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A Micro Genetic Algorithm with Cauchy Mutation for Mechanical Optimization Design Problems

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Abstract: This study develops a Micro Genetic Algorithm with Cauchy mutation(MGAC) for the mechanical optimization design problems. The mechanical optimization design problems are very important optimization problems in engineering, with the characteristics of multi-variables, complex objectives and non-linear constraints. In this algorithm, the MGAC firstly employed the blend crossover operator called BLX-α to increase the global searching ability of traditional Micro Genetic Algorithm; then, the MGAC selected the Cauchy mutation operator for keeping individual diversity and solving the premature convergence. In addition, the population pool was used to reduce the blindness of the individual regeneration in the re-initialization stage. The parameter optimization design of the planetary gears transmission showed the effectiveness of the MGAC algorithm.

Key words: Micro genetic algorithm, mechanical optimization design, blend crossover, cauchy mutation, planetary gears transmission

INTRODUCTION

The modern mechanical optimization design (Rao, 2009) is the key problem in researching new mechanical products, so the reasonable method of optimization design can lower the product cost and shorten the developing cycle (Corriveau *et al*., 2010). With the global market competition becoming more and more intense, enterprises focus on reducing the research and development period and improving design of products with more complicated structures. The product optimization designs become more and more complex integrated optimizations which are multi-disciplinary and multi-objective. There are some traditional optimization design methods, such as the Optimality Criteria Method (OCM) (Rao, 2009; Zavadskas *et al*., 2009) and the Mathematical Programming Method (MPM) (Lee and Wu, 2009; Saigo *et al*., 2009). For different types of optimization problems, the OCM chooses suitable optimization criterion for converging to the optimal solution or approximate optimal solution. That makes the OCM have common problems of poor universal application. The MPM is always along with too many times iterative computations and frequency transformation which has low computing efficiency. Traditional optimization design methods have these shortages which greatly limit their application and spread. Previous studies have proposed several meta-heuristics (genetic algorithm, evolutionary algorithm) which have been successfully applied to solve the mechanical optimization design problems. The meta-heuristics don't need the derivative information of the objective functions while the best optimization solution of overall situation can be achieved. Heuristic algorithm provides new ideas and methods for the optimization of complex mechanical design.

The Genetic Algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of Evolutionary Algorithms (EA) which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection and crossover. The GA algorithms have been used for the optimization problems with successful solutions (Ze-Su *et al*., 2007; He *et al*., 2010; Jiang *et al*., 2011; Mosavi, 2011; Qasem and Shamsuddin, 2010; Mohammadzadeh *et al*., 2008). Chiu (2010) solved the numerical assessment of path planning for an autonomous robot passing through multi-layer barrier systems using the Genetic Algorithm. Based on GA, Lai-Jun *et al*. (2009) proposed a new evolutionary algorithm based on Particle Swarm Optimization (PSO) to solve government-funded traffic problems. Al-Husainy (2007) used the genetic algorithm for compressing images with a well performance.

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The term Micro Genetic Algorithm (MGA) refers to a small-population genetic algorithm with re-initialization (Tiwari *et al*., 2008). The idea was suggested by some theoretical results obtained by Goldberg (1989), according to a population size of 3 which was sufficient to converge, regardless of the chromosomal length. MGA first generates a small randomly population and applies it to the genetic operators until reaching nominal convergence. Then it generates a new population by transferring the best individuals of the converged population to the new one. The remaining individuals would be randomly generated.

Krishnakumar (1990) firstly made an implementation of the MGA who used a population size of 5, a crossover rate of 1 and a mutation rate of zero. His approach also adopted an elitist strategy that copied the best string found in the current population to the next generation. Selection was performed by holding 4 competitions between strings that were adjacent in the population array and declaring to the individual with the highest fitness as the winner. Krishnakumar compared his MGA against a simple GA (with a population size of 50, a crossover rate of 0.6 and a mutation rate of 0.001). Krishnakumar (1990) reported faster and better results with his MGA on two stationary functions and a real-world engineering control problem (a wind-shear controller task). After him, several other researchers have developed applications of MGA. Tiwari *et al*. (2009) proposed an effective method of the hybrid Archive-based Micro Genetic Algorithm (AMGA) on the performance assessment of the CEC09 test problems.

