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Improved Particle Swarm Algorithm Based Multi-Objective Optimization of Diaphragm Spring of the Clutch

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1. Introduction

In urban working conditions with congested roads, continuous gear switches are needed for mechanical transmissions; therefore, frequent combination and separation are necessary for clutches. There are some difficulties of mechanical clutches during the use procedures such as the difficulty in gear engaging due to halfway separation, starting shaking and clutch slipping [1]. The above faults are often caused by imperfect design on multiple indexes including the operating pressure and the pedal depth of the device. Therefore, it plays practical roles to optimize the core component, i.e., the diaphragm spring.

Actually, the optimization on the diaphragm spring of the clutch is a multi-objective optimization problem. The traditional optimization on the diaphragm spring of the clutch is mainly conducted by two methods. Method One, the multi-objectives are translated to single objectives with common methods of penalty function and GA [2-5]. Such as, the minimum of average compressing force of spring within the scope of the friction slice wear and the driver's minimum manipulating force on separating bearings as optimization objectives is solved by the ant algorithm [2].The genetic algorithms are introduced in the multi-optimum design for diaphragm spring. Shape optimization of an automobile clutch diaphragm spring is performed using a genetic algorithm[3]. A multi-object optimization model was proposed, and a modified genetic algorithm(MGA) was then developed to obtain optimum design solution of the diaphragm spring of the open dry clutch[4]. A mathematical model to optimize its parameters to improve clutch reliability is set up by GA [5].This method has a disadvantage that the weighting coefficient shall be determined by decision makers.

The other method is the multi-objective optimization, with the specific methods of NSGA-II and PSO algorithms [6-10]. For example, a multi-objective optimization model of diaphragm spring is built. On the basis of that, on-dominated Sorting Genetic Algorithm (NSGA- II) based on Pareto optimal theory is employed to seek the optimal construction design scheme[6]. A new optimization target function is proposed. Based on the optimization function, the result of the clutch diaphragm spring in a car is analyzed by the non-dominated sorting genetic algorithm (NSGA-II) [7]. The Particle swarm optimization (PSO) is used for the optimal machining tolerance allocation of over running clutch assembly to obtain the global optimal solution[8]. Particle Swarm Optimization (PSO) algorithm with global convergence is used for multi-objective optimization design of pull-type clutch diaphragm spring[9, 10]. In previous research, some hybrid methods based on using the PSO were developed [11, 12], such as hybridizing the particle swarm optimization (PSO) algorithm_ENREF_13 and the Nelder–Mead (NM) simplex search algorithm [12].

Some other scholars have conducted improved researches on the diaphragm spring. For example, by considering the pedal characteristics and vibrations of pressure plate as objective functions, a multi-objective Pareto optimization problem is solved [13].Yang and Kim established a mathematical model on the diaphragm spring of clutch cover and to identify the basic characteristics for each mathematical model. Although the artificial intelligence algorithm has been utilized in the above literatures, there is no nonlinear constraint in the multi-objective optimization model. Standard algorithms deal with unconstrained optimization problems, and a lot of optimization problems are nonlinearly constrained in engineering practices [14-16]. The optimization on the diaphragm spring of the clutch includes nonlinear constraints, with some difficulties in wide applicability and rate of convergence. Aiming at the difficulty in local extremum caused by pre-maturity of inertia weight and treatment on nonlinear constraint conditions of standard particle swarm optimization (PSO), the improved algorithm based on dynamic weight and hierarchical penalty function in consideration of the degree of congestion is proposed in this article to improve the particle swarm algorithm, so as to verify the correctness of the model and the algorithm. Besides, comparisons are made with the penalty function method, the genetic algorithm, the multi-objective optimized algorithm (NSGA-II) and the standard particle swarm optimization (PSO).

The structure of this article is listed as follows: The first part involves in the establishment of the multi-objective optimization mathematical model of the diaphragm spring; the second part introduces the improved genetic algorithm based multi-objective mathematical model, including the dynamic weight and the improved particle swarm optimization with the hierarchical penalty function by taking the congestion degree into consideration; the third part is simulation experiment and results discussion; the final part involves in the conclusion.

