A Compound Optimization Algorithm and its Application to Optimization of Automobile Gearbox

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Abstract
The elite multi-parent hybrid optimization algorithm is widely used to solve the optimization problem of complex function. However, it isn't good to keep the diversity of population in the search process. The artificial fish swarm algorithm (AFSA) has the advantages such as strong robustness, good global convergence and independent of initial value. But in general, the convergence is faster at the beginning of the algorithm and slower in the later, and it is hard to get the accurate optimal solutions. In this paper, the compound algorithm was proposed that combining the elite multi-parent hybrid optimization algorithm and AFSA. Firstly, the rough optimization is carried out by AFSA, and then the accurate optimization is implemented by the elite multi-parent hybrid optimization algorithm. The procedure as AFSEMEOA1.0 written in MATLAB is to optimum design of automobile gearbox. Optimization example shows that the algorithm has characteristics of no special requirements for the optimization design problem, better universality, and reliable operation, higher calculation efficiency and stronger global convergence ability.

Key words: Artificial Fish Swarm Algorithm, Elite Multi-Parent Evolutionary Optimization Algorithm, Gearbox Optimization, Hybrid Discrete Variable.

1. INTRODUCTION
Automobile gearbox is an important part of the automobile. In order to make automobiles with good dynamic performance, an ideal automobile gearbox should have the smallest volume, the lightest quality, the most saving material and the lowest cost under the condition of reliable work. At present, the lightweight has become important indicator checking advanced nature in the design to gearbox. It is the optimization design problem with hybrid discrete variable containing integer variables and discrete variables and continuous variables for the optimization design to the automobile gearbox, whose objective function often makes the quality minimum under the condition of guarantee the strength and the stiffness of parts (Luo and Liao, 2009) It is the most meaningful and but also more difficult in mathematical programming and operations research for discrete variable optimization (Wang and Gong, 2014). The traditional optimization methods such as continuous and differentiable have strong constraint for the objective function, and these methods have strong dependence on optimization problem. At the same time, the algorithm results are related to the selection of initial values and easily trapped in local minimum. In recent years, the booming evolutionary algorithm with the global optimality, parallelism and efficiency has been widely used in function optimization. With the help of the evolution of nature, the evolutionary algorithm overcoming the drawback of traditional numerical method as a global optimization method for multiple clues is based on the population and random search mechanism. It has been attracted widespread attention of evolutionary computation in the field of optimization application, and various forms of evolution algorithm emerge in endlessly. A new evolutionary algorithm based on group random search in the subspace search was proposed, and this algorithm is easy to implement. On the basis on the above algorithm, an elite-subspace evolutionary algorithm was presented by adopting the elite-preservation strategy (Luo, Che and Xiao, 2014). Constructing dynamic penalty function, the elite multi-parent hybrid optimization algorithm with hybrid discrete variable was developed for the engineering optimization design to the three-axis four-speed automobile gearbox (Che, Luo and Liu, 2014). The elite multi-parent hybrid optimization algorithm mainly for complex function optimization problems and the efficiency is better than other optimization algorithms. However, this algorithm consists of hybrid operation without mutation so as not to keep the diversity of population in the search process. If this is a great amount of calculation, the ability to find global optimal solution could be greatly reduced, and in the later stages of the algorithm the convergence speed is slow and easy to fall into local optimum. Artificial fish swarm algorithm (AFSA) has strong robustness, good global convergence, and independent on initial value (Chen, Liu, Huang and Fu, 2012; Gao, Wang, Li and...
ALGORITHM TO OPTIMIZE HYBRID DISCRETE VARIABLES

2. COMPOUND ALGORITHM BASED ON AFSA AND ELITE MULTI-PARENT OPTIMIZATION ALGORITHM TO OPTIMIZE HYBRID DISCRETE VARIABLES

2.1 Elite multi-parent hybrid optimization algorithm

The optimization problem is considered as:

$$\min f(x) \in \mathbb{R}^D = \{x \in S, x_1 \leq x_2 \leq \ldots \leq x_n, f(x) = 0, j = 1, 2, \ldots, p\}$$

where, \( S \subseteq \mathbb{R}^n \) is the search space, \( l_i \leq x_i \leq u_i (i = 1, 2, \ldots, n) \), \( f \) is the objective function, \( n \) is the number of variables, \( D \) is the set of feasible points, \( g_i \) is the constraint function and \( q \) is the number of constraints.