In this study, a Micro Genetic Algorithm with Cauchy mutation (MGAC) was proposed to deal with the mechanical optimization design problems more effectively. In this algorithm, the MGAC firstly employed the blend crossover operator called BLX-α to increase the local searching ability of traditional Micro Genetic Algorithm; then, the MGAC selected the Cauchy mutation operator for keeping individual diversity and solving the premature convergence. In addition, the population pool was used to reduce the blindness of the individual regeneration in the re-initialization stage. Compared with state-of-the-art algorithms available in the literature, we showed the effectiveness of this approach empirically on the optimization problems of the parameter optimization design of the Planetary Gears Transmission.

MECHANICAL OPTIMIZATION DESIGN MODEL

With the global market competition becoming more and more intense, enterprises focus on reducing the R and D period and improving design of products with more complicated structures. The product optimization designs become more and more complex integrated optimizations which are multi-disciplinary and multi-objective.

Gears transmission is widely used in various mechanical equipments and gears are indispensable to the transmission mechanism (Marsha, 2009). The gear transmission development level has been considered as a symbol of its technological standards and integral power of the country. In recent years, new material technology and advanced manufacture technology have greatly promoted the development of gears transmission. This trend makes the parameter optimization design of the gear transmission become more and more important in the design process (Bingliang *et al*., 2008; Qin *et al*., 2008). We use the gear transmission model as the mechanical optimization design model and analysis the parameters and the structures. In this study, the 2K-H type straight tooth planetary gear (Zhen-Ping *et al*., 2009) is taken as an example for the sake of ease in research.

In a 2K-H planetary gear transmission mechanism (Lei *et al*., 2008), sun gear is as the input component and planet carrier is as the output component. The transmission ratio is $i_{aH} = 5.14$ and the relative error of i_{aH} is $\Delta i<1\%$. The input shaft torque is $T_a = 1800$N.m. Gear material is 40Cr and heat treatment method is cementation quenching. The allowable bending stress and the allowable contact stress for the gear are respective $[\sigma_F] = 158$ N/mm^2 and $[\sigma_H] = 790$ N/mm^2.

Optimization design objective for the planetary gear is the minimum of the planetary gears' volume. The main parameters are the sun gear volume and planetary gear volume, therefore the minimum volume of the sun gear and all the planets is as objective function:

$$V = V_s + CV_p = \frac{\pi}{4} m^2 b\left(z_s^2 + Cz_p^2\right) \tag{1}$$

where, V_s, V_p are respective the volume of the sun gear and the planetary gear; m is the gear mold number; b is the gear width; z_s, z_p are respective the teeth number of the sun gear and the planetary gear. C is the number of the planetary gears, C = 3.

According to the ratio formula of 2K-H planetary gear transmission, when the sun gear is as the input and the planet carrier is as the output, the transmission ratio is shown as Eq. 2.

$$i_{aH} = 1 + z_r/z_s \tag{2}$$

where, z_r is the teeth number of the ring gear.

Based on the concentric condition of planet tooth gear train, the following Eq. 3 is reasonable.

$$z_p = \frac{z_r - z_s}{2} \tag{3}$$

According to the Eq. 2 and 3, the objective function is converted to Eq. 4:

$$\min V = \frac{\pi}{4} m^2 b z_s^{\,2} \left[4 + 3(i_{aH} - 2)^2 \right] \tag{4}$$

In addition, there are three types of constraints in the model as follows:

Gear strength constraint: To the planetary gear design, the bending strength and the contact strength between the planet gear and the sun gear are usually considered as shown in Eq. 5 and 6.

$$\sigma_F = \frac{13^3 \cdot K_A \cdot T_a \cdot K_V \cdot Y_F}{m^2 \cdot b \cdot z_s \cdot C} \le [\sigma_F] \tag{5}$$

$$\sigma_H = \sqrt{\frac{800^3 \cdot K_A \cdot T_a \cdot K_V \cdot i_{aH}}{m^2 \cdot b \cdot z_s^{\,2} \cdot C \cdot (i_{aH} - 2)}} \le [\sigma_H] \tag{6}$$

where, K_A is the application factor, $K_A = 1.4$; K_V is the dynamic load factor, $K_V = 1.265$; T_a is the input shaft torque; Y_F is the factor for the tooth, $Y_F = 6$.