2. Multi-objective optimization model of the diaphragm spring

The main structural parameters of diaphragm spring is illustrated in the reference [6-7].

In order to ensure the reliable transmission of torque in the work of the spring, it is hoped that the compression force of the spring does not decrease during the wear process of the friction plate, and the change is as small as possible. Therefore, the compression force difference $|F_a - F_b|$ between the old and the new state of the friction plate is taken as the objective function as small as possible.

$$F_a = \frac{\pi E h \lambda_a ln\left(\frac{R}{r}\right)}{6(1-\mu^2)(R_1-r_1)^2} \bullet \\ \bullet \left[\left(H-\lambda_a \frac{R-r}{R_1-r_1}\right)\left(H-\frac{\lambda_a R-r}{2R_1-r_1}\right)+h^2\right], \quad (1)$$

$$F_b = \frac{\pi E h \lambda_b ln\left(\frac{R}{r}\right)}{6(1-\mu^2)(R_1-r_1)^2} \bullet \\ \bullet \left[\left(H-\lambda_b \frac{R-r}{R_1-r_1}\right)\left(H-\frac{\lambda_b R-r}{2R_1-r_1}\right)+h^2\right]. \quad (2)$$

From formula (1) and formula (2), the expression for the first objective function is formula (3):

$$F_1(X) = min|F_a - F_b|. \quad (3)$$

When the clutch is separated, the loading point of the diaphragm spring changes, and the thrust F_c of the release bearing is acted on the separation finger at the small end of the diaphragm spring, and the deformation of the action point is λ_c.

$$\lambda_c = \frac{r_1-r_f}{R_1-r_1}\lambda_b, \quad (4)$$

$$F_c = \frac{R_1-r_1}{r_1-r_f}F_b. \quad (5)$$

From formula (4) and formula (5) into formula (2), the relational expression of the release bearing thrust F_c can be obtained:

$$F_c = \frac{\pi E h \lambda_b ln\left(\frac{R}{r}\right)}{6(1-\mu^2)(R_1-r_1)(r_1-r_f)} \bullet \\ \bullet \left[\left(H-\lambda_b \frac{R-r}{R_1-r_1}\right)\left(H-\frac{\lambda_b R-r}{2R_1-r_1}\right)+h^2\right]. \quad (6)$$

Formula (6) is the operating force generated by the diaphragm spring when the clutch is disengaged.

The expression for the second objective function is formula (7):

$$F_2(X) = \frac{\pi E h \lambda_b ln\left(\frac{R}{r}\right)}{6(1-\mu^2)(R_1-r_1)(r_1-r_f)} \bullet \\ \bullet \left[\left(H-\lambda_b \frac{R-r}{R_1-r_1}\right)\left(H-\frac{\lambda_b R-r}{2R_1-r_1}\right)+h^2\right]. \quad (7)$$

Optimized objective function:

$$F(X) = \\ = \begin{cases} F_1(X) = min|F_a - F_b| \\ F_2(X) = \dfrac{\pi E h \lambda_b ln\left(\frac{R}{r}\right)}{6(1-\mu^2)(R_1-r_1)(r_1-r_f)} \bullet \\ \qquad \left[\left(H-\lambda_b \dfrac{R-r}{R_1-r_1}\right)\left(H-\dfrac{\lambda_b - r}{2R_1-r_1}\right)+h^2\right] \end{cases}, \quad (8)$$

where: F_b is the working pressure at the working point B of diaphragm spring; F_a is the working pressure at the working point A when the diaphragm spring reaches the wear limit; H is cone height of the disc spring; h is spring diaphragm thickness; R_1 is the radius of the pressure plate's loading point; r_1 is the radius of loading point of the support ring; r_f is action radius of the separating bearing force; R is the big end radius of the disc spring; r is the small end radius of the disc spring; λ_a is diaphragm spring deformation at point A; λ_b is diaphragm spring deformation at point B; E is elastic modulus of material; μ is the Poisson ratio.

