

The Mechanical Reliability Optimization Based on the Improved Artificial Bee Colony Algorithm

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The reliability is the factor that can't be ignored in the optimization design of the mechanics. In the large complex mechanical systems, especially in the closed-state function systems, the reliability based optimization has the features that the convergence speed is slow, and process easily get trapped in the local optima because of the stronger nonlinearity of the systems. In order to conquer these weaknesses in the reliability optima process, the paper proposes an improved artificial bee colony algorithm, this new algorithm uses the genetic hybrid genes and the chaotic-search strategy, and make the optima process convergence quickly and avoid get trapped in the local optima easily. This paper achieves the best design objective value base on the high reliability in the mechanical system with the parameterized virtual prototyping technology and the improved artificial bee colony. At last, paper proofs this method's effectiveness and practically through an engineering example.

1. Introduction

The mechanical optimization is the process of searching the optimal value of the mechanical parameters satisfying some certain constraints. With the performance of the institutions increasingly complex, the design requirements are more and more stringent. Especially to the mechanical system under the very important task, the reliability of the system is the factor that can't be ignored. Achieving the optima value of the mechanical's parameters with the constrains of high reliability is the development trends of the mechanical design, and it is also a strong demand for engineering. The mechanical reliability optimization, especially to the complex mechanical system, because of the system's strong nonlinear, is always very complex and costs too much time, so the choice of a good optimization algorithms is very meaningful. Different algorithms have different accuracy, feasibility and the time-costing. The optimization method applied in the field of structural optima mainly divide into three categories: subgradient optima algorithm, approximate optima algorithm and the binoic optima algorithm (Park et al., 2010). These algorithms have their own advantages and shortages, subgradient optima algorithm can coupled with CAE directly, but need accuracy math model and cost too much time (Dai et al., 2008); the approximate optima algorithm use low-order polynomial approximate the actual objective function and can improve the computational efficiency, but this algorithm is not accuracy enough in most cases (Qudjene et al., 2009); the binoic optima algorithms are very popular in recent years, and many optimization computation methods are studied: such as genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and these methods have been widely used. Motivated by the specific intelligent behaviors of honey bee swarms, Karaboga in 2005 proposed the artificial bee colony (ABC) algorithm to optimize multivariable and multimodal continuous functions (Karaboga et al., 2005, Karaboga et al., 2011). Kang use the ABC algorithm in parameters inversion of the concrete dam (Kang et al., 2009), Hu uses the ABC in solving the robot path planning (Hu et al., 2009), Sonmez use the ABC in truss optimization problem (Sonmez et al., 2011), and all these applications have good results. But the application of the ABC algorithm in the field of the mechanical reliability optimization is very less.

2. The theory of mechanisms' reliability

The mechanical reliability optimization has two meanings: the first is the optimization process with the objective of the reliability; and the second is the optimization process with the constraints of the reliability(Zhang Yimin,2010).The mechanical reliability optimization in this paper is the optimization process of the mechanical system's parameters based on the high reliability in the task execution process. The optimization model is:

$$\begin{aligned} \min f(x) \\ \text{s.t. } g_j(x) \geq 0 \quad j = 1, 2, \dots, m \end{aligned} \quad (1)$$

Where the x represents the design variables, m represents the number of the constrains. Generally, the objective function $f(x)$ and the constrain function $g_j(x)$ are related with the parameters. In the mechanical reliability optimization , the reliability is modeled with the Stress-Strength interference model: the reliability limit state function of the mechanical system $g(X)$ is built based on the system's motive performance. The state function can be defined by the function consisted of random variables X_1, X_2, \dots, X_n representing n random factors. The random variables $X = X_1, X_2, \dots, X_n$ are called as basic variables, if $g(X) > 0$, the mechanical system is reliability ,otherwise , it is failure. The mechanical reliability optimization models can be converted to:

$$\begin{aligned} \min \max f(x, p) \\ \text{s.t } \min g_j(x, p) \geq 0 \end{aligned} \quad (2)$$

In the mechanical reliability optimization, the optimization process is so called closet-state function problem because of the complexity of the mechanical system, and the reliability state function of the mechanical system can not be given directly. In this case, the general method is visible reliability function. This paper visible the closet-state function of the complex mechanical system with the method of the parameterized virtual prototyping technology and the second sequence response surface. Then builds the optimization model, and at last solves the optimization with the improved artificial bee colony algorithm proposed in the paper. The concrete steps are as follows:.