Adjacent conditions constraint: In the gear, the adjacent conditions constraint between the planetary gears must be Eq. 7:

$$\frac{z_s}{2}(i_{aH} - 2)\left(1 - \sin\frac{\pi}{C}\right) - z_s \sin\frac{\pi}{C} + 2 < 0 \tag{7}$$

Design variable constraint: The design variable constraints in the model as follows:

$$\begin{cases} 17 \le z_s \le 37 \\ 10 \le b \le 136 \\ 2 \le m \le 8 \end{cases} \tag{8}$$

To sum up, there are three design variables which are z_s, b and m. The 2K-H planetary gear transmission design model can be described as Eq. 9.

$$\begin{aligned} & \min V = \frac{\pi}{4} m^2 b z_s^{\,2} \left[4 + 3(5.14 - 2)^2 \right] \\ & \text{st} \begin{cases} 17 \le z_s \le 37 \\ 10 \le b \le 136 \\ 2 \le m \le 8 \\ \sqrt{\dfrac{800^3 \cdot 1.4 \cdot 1800 \cdot 1.265 \cdot 5.14}{3m^2 \cdot b \cdot z_s^{\,2} \cdot (5.15 - 2)}} \le 790 \\ \dfrac{13^3 \cdot 1.4 \cdot 1800 \cdot 1.265 \cdot 6}{3m^2 \cdot b \cdot z_s} \le 158 \end{cases} \end{aligned} \tag{9}$$

THE MGAC ALGORITHM

The main flowchart of the MGAC algorithm: In this study, we propose a Micro Genetic Algorithm with Cauchy mutation (MGAC) for solving the mechanical optimization design problems. Figure 1 shows the main flowchart of the MGAC algorithm. The iterative processes are follows:

Step 1: In the initial stage, the parameters and population are initialized. The MGAC generates the initial population randomly with 4 individuals and calculates the fitness function of each individual

Step 2: The tournament selection is employed to obtain 2 individuals randomly. After compared the fitness function of 2 individuals, an individual with a better fitness will be one parent. With the same approach, the other parent will be obtained by the two remaining individuals. Then the blend crossover operator (BLX-α) and the Cauchy mutation operator are used for guiding the generation of the offspring. New individuals are deposited in the population pool until the whole new population has replaced the old population

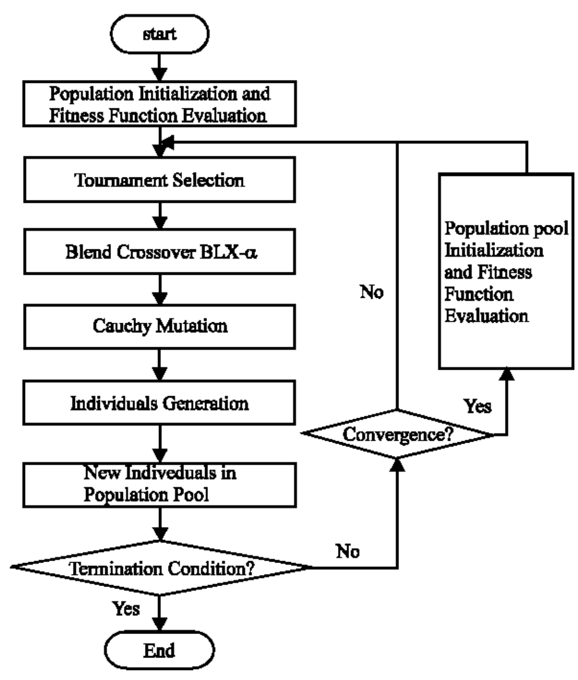

Fig. 1: Flowchart of the MGAC

Step 3: Stop when the stop criteria are met, output the best fitness in the current population as result of optimization. else go to Step 4

Step 4: Compare the measure of population diversity. If there is a variance of more than 5% between the best fitness individual and others, go to Step 2 directly. Otherwise, re-initialize population and calculate individual fitness, then go to Step 2

The blend crossover operator: This study employed the blend crossover operator for improving the search ability for global optimization. The blend crossover (BLX-α) was proposed by Eshelman and Schaffer (1993) which showed good search ability for separable fitness functions. In the BLX-α, offspring are generated as follows (Takahashi and Kita, 2001):

- Choose two parents x^1, x^2 randomly from the population
- A value of each element x^c_c of the offspring vector x^c is chosen randomly from the interval $[X^1_i, X^2_i]$ following the uniform distribution, where:

$$\begin{aligned} X_i^1 &= \min\left(x_i^1, x_i^2\right) - \alpha \cdot d_i \\ X_i^2 &= \max\left(x_i^1, x_i^2\right) + \alpha \cdot d_i \\ d_i &= \left|x_i^1 - x_i^2\right| \end{aligned} \tag{10}$$

In Eq. 10, x^1_i and x^2_i are the i-th elements of x^1 and x^2, respectively and α is a positive parameter.

For the value of α, this study use 0.5 and the blend crossover (BLX-α) can be described by BLX-0.5. The mechanism of BLX-0.5 is adaptive search. That means if the parents have obvious individual differences, the offspring have the possibility of the obvious individual differences. The BLX-0.5 operator is considerably disruptive crossover operators and could be combined with more biased selection schemes. They cause for saving the variety in the population and keep out of premature convergence.

