Journal of Information Technology and Engineering
Vol. 3 No. 1 (June, 2018)

Parameters Optimization for Control System Model based on Genetic Algorithm

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Received: 23rd March 2017 Revised: 14th April 2017 Accepted: 10th September 2017

Abstract: *The parameters optimization for a control system model is very important, especially for a large amount of parameters. In accordance with genetic algorithms, an approach concerning parameter optimization for control systems is quite practical and feasible. Moreover, it has been indicated that results of parameters optimization for the control system are perfect in terms of numerous analysis. A survey on the development of the optimization of model for parameters identification is given in this paper. The performance function is built based on the maximization of energy. The problem could be converted into a nonlinear optimization problem with constraints. Because of its unique characteristics, genetic algorithms might be applied to this problem in order to obtain a global-optimal solution. The above-mentioned approach could be verified by the practical system as mentioned in this paper. Therefore, it is possible that the optimum performance could be achieved successfully with the aid of genetic algorithms without numerous calculations. The genetic algorithm has fast convergence for optimization while the simulated annealing algorithm is good at achieving the overall optimization. This paper combines the two algorithms' advantages to form a new one called the improved genetic algorithm.*

Key words: *Identification, Optimization, Genetic Algorithms, Annealing Algorithms.*

1. INTRODUCTION

The genetic algorithm, which is different from the traditional search algorithms [1-3], is a kind of bionic algorithms. First, a group of initial population is produced at random during the searching process. In the group, each individual that is called a chromosome is one answer to the problem. And then these chromosomes begin to evolve gradually in terms of the following iteration, which is called a genetic way. As to whether each generation is good or not, it might be mainly determined by its fitness. The chromosomes of the offspring, which are produced in the next generation, would be formed by the crossover and mutation calculation in the previous generation. In the new generation, the offspring that are kept or eliminated are basically determined according to the values of the fitness. Besides, the size of population might be considered as a constant. The more the fitness of the individual is high, the more the probability of being retained is most probably high. Because of the convergence of genetic algorithms, the best chromosome after some generations, which is viewed as the best answer, could be eventually obtained.

2. THE SIMPLE GENETIC ALGORITHM

The technology of optimization, a practical method based on mathematics, might be used to acquire the optimal solution for engineering problems. The area in relation to the optimization methods is considerably widespread. Principally, there are two basic categories: the functional optimization problem and the building-up optimization problem. As to the functional optimization problem, there are some basic genetic operations [4].

The main procedure for optimization by genetic algorithms [5] is as follows:

(1) Determine the decision variable and its restricted conditions, that is to say, determine the phenotype of individual and the solution space of the problem.
(2) Build up the optimization model, that is, determine the type of the object function and its form of mathematical description or the method of quantification.
(3) Determine the encoding method of chromosome to express the applicable solution, namely, determine the gene type of individual and the searching space of the genetic algorithm.
(4) Determine the method to decode, to put it another way, determine the corresponding relation or switching method for the change from the gene-type of individual to the phenotype of individual.
(5) Determine the quantification evaluating method of the fitness of individual. In other words, determine the switching principle for the change from the value of object function to the fitness of individual.
(6) Design the genetic operators, that is, determine the specific operating methods of the genetic operators,

such as the selection, the crossover and the mutation operations.

(7) Determine the relevant running parameters of genetic algorithm, say, determine some parameters in the genetic algorithm such as the dimension of population, the termination conditions, the crossover rate and the mutation rate.

3. THE RESEARCH FOR PARAMETERS OPTIMIZATION

Under the action of the exciting force "f", the differential equation of motion without damping system for the model structure may be expressed as follows:

$$M\ddot{x} + Kx = f \tag{1}$$

where x is the displacement vector of the system in the physical space, and M, K are respectively the mass and the stiffness matrix of the system. Then the displacement vector is given by

$$x = \phi q \tag{2}$$

where q is the displacement vector of the system in the mode, ϕ is the matrix of predominant type. Using this equation, Eq. (1) may be written as

