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Research Article

Relay Optimization Design Algorithm Based on Swarm Intelligence

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Abstract: In this study, particle swarm optimization algorithm is developed under the inspiration of behavior laws of bird flocks, fish schools and human communities and it is high convergence speed. Moreover, aim at the disadvantages of traditional genetic algorithm, we proposes a new algorithm based on particle swarm optimization algorithm, the new algorithm keeps not only the fast convergence speed characteristic of PSO, but effectively improves the capability of global searching as well. The experiment results showed this new algorithm is effective for relay optimization design.

Keywords: Genetic algorithm, particle swarm optimization, relay optimization design, relay volume model

INTRODUCTION

Relay products consist of machines, electrical, magnetic, thermal and many of the products but also possesses the electrical, magnetic, thermal coupling effect and some need to consider the stress and deformation, mechanical strength, kinematics and gas dynamics, for a long time, traditional relay design methods are by virtue of experience and static characteristics, or by reference to the structural parameters of the existing products and technical performance parameters, a number of specific design calculations and proposed the design model, then begin the product trial, often repeated this process to be get more satisfactory results, which lead to a very long product development cycle and high cost (Yu, 2003).

Optimal Design of relay products determine the design parameters in the given load conditions or environmental conditions, the state of relay products, geometry or other factors within the scope of restrictions and make sure of the design parameters, object function, constraints in order to form an optimized design model and select the appropriate optimization method to obtain the best design of a series of work. Therefore, using modern design methods to achieve the automation of intelligent design of the relay product, either in theory or in economic benefits is of great significance. Mathematical model of the relay volume involves in mechanical, electrical, magnetic, thermal, etc., the objective function and constraints are highly nonlinear function, traditional design algorithm trapped into the local minimum easily.

Particle Swarm Optimization (PSO) algorithm was an intelligent technology first presented by Kennedy and Eberhart (1995) and it was developed under the inspiration of behavior laws of bird flocks, fish schools and human communities. If we compare PSO with Genetic Algorithms (GAs), we may find that they are all maneuvered on the basis of population operated. But PSO doesn't rely on genetic operators like selection operators, crossover operators and mutation operators to operate individual, it optimizes the population through information exchange among individuals. PSO achieves its optimum solution by starting from a group of random solution and then searching repeatedly. Once PSO was presented, it invited widespread concerns among scholars in the optimization fields and shortly afterwards it had become a studying focus within only several years. A number of scientific achievements had emerged in these fields (Clare and Kennedy, 2002; Coello and Lechuga Mopso, 2002; Kennedy, 1997). PSO was proved to be a sort of high efficient optimization algorithm by numerous research and experiments (Oscan and Mohan, 1998). PSO is a meta-heuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, meta-heuristics such as PSO do not guarantee an optimal solution is ever found. More specifically, PSO does not use the gradient of the problem being optimized, which means PSO does not

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require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and quasi-Newton methods. PSO can therefore also be used on optimization problems that are partially irregular, noisy, change over time, etc. This study introduces the PSO algorithm and use this algorithm solves the relay volume optimization design because of the PSO algorithm has high convergence speed.

PARTICLE SWARM OPTIMIZATION ALGORITHM

Algorithm introduction: Several challenges arise in optimization. First is the nature of the problem to be optimized which may have several local optima the optimizer can get stuck in, the problem may be discontinuous, candidate solutions may yield different fitness values when evaluated at different times and there may be constraints as to what candidate solutions are feasible as actual solutions to the real-world problem. Furthermore, the large number of candidate solutions to an optimization problem makes it intractable to consider all candidate solutions in turn, which is the only way to be completely sure that the global optimum has been found. This difficulty grows much worse with increasing dimensionality, which is frequently called the curse of dimensionality, a name that is attributed to Bellman (2003), see for example. This phenomenon can be understood by first considering an n-dimensional binary search-space. Here, adding another dimension to the problem means a doubling of the number of candidate solutions. So the number of candidate solutions grows exponentially with increasing dimensionality. The same principle holds for continuous or real-valued search-spaces, only it is now the volume of the search-space that grows exponentially with increasing dimensionality. In either case it is therefore of great interest to find optimization methods which not only perform well in few dimensions, but do not require an exponential number of fitness evaluations as the dimensionality grows. Preferably such optimization methods have a linear relationship between the dimensionality of the problem and the number of candidate solutions they must evaluate in order to achieve satisfactory results, that is, optimization methods should ideally have linear time-complexity O(n) in the dimensionality n of the problem to be optimized.