Supposed

$$H(x) = h(x) = \sum_{i=1}^{n} \mu(\varphi_i(x)) \delta(\Delta_i(x)) + \sum_{j=1}^{q} \mu(\varphi_j(x)) \delta(\mu_j(x))$$

where \( \varphi_i(x) = \max \{0, g_i(x)\} \), \( \varphi_j(x) = \mu_j(x) \), \( h \) is the punishment intensity, and the functions as \( \mu(\cdot), \delta(\cdot) \) are dependent on the specific issues (Luo and Liao, 2009).

\( a \) is a bigger positive number. The logic function is defined as follows (Luo and Liao, 2009 Luo, Che and Xiao, 2014; Luo, Che and Xiao, 2014):

$$\text{better}(x_i, x_j) = \begin{cases} \text{True}, & \text{if } H(x_i) < H(x_j) \\ \text{False}, & \text{if } H(x_i) > H(x_j) \\ \text{True}, & \text{if } (H(x_i) = H(x_j)) \land (f(x_i) \leq f(x_j)) \\ \text{False}, & \text{if } (H(x_i) = H(x_j)) \land (f(x_i) > f(x_j)) \end{cases}$$

If \( \text{better}(x_i, x_j) \) is true, \( x_i \) is better than \( x_j \), otherwise \( x_j \) is better than \( x_i \).

The calculation steps of the algorithm are as follows:

Step 1: Randomly generating the initial group \( P_0 = \{x_1, x_2, \ldots, x_N\} \) in the search space \( S \), where \( N \) is the number of the initial group and \( t = 0 \).

Step 2: Sorting the group \( P_t \) from good to bad according to \( \text{better}(x_i, x_j) \), it is still denoted to \( P_0 = \{x_1, x_2, \ldots, x_N\} \), where \( x_1 \) is the best individual and \( x_N \) is the worst.

Step 3: Switching to Step 5 when \( \text{better}(x_{\text{worst}}, x_{\text{best}}) \) is true, that is, the best individual is the same as the worst.

Step 4: Selecting \( K (K \leq M) \) best individuals of \( P_t \) as \( \{x_1, x_2, \ldots, x_K\} \) and randomly picking \( (M - K) \) individuals as \( \{x_{K+1}, x_{K+2}, \ldots, x_M\} \) from the remaining individuals, \( V = \{x | x \in S, x = \sum_{i=1}^{N} a_i x_i\} \) individuals form the subspace \( V = \{x | x \in S, x = \sum_{i=1}^{N} a_i x_i\} \) where \( \sum_{i=1}^{N} a_i = 1 \) and \(-0.5 \leq a_i \leq 1.5\). In the subspace, \( L \) points are randomly selected to get \( \text{better}(x, x_{\text{worst}}) \) new individuals where the best individual is denoted to \( \text{better}(x, x_{\text{worst}}) \). But as the complexity and scale of optimization problem expands unceasingly, AFSA also exists some deficiencies in the application. These deficiencies mainly manifested in the following four points: (1) If the optimization domain is large or changes gently, the optimization speed converge to global optimal solution will slow and the search performance will degenerate. (2) The converge speed is generally faster at the beginning of the optimization but often slower in the late. (3) In this algorithm, the accurate optimal solutions are hard to get, only is easier to find a satisfactory solution domain. (4) There is a great defect in computational complexity. Aiming at these deficiencies of AFSA, the compound algorithm was proposed that combining the elite multi-parent hybrid optimization algorithm and AFSA in this paper. Firstly the rough optimization is carried out by AFSA, and then the accurate optimization is implemented by the elite multi-parent hybrid optimization algorithm. The procedure as AFSEMEOA1.0 is written in Matlab. The optimization example for the three-axis four-speed automobile gearbox shows that the compound algorithm has characteristics of no special requirements for the optimization design problem, better practicability, reliable operation and stronger global convergence ability.
In Step 4, \( \kappa \) elite individuals of \( P \) become partial basis in the subspace \( V \) so as to make full use of the valuable information of the solutions to make the algorithm faster converge to the optimal solution. It is especially suitable for single-peak function optimization problems (Luo and Liao, 2009). Numerical experiments show that the elite preservation strategy can obtain significantly faster convergence. For \( K \), it is not the bigger for the better. In spite of the better use of solution information when \( K \) is bigger, the bigger \( K \) is, the smaller the DOF of the basis in the subspace \( K \) is. That is easy to make the solutions hovering in local area of the search space and trapping in the local optimal solutions for multimodal functions. The selection to \( K \) has a relationship with the value of \( M \). If \( M \) is bigger, \( K \) can be selected to the larger. \( L \) individuals in the subspace \( V \) are selected in order to more effectively use the information of the subspace. For the optimization problem, generally \( K = M / 2 \) or smaller, and \( L = M \) where \( M \) generally is selected (1-3) times of the variable number.