$$M\phi\ddot{q} + K\phi q = f \tag{3}$$

Hence, the system equation becomes

$$\ddot{q}_i + 2\varsigma_i w_i \dot{q}_i + w_i^2 q_i = \phi_i^T f \tag{4}$$

And the model of structure in the space form of state could be given by

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx \end{aligned} \tag{5}$$

in which

$$A = \begin{pmatrix} 0 & 1 \\ -M^{-1}K & -M^{-1}C \end{pmatrix}$$

and

$$B = \begin{bmatrix} 0 \\ B(x_a) \end{bmatrix}, \ C = [C(x_s), 0]$$

where $B(x_a)$, $C(x_s)$ are respectively the functional matrices which take the position as the variables. The object function is considered as the sum of signals which are obtained by the piezoelectricity sensors and the value of function is the maximum at the probable placement points. Thus the object function may be given as

$$J = \sum_{i=1}^{n} abs(q_i - q_{i+3}) \tag{6}$$

And the restricted condition is: $x_a \in X_a$, $x_s \in X_s$.

The optimal placement is found out according to genetic algorithms. The related data is cited as follows: The dimension of population: M=100, the highest heredity generation: T=200, the crossover rate p_c: 0.3, 0.4, 0.5, 0.6, 0.7, and the mutation rate p_m: 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05. Fig. 1 displays the influence of the mutation rates over the optimal result under the different crossover rates.

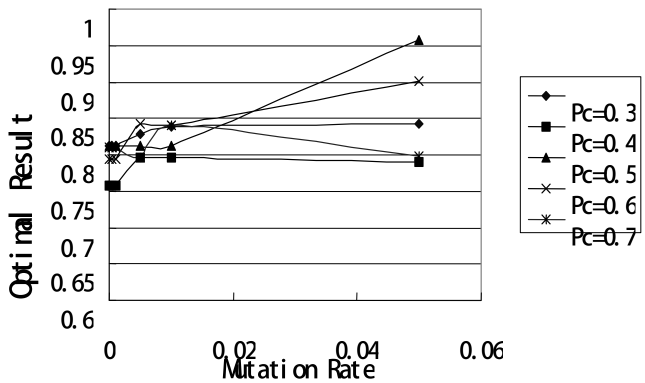

Figure 1: Optimal Results Versus Mutation Rates

Likewise, Fig. 2 shows the influence of the mutation rates on the heredity generation of optimization under the different crossover rates. It seems quite clear that the heredity generation exerts a great influence on the calculation efficiency of genetic algorithm). That is to say, if the heredity generation T is too high, the convergent process of the optimal solution may be time-consuming. It would make it quite impractical to acquire the stably optimal solution rapidly and effectively in a limited time.

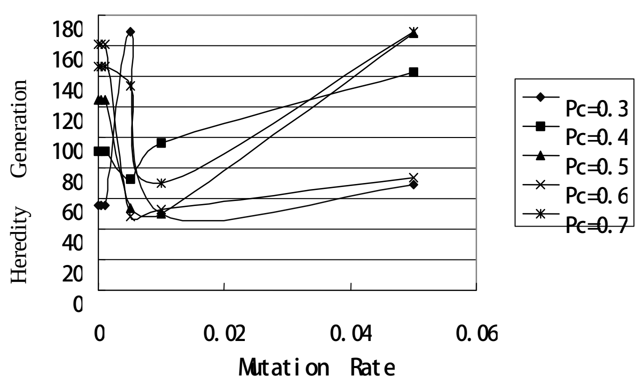

Figure 2: Optimal Efficiencies Versus Mutation Tates

From the results in Fig. 1 and Fig. 2, it is clear that in the different crossover rates, it is higher mutation rate that might be responsible for the better solution. However, at the same time the number of heredity generation for searching the optimal solution may be also larger than before. It may be deduced that the increase in mutation rates which could bring more new individuals, is of great benefit to finally obtain the better optimal solution. Nevertheless, exorbitantly high mutation rate would possibly affect the stability of population, or even result in failure to acquire the fine optimal solution. This phenomenon is also visible in the calculation results.

Similarly, the variety of the crossover rates could have much impact on the optimal solution and the optimal efficiency. The increase of the crossover rate could be very helpful to get the better new individuals effectively; nonetheless, it would also have considerable negative influence on the excellent individuals in the encoding cluster. Therefore, the optimal solution would be obtained effectively only when the crossover rate and the mutation rate are both selected properly.