Another challenge in optimization arises from how much or how little is known about the problem at hand. For example, if the optimization problem is given by a simple formula then it may be possible to derive the inverse of that formula and thus find its optimum. Other families of problems have had specialized methods developed to optimize them efficiently. But when nothing is known about the optimization problem at hand, then the No Free Lunch (NFL) set of theorems by Wolpert and Macready (1997) states that any one optimization method will be as likely as any other to find a satisfactory solution. This is especially important in deciding what performance goals one should have when designing new optimization methods and whether one should attempt to devise the ultimate optimization method which will adapt to all problems and perform well. According to the NFL theorems such an optimization method does not exist and the focus of this thesis will therefore be on the opposite: Simple optimization methods that perform well for a range of problems of interest.

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered. Formally, let f: Rn → R be the cost function which must be minimized. The function takes a candidate solution as argument in the form of a vector of real numbers and produces a real number as output which indicates the objective function value of the given candidate solution. The gradient of f is not known. The goal is to find a solution a for which f (a) ≤ f (b) for all b in the search-space, which would mean a is the global minimum. Maximization can be performed by considering the function h = -f instead.

PSO was presented under the inspiration of bird flock immigration during the course of finding food and then be used in the optimization problems. In PSO, each optimization problem solution is taken as a bird in the searching space and it is called "particle". Every particle has a fitness value which is determined by target functions and it has also a velocity which determines its destination and distance. All particles search in the solution space for their best positions and the positions of the best particles in the swarm. PSO is initially a group of random particles (random solutions) and then the optimum solutions are found by repeated searching. In the course of every iterations, a particle will follow two bests to renew itself: the best position found for a particle called pbest; the best position found for the whole swarm called gbest. All particles will determine following steps through the best experiences of individuals themselves and their companions.

For particle id, its velocity and its position renewal formula are as follows:

$$V_{id}^{'} = \omega V_{id} + \eta_1 rand()(P_{idb} - X_{id}) + \eta_2 rand()(P_{gdb} - X_{id}) \quad (1)$$

$$X_{id}^{'} = X_{id} + V_{id}^{'} \quad (2)$$

In here,

- ω = Called inertia weight, it is a proportion factor that is concerned with former velocity $0<\omega<1$
- η_1 & η_2 = Constants and are called accelerating factors, normally $\eta_1 = \eta_2 = 2$
- rand () = Random numbers
- X_{id} = The position of particle id
- V_{id} = The velocity of particle id
- P_{id}, P_{gd} = Separately the best position particle id has found and the position of the best particles in the whole swarm

In formula (1), the first part represents the former velocity of the particle, it enables the particle to possess expanding tendency in the searching space and thus makes the algorithm be more capable in global searching; the second part is called cognition part, it represents the process of absorbing individual experience knowledge on the part of the particle; the third part is called social part, it represents the process of learning from the experiences of other particles on the part of certain particle and it also shows the information sharing and social cooperation among particles.

The flow of PSO can briefly describe as following: First, to initialize a group of particles, e.g., to give randomly each particle an initial position Xi and an initial velocity Vi and then to calculate its fitness value f. In every iterations, evaluated a particle's fitness value by analyzing the velocity and positions of renewed particles in formula (1) and (2). When a particle finds a better position than previously, it will mark this coordinate into vector P1, the vector difference between P1 and the present position of the particle will randomly be added to next velocity vector, so that the following renewed particles will search around this point, it's also called in formula (1) cognition component. The weight difference of the present position of the particle swarm and the best position of the swarm P_{gd} will also be added to velocity vector for adjusting the next population velocity. This is also called in formula (1) social component. These two adjustments will enable particles to search around two bests.

The most obvious advantage of PSO is that the convergence speed of the swarm is very high, scholars like Clare and Kennedy (2002) has presented proof on its convergence.

