlisle. A and Dozier. G [3] recommended setting swarm size to 30. Zhang Long and Wang Huakui [4] proposed that the range [0.4, 0.9] is a good area to choose w from. But, there is no analysis about both swarm size and inertial weight selection on PSO optimizing performance in system identification.

In this paper, through lots of simulations, we present a set of the two parameters, with which PSO method has a better performance in system identification.

II. PSO ALGORITHM AND ITS APPLICATION IN SYSTEM IDENTIFICATION

A. PSO Algorithm

In a particle swarm optimizer, instead of using genetic operators, these individuals are "evolved" by cooperation and competition among the individuals themselves through generations. Each particle adjusts its flying according to its own flying experience and its companions' flying experience. Each individual is named as a "particle" which, in fact, represents a potential solution to a problem.

Within a D-dimension search place, there are a total of N particles. The i-th particle is represented as X_i=(x_{i1},x_{i2},......,x_{iD}). The best previous position (the position giving the best fitness value) of any particle is recorded and represented as P_i=(p_{i1},p_{i2},......,p_{iD}). The index of the best particle among all the particles in the population is represented by the symbol P_g=(p_{g1},p_{g2},......,p_{gD}).The rate of the position change for particle i is represented as V_i=(v_{i1},v_{i2},......,v_{iD}). For each iteration, each particle according to the following equation updates itself:

$$v_{id}(k+1) = \mathrm{w}v_{id}(\mathrm{k})+c_1r_1(p_i - x_{id}(\mathrm{k})) + c_2r_2(p_g - x_{id}(\mathrm{k})) \quad (1)$$

$$x_{id}(\mathrm{k}+1) = x_{id}(\mathrm{k}) + v_{id}(\mathrm{k}+1) \quad (2)$$

where c_1 and c_2 are two positive constants, r_1 and r_2 are random numbers between [0, 1], w is inertia weight which used to control the influence of previous velocity on the current velocity.

B. PSO in System Identification

PSO applies to the system identification, a typical second-order discrete system transfer function as an example:

$$\mathrm{G(z)} = \frac{c+dz^{-1}}{1+az^{-1}+bz^{-2}} \quad (3)$$

The closer identification system output y(t) and actual system output y_0 (t) is, the better identification is. The performance of each particle is measured according to the fitness function [5] below:

$$\mathrm{f} = \sqrt{\textstyle\sum_1^n [y(t) - y_o(t)]^2 /\mathrm{n}} \quad (4)$$

where n is identification data length. Corresponding to the position X_i of particle, the transfer function is:

$$\mathrm{G(z)} = \frac{x_{i3}+x_{i4}z^{-1}}{1+x_{i1}z^{-1}+x_{i2}z^{-2}} \quad (5)$$

The step response of equation (5) is just y(t) in equation (4). Then, the value of equation (4) is just the performance of each particle, the smaller the better. All of the particles keep updating themselves according to equation (1) and (2) until satisfy the stop condition.

The algorithm in system identification is depicted as follows:

Step1: Initialized parameters in PSO algorithm, including initial search position X_i, particle velocity V_i, inertial weight w, swarm size N, c_1 and c_2.

Step2: Based on position X_i calculate fitness value of each particle according to equation (4) and (5). If current fitness value is smaller than the previous, let the current replace the previous as P_i.

Step3: Calculation fitness value of each particle according to position P_1,P_2,······,P_N, let position of the particle which has the smallest fitness value be as P_g.

Step4: Update the velocity of each particle and the coordinate position according to equation (1) and (2).

Step5: Judge whether the iteration number satisfy the set value or meet the stop condition: the absolute value of the difference between fitness of current P_g and previous P_g is less than 10^{-6}, and fitness value of current P_g is less than 5×10^{-4}. If it is meet, stop iterating, otherwise go to the step 2.

C. Selection of swarm size and inertia weight

Currently, the study of PSO algorithm focused on two aspects, one is to improve the algorithm itself, the other is the impact of parameter settings on algorithm optimization performance. There are three parameters, inertial weight w, swarm size N and constants c_1、c_2, which affect performance of PSO algorithm. Normally c_1 and c_2 [6] are taken as 2. This article will do some research on setting of swarm size and inertia weight.

The inertia weight w is a very important parameter in PSO algorithm and could be used to control algorithm global search ability and local search ability. Y. Shi and R.C. Everhart [7] proposed that the range [0, 1.4] is a good area to choose w from. The larger inertia weight is helpful to enhance the global search ability of algorithm. And the smaller inertia weight is helpful to improve the local search ability. This paper chooses w from the range [0.5, 0.8] in steps of 0.1.

Zhang Wenfen [8] proposed that choice of swarm size N is influenced by the number of unknowns. When there is a larger number of unknows, increasing swarm size can significantly improve the performance of PSO. But when swarm size increases to a certain extent, the increase of algorithm performance that swarm size brings has been not very evident. Wang Weibo [2] proposed swarm size should be between 20 and 50.Carlisle. A and Dozier. G [3] recommended setting swarm size to 30. This paper selects N as 20, 30, 40, 60.