Design Variable [7]:

$$X = [x_1, x_2, x_3, x_4, x_5, x_6, x_7]^T = \\ = [H, h, R, r, R_1, r_1, \lambda_b]^T. \quad (9)$$

The constraints of the diaphragm spring of the clutch include both linear constraints and nonlinear ones. The constraint conditions are listed as follows:

$$\begin{cases} s.t \quad g_1(x) = x_1/x_2 \le 2.2 \\ g_2(x) = x_1/x_2 \ge 1.6 \\ g_3(x) = x_1/(x_3 - x_4) \le \pi/15 \\ g_4(x) = x_1/(x_3 - x_4) \ge \pi/20 \\ g_5(x) = x_3/x_4 \le 1.35 \\ g_6(x) = x_3/x_4 \ge 1.2 \\ g_7(x) = x_5 \le D/2 \\ g_8(x) = x_5 \ge (D+d)/4 \\ g_9(x) = \sigma - 1500 \le 0 \\ g_{10}(x) = F_{\max} - F_a \le 0 \\ g_{11}(x) = x_3/x_2 < 50 \\ g_{12}(x) = x_3/x_2 > 30 \end{cases}. \tag{10}$$

3. Improved particle swarm optimization

3.1. Dynamic inertia weight

Particle swarm optimization (PSO) has strong optimization ability in the application process, but PSO algorithm also has disadvantages like other global optimization algorithms, such as premature local convergence and late oscillation. For these problems, inertia weight is the most important adjustable parameter, and the balance between global search and local search can be achieved through inertia weight. The inertia weight embodies the ability of the particle to inherit from the previous particle. Aiming at the problem of the PSO algorithm of local optimum due to early-maturity, the dynamic weight based particle swarm optimization is adopted in this article to regulate the inertia weight in a dynamic way, with the following formula:

$$w(i) = w_{max} - \frac{u(w_{max} - w_{min})}{u_{max}}. \tag{11}$$

In formula (11), $w(i)$ is the dynamically regulated inertia weight, and w_{max} and w_{min} are maximum value and minimum value of $w(i)$; i is the iteration algebra at present, and u_{max} is the maximum step number of iteration; u is current iteration step.

3.2. Hierarchical dynamic penalty function

In order to solve the constraint optimization problems, traditional solutions are mainly adopted including the gradient projection method, the reduced gradient method, the penalty function method and the barrier function method; however, the single use of the methods leads to low efficiency or limited applicable ranges. The penalty function technology solves the problem of constraint optimization through penalty constraint conditions. If the penalty function has very high penalty value, the optimization algorithm is often restrained to local minimum solution; if the penalty function is very low, it is difficult to find out feasible optimal solution. Penalty function relies on the constraint conditions, and the penalty value is corrected in a dynamic way with the change of the constraint value. The solution process of the hierarchical dynamic penalty function algorithm does not depend on the analysis nature of the objective function; at the same time, it can be restrained in global optimal solution with large possibility.

The definition of the penalty function is listed as follows:

$$F(x) = f(x) + h(k)H(x), x \in S \subset R^n. \tag{12}$$

In which $f(x)$ is the initial objective function of the constraint optimization problem; $h(k)$ is the factor of the penalty function; k is the iteration times of the particle swarm optimization; i.e., the penalty function value of the random constrained optimization method increases with the growth of the number of iteration. $H(x)$ is a multi-level allocated penalty function, with the following definition:

$$H(x) = \sum_{i=1}^{m} \theta(q_i(x)) q_i(x)^{\gamma(q_i(x))}. \tag{13}$$

In which $q_i(x) = max\{0, |g_i(x)|\}, i = 1, \ldots, m$, and m is the number of the restraint conditions; function $q_i(x)$ is the corresponding violating restraint function; $g_i(x)$ is the restraint function; $\theta(q_i(x))$ is a multi-level distribution function; $\gamma(q_i(x))$ is the number of levels of the penalty function. Functions $q_i(x)$, $\theta(q_i(x))$ and $\gamma(q_i(x))$ depend on the constraint optimization problems, with the following penalty regulations[17].