Experiment verify: In order to verify the convergence speed of the PSO algorithm, we selected four benchmarks function and compared the results with traditional Genetic Algorithm (GA). Figure 1 shows the Schaffer function:

F1: Schaffer function:

$$\min f(x_i) = 0.5 - \frac{(\sin^2\sqrt{x_1^2 + x_2^2} - 0.5)}{[1 + 0.001(x_1^2 + x_2^2)]^2}, -100 \le x_i \le 100$$

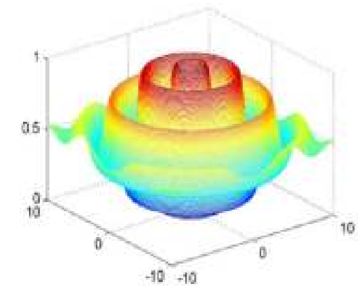

Fig. 1: Schaffer function

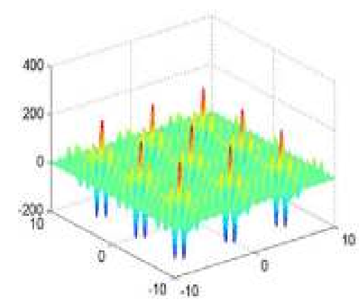

Fig. 2: Shubert function

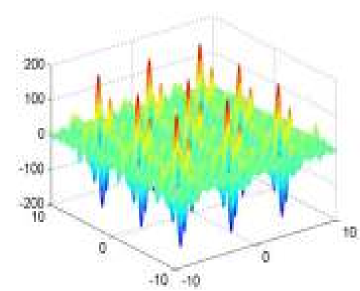

Fig. 3: Hansen function

In this function the biggest point is in the situation where $x_i = (0, 0)$ and the global optimal value is 1.0, the largest in the overall points for the center and 3.14 for the radius of a circle on the overall situation from numerous major points of the uplift. This function has a strong shock; therefore, it is difficult to find a general method of its global optimal solution.

F2: Shubert function:

$$\min f(x,y) = \left\{\sum_{i=1}^{5} i\cos\left[(i+1)x + i\right]\right\} \times \left\{\sum_{i=1}^{5} i\cos\left[(i+1)y + i\right]\right\},$$
$$x, y \in [-10,10]$$

This function has 760 local minimum and 18 global minimum, the global minimum value is -186.7309. Figure 2 shows the Shubert function.

F3: Hansen function:

Table 1: Experiment results comparison

Function	Algorithm	Convergence times	Optimal solution
F1	GA	72	1.0000000
	PSO	75	1.0000000
F2	GA	75	-186.7309090
	PSO	80	-186.7309090
F3	GA	85	-176.5417930
	PSO	90	-176.5417930
F4	GA	23	-1.0316280
	PSO	56	-1.0316280

$$\min f(x,y)=\sum_{i=1}^{5} i\cos((i-1)x+i)\sum_{j=1}^{5} j\cos((j+1)y+j),$$
$$x,y\in[-10,10]$$

This function has a global minimum value -176.541793, in the following nine point (-7.589893, -7.708314), (-7.589893, -1.425128), (-7.589893, 4.858057), (-1.306708, -7.708314), (-1.306708, -1.425128), (-1.306708, 4.858057), (4.976478, -7.708314), (4.976478, -7.708314), (4.976478, 4.858057) can get this global minimum value, the function has 760 local minimum. Figure 3 shows the Hansen function.

F4: Camel function:

$$\min f(x,y)=\left(4-2.1x^2+\frac{x^4}{3}\right)x^2+xy+\left(-4+4y^2\right)y^2,$$
$$x,y\in\left[-100,100\right]$$

Camel function has 6 local minimum (1.607105, 0.568651), (-1.607105, -0.568651), (1.703607, -0.796084), (-1.703607, 0.796084), (-0.0898, 0.7126) and (0.0898, -0.7126), the (-0.0898, 0.7126) and (0.0898, -0.7126) are the two global minimums, the value is -1.031628.

In the experiment, each case is repeated for 100 times. Table 1 shows the statistics of our experimental results in terms of accuracy of the best solutions. GA found the known optimal solution to F1 72 times out of 100 runs, found the known optimal solution to F2 75 times out of 100 runs, found the known optimal solution to F3 85 times out of 100 runs, found the known optimal solution to F4 23 times out of 100 runs; PSO algorithm is efficiency for the four cases: found the known optimal solution to F1 75 times out of 100 runs, found the known optimal solution to F2 80 times out of 100 runs, found the known optimal solution to F3 90 times out of 100 runs and found the known optimal solution to F4 56 times out of 100 runs.