### 2.2 Artificial fish swarm algorithm

Artificial fish swarm algorithm (AFSA) is a common optimization model based on animal behavior, which simulates the feeding and survival activities of fish swarm to seek the global optimal solution in the space (Chen, Liu, Huang and Fu, 2012; Gao, Wang, Li and Hao, 2013; Li, Gao, Li and Hou, 2017; He, Qi, Jia, Ruan, 2016). In certain waters, the fish can generally find places that are rich in nutrients and gather in groups. In the process of this kind of group activities, there is no uniform coordinator, but it can be achieved through the adaptability behavior of each individual fish. There are can be summed up in three typical behaviors of fish life habits, this kind of group activities, there is no uniform coordinator, but it can be achieved through the adaptability behavior evaluation and collision behavior. AFSA adopts a bottom-up design method: Firstly the individual model of artificial fish is constructed, secondly the state of the optimal artificial fish individual is recorded by bulletin board to determine behavior evaluation method and termination conditions, thirdly individuals adaptively choose appropriate behavior in the optimization process, finally the global optimal result is presented through the group or an individual.

Set the current state of the artificial fish individual \( i \) as \( X_i = (x_{i1}, x_{i2}, \cdots, x_{in}) \), the food concentration on the location of fish swarm as \( Y = F(X) \) for the solving objective function, the distance between fish individuals as \( d_{ij} = \| X_i - X_j \| \), the sight range of fish individual as \( V \), crowding factor as \( \delta \), the movement length of the fish swarm as \( S \) and the times of repeated attempts in foraging behavior as \( \mu \). The behavior of artificial fish swarm is described as follows:

1. The foraging behavior is that the fish swims in the direction of the more food. Assuming that the artificial fish swarm \( X \) randomly selects a state \( X_i \) as Eq.(2) in the vision field \( V \) where \( d_{ij} < V \). If \( F(X_i) < F(X_j) \), according to Eq.(3) \( X \) makes a step forward in the direction of \( X_i \) to arrive in a new better state; otherwise, \( X \) continues to randomly select a state \( X_j \) within its vision field to judge whether meet the forward conditions. After repeatedly trying a few times, if a better state still isn’t found, \( X \) randomly moves a step and arrive a new state, where \( R_i \) and \( R_j \) are random numbers between 0 and 1.

\[
X_{i} = X_{i} + V_{i} \cdot R_{i}
\]

\[
X'_{i} = X_{i} + \frac{X_{i} - X'_{j}}{V_{i} - X} \cdot R_{i} \cdot S
\]

(2)

(3)

2. Bunching behavior is that every fish swims as far as possible to the center of the adjacent partners in the process of moving and avoids overcrowding. Assuming the number of partners of the artificial fish swarm \( X \) within its vision search field \( V \) as \( n_j \), the center position as \( X_c \), the food concentration on the center position as \( Y_c \), if \( Y_c / n_c > \delta Y \), the center position is better and not too crowded, and \( X \) moves a step in the direction of the center position of partners as shown in the following equation:

\[
X'_{i} = X_{i} + \frac{X_{i} - X'_{j}}{V_{i} - X} \cdot R_{i} \cdot S
\]

(4)

Otherwise, the foraging behavior is carried out where \( R_i \) is a random number between 0 and 1.

3. Collision behavior is that a fish chases the most active in the nearby. Assuming the biggest function value \( Y_j \) in the partners of the artificial fish swarm \( X \) within its vision search field \( V \) as the greatest partner \( X_j \), if \( Y_j / n_j > \delta Y \), \( X_j \) has the better food concentration and is not too crowded, and \( X \) moves a step in the direction of this position of partners, otherwise, the foraging behavior is carried out.
(4) Update the bulletin board. Bulletin board is used to record the condition of the optimal artificial fish individual. In the process of optimization, every artificial fish individual will verify own state $X_j$ and the state of the bulletin board $X_{best}$ after each action. If $R(X_i)<R(X_{best})$, its own status is superior to one of the bulletin board, and then $X_{best}$ is replaced by $X_j$.

(5) Random behavior. Artificial fish swarm random walk within its vision field without performing any other action.

The calculation steps of AFSA are as follows:

Step 1: Initializing the population size of artificial fish swarm $N$, the visible range $V$, the moving step length $S$, the crowded degree factor $\delta$, the maximum algorithm perform times $M$, the repeated attempt times in foraging behavior $N$. 

Step 2: Calculating the food concentration value $Y$ of each individual artificial fish in initial fish swarm at the current position and comparing their values. The maximum joins in the bulletin board and this individual is assigned to the bulletin board $Y_i$.