$$\gamma(q_i(x)) \begin{cases} 1, \ q_i(x) < 1 \\ 2, \ q_i(x) \ge 1 \end{cases}, \tag{14}$$

$$\theta(q_i(x)) \begin{cases} 10, & q_i(x) < 0.001 \\ 20, & 0.001 \le q_i(x) \le 0.1 \\ 100, & 0.1 < q_i(x) < 1 \\ 300, & q_i(x) \ge 1 \end{cases}. \tag{15}$$

3.3. The particle swarm optimization with the hierarchical penalty function in consideration of the degree of congestion

1. The method to determine the degree of congestion: The calculation of the degree of congestion is an important process ensuring the population diversity, with the following function pseudo code:

a) make $n_d = 0$, n=1,2,3, ..., N;

b) as for each objective function:

– rank the populations based on the objective function;
– make the degree of congestion of two individuals on the boundary as infinite, i.e., I_d=N_d;
– calculate

$$n_d = n_d + (f_m(i+1) - f_m(i-1)), n = 2, 3, ..., N-1.$$

2. The comparison operator of the degree of congestion: After the quick non-dominated ranking and the calculation of the degree of congestion, each individual n in the population acquires two properties: the non-dominated ranking n_{rank} and the degree of congestion n_d. By utilizing the two properties, it is available to distinguish the dominating relationship and the non-dominating relationship between any two individuals in the population. The comparison operator of the degree of congestion is defined as $\ge_n$, and the comparison basis for ranking of individuals is

$i \geq_n j$; i.e., the individual i is superior to the individual j, if and only if $i_{rank} < j_{rank}$ or $i_{rank} = j_{rank}$, and $i_d > j_d$. An improved particle swarm optimization procedure for multi-objective optimization is illustrated in Fig. 1.

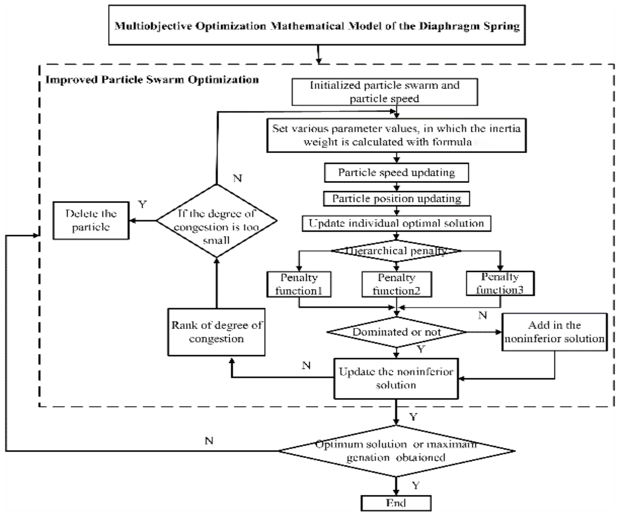


Fig. 1 Improved PSO procedures for multi-objective optimization of diaphragm spring of the clutch