The cauchy mutation operator: Different from the MGA, this paper used Cauchy mutation operator to avoid falling into local optimum.

The Cauchy density function is defined by:

$$f(x) = \frac{1}{\pi}\frac{t}{t^2 + x^2} \quad -\infty < x < \infty \tag{11}$$

In Eq. 11, t>0 is a scale parameter. The Cauchy distributed function is:

$$F_t(x) = \frac{1}{2} + \frac{1}{\pi}\arctan\left(\frac{x}{t}\right) \tag{12}$$

Cauchy mutation can generate random number in a longer range than Gaussian mutation, it is conducive to large-scale search. Application of Cauchy mutation operator can increase the diversity of individual populations to avoid falling into local optimum. So the Micro Genetic Algorithm with Cauchy mutation (MGAC) has a faster convergence speed than MGA.

THE EXPERIMENTS

To verify the applicability of the proposed MGAC algorithm, the MGAC was applied to the parameter optimization design of the Planetary Gears Transmission. For a fair machine-independent comparison, the number of iterations in MGAC was limited to 200. To make the experiments more objective and more comprehensive, the traditional MGA algorithm was used for the same model which employed the Arithmetic Crossover operator (Shopova and Vaklieva-Bancheva, 2006) (crossover probability is 0.7) and Gaussian mutation operator. The MGAC and MGA were implemented in JAVA 1.6 and all the experiments were performed on a PC with 1.86 GHz CPU and 2 GB RAM running the Windows XP operating system.

In the preliminary experiments, a trial-and-error strategy was employed to obtain suitable control parameter values for each algorithm. This study used the following parameters: the number of the population, NP = 4 and the number of sub-problems, S = 4.

Table 1 and 2 gave the performances of MGAC and several methods from the literature. This study compared MGAC with Complex Method, (Li and Zhu, 2004) and MGA. Table 1 listed the optimal results of 2K-H planetary gear transmission. The MGAC ranked 3rd for z_s and all 1st for b, m and V respectively. In this situation, the performance of the Complex Method is the worst of the four kinds of algorithms. Table 2 listed the parameters optimization of 2K-H planetary gear transmission results which were passed through analysis and resolving in engineering application. From the Table 2, the MGAC ranked 1st for the optimization. That is to say the MGAC can produce better solutions for the optimization of 2K-H planetary gear transmission. The MGAC algorithm can solve the mechanical optimization design problems effectively.

The reason for the improved performance is that MGAC combines the advantages of the Blend crossover and the Cauchy mutation operator. The Blend crossover is used for improving search ability for global

Table 1: Results of 2K-H planetary gear transmission optimization

Algorithm	References	z_s	b	m	V
Complex					
Method	(Li and Zhu, 2004)	17.002	97.611	5.742	1.342×107
GA	(Li and Zhu, 2004)	17.115	82.295	5.259	0.962×107
MGA	Comparison test	17.225	80.478	5.084	0.889×107
MGAC	This study	17.201	78.458	4.925	0.812×107

MGAC: Micro genetic algorithm with cauchy mutation

Table 2: Parameters of 2K-H planetary gear transmission optimization

Algorithm	References	b (mm)	m (mm)	V	(mm 3)
Complex					
Method	(Li and Zhu, 2004)	20	97	5.5	1.676×107
GA	(Li and Zhu, 2004)	20	82	5	1.172×107
MGA	Comparison test	20	80	5	1.142×107
MGAC	This study	20	78	5	1.114×107

z_s: The teeth number of the sun gear, m: The gear mold number, b: The gear width, V: Volume of the sun gear and all the planets

optimization. The Cauchy mutation is employed to search local optima to fill the gaps of the MGAC such as poor local search ability and the lower velocity of convergence.

CONCLUSION

This study presented a Micro Genetic Algorithm with Cauchy mutation (MGAC) to deal with the mechanical optimization design problems. In this algorithm, the MGAC firstly employed the blend crossover operator called BLX-α to increases the global searching ability of traditional Micro Genetic Algorithm; then, the MGAC selected the Cauchy mutation operator for keeping individual diversity and solving the premature convergence. The population pool was used to reduce the blindness of the individual regeneration in the re-initialization stage. Compared with state-of-the-art algorithms available in the literature, the MGAC can produce better solutions for the optimization of 2K-H planetary gear transmission. The MGAC algorithm can solve the mechanical optimization design problems effectively.

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