Step 3: Fish swarm are in a state of foraging behavior, collision behavior and bunching behavior.

Step 4: Calculating the objective function and choosing the optimal value. Every artificial fish individual will verify own value $Y$ and $Y_i$ in the bulletin board. If $Y$ is superior to $Y_i$, $Y$ replaces $Y_i$.

Step 5: Judging the termination condition of AFSA. It is determined whether a record on the bulletin board has reached the preset minimum food concentration. If it has reached, the output calculation result is output, i.e., bulletin board record; otherwise, the algorithm will skip to Step (3).

Step 6: Optimizing the termination conditions. If the judgment is equal to the preset, this algorithm is terminated; otherwise, the algorithm will skip to Step (3).

### 2.3 Engineering treatment method of design variables (Luo and Liao, 2009; Che, Luo and Liu, 2014)

1. Discretization of discrete design variables

In elite multi-parent hybrid algorithm, since the new updated individual is continuous variable, the variable should be discrete after each round of update operations. The discretization method for integer design variables is similar to one for non-equidistant discrete variable, but the difference is that the value space is nonnegative integers in the given upper and lower bounds.

2. Engineering treatment of continuous design variables

In engineering optimization design, although some design variables is continuous in the form, but its value is still under restrictions of machinery manufacturing precision and design specification. If in the optimization design the data are calculated according to floating-point number or double-precision real in the programming language and then in the decimal place is conducted in data processing according to practical requirements, the final design scheme may not be the optimal solution, and even may not satisfy the constraint conditions. Therefore, in the calculation process the result must be practice to a given decimal digits according to the requirements of practical engineering.

### 2.4 The compound algorithm based on AFSA and elite multi-parent hybrid optimization algorithm to optimize hybrid discrete variables

The calculation steps of the algorithm are as follows:

Step 1: Initializing each parameter and the termination accuracy $\varepsilon$, and generating the initial population $N$.

Step 2: Calculating the food concentration value $Y$ of each individual artificial fish in initial population $N$ at the current position and comparing their values. The maximum joins in the bulletin board and this individual is assigned to the bulletin board $Y_i$.

Step 3: Fish swarm are in a state of foraging behavior, collision behavior and bunching behavior.

Step 4: Calculating the objective function and choosing the optimal value. Every artificial fish individual will verify own value $Y$ and $Y_i$ in the bulletin board. If $Y$ is superior to $Y_i$, $Y$ replaces $Y_i$.

Step 5: Judging the termination condition of AFSA. It is determined whether a record on the bulletin board has reached the preset minimum food concentration. If it has reached, the algorithm will skip to Step (6); otherwise, the algorithm will skip to Step (3).

Step 6: For the optimized population $N$, sorting the population according to $\text{better}(x_i, x_{best})$ and determining the best individual $x_{best}$ and the worst $x_{worst}$.

Step 7: According to Step(4) in the elite more-paternal hybrid algorithm, generating new individuals.
Step 8: If $x_{worst}$ is superior to the worst individual $x_{worst}$ of the population, $x_{worst}$ will insert into the population. If $x_{worst}$ is better than the best individual $x_{best}$, $x_{worst}$ instead of $x_{best}$.

Step 9: Optimizing the termination conditions $|x_{best} - x_{worst}| \leq \varepsilon$. If the requirement is met, the optimal solution is obtained and the algorithm ends; otherwise, the algorithm will skip to Step (6).

The procedure AFSEMOA1.0 based on this algorithm was written in Matlab.

3. AUTOMOBILE GEARBOX OPTIMIZATION

The optimization mathematical model of Automobile gearbox is as follows (Luo and Liao, 2009):

$$F(x) = \frac{\pi b_{f}}{4} \left[ \sum_{j=1}^{n} \left( \frac{m_{ai}}{\cos \beta_{j}} \right)^{2} \left( z_{j}^{2} + z_{j}^{2} \right) \right]$$