4. Simulation experiment and results discussion

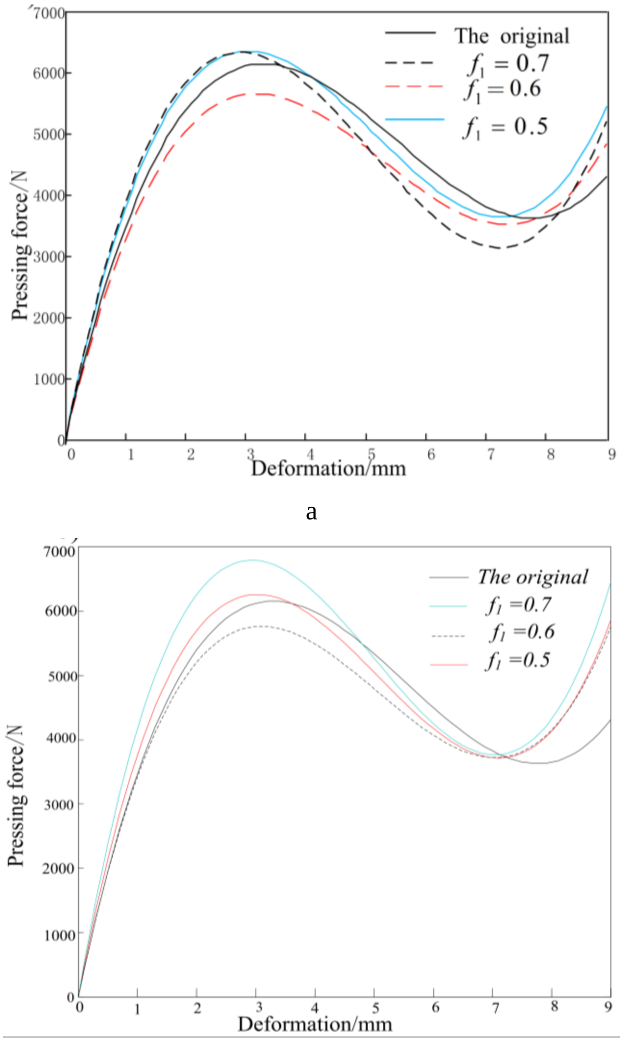
The optimization design of the clutch of the pull type diaphragm spring of a passenger car is taken as an example. The maximum torque of the engine is 265 N. m, and the back-up coefficient β=1.8, and the friction factor is 0.3, and the diaphragm spring material is 60si2MnA, and the allowable stress is 1400-1600 MPa, and the Poisson's ratio is 0.3, and the wear limit is 3.2 mm, and the separation stroke is 3.5 mm. n is often taken as 18; for passenger cars, b is often taken as 9-12 mm. Experimental parameters design of optimization variables is illustrated in Table 1.

Table 1

Experimental parameters design of optimization variables

Objective function	Algorithm
$f_1F_1(X)+ f_2F_2(X)$	Penalty function method
$f_1F_1(X)+ f_2F_2(X)$	Genetic algorithm (GA)
$F_1(X)$, $F_2(X)$	NSGA-II
$F_1(X)$, $F_2(X)$	PSO
$F_1(X)$, $F_2(X)$	Improved PSO

The characteristic diagram of diaphragm spring is illustrated in Fig. 2. According to Fig. 2, a, when f_1=0.7, the steering separation force is relatively small, the manipulation is light, but the compression stability is worse, and when f_1=0.6, the compression is more stable but the steering separation force is not changed, and f_1=0.5 is worse than before optimization. When the weighting factor is near to 0.6, the optimization result is favorable. But it also shows the disadvantage of the method; i.e., it is difficult to find out the optimal weighting factor or acquire the optimal optimization result. According to Fig. 2, b. When f_1=0.7, it is worse than before optimization and f_1=0.6, the compression is more stable but the steering separation force is nearly not change. When f_1=0.5, the compression stability is more stable but steering separation force is worse than the optimization. Therefore, the optimization result of 0.6 is slightly better. However, it is difficult to find out the optimal weighting factor or acquire the optimal optimization result too.