According to the calculation results, it may be found that when the crossover rate p_c equals to 0.5 and the mutation rate p_m equals to 0.05, the algorithm finally achieves the optimal solution in the 168*th* generation. Under these conditions, the optimal position of actuators is $x_a = 187$, and the optimal positions of sensors are respectively

$$x_{s_1} = 166, x_{s_2} = 180, x_{s_3} = 184, x_{s_4} = 187, x_{s_5} = 208 .$$

Obviously, the genetic algorithm has much higher calculation efficiency than the common algorithms. Fig. 3 shows the relation between the whole population average value in the optimization function and the evolutionary generation. And then Fig. 4 indicated the relation between the optimal value of the function for individuals and the evolutionary generation.

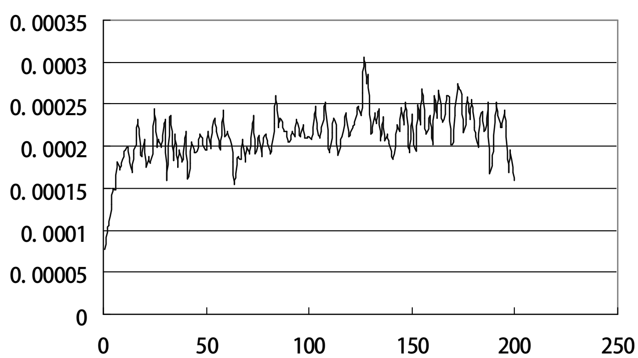

Figure 3: Average Value Versus Evolutionary.

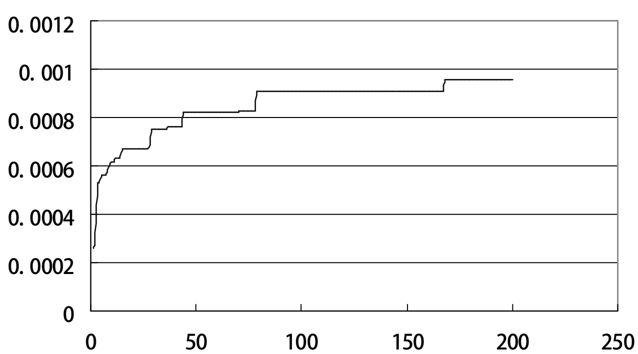

Figure 4: Optimal Value Versus Evolutionary

Based on Fig. 3 and Fig. 4, it could be assumed that the algorithm can rapidly and effectively ascertain the optimal placement of actuators and sensors. Though the values of the object functions in the original generations are unstable, the parameters would be gradually stable around the optimal position with the development of the heredity generation.

It may be obvious that one parameter is rather necessary to assure the sensors be in a proper distance, in order to avoid placing the sensors repeatedly because the distance between two points is too small. So one restricted condition for the optimal placement could be determined: If $(x_i - x_j) < n$, then the fitness value = 0, in which i and j are expressed as the positions of the different sensors respectively. n is denoted as the dimension of the assigned distance. The "fitness value" is the value of the fitness function. It could be explained as following: If the sensors are too close between each other, the corresponding value of the fitness function is assumed to be zero at once. Because of the local placement of sensors, therefore, it seems very possible to avoid placing the unnecessary sensors or causing the loss of the possible information for structure damage.

4. RESULTS COMPARISON

The genetic algorithm, a kind of optimization algorithm in common, has fairly simple coding and encoding technology and genetic operation, moreover, optimization is free from any restriction. Running side by side and searching solution in the global space are the two most remarkable characteristics). And in contrast with GA, the most remarkable advantage of the algorithm is looking for globally optimal solution in the overall situation of goal function at random combined the probabilistic jumping property of simulated annealing with constant decline of temperature parameter. That is to say, locally optimal solution can probably jump out, and then tend towards the overall situation optimum finally. But for the optimal solution, algorithm would perhaps expect a higher initial temperature, slower drop in the temperature speed, lower temperature of completion and many enough samples at the every temperature. As a result, it always needs a longer optimizing process, which is the main shortcoming of SA algorithm [6].

On the basis of its procedure already been compiled, one could make certain comparison between them. At first the contrasting picture lines are illustrated in Fig. 5 and Fig. 6.

From the graphs, for SA algorithm, the value of goal function has remarkable disparity extremely in the first about 80 generations. It even indicates that initial stage not only accepts solution with high-quality but also comparatively inferior quality solution with certain probability in the optimization process. This contributes to jumping out and entirely reaching the global optimization in the process of iterating. On the contrary, the optimization results of the genetic algorithm are comparatively mild, and have very fast convergence from about 50 generations, indicating that it is vastly superior in speed of optimization.