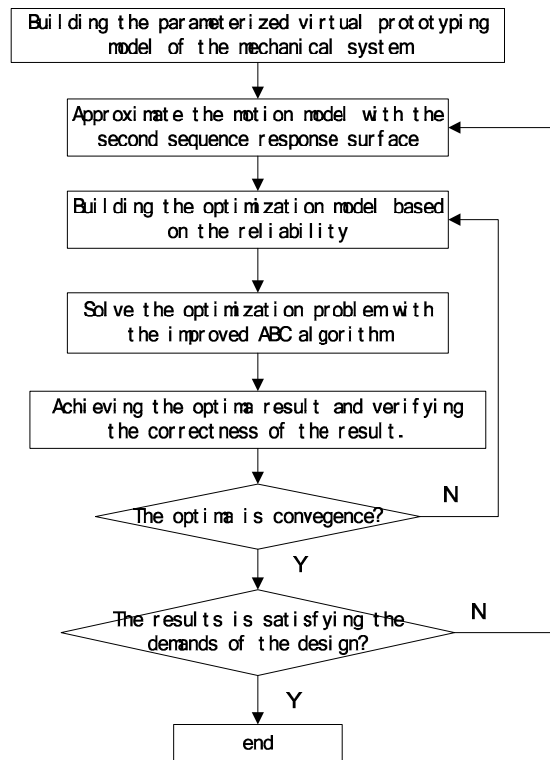


Figure 1:the flow diagram of reliability analysis based on the improved ABC algorithm

3. The improved artificial bee colony algorithm

3.1 The Standard artificial bee colony algorithm

The artificial bee colony(ABC) consists of three groups of bees: employed bees, onlookers and scouts. Half of the colony consists of employed bees, and the other half includes onlooker bees. Employed bees search the food around the food information to onlooker bees. Onlooker bees tend to select good food sources from those found by the employed bees, and then further search the food around the selected food source. Scouts abandon their food sources and search new ones.

In the ABC algorithm, the position of a food source represents a possible solution to the optimization problem, and the nectar amount of a food source corresponds to the profitability (fitness) of the associated solution. Each food source is exploited by only one employed bee. In other words, the number of employed bees is equal to the number of food sources existing around the hive (number of solutions in the population). The employed bee whose food source has been abandoned becomes a scout. An onlooker bee chooses a food source depending on the probability value P_i associated with that food source,

$$P_i = \text{Fitness}(f_{i,t}) / \sum_{1 < i < S} \text{Fitness}(f_{i,t}) \quad (3)$$

where $\text{Fitness}(f_{i,t})$ is the fitness value of solution i ; N is the number of food sources which is equal to the number of employed bees or onlooker bees. In order to produce a candidate food position $V_i = [v_{i,1}, v_{i,2}, \dots, v_{i,D}]$ from the old one $X_i = [x_{i,1}, x_{i,2}, \dots, x_{i,D}]$ in memory, the ABC uses the following expression:

$$v_{i,j} = x_{i,j} + \Phi_{i,j}(x_{i,j} - x_{k,j}) \quad (4)$$

where $k \in \{1, 2, \dots, S\}$ and $j \in \{1, 2, \dots, D\}$ are randomly chosen indexes; k is different from i ; D is the number of variables (problem dimension); $\Phi_{i,j}$ is a random number in the range $[-1, 1]$.

After each candidate source position is produced and evaluated by the artificial bee, its performance is compared with that of the old one. If the new food source has an equal or better quality than the old source, the old one is replaced by the new one. Otherwise, the old one is retained.