III. SIMULATION

We choose discrete transfer function below as identification object.

$$G(z) = \frac{1+0.5z^{-1}}{1-1.5z^{-1}+0.7z^{-2}} \tag{6}$$

The step response of equation (6) is just $y_0(t)$ in equation (4). The maximum number of iterations [9] is set to 2000.

According select of inertia weight w and population size N, there are a total of 16 kinds of combinations of parameters for simulation. For each combination, calculate 20 times with PSO algorithm, then , count average number of convergence reflecting algorithm speed and average fitness reflecting algorithm accuracy. Statistical result is shown in Fig.1 to 2.

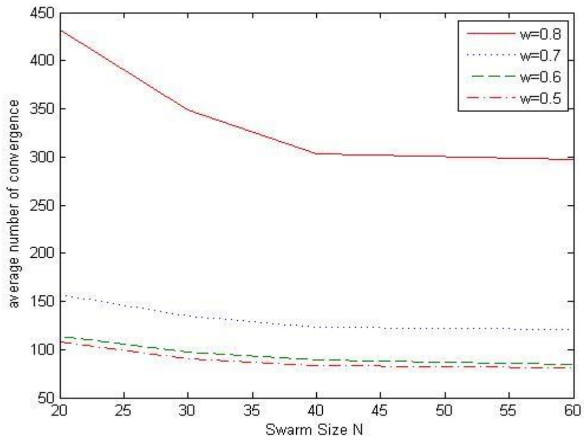

Fig. 1. Average number of convergence

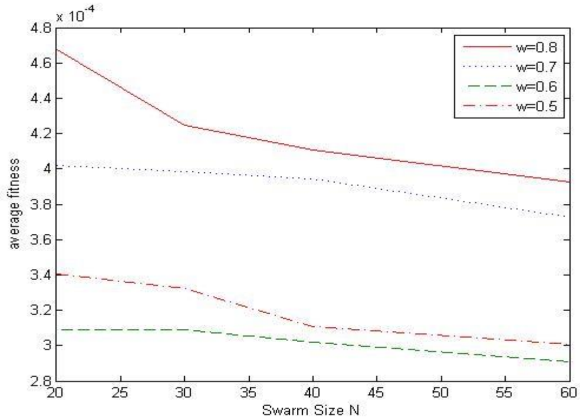

Fig. 2. Average fitness

As shown in Fig.1 to 2, it can be found as follows:

1) When choosing w from the range [0.5, 0.8], both average number of convergence and average fitness reduce with the increase in swarm size N. From N=20 to N=30, average number of convergence has a very significant change; from N=30 to N=40, average number of convergence has a certain degree of change; from N=40 to N=60, it has been very close to each other on average number of convergence.

2) When w is a fixed value, from N=20 to N=60, average fitness showed a small amount of a decreasing trend.

3) When N is a fixed value, from w=0.8 to w=0.7, average number of convergence has a very significant change; from w=0.7 to w=0.6, average number of convergence has a certain degree of change; from w=0.6 to w=0.5, it has been very close to each other on average number of convergence.

4) When N is a fixed value and w=0.6, average fitness reaches a minimum.

Under conditions of N=40 and w=0.6, the identification result of equation (6) is as follows,

$$G(z) = \frac{0.8262+0.6738z^{-1}}{1-1.4999z^{-1}+0.6999z^{-2}} \quad (7)$$

Identification curve is shown in Fig.3.

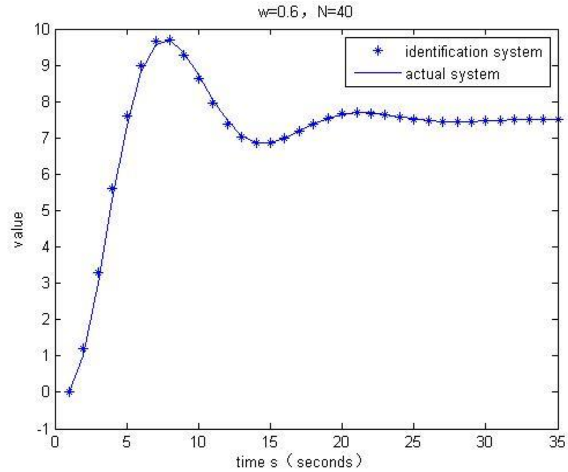

Fig. 3. w=0.6,N=40,Identification curve

It can be found that the identification result meets industry requirements.

IV. Conclusions

PSO can be successfully applied to the system identification of the discrete transfer function. The affect of Inertia weight w and swarm size N selection on system identification is as follows:

1) Swarm size N selection has a great impact on the performance of PSO. When N<40, as N increases, the performance of PSO in system identification improves significantly; When N>40, as N increases, the performance has almost no improvement. N=40 is a good choice.

2) When N is a fixed value, as inertial weight w decreases from 0.8, the performance of PSO in system identification improves; when w reduces to the range of [0.5, 0.6], the performance has almost no improvement. w=0.6 is a good choice.

Through the above analysis, it can be concluded that in system identification, under conditions of N=40 and w=0.6, PSO has a better performance of both speed and accuracy.

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