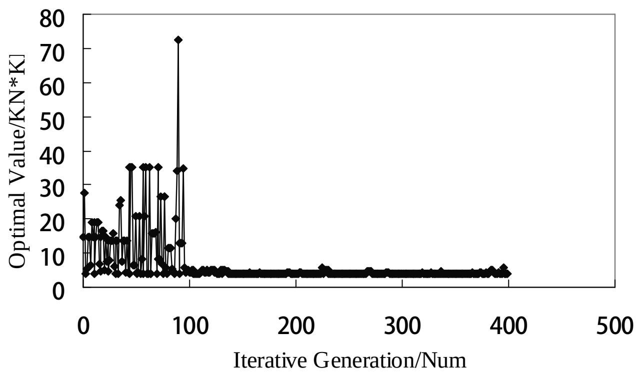

Figure 5: The iterative time and optimal result of annealing algorithm.

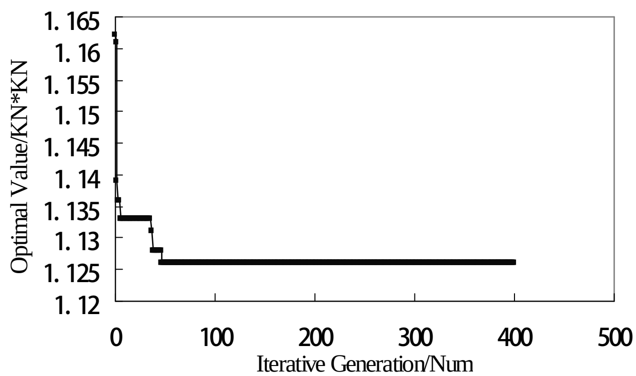

Figure 6: The iterative time and optimal result of genetic algorithm.

As to the problem of identification for parameters of MR damper, the GASA algorithm could be used for optimization. It mainly applies the Boltzmann tactics in the simulated annealing algorithm to control the crossover and mutation operations of genetic algorithm. The competition between the chromosome in father generation and son generation is involved. In addition, the convergence of optimal result could also jump out of the local optimization to the overall optimization by using the simulated annealing characteristics.

4.1 The Algorithm Model

First, an object function still needs to be determined according to the general processes of genetic algorithm. Then in accordance with the actual situation, the restricting conditions are enumerated. Based on these, the variables are coded. And the selection, crossover, mutation and simulated annealing operations are taken in action. Lastly, the individuals would be decoded. And then one may evaluate the rationality of solutions. These operations could be done repeatedly until the optimal result could be eventually acquired.

The common purpose of both of algorithms is to assure that the error between the damping force calculated from the model and experimental force is the relatively minimum. The object function can be given by

$$f(x) = \sum (F_i - f_i)^2 = \sum (\delta_i)^2 \tag{7}$$

To evaluate the fitness of individuals, the fitness function is assumed as follows

$$Fit(f(x)) = \begin{cases} c_{\max} - f(x), & f(x) < c_{\max} \\ 0, & \text{others} \end{cases} \tag{8}$$

For the above-mentioned model and the determined coding form, the GASA algorithm can be used for calculation. The concrete processes are as follows.

The initial population is produced. The size of population is 50. In the solution space, N chromosomes are produced at random. The length of the binary coding bunch is $10 \times M$. M is the number of parameters to be identified in the problem. In this paper it is taken as 2.

To the chromosome of population, the following steps are executed repeatedly until the lapsed condition is satisfied.

The selection: The fitness $Fit(f(x_i), k)$ of every chromosome x_i in the population is checked, in which, k is the number of evolution generation. The initial generation is 0. Then the relative fitness is calculated by [7-8]:

$$p_i^k = \frac{Fit(f(x_i), k)}{\sum_{j=1}^{N} Fit(f(x_j), k)} \tag{9}$$

Its value is the probability in which every chromosome is inherited into the next generation. According to the probability, the number of times of the chromosome selected can be determined, and the new chromosomes are produced again.

The crossover: The individuals in the population x_i' mate each other at random. For every individuals group, one position behind a certain gene is selected at random as the crossover point. At this point some chromosomes of two individuals exchange and two new individuals could be produced. This step is done repeatedly until the new population x_i'' is produced. The crossover probability is taken as 0.7.