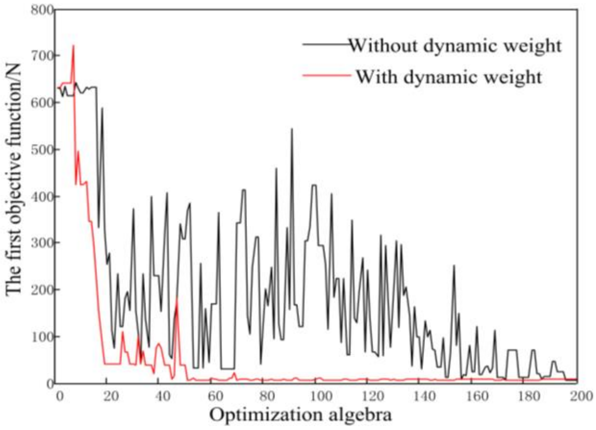
a

b

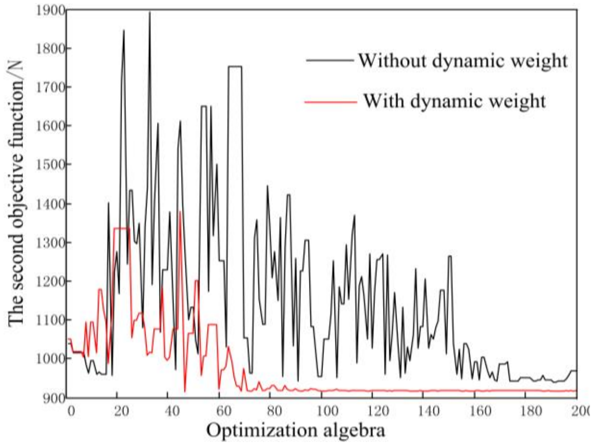
Fig. 2 Characteristic diagram of diaphragm spring: a) penalty function method; b) genetic algorithm method

Comparison diagram of dynamic weight PSO Algorithm is illustrated in Fig. 3. It can be acquired from Fig. 3 that based on the comparisons on the optimization results between the dynamic weight based PSO algorithm and the traditional PSO algorithm, after the use of the dynamic weight on the PSO, the function values of the first objective and the second objective of the diaphragm spring optimization are more stable, which illustrate that there are significant improvements on the convergence, accuracy degree and efficiency of the algorithm.

The comparisons on the characteristic graph of diaphragm spring are illustrated in Fig. 4. According to Fig. 4, a, the PSO algorithm lays emphasis on the optimization of the first target function, leading to very significant optimization result of the first target function, and the pressing force within the abrasion range is more stable; however, the optimization on the second target function is not very significant. Similar to the optimization result of NSGA-II, it also has significant disadvantages, and it is needed to conduct further optimization to the second target. According to Fig. 4, b, the optimization result is ideal. Compared with the NSGA-II algorithm, the change on pressing force within the abrasion range is smaller; in addition, the separating force during the separation of the clutch is also reduced. The optimization result is superior to the NSGA-II algorithm.



a

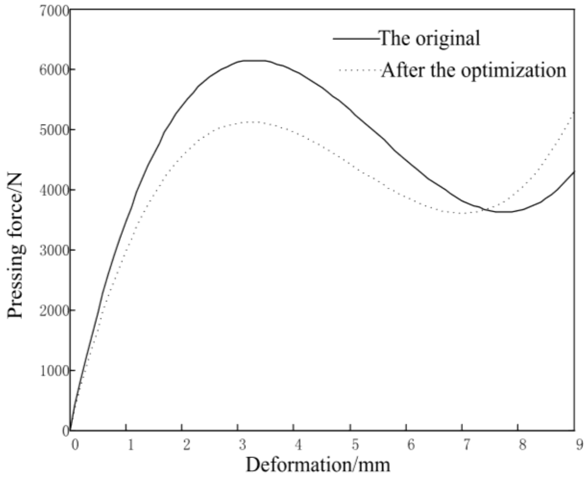


b

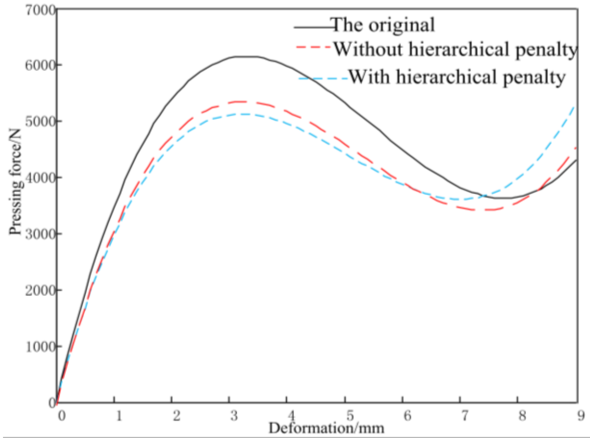
Fig. 3 Comparison diagram of dynamic weight PSO algorithm: a) first objective; b) second objective

On this basis, the analysis with hierarchical penalty function in consideration of degree of congestion is as shown in Fig. 6. According to Fig. 5, the Pareto solution of point G is selected as the result of the improved PSO algorithm, which is compared with the penalty function method, the genetic algorithm (GA) [18], the multi-objective genetic algorithm (NSGA-II) [7] and the standard particle swarm optimization (PSO) [8]. The optimization scheme of the structural parameters of the diaphragm spring of the clutch is illustrated in Table 2 and the comparison on performance parameters is illustrated in Table 3.