3.2 The improved artificial bee colony algorithm

In the ABC algorithm, in order to avoid trapped into the local optima, paper learn from the cross-portfolio and the variation in the genetic, the strongest individual fitness bee in the employed bee s is the queen bee, and its fitness is $g_i(x)$, and the onlooker bee is the drone bee. After the mating of the drone and the queen bee, it will generate a employed bee and a new drone. The stronger offspring bee will replace the parents bee, the drone colony and the employed bee colony get updated by the advantage selective. The update of the drone makes the solution convergence faster in global optimization process; and the updating of the employed bees makes the colony variable, and avoids premature convergence at the same time.

The drone colony, employed bee colony and the queen bee all have their fitness themselves. The drone colony are selected by the roulette, the individual has strong fitness would be selected in large probability, and it will mate with queen bee, transforming its genetic information to the next generation. The probability of the individual be selected is:

$$p_i = \frac{g_{m_i}(x)}{\sum_{i=1}^n g_{m_i}(x)} \quad (5)$$

where p_i is the probability, $g_{m_i}(x)$ denotes the fitness of the no. i drone.

According to the fitness mating probability P and the mating times c , the drone mating with the queen bee, the fitness mating probability is:

$$P_i = \frac{p_i \left(\sum_{i=1}^n g_{m_i}(x) \right)}{\sum_{i=1}^n g_{m_i}(x) + r_0} \quad (6)$$

Where r_0 is the minimum probability, the function of mating times is

$$c_i = L(1 - P_i) + a_0 \quad (7)$$

Where L is the length of the chromosome, a_0 is the minimum cross times.

The new employed bee colony is generated after the mating of the drone and the queen bee. The new and old employed bee colony is sorted, the strong fitness individuals are retained. So there will be a new employed bee colony. In the new employed bee colony, the employed bee with large fitness are selected to compare with the old queen bee, if the employed bee's fitness stronger than the old queen bee's fitness, it will replace the queen bee, otherwise, remain the queen bee.

The optimization of the queen bee is the critical of the whole paper. The queen bee needs to update itself through the optimization in the area, in order to avoid the best object escape. The traditional genetic algorithm costs a long time in the optimization searching, so this paper proposes a chaotic search in the optimization process. Chaotic search method has the performance of ergodicity, randomness and regularity, it could completed the local optimization efficiently. The process of chaotic search are :

1)Generating a d-dimensional initial random $M_0 = m_{0,1}, m_{0,2}, \dots, m_{0,d}$. $m_{0,k} \in (0,1)$ and the difference between the variables are small.

2)On the base of the initial vector M_0 , chaotic sequence $M_0, M_1, M_2, \dots, M_n$ is generated by the Logistics equation.

$$M_{i+1} = uM_i (1 - M_i), \text{ where } u \text{ is the control variable, and when } u = 4, \text{ it is complete coverage.}$$

3)Ergodic of the area belong to the queen bee Z_m with chaotic sequence and the equation, the better location queen bee area Z_m' will be found

$$Z_m' = Z_m + R \times rand() \times m_i, \text{ and } rand() \in \{-1, 1\}; t \in (1, n) \quad (8)$$

Where R was the radius of the queen bee area Z_m .

Contrasting the results of Matlab and the Adams, it shows that, the sensitivity of the small piston's length is the highest in Matlab result, and in the Adams, the effect of the mall piston's length is the largest, it denotes that the result is rational.

4. The engineering example

A transmitter consists with the components of a igniter, a gunpowder box, a launch base, four large pistons, four small pistons, four links, four mass blocks etc. The working principles are : first, the gunpowder is ignited and explodes. The explosion power generated by the gunpowder promotes the large pistons in the launch base instantly. The large piston promotes the small pistons through contact. At last, the small pistons promote the mass blocks by the links. The explosion power makes the four mass blocks have a very large initial velocity in the process. This paper have done some study on the motion reliability of the mass blocks' velocity in the defined explosion power force.