The mutation: In the population one individual is selected at random. One character value of this individual's chromosome is changed in a certain probability. In the paper, the binary coding is adopted. So this operation is changing the value 1 to 0 or changing 0 to 1. The mutation probability is usually low. It's taken as 0.06.

The simulated annealing operation: The initial temperature could be determined by the expression $T_0 = -(f_w - f_b)/\ln(p_r)$. In the equation, f_w and f_b are separately the object function values of the worst individual and the best one in population. The probability p_r is taken as 0.4. The following state producing function is given by

$$x_{i+1} = x_i + r \times S \times (U_{\max} - U_{\min}) \tag{10}$$

$$S = S_0 \times \exp(-\frac{t}{K}) \tag{11}$$

In which, r is the random number between 0 and 1. S_0 is the random perturbing parameter which is taken as 0.2. t is the iteration number at present. K is the maximum iteration number. Meanwhile, the condition $\min\{1, \exp(-\Delta / t_k)\} > random[0,1]$ is used to judge whether the new state could be accepted. Δ is the object difference between the new and old state. t_k is the temperature of the generation at present.

The annealing control is done. The annealing function $T_{k+1} = \lambda \times T_k$ is used for annealing. λ is taken as 0.95. If the evolution generation is up to the maximum iteration generation 200, the chromosome with the highest fitness is appointed as the result of the GASA algorithm. The algorithm ceases at the same time.

4.2 The Experimental Results

Based on the above control parameters and the iteration principle, the improved genetic algorithm with the simulated annealing characteristic is achieved. The model parameters of MR damper using in the experiment can be identified by base of these. Through the iteration calculation of the algorithm process, the optimal parameters c_0 and w could be eventually obtained). Their identified values are 0.015836 and 0.493646 respectively. The value of object function is 0.014209. According to these parameters, the relation curve between the displacement and damping force can be obtained). The relation curve between the iteration number of times and the optimization result can be shown in Fig. 7.

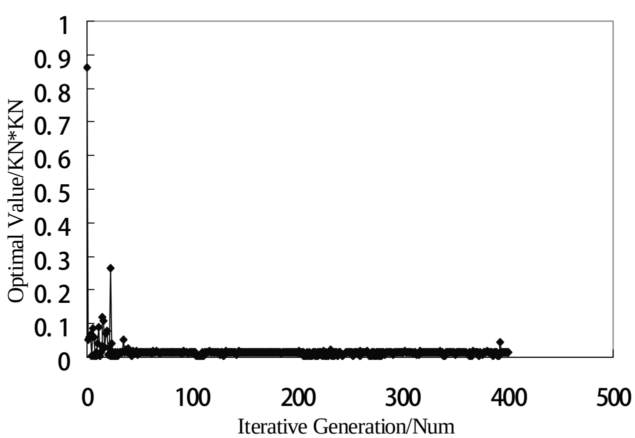

Figure 7: The iterative time and optimal result of the mixed algorithm.

To conclude, the calculation results based on the identified parameters have very tiny errors with the experiment, in contrast to the optimization results of genetic algorithm and simulated annealing algorithm). The iteration solution also arrives at the final convergence very quickly. This is a satisfying method for the identification problem in this paper. The GASA algorithm can assure the variety of the selected population and avoid the early convergence. Besides, it can accept some bad solutions in a certain probability at the initial iteration stage to obtain the overall optimization. Therefore, the improved genetic algorithm has the good ability for the identification of parameters.

5. CONCLUSIONS

As to the optimal parameters for control system model, the genetic algorithm is used to achieve the optimal parameters. The calculation results have proved the feasibility and superiority of the algorithm, and also provide the effective base for the work in future. All the parameters of genetic algorithm have some effects on the result and efficiency of the solution. But there isn't a theoretical basis on how to select the proper parameters. The range of values can be only determined through some initial calculations in the application.

The genetic algorithm contains the fine capacity for global searching. But there are also some imperfect aspects in the process of application, such as the bad capacity for local searching. Simulated annealing algorithm was integrated into the standard genetic algorithms to gain the better effects on the local optimization. Consequently, for the optimal parameters for control system, there will be a mixed optimization method which is much better.

ACKNOWLEDGMENTS

The work described in this paper was supported by National Natural Science Foundation of China, Grant No. 50578058.

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