Min S.t. $C = \left[ g_{1}, g_{2}, \ldots, g_{9} \right] \leq 0, \ C_{eq} = \left[ h_{1}, h_{2}, \ldots, h_{9} \right] = 0$

where, $x = [n_{1}, n_{2}, n_{3}, n_{4}, n_{5}, n_{6}, n_{7}, n_{8}, n_{9}, z_{1}, z_{2}, z_{3}, z_{4}, z_{5}, z_{6}, z_{7}, z_{8}, z_{9}, z_{10}]^{T}$

$$g_{1} = m_{a} z_{1} \sin \beta_{1} - m_{a} z_{3} \sin \beta_{2} - 100 \leq 0$$
$$g_{2} = m_{a} z_{2} \sin \beta_{2} - m_{a} z_{4} \sin \beta_{3} - 100 \leq 0$$
$$g_{3} = m_{a} z_{1} \sin \beta_{3} - m_{a} z_{5} \sin \beta_{4} - 100 \leq 0$$
$$g_{4} = m_{a} z_{2} \sin \beta_{4} - m_{a} z_{6} \sin \beta_{5} - 100 \leq 0$$
$$g_{5} = m_{a} z_{1} \sin \beta_{5} - m_{a} z_{7} \sin \beta_{6} - 100 \leq 0$$
$$g_{6} = m_{a} z_{2} \sin \beta_{6} - m_{a} z_{8} \sin \beta_{7} - 100 \leq 0$$
$$g_{7} = k_{2}^{2} \frac{T_{max} i_{g} \eta_{g}}{2 \cos \beta_{1}} - m_{a} \left( z_{1} + z_{2} \right) \leq 0$$
$$g_{8} = -k_{2}^{2} \frac{T_{max} i_{g} \eta_{g}}{2 \cos \beta_{1}} + m_{a} \left( z_{1} + z_{2} \right) \leq 0$$
$$g_{9} = k_{3}^{2} \frac{T_{max} i_{g} \eta_{g}}{2 \cos \beta_{3}} - m_{a} \left( z_{5} + z_{6} \right) \leq 0$$
$$g_{10} = -k_{3}^{2} \frac{T_{max} i_{g} \eta_{g}}{2 \cos \beta_{3}} + m_{a} \left( z_{5} + z_{6} \right) \leq 0$$
$$g_{11} = k_{4}^{2} \frac{T_{max} i_{g} \eta_{g}}{2 \cos \beta_{4}} - m_{a} \left( z_{7} + z_{8} \right) \leq 0$$
$$g_{12} = -k_{4}^{2} \frac{T_{max} i_{g} \eta_{g}}{2 \cos \beta_{4}} + m_{a} \left( z_{7} + z_{8} \right) \leq 0$$
$$g_{13} = k_{5}^{2} \frac{T_{max} i_{g} \eta_{g}}{2 \cos \beta_{5}} - m_{a} \left( z_{9} + z_{10} \right) \leq 0$$
$$g_{14} = -k_{5}^{2} \frac{T_{max} i_{g} \eta_{g}}{2 \cos \beta_{5}} + m_{a} \left( z_{9} + z_{10} \right) \leq 0$$
$$g_{15} = G_{f} \left[ \cos \alpha_{max} + \sin \alpha_{max} \right] r_{c} - i_{1} \leq 0$$

$$g_{16} = -i_{1} - \frac{F \cdot r_{c} \cdot r_{e}}{T_{max} i_{g} \eta_{g} r_{e}} \leq 0$$
$$g_{17} = i_{1} - 1.8 i_{2} \leq 0$$
$$g_{18} = i_{2}^{2} - i_{1} i_{3} \leq 0$$
$$g_{19} = 1.5 i_{3} - i_{2} \leq 0$$
$$g_{20} = 1.5 i_{2} - i_{1} \leq 0$$
$$g_{21} = 12 - z_{8} \leq 0$$
$$g_{22} = z_{8} - 17 \leq 0$$
practicability, reliable operation and stronger global convergence ability.

discriminate the compound algorithm based on AFSA and elite multi

variables and accurate to two decimal places, transmission ratio

Note:

The axial overlapping coefficient constraints

Table 1. Optimum results

<table>
<thead>
<tr>
<th>Design variables</th>
<th>Solutions before optimization (Liu, and Cui, 2004)</th>
<th>Solutions after optimization (Liu, and Cui, 2004)</th>
<th>Solutions (Luo and Liao,2009)</th>
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Notes: The axial overlapping coefficient constraints are not considered, and the parameters before optimization do not meet some constraints. All constraints are considered.
4. CONCLUSIONS

(1) The compound algorithm was proposed that combining the elite multi-parent hybrid optimization algorithm and AFSA. Firstly, the rough optimization is carried out by AFSA, and then the accurate optimization is implemented by the elite multi-parent hybrid optimization algorithm.

(2) The calculation steps are given, and the procedure AFSEMEOA1.0 was written in MATLAB to optimum design of automobile gearbox.

(3) The procedure reasonably deals with the value problem of hybrid discrete variables in optimization design. The proposed algorithm has characteristics of no special requirements for the optimization design problem, better universality, reliable operation, stronger global convergence ability, convenient and effective for optimization and robust design problem with hybrid discrete variables.

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