RELAY VOLUME OPTIMIZATON DESIGN

Relay volume model: Relay optimization goal is strive to energy conservation, save materials, reduce core collision energy and other factors, to prevent the contact bounce and the premise is to ensure reliable electrical action and release. During the optimization process, material cost, size, power consumption, the collision energy and other factors are to be considered, so it is belonging constrained nonlinear programming problem.

The relay volume consists of coil volume and the volume of the magnetic conductor, the volume of the magnetic conductor composed by the core, the pole piece, the armature and the yoke composition. The volume of coil is $\pi\, h_c(R_0^2-r_c^2)$, the volume of armature is $2R_0ba_x$, the volume of yoke composition is $2R_0ba_e + a_eb\,(h_c + a_j)$, the volume of pole piece is $\pi r_j^2 a_j$, the volume of core is $\pi r_c^2 h_c$. If each part of the volume is obtained, the sum is the volume of the relay, we can represent the volume of relay use the formula (3) (Lingling, 2004):

$$V\approx \pi\, r_c^2 h+2R_0 b\left(a_x+a_e\right)+a_e b\left(h_c+a_j\right)+\pi\, r_j^2 a_j \quad (3)$$

If we make $a_xb = a_eb\ \pi r_c^2$ and $a_j=\frac{r_c}{2}\left[1-\left(\frac{r_c}{r_j}\right)^2\right]$, then we can get the volume of relay like the following formula:

$$V=\pi\, h_c R_0^2+\pi\, r_c^2 h_c+4\pi\, r_c^2 R_0+\frac{\pi}{2} r_j^2 r_c-\frac{\pi}{2}\frac{r_c^5}{r_j^2} \quad (4)$$

The size of each part of the relay cannot arbitrarily change and the determination of the size of each part must comply with the relay design constraints, these constraints include: the electromagnetic force constraints; magnetic induction value constraints; coil temperature rise constraints and design parameters rationality constraints. For this reason, we selected four design variables: coil outer radius as x_1, the radius of the core columns as x_2, coil height as x_3, pole piece radius as x_4, then bring the various physical constant value and related constraints into the relay volume formula to get the following formula:

$$\min V(x)=\frac{1.5913*10^{-10}}{x_2^3}\left[x_3x_1^2+x_3+4x_1+\frac{1}{2}\left(x_4^2-\frac{1}{x_4^2}\right)\right]$$

St.

$$g_1\left(X\right)=1.0764*10^{-6}*\frac{x_3^2x_1\left(x_1-1\right)}{x_2^3\left(x_1+1\right)}\left[\frac{3.1416x_4^2}{x_2^3}\left(1+\frac{x_4^2}{4x_1^2}\right)+\right.$$
$$\left.\frac{32\left(x_4-x_4^{-1}\right)}{\left(1-x_4^{-2}+4x_2\right)^2}-0.9\right]-1.8\geq 0$$

$$g_2(X)=1.4-1.4112*10^{-6}*x_3*\sqrt{\frac{\left(x_1-1\right)x_1}{\left(x_1+1\right)x_2}}*$$
$$\left\{\frac{3.1416}{x^2}\left(x_4^2+\frac{x_4^4}{4x_1^2}\right)+0.9x_2+\frac{3x_4^3+x_4^2-1}{x_4^2}+\right.$$
$$\left.\frac{8x_4\left(x_4^2-1\right)}{x_4^2+4x_2x_4^2-1}+\frac{3.1416x_3}{\ln\left(x_1+\sqrt{x_1^2-1}\right)}\right\}\geq 0$$

Table 2: Relay volume optimization results comparison

Volume without optimization (mm^3)	Volume optimization by HGA (mm^3)	Volume optimization by PSO (mm^3)
1617.78	1266.60	1194.41

Table 3: Design parameter before optimization

Name of design parameter	Parameter's value (mm)	Design variable's value (mm)
Coil outer radius (x_1)	6.00	2.60870
Core columns radius (x_2)	2.30	0.16087
Coil height (x_3)	9.00	3.91304
Pole piece radius (x_4)	4.00	1.73913

Table 4: Design parameter optimization by HGA

Name of design parameter	Parameter's value (mm)	Design variable's value (mm)
Coil outer radius (x_1)	5.26	2.21259
Core columns radius (x_2)	2.38	0.15571
Coil height (x_3)	7.71	3.24290
Pole piece radius (x_4)	4.98	2.09468