4.1 The reliability analysis and computation of the transmitter model

It is a closet-state reliability problem, in order to save the cost of the computation, paper use the Adams-Matlab platform to solve it. The random variables in the transmitter model are: driving force F, coefficient of friction u, the mass of the mass blocks m1, the mass of the large pistons m2, the mass of the small pistons m3, the length of the small piston l. the mean and variance of the random variables are in the table 1

It is considered that if the initial velocity of the mass blocks lower than the requirement, the mechanism is failed in its reliability analysis. And its limited state function is:

$$y = sim(m_1, m_2, m_3, F, \mu_1, \mu_2, l) - g \quad (9)$$

The variable g denotes the requirement velocity of the mass blocks, $sim(m_1, m_2, m_3, F, \mu_1, \mu_2, l)$ is the expression of its real velocity, and it is calculated by the Adams. This paper approximates the closet-state function with the method of the second sequence response surface. The approximate result is as in

Table 1: the mean and variance of the random variables

variable	mean	Variation coefficient	Distribution types
F	10000	0.5	Extreme value distribution
m1	0.93	0.01	Normal distribution
m2	0.031	0.01	Normal distribution
m3	0.076	0.01	Normal distribution
l	94	0.01	Normal distribution
u1	0.1	0.05	Normal distribution
u2	0.15	0.05	Normal distribution

Figure 2, and its approximate accuracy is 99.47%. In the process of solving, the paper simulates and calculates the reliability with the Monte-Carlo method and the Center-Normal Adaptive Importance Sampling method. The motion reliability and sensitivity of the transmitter simulated by the Matlab and the Adams are in the table 2.

Table 2: the simulation results by different algorithms

Simulation methods	The samples	reliability	CPU time (s)
Monte-Carlo	10000	0.9935	375.8
Center-Normal Adaptive Importance Sampling	14	0.9946	5.48

4.2 The mechanical reliability optimization

Based on the reliability analysis of the transmitter, we build the optimization model as follows. First identifying the optimization object function:

$$\min Z = \min l$$

Constraints

The range constraints of the variables

$$l \in [90, 100]; u_1 \in [0.09, 0.10]; u_2 \in [0.09, 0.10]$$

$$m_1 \in [0.83, 1.022]; m_2 \in [0.027, 0.034]; m_3 \in [0.068, 0.083]$$

$$F \in [90900, 100100]$$

The constraint of the reliability

$$P(\text{sim}(m_1, m_2, m_3, F, u_1, u_2, l) - g) \geq 0.9973 \quad (10)$$

The results of the optimization are as follows,

The best optimization result is: $l = 93.7959500018$.

And at this time, the reliability of the system is: $R = 0.99839$.

4.3 Result analysis

Compared with the ant colony algorithms, the improved artificial bee colony algorithm convergences more quickly in the optimization process. As showed in the Figure 3, in the same convergence condition, the improved ABC algorithm needs about 120 times, but the AC algorithm needs more than 250 times. The improved ABC is obviously better than the AC in the computation efficient. On the base of the compare of the improved ABC and the AC algorithms, the paper analyzed the optimization process with the standard artificial bee colony, the process trapped in the local optima, as in Figure 4. It proofs that the improved ABC algorithm has advantages in this case.

Then the paper compare the optimization based on the reliability with the optimization based no reliability. The optimization without the constrains of the reliability shows that the shorter of the length of the small pistons, the better of the mechanical system. The optima result is 90.05241, but calculates the reliability with this value, the reliability of the system is 0.9584, it obviously not satisfies the demands. The reliability calculated with optima results without the constrains of the reliability is as in Figure 5.