According to Table 3: 1) the working point of the clutch friction plate of the diaphragm spring is *a* and the working pressing force is F_a; i.e., when the working point of the diaphragm spring moves from point *a* to point *b*, the working pressing force is F_b. The difference between F_a and F_b is the change on pressing force. It illustrates that the clutch can work in *a* stable and reliable way in condition of abrasion of friction plate. As for the above optimization schemes, the difference between F_a and F_b is not great. The penalty function method is 351 N; the genetic algorithm is 259 N; the NSGA-II is 181 N; the particle swarm optimization is 175 N; the improved particle swarm is 151 N. The change on the pressing force of the improved particle swarm algorithm is the least, illustrating that the clutch of the diaphragm spring can still work in a normal way within the wear limit, leading to better optimization result on elastic characteristic curve and more stable pressing force. The difference between the working point and the wear limit point of the improved particle swarm optimization is the least, with no significant change on pressing force and meet the requirements of the objective function, followed by standard PSO. The pressing force of the improved PSO is increased by 3.24%, with more stable pressing force.



a



b

Fig. 4 Characteristic diagram of diaphragm spring: a) dynamic weight PSO; b) hierarchical penalty function PSO

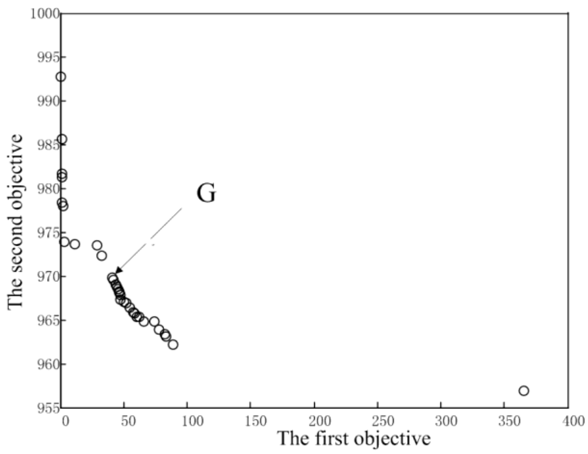


Fig. 5 Solution set of final noninferior solutions of PSO algorithm with hierarchical penalty function in consideration of degree of congestion

2) The thorough separation point of each scheme to the second objective function is reduced than the original scheme, illustrating the separation stroke of the diaphragm spring clutch is reduced, and the average value of the separation operating force of drivers is also greatly reduced. The most ideal scheme is the improved particle swarm algorithm, and the separating force is reduced by 20.09 % compared with the original scheme. In conclusion, the improved particle swarm algorithm is ideal.

Table 2

Comperation of optimized structural parameters with original ones

Structural parameter	H, mm	h, mm	R, mm	r, mm	R_1, mm	r_1, mm	λ_b
Original parameter	5.8	2.93	145.7	116.8	143.66	116.1	4.80
Penalty function	5.24	2.80	140.00	115.00	138.68	115.00	4.21
GA [18]	5.20	2.80	140.04	115.18	138.80	114.00	4.02
NSGA-II [7]	5.21	2.81	140.35	115.48	140.66	114.50	4.01
PSO [10]	5.1	2.68	142.7	122.07	141.25	120.6	4.20
Improved PSO	5.9192	2.9248	146.19	115	145	115	4.44

Table 3

Comperation of optimized performance parameters with original ones

Performance parameters	F_b, N	F_a, N	F_c, N	$\lvert F_b - F_a \rvert$, N	$\lvert F_b - F_a \rvert / \lvert F_b \rvert$, %
Original parameter	5226	5925	3817	699	13.37
Penalty function	4834	5185	3709	351	7.23
GA[18]	4757	5016	3715	259	5.44
NSGA-II[7]	4422	4603	3567	181	4.09
PSO[10]	4753	4928	3300	175	3.68
Improved PSO	4650	4801	3050	151	3.24

Comparison diagrams of elastic characteristic of diaphragm spring of various algorithms are illustrated in Fig. 6. According to Fig. 6, among the five optimization algorithms, the improved particle swarm algorithm has the most ideal result, with the gentlest pressing force changes within the wear ranges and smaller separating force. Therefore, this algorithm provides the optimization of diaphragm spring with a feasible algorithm. With The time-consuming comparison, Multi-objective genetic algorithm is the fastest, however improved PSO is almost the same time as the planned function and GA algorithms.

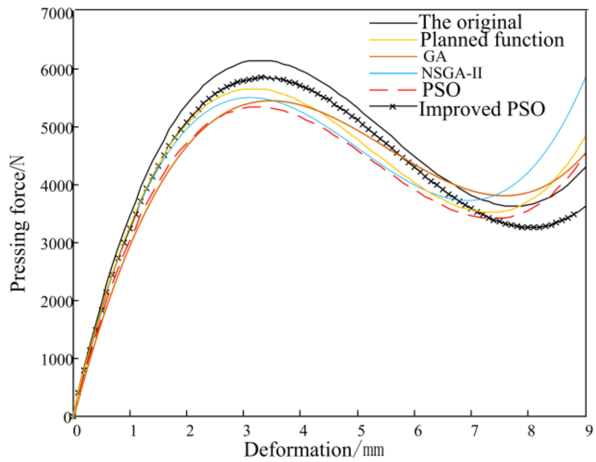


Fig. 6 Comparison diagrams of elastic characteristic of diaphragm spring of various algorithms

5. Conclusion

Aiming at the diaphragm spring component of passenger car clutch, this study proposes a multi-objective optimization model with the minimum difference of diaphragm spring pressing force between new and old work conditions of friction disk and the separating operating force of drivers on the release bearing device. Main conclusions are listed as follows:

1) In the multi-objective optimization model of the diaphragm spring, it proposes an improved particle swarm multi-objective optimized algorithm, which is utilized for optimized analysis on the diaphragm. The results show that the improved PSO effectively solves the difficulty of local extremum due to early-maturity and treatment in nonlinear constraint with the standard PSO method. At the same time, the improved PSO has better convergence and stability.

2) The pressing force stability and the steering separation lightness of the diaphragm spring with improved PSO is better. It is compared with the penalty function method, the genetic algorithm, the multi-objective optimized algorithm (NSGA-II) and the standard particle swarm optimization (PSO). The results show that the pressing force of the diaphragm spring with the improved PSO is increased by 3.24%, and the steering separation force is decreased by 20.09%.

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IMPROVED PARTICLE SWARM ALGORITHM BASED MULTI-OBJECTIVE OPTIMIZATION OF DIAPHRAGM SPRING OF THE CLUTCH

S u m m a r y

Considering that diaphragm spring is the core component of the mechanical clutch, the optimization to which plays practical roles in engineering practices, the multi-objective optimization model for the diaphragm spring of the clutch is established in this article. Aiming at the difficulty in local extremum due to pre-maturity of inertia weight and treatment on nonlinear constraint condition of standard particle swarm optimization (PSO), the improved particle swarm algorithm (Improved PSO) based on dynamic weight and hierarchical penalty function in consideration of the degree of congestion is proposed in this article to improve the original particle swarm algorithm. According to the results of calculating examples, the improved particle swarm algorithm can achieve better global searching ability and convergence ability; when compared with the calculating results of the penalty function algorithm, the genetic algorithm and the NSGA-II algorithm, the pressing force of the diaphragm spring with the new algorithm is increased by 3.24%, and the steering separation force is decreased by 20.09%. The diaphragm spring has better pressing force stability and operating lightness, verifying the correctness of the model and the algorithm proposed in this article.

Keywords: clutch diaphragm spring; improved particle swarm optimization algorithm; nonlinear constraint; multi-stage Fractional penalty function.

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