Table 5: Design parameter optimization by PSO

Name of design parameter	Parameter's value (mm)	Design variable's value (mm)
Coil outer radius (x_1)	5.063	2.133750
Core columns radius (x_2)	2.373	0.155918
Coil height (x_3)	7.585	3.196390
Pole piece radius (x_4)	5.063	2.133680

$$g_3(X) = 85 - 0.925 * \frac{\left(x_1^2 - 1\right)}{x_1 x_2} \geq 0$$

$$g_4(X) = x_1 - x_4 > 0$$

$$g_5(X) = \frac{x_3}{x_1} - 1.33333 \leq 0$$

$$g_6(X) = 1.5 - \frac{x_3}{x_4} \geq 0 \tag{5}$$

Formula (5) is the relay volume model we want to get and we will use optimization algorithm to get the minimum value for this model.

Particle selection strategy: Genetic algorithm is usually complete the selection operation based on the individual's fitness value, in the mechanism of intergenerational elite, the population of the front generation mixed with the new population which generate through crossover and mutation operations, in the mixed population select the optimum individuals according to a certain probability. The specific procedure is as follows:

Step 1: Using crossover and mutation operations for population P1 which size is N then generating the next generation of sub-populations P2

Step 2: The current population P1 and the next generation of sub-populations P2 mixed together form a temporary population

Step 3: Temporary population according to fitness values in descending order, to retain the best N individuals to form new populations P1

The characteristic of this mechanism is mainly in the following aspects. First is robust, because of using this selection strategy, even when the crossover and mutation operations to produce more inferior individuals, as the results of the majority of individual residues of the original population, does not cause lower the fitness value of the individual. The second is in genetic diversity maintaining, the operation of large populations, you can better maintain the genetic diversity of the population evolution process. Third is in the sorting method, it is good to overcome proportional to adapt to the calculation of scale.

Relay volume optimization design: We use PSO algorithm solve the relay volume optimization problem and get the optimal design parameters, then compare the results showed in Lingling (2004). In the study (Lingling, 2004) the author introduce the optimization algorithm named Hybrid Genetic Algorithm (HGA), the author use the HGA optimization the design parameters.

We can bring these design parameters into the formula (4) and calculate the volume. In the Table 2 is the volume comparison calculated by the design parameters from the Table 3, 4 and 5. As can be seen from Table 2, the optimization result of the PSO algorithm proposed in this study, volume decreases of 26.05% compared with without optimization, compared with HGA the volume is reduced by 5.7%.

CONCLUSION

Mathematical models of many real life problems turn out to be nonlinear in nature, having local as well as global optimal solutions. Usually, it is more difficult to obtain global optimal solution (s), as compared to local optimal solutions of nonlinear optimization problems, but in many cases it is advantageous and sometimes even necessary, to search for the global optimal solution (s). In engineering optimization fields, there are many nonlinear optimization problems. We use our proposed algorithm based on PSO and use it solve the relay volume optimization in engineering optimization fields. From the results, we can find our algorithm is efficiency.

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REFERENCES

Bellman, R., 2003. Dynamic Programming. Princeton University Press, Mineola, NY, pp: 340, ISBN: 0486428095.

Clare, M. and J. Kennedy, 2002. The particle swarm - explosion, stability and convergence in a multidimensional complex space. IEEE T. Evol. Comp., 6(1): 58-73.

Coello, C.A. and M.S. Lechuga Mopso, 2002. A proposal for multiple objective particle swarm optimization. IEEE Proceeding World Congress on Computational Intelligence, pp: 1051-1056.

Kennedy, J., 1997. The particle swarm: Social adaptation of knowledge. Proceeding IEEE Conference on Evolutionary Computation, pp: 3003-3008.

Kennedy, J. and R.C. Eberhart, 1995. Particle swarm optimization. IEEE International Conference on Neural Networks, pp: 1942-1948.

Lingling, L., 2004. Construction method of relay product design and evaluation of expert system. MA Thesis, Hebe University of Technology, Shijiazhuang.

Oscan, E. and C.K. Mohan, 1998. Analysis of a simple particle swarm optimization system. Intelligence Engineering Systems through Artificial Neural Networks, pp: 253-258.

Wolpert, D.H. and W.G. Macready, 1997. No free lunch theorems for optimization. IEEE T. Evol. Comp., 1(1): 67-82.

Yu, L., 2003. Micro-electromagnetic polarized relay design based on MEMS. MA Thesis, University of Electronic Science and Technology, Chengdu.