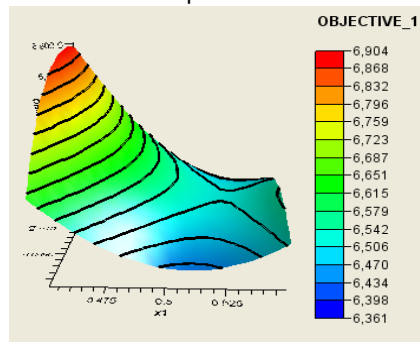


Figure 2 the result of the response surface

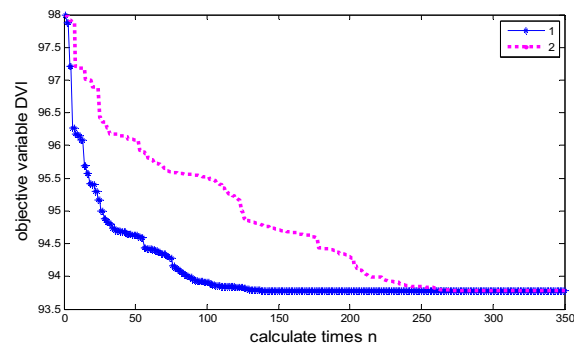


Figure 3 The calculate times of the improve ABC algorithm and the AC algorithm

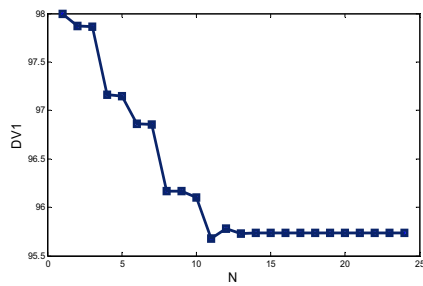


Figure .4 trapped in the local optima

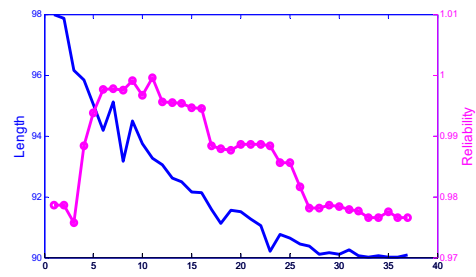


Figure .5 the reliability calculated by the results with the constrain of reliability

5. Conclusions

This paper proposes the mechanical reliability optimization, compared with the traditional mechanical optimization, this method can get the option value of the mechanical parameters as well as the high reliability of the performance. This is the development trend of the mechanical design, and is also a inevitable requirement.

In the process of the mechanical reliability optimization, this paper proposes an improved artificial bee colony algorithm, compared with the traditional artificial bee colony and the genetic algorithms, it has the advantages of the good convergence, stronger ability of global optimization, it can avoid getting in local optimization in the process of the complex mechanical system's reliability optimization. This method has a wide range of engineering significance not only significant savings in the cost of computing, but also can get a more accurate results.

References

- Dai L, Guan Z Q, Chen BS, et al. An Open Platform of Shape Design Optimization for Shell Structure[J].
- Hu Zhonghua, Zhao Ming, Research on Robot Path Planning Based on ABC Algorithm[J]. Electric Welding Machine, 2009, 39(4): 93-96.
- Karaboga D, Basturk D. On the Performance of Artificial Bee Colony(ABC) Algorithm[J]. Applied Soft Computing, 2008, 8(5): 687-697.
- Karaboga D, Akay B. A Modified Artificial Bee Colony(ABC) Algorithm for Constrained Optimization Problems[J]. Applied Soft Computing, 2011, 11(4): 3021-3031.
- Kang Fei, Li Junjie, Xu Qing, et al. Improved Artificial Bee Colony Algorithm and Its Application in Back Analysis[J]. Water Resources and Power, 2009, 27: 126-129.
- Park H S, Dang X P. Structural Optimization Based On CAD-CAE Integration and Metamodeling Techniques [J]. Computer-Aided Design, 2010, 42(1): 889-902.
- Qudjeme M, Ayed L B, Delameziere , et al. Shape Optimization of Clinching Tools Using the response Surface Methodology with Moving Least-square Approximation[J]. Journal of Materials Processing Technology, 2009, 208(1): 289-296.
- Sonmez M. Artificial Bee Colony Algorithm for Optimization of Truss Structures[J]. Applied Soft Computing, 2011, 11(1): 2406-2418.
- Structural and Multidisciplinary Optimization, 2008, 35(2): 609-622.
- Zhang Yimin. Connotation and Development of Mechanical Reliability-based Design[J]. JOURNAL OF MECHANICAL ENGINEERING, 2010, 46(14